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Quantitative assessment of 3D foot shape using statistical shape analysis

Kwantitatieve beoordeling van de 3D-voetvorm via statistische vormanalyse

Proefschrift voorgelegd tot het behalen van de graad van

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aan de Universiteit Antwerpen, te verdedigen door

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"To study the abnormal is the best way of understanding the normal."

WILLIAM JAMES

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It's been six and a half years since my very first day at Vision Lab. What an unforgettable and exciting experience this was.

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This thesis would not be a thesis without some words in my mother tongue, so I will switch to it now. Најпре, хвала свим пријатељима који су ме подржали на овом нимало лаганом путу и који су увек радо слушали моје муке током овог дугог периода, нарочито женама из средње, а посебно мојој куми Дари, као и мојим јахачима апокалипсе са факса. Посебно хвала мојим родитељима, захваљујући чијој животној филозофији увек тежим вишим циљевима. Мислим да не могу правим речима довољно описати захвалност мојим "селицама" које су ме увек подржавале, бодриле, охрабривале и веровале у мене када вероватно ни сама нисам. Желим да захвалим мом мужу Милошу, који је пристао да буде мој сапутник на овом сулудом путовању, који вероватно једини изистински зна борбу коју смо истрпели, али коју смо заједничким снагама издржали. Хвала за сву помоћ, подршку и стрпљење, никад ти то нећу заборавити! За крај, хвала мојој ћерки Лари за веру и снагу коју сам добила твојим рођењем, за истрајност и наду да је све могуће иако не изгледа тако.

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Contents

Summary

A human foot has a complex geometry which results in a variation in shape. For the creating and validating shoe and orthotic designs, a quantitative description of the foot shape is of particular use. These designs are usually based on simplified representations of the human foot, often through 1D measurements. However, the inconsistency and incompleteness in these measurements led to the need for the analysis of higher dimensional (2D and 3D) foot shape representations. Although the analysis of 2D footprints provides a quantitative description of foot shape, it lacks information along the vertical dimension. In addition to foot shape measurements, the identification of abnormal foot shape regions is an area of open research. Typically, an experienced professional is required to assess foot shape anomalies. The automation of this foot assessment would be desirable to both reduce the barriers to foot shape assessment, and to eliminate subjectivity introduced through human influence during the assessment. These observations suggest that an automatic and a quantitative description of the entire 3D foot shape is needed. Moreover, the analysis of foot shape on a population level, such as normal feet, would be beneficial in terms of comparing an individual foot shape to this normative population to examine the shape differences.

In this research, the focus is on the automated assessment of 3D foot shape as represented by a high-resolution triangular mesh. A population of these shapes could be quantitatively described through statistical shape analysis. This analysis provides a statistical shape model (SSM) that consists of the average 3D foot shape of the population and the main shape variations present in the population. Such an SSM could then be used to identify foot shape abnormalities. These techniques can then serve as a possible response to current challenges. This thesis presents the main challenges present in the field of foot assessment along with the proposed SSM approaches to address them.

In Chapter 2 of this thesis, an overview of the literature on foot assessment is provided. Usually, it is not clear which measurements to collect and which technique to apply to fully assess foot shape. We analyzed available literature to highlight the advantages and the limitations of various measurements used for foot assessment. Additionally, we describe the available techniques for foot shape analysis. We further discuss how these techniques are applied for footwear and orthotic applications and suggest techniques available from other fields. Most notably, we found promising results in the studies that analyze 3D foot shape. These valuable results should be further explored to resolve the current needs and challenges in the field of foot assessment.

Chapter 3 introduces a method for quantitative and automatic description of 3D normal foot shapes. The main motivation for this study is the huge variety of shapes present in normal foot shape. The insights into how the foot shape differs between subjects that have normal foot shape could be beneficial for shoe and orthotic designers. To address this challenge, we propose a technique that describes a population of 3D foot shapes based on statistical shape analysis. To apply the statistical analysis we need to register the meshes. First, we present the technique for foot shape registration. This is achieved through anatomical and spatial alignment of the foot shapes. During the anatomical alignment we transform the vertices of a mesh to establish the correspondence, while during the spatial alignment the meshes are overlapped and transformed spatially. Then, the population of foot shapes is described through the average foot shape and main shape variations. Furthermore, we examine how the normal foot shape is influenced by some additional personal characteristics, such as age and sex. These insights may be useful for product designers to improve the quality of shoe fit.

In Chapter 4, we expand on the methods from the previous chapter. Here, we introduce a technique that explains the variations present in a normative population of feet and estimates the normal foot shape based on personal characteristics. This method is used to detect significant 3D shape anomalies on the foot. The foot shape is usually examined for abnormalities purely visually by foot professionals. This approach lacks the objectivity that is indispensable for reliable identification of foot abnormalities. We attempt to objectify the abnormality detection of foot shape by introducing a statistical analysis that compares the test foot to a normative foot population. The outcome of this approach is that detected regions of abnormal foot shape are highlighted. Specifically, the proposed technique explains what part of the foot is abnormal and to what extent that is the case. The proposed technique could be beneficial to foot assessment since it allows comparison between an individual's foot shape and a normative population, resulting in a regional mapping of foot abnormalities while eliminating the subjectivity present in visual foot assessment.

Finally, in the last part of this thesis, we draw conclusions and discuss future work along with possible improvements in foot shape assessment. Here, we consider additional improvements in foot assessment by involving shape analysis based on non-linear approaches. In addition, we investigate the possibilities for dynamic 3D foot measurements. We also discuss the possibilities to employ cheaper measurement equipment that would hopefully generate measurements with similar properties as the ones obtained using high-resolution equipment. Such a novel equipment would make the automatic 3D foot assessment more affordable for broad use.

Samenvatting

Een menselijke voet heeft een complexe anatomie die resulteert in een enorme hoeveelheid vormvariaties. Een kwantitatieve beschrijving van de voetvorm is nuttig voor fabrikanten van schoenen en orthesen, voor het genereren en valideren van hun ontwerpen. Deze ontwerpen zijn meestal gebaseerd op een vereenvoudigde weergave van de menselijke voet, afgeleid van 1D-metingen of 2D-voetafdrukken. De analyse van een dergelijke weergave van de voetvorm mist echter de informatie langs de verticale dimensie. Bovendien zou de identificatie van abnormale gebieden op basis van 1D of 2D metingen van de voetvorm onvolledig zijn. In dit onderzoek ligt de focus op de 3D-voetvorm, weergegeven door een maas van driehoeken van hoge resolutie. Als er een populatie van 3D-voetvormen beschikbaar is, kan een statistisch vormmodel (SSM) worden gebouwd. Dit model bestaat uit de gemiddelde 3D-voetvorm van de populatie en de belangrijkste vormvariaties die in de populatie aanwezig zijn. Een dergelijk model kan de populatie van voetvormen kwantitatief beschrijven.

Dit proefschrift bestaat uit drie delen. Deel I is de inleiding van dit proefschrift. Eerst wordt de anatomie en vormvariatie van de voet geïntroduceerd. Vervolgens bespreken we de belangrijkste uitdagingen op het gebied van voetbeoordeling. Een voetvorm wordt meestal geanalyseerd door middel van enkele numerieke metingen. De inconsistentie in deze metingen noodzaakt echter een analyse van hoger dimensionale voetrepresentaties, zoals 2D en 3D. Bovendien is de automatisering van de voetbeoordeling wenselijk om subjectiviteit te elimineren die door menselijke invloed tijdens de beoordeling wordt geïntroduceerd. Bovenstaande uitdagingen suggereren dat een automatische en kwantitatieve beschrijving van de gehele voetvorm noodzakelijk is. Bovendien zou de analyse van de voetvorm op populatieniveau, zoals gezonde voeten, gunstig zijn voor het vergelijken van een individuele voetvorm met deze normatieve populatie, om de vormverschillen in kaart te brengen. Verder beschrijven we de mogelijke benaderingen om deze uitdagingen aan te pakken. Tot slot geven we een overzicht van de thesisbijdragen.

Deel II bestaat uit de drie bijdragen. In hoofdstuk 2 wordt een overzicht gegeven van de literatuur over voetonderzoek. Vaak is het onduidelijk welke metingen moeten worden verzameld en welke techniek moet worden toegepast om de voetvorm volledig te beoordelen. Via literatuuronderzoek hebben we de voor- en nadelen van verschillende voetbeoordelingsmethoden, opgelijst. Daarnaast beschrijven we de beschikbare technieken voor voetvormanalyse. Verder bespreken we hoe deze technieken worden toegepast voor schoenen en orthesen.

Hoofdstuk 3 introduceert een methode voor kwantitatieve en automatische beschrijving van gezonde 3D voetvormen. De belangrijkste motivatie voor dit onderzoek is de enorme verscheidenheid aan vormen binnen een populatie van gezonde voeten. De inzichten in hoe de gezonde voetvorm verschilt tussen gezonde proefpersonen kan van nut zijn voor schoen- en orthesenontwerpers. Hiertoe, hebben we een techniek voorgesteld die een populatie van 3D-voetvormen beschrijft op basis van statistische vormmodelering. Eerst presenteren we de techniek voor voetvormregistratie op basis van anatomische en ruimtelijke uitlijning van de voetvormen. Vervolgens wordt de populatie voetvormen beschreven door middel van de gemiddelde voetvorm en hoofdvormvariaties. Verder hebben we ook onderzocht hoe de gezonde voetvorm wordt beïnvloed door persoonlijke kenmerken, zoals leeftijd en geslacht.

In hoofdstuk 4 breiden we de methode uit het vorige hoofdstuk uit. Hier introduceren we een methode die niet alleen de variaties in een gezonde voetpopulatie verklaart, maar ook de gezonde vorm schat op basis van persoonlijke kenmerken. Deze methode wordt gebruikt om significante vormafwijkingen op 3D-voetvormen te detecteren. De voetvorm wordt meestal puur visueel onderzocht door voetprofessionals. Deze benadering mist echter objectiviteit die cruciaal is voor een betrouwbare identificatie van voetafwijkingen. We proberen de detectie van afwijkingen van de voetvorm te objectiveren door een statistische analyse te introduceren die de testvoet vergelijkt met een gezonde voetpopulatie. De resultaten van deze aanpak zijn de gedetecteerde afwijkingen die op de voetvorm zijn gemarkeerd. Via de voorgestelde techniek kan ook aangeduid worden welk deel van de voet abnormaal is en in welke mate dat het geval is. Hierdoor kan een testvoet objectief vergeleken worden met een normatieve populatie, en een ruimtelijke map van de voetafwijkingen verschaft worden.

We bespreken toekomstig werk en mogelijke verbeteringen in voetonderzoek in deel III. Hier beschouwen we aanvullende verbeteringen in voetbeoordeling via vormanalyse op basis van niet-lineaire benaderingen. Daarnaast onderzoeken we de mogelijkheden voor dynamische 3D voetmetingen. Verder bespreken we de mogelijkheden om goedkopere meetapparatuur te gebruiken, die nog steeds metingen zou opleveren met vergelijkbare eigenschappen als die verkregen met behulp van apparatuur met een hoge resolutie. Deze nieuwe apparatuur zou de automatische 3D-voetbeoordeling betaalbaarder maken voor breed gebruik. Ten slotte wordt het proefschrift afgesloten met het curriculum vitae van de auteur, evenals de lijst van publicaties die aan dit proefschrift zijn voorafgegaan.

List of Abbreviations

2D	Two dimensional
3D	Three dimensional
4D	Four dimensional
ADA	Archetypoid analysis
ANOVA	Analysis Of Variance
BMI	Body Mass Index
DNA	Deoxyribonucleic acid
FDR	False Discovery Rate
HAA	hallux abductus angle
MLR	Multiple Linear Regression
MSE	Mean Squared Error
PCA	Principal Component Analysis
PC	Principal Component
SSM	Statistical Shape Model

Part I

Introduction

1.1 Background

An average person spends around 10% of their lifetime on their feet, standing, walking, or running. Moreover, feet are the foundation of the human body, which suggests that healthy feet can improve overall body health. From an anatomical point of view, each foot is made up of 28 bones, 30 joints, and more than 100 muscles, tendons, and ligaments, all of which work together to provide support, balance, and mobility. A solid understanding of anatomy along with the basic understanding of the foot biomechanics are essential to effectively diagnose and treat patients with foot and ankle problems. In such a case, a gait analysis combined with 3D foot shape analysis would at least assist in diagnosis. Anatomical structures (tendons, bones, joints, etc) tend to hurt exactly where they are injured or inflamed. These injuries are commonly followed by swelling of the foot, in this way changing the foot shape. The main point is that some anatomical information can be obtained from a static 3D foot shape. Some of the anatomical structures in the foot are fairly superficial and can be easily palpated. Good examples for this are the lateral malleolus and medial malleolus. The information about these anatomical elements is usually salient from the external foot shape and commonly used in the clinical environment when examining the foot (e.g. foot posture index [35] . Another example is a hallux valgus, a foot anomaly represented by a deformation at the joint between the hallux and the first metatarsal [16]. This too is easily noticeable from external foot shape. Moreover, foot function is related to foot anthropometrics which are a subset of the 3D foot shape information [29]. The above examples highlight that there is a link between underlying anatomy and the external 3D foot shape. They also emphasize the importance of assessing the foot surface and suggest that the objective assessment of the entire foot geometry is valuable. Yet, an expert with anatomical knowledge would be required in the process of interpreting the findings of such an algorithm. Such a complex inner structures of the foot, gathered in a small space of the human body, cause a huge variation in geometric features of the foot.

The variability of a foot shape is frequently discarded as people tend to describe the foot shape by identifying common shape characteristics. As widely known, and sometimes still used in practice, the 'simplest' way of ancestry determination, without performing DNA analysis, is based on the foot shape. Basically, foot ancestry is based on five foot types: Egyptian, Roman, Greek, German, and Celtic (Figure 1.1). Each foot type has a unique design, represented through foot outline and the toe lengths particular for each foot type. Although it is possible to categorize the feet according to these characteristics, there is no scientific proof that ancestry determines the shape of the foot. Over centuries, these ancient foot types were mixed through the generations which results in a wide variety of foot shapes being present nowadays [31]. Another approach that describes foot shape based on common shape characteristics relies on arch height. Commonly, foot arch is categorized in three distinctive groups pes cavus (high arch), pes planus (low arch), and a normal arch. Although, these approaches identify common shape characteristics they neglect individual shape characteristics.

Historically, the foot has had a crucial role as a unit measure since ancient times. The human body has been used to provide the basis for units of length. The foot has found its place within land measurements, among the other parts of the body, such as a thumb and a palm. The first attempt to standardize the unit of land measurement defined as 16 feet long, the rod, was done by the mathematician Jakob Köbel in the 16th century. The question of whose feet should be used was solved by picking

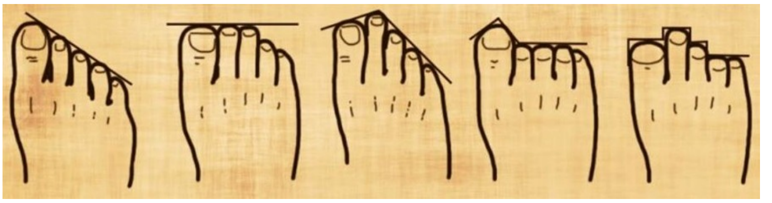

Figure 1.1: **Foot ancestry.** Foot types left to right: Egyptian, Roman, Greek, German, Celtic. [source]

16 individuals and lining them up toe to heel to define the official length of a rod. Interestingly enough, the identity of these individuals was not discarded. Moreover, the individuals' identities were the key to the legitimacy of the rod. In this period of history the notion of the average foot length, in which the unique characteristics of any particular foot were discarded, was still far from being recognized.

The human foot along with its unique shape characteristics has been anatomically formed through evolution. At first, the foot was adapted to barefoot walking on natural substrates, long before footwear was invented. However, the regular use of footwear through centuries affected the foot shape. It has been shown that different environmental and everyday habits such as shoe wearing habits and frequency of sports activity influence the foot shape [2, 13]. In addition, some personalized characteristics such as sex, age, and genetics have been shown to have a significant influence on adult foot shape [24, 26, 40, 41, 44]. Due to the large variability of geometrical features of a foot and different influences that affect foot shape, its assessment has been subject of study through the decades.

1.2 Research Motivation

The foot shape has an important role in several disciplines, including orthopedics, orthotic design, footwear, podiatry, rehabilitation, and sport sciences [2, 13, 20, 22, 24, 26, 27, 41, 44]. Everyday footwear use also emphasized the necessity of comprehensive foot shape assessment. The main challenge of foot assessment is to describe the full range of foot shape variations and to consider all the factors that contribute to its variation. Having the full range of geometric foot features could lead to a well-fitted shoe design and the increase of comfort. Yet, the methodology for foot shape assessment is outdated compared to research fields that study other parts of the human body. It has been shown that wearing uncomfortable shoes, which do not provide the right support, leads to foot pain and causes a variety of foot disorders studied in different fields such as orthopedics, podiatry and rehabilitation [11, 12]. The methodology that provide insights into how a 3D foot's shape deviates from the normal foot shape could be significant for these fields. It could also be beneficial for the diagnosis, treatment, and prevention of the foot injuries such as plantar fasciitis (heel pain), metatarsalgia (painful and inflamed ball of the foot), and pathologies such as pes cavus (high foot arch), pes planus (low foot arch), and hallux valgus (first toe deviation from its axial position) (Figure 1.2). Finally, an advanced foot assessment system which quantitatively and automatically explains how foot shape varies between individuals would be valuable for the design of the insoles and custom-built shoes.

Figure 1.2: **Foot disorders.** Some foot injuries and pathologies along with the location of their appearance on foot (light red), left to right: hallux valgus, flat foot (pes planus), metatarsalgia

Traditional procedures for foot assessment rely on distinctive measurements of foot shape and analyze foot shape through single numerical measurements such as lengths, widths, angles, girths, heights, and circumferences [3, 7, 9, 18, 32, 36, 37, 39, 43](Figure 1.4a). These measurements are obtained by a trained professional using conventional measurement equipment such as a tape, sliding caliper, and Brannock device (Figure 1.3). The inconsistency in the selection of these measurements highlighted the necessity of capturing the more relevant information at once, such as 2D footprints. The reason for the ubiquitous use of footprints is that they can be relatively easily obtained, measured, and preserved by using wax, plaster, foam, or dynamic pressure plates [1, 5, 14, 42] (Figure 1.3). Despite the potential loss of information along the vertical dimension, 2D footprints have been used to quantitatively categorize various foot typologies [27, 34, 46]. The foot dynamics, captured in the plantar pressure images, have also proved to be important for foot assessment[14]. For example, the study of Boot et al. [4] suggested the outlier detection approach applied to plantar pressure videos may ultimately improve the ability to diagnose foot complaints. However, it has been demonstrated that there is significant additional information in 3D shape compared to 2D footprints [25]. Nevertheless, the 3D foot shape could not be fully recovered from lower-dimensional foot measurements [45].

Figure 1.3: **Some measurement equipment used to evaluate foot shape.** From left to right: Brannock device, plantar pressure plate, 3D laser scanner.

The selection of the foot measurements is coupled with the techniques for foot assessment. Typically, the less detailed the measurement is (such as 1D foot dimension), the simpler the analysis techniques. Some advanced methods have been developed to assess foot shape. Traditionally, the straightforward methods quantify foot shape using the classification techniques. Such methods categorize the foot shape into pre-defined groups based on characteristics such as arch height and hallux angle [10, 16, 35]. These approaches rely on a pure visual appraisal of the examiner, which was shown to be subjective and which varied between examiners [23]. In addition, there are not many studies that classify feet based on arch from the entire 3D foot shape, possibly due to lack of comprehensive analysis techniques. In recent years, there has been an attempt to assess the foot shape through objective methodology that analyzes single foot measurements and 2D footprints (Figure 1.4b) using statistical analysis [6, 8]. Despite the objective methods that describe foot geometry, these approaches do not involve the analysis of the whole 3D foot shape (Figure 1.4c), with the 3D aspect being important for the design of footwear [17, 27, 28, 30]. The knowledge gap present in the field can be summarized as following:

- The incompleteness in the selection of the measurements to capture the salient 3D foot geometry,
- The lack of quantification techniques for the 3D shape variations present in population of feet, and
- A lack of framework for the statistical analysis of the 3D foot shape on a subject level.

The above limitations have exposed methodological challenges in the quantitative description of the complex geometry of foot shape:

- Developing a procedure to statistically describe the 3D foot shape of a normal population.
- Providing the methodology to examine the variety of factors that influence the 3D geometry of foot shape.
- Providing a novel technique that identifies and highlights, in 3D, the regions of the foot which significantly deviate from the normal foot.

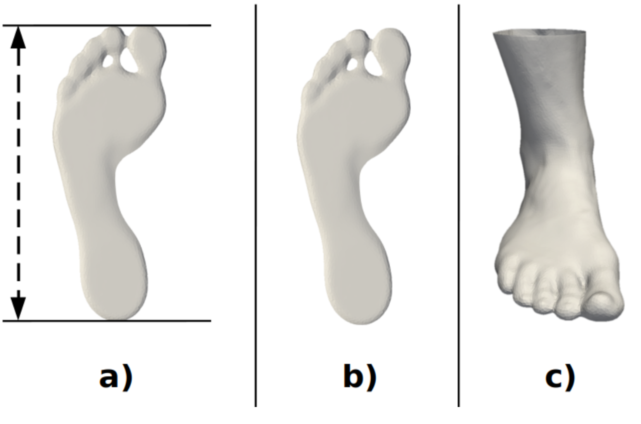

Figure 1.4: **Example of different approaches for measuring the foot shape.** (a) A single measurement of foot shape represented as length, width or similar; (b) A 2D measurement of foot shape represented as a footprint; (c) A 3D foot shape represented as a mesh.

1.3 Research Approach

The overarching objective for this research is to develop methodology for the statistical analysis of 3D foot shape. This research was focused on the methodology to automate and objectify foot assessment of a normal foot shape, as well as the foot with disorders. First, we discuss the available techniques applied in the field, along with the measurement types employed in these techniques. Then, we give a methodology that examines the variations of a population of normal foot shapes, based on SSM. This technique is further extended to the identification of abnormal regions of foot shape.

For the purpose of this study, a set of 3D foot shapes was collected. The participants were recruited completely voluntarily in RS Lab runners' shoe stores in Zwijndrecht and Paal-Beringen, Belgium. A 3D scan of the external foot surface was collected along with 2D plantar pressure images. In addition, the participant's age, height, weight, sex, amount of physical activity (in hours per week), and foot loading (half and full loading) were also recorded.

For this research, we defined a set of normal foot shapes to serve as a baseline for subsequent modeling and experiments. The feet of each individual were 3D scanned by trained physical therapists. These feet had never been diagnosed with foot pathology or injury requiring medical intervention, had no foot complaints (i.e. no foot pain), and no incidental findings were found at the time of data collection, as evaluated by a physical therapist [FOOTWORK]. For some experiments, we also constrained arch height to fall within a normal range. These criteria were chosen with the aim of validating different aspects of the methodology.

As a consequence of the whole data collection procedure, our analysis can have several potential limitations:

- We considered only a limited subset of feet as our normal feet population, which limits the effect sizes we can observe.

- During the recruitment, not all potentially useful information was collected, the result of which may impact the interpretation of our experimental results. For example, the amount of physical activity a participant performs was recorded but the type and intensity of the activity were not.

- As the participants were recruited in running shoe stores, there could be a bias within our cohort towards the people who regularly run.

- Some healthy feet are left out of the normal population due to different reasons such as our strict limits on arch height, incomplete 3D scans, or noisy data. Therefore, the recruited cohort might not be indicative of the general population.

However, the selection of such a population is sufficient to perform a proof-of-concept of the methodology presented in this thesis.

In addition to the above normal population, individuals with common foot disorders (such as hallux valgus, metatarsalgia, plantar fasciitis) were also recruited and had their data collected. This population of foot shapes has been used in Section 4 for the testing purposes and will be described further there.

The main contributions of this research are focused on the methodology development for analysis of static 3D foot shape.

1.3.1 Foot shape data collection and analysis techniques: a review

Quantitative description of foot shape is an important task for a number of different applications related to the ergonomic design of footwear and foot orthotics. In the past, numerous measurement procedures have been developed to assess foot shape. Many of them involve measurements of single foot characteristics such as foot width or arch height. In recent years, an increasing number of studies has been focused on the measurements which capture more foot characteristics at once, particularly 2D footprints and 3D shape. This advancement was enabled by the recent improvements of measurement equipment such as 2D imaging systems and 3D scanners. Although, there are numerous measurement procedures, new measurement equipment, and a variety of analysis techniques applied to describe the foot shape, a review of the above is still missing in this field.

Motivation for the study

Normally, it is not clear which foot measurements should be collected to fully assess foot shape. In addition, there are various techniques for foot assessment applied for different applications in the fields of orthotic and footwear design. These techniques are not standardized in terms of use for multiple applications. In addition, foot assessment techniques inevitably depend on the measurement type. Ideally, there are several aspects that should be determined prior to the foot assessment such as (i) choice of the foot characteristics to include in the study; (ii) level of automation; and (iii) choice of analysis techniques.

High level of the approach

We used the PRISMA review protocol [PRISMA] to select the relevant literature for a review of foot shape assessment techniques. The PRISMA protocol is divided into four main steps: study identification, study screening, study eligibility, and study inclusion (summarized in Fig. 1.5).

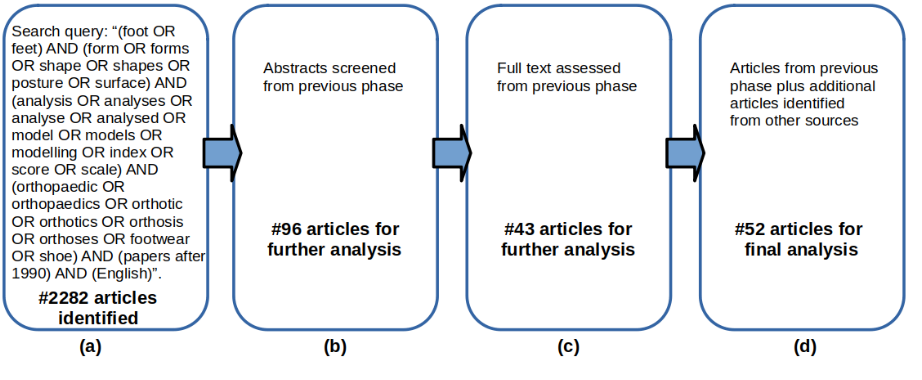

Figure 1.5: **Four steps of PRISMA review protocol.** (a) Study identification; (b) Study screening; (c) Study eligibility; (d) Study inclusion.

In the first phase of the protocol, we performed the initial literature search where the criteria were the studies that analyze the adult foot shape in orthopedic and footwear applications. In the second phase of the protocol, we reviewed all abstracts of the articles identified in the previous phase. Numerous articles are discarded in this phase as they were not related to foot shape (e.g. gait analysis), not related to the whole foot (e.g. the analysis of specific bones), or outside of the adult range (18+ years old) of this study. In the third phase, the full-text articles extracted from the screening phase were read. Only the articles whose main study is foot shape analysis have been used for further analysis. In the last phase, we have analyzed the selected articles from the previous phase and the articles meeting the criteria identified from other sources.

Summary of Results

We identified several parameters to be considered when assessing the foot shape: the choice of measurements, the level of automation, and the analysis techniques used. Three main approaches were identified when it comes to measurement choice: purely qualitative (e.g. visual assessment of foot posture), anthropometric (e.g., lengths, angles, circumferences, indexes), and geometric (e.g. surfaces). Additionally, it is feasible to determine the automaton level of the measurement procedure. Three levels were recognized: i) manual, where the experienced examiner is required to measure and assess foot; ii) semi-automatic, where some salient points of the foot are annotated by the experienced examiner while the rest of the measurement procedure is automated; iii) and automatic, where the measurement procedure is completely automated without human interference. We highlighted the variety of techniques for foot analysis that are closely coupled to the data type and the subsequent area of application. Four groups of analysis techniques were distinguished: shape variation, comparison between groups, prediction of specific parameters, and shape classification. These findings could be used as suggestions and guide one towards appropriate parameters selection for foot assessment.

1.3.2 Three-dimensional quantitative analysis of healthy foot shape: a proof of concept study

Motivation for the study

A foot shape, as represented through complex geometry, is important in several biomedical disciplines. The knowledge of how feet vary between individuals could be beneficial when designing shoes and orthoses, or in clinical diagnosis. The huge amount of variation present in foot shape appears to be the consequence of complex foot anatomy. In addition, we employ multivariate linear regression to investigate the how different factors such as physical characteristics (e.g. age, sex, BMI), and the amount of physical activity, influence the geometry of 3D foot shape. All these suggest that a quantitative description of 3D foot shape is needed. Usually, the approaches that analyze foot morphology are based on 1D measurements or 2D footprints [13, 19, 34, 46]. Although these approaches examine foot shape quantitatively, they do not describe the entire 3D foot shape.

High level of the approach

We propose a method to describe the shape variation of the whole 3D foot shape based on statistical shape analysis. This technique consists of three parts. First, we align the 3D shapes anatomically through the identification of homologous elements between shapes (Figure 1.6b). These elements possess the same or similar structure in terms of their local appearance and context. Then, all 3D shapes are spatially aligned (Figure 1.6c). Finally, these alignment steps allow a statistical analysis of 3D foot meshes. We applied PCA to investigate major shape variations of, what we define as, a normal population 3D foot shape. In essence, PCA represents each 3D foot shape as the sum of the average 3D foot shape and weighted contributions of each component of shape variation (Figure 1.7). In addition, we employ multivariate linear regression to investigate the how different factors such as physical characteristics (e.g. age, sex, BMI) and the amount of physical activity influence the geometry of 3D foot shape.

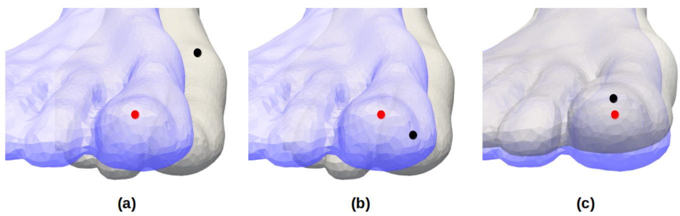

Figure 1.6: **Anatomical and spatial alignment of 3D shapes** (a) The example of two foot shapes represented as meshes in 3D space. The red vertex (ordered as 2532nd point in 3D space) located on the top of the first finger of the blue mesh and the analogous match (the black vertex) with the same order but different anatomical location on white mesh (b) After anatomical alignment, both vertices (red and black) have the same order and same anatomical location on the corresponding mesh. (c) After spatial alignment the distance between the red and the black vertex is minimized.

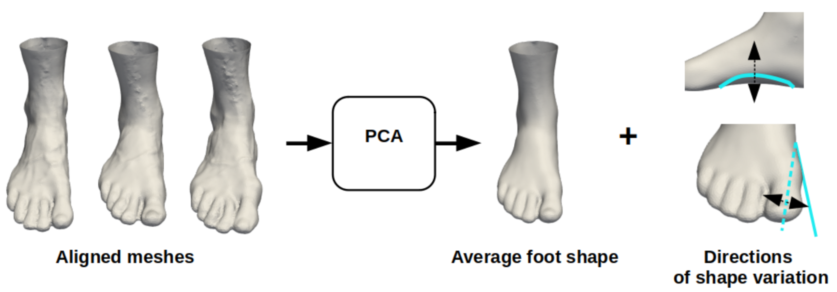

Figure 1.7: **PCA analysis.** The spatially aligned meshes are provided as input to a PCA. The outputs of PCA are the average foot shape and the main directions of shape variations, such as variation of the arch height and the first toe angle. PCA extracts orthogonal modes of shape variation, that are not always reflected through simple localised shape variations but can also consist of a combination of several shape variations.

Summary of Results

We provide the main shape variations present in our normal foot population across all three dimensions, such as variations between high arched and low arched feet, between feet with a narrow ball width and feet with a wide ball width, variations in ankle width, in the position of hallux bone, in the shape of toes, in midfoot width, and in the directions of the toes. Additionally, body-mass index, age, gender, and the amount of physical activity showed to have a significant influence on 3D foot shape. We only investigated the differences between half and fully loaded feet, and differences between left and right foot which made the effect small enough that we did not have the statistical power to identify the influence on foot shape. These insights suggest the need for establishing the methodology to objectively analyse the 3D foot shape for clinical diagnosis as well as for the improvement of the quality of shoe fit.

1.3.3 Subject-specific identification of three dimensional foot shape deviations using statistical shape analysis

Motivation for the study

While numerous articles suggest how to describe foot shape, the method which tests whether the 3D foot shape falls within the range associated with the normative population of foot shapes has not yet been developed. Here a normative population of foot shapes consists of normal arched feet, while test population consists of flat-arched feet, high-arched feet and feet with hallux valgus. Detection of shape anomalies is one of the most important in outlier detection and answering it often relies on the outcome of a statistical test (e.g. t-test, analysis of covariance, etc...)[21]. To date, there is no method found in the literature that provides more than a single global label of whether a foot shape deviates significantly compared normative population or not. In particular, the automatic localization of abnormally-shaped foot regions has not yet been examined. Such a system that could explain what part of the foot is abnormal, and to what extent that is the case, would be beneficial for foot care professionals in two ways. First, it would eliminate the subjectivity seen in visual assessments and second, it would allow non-experts to perform foot shape assessment.

High level of the approach

We propose a subject-specific analysis technique that can flag foot regions that have significant shape deviation compared to what is present in a training population of feet. Our technique consists of two parts. First, we generate a normative statistical model, which is then used in the second part to compare the new test foot to.

In the first phase, we generate a normative statistical model that captures, at the scale of each vertex, the distribution of residuals for a group of, as we described, normal normal-arched feet. To obtain residuals distributions, we extend our previous statistical modelling technique using principal component regression. This allows us to not only investigate the variations present in training population of 3D foot shapes but also estimate the 3D normal foot shape based on a person's factors (e.g. age, sex, BMI. These contributions allow us to model, at each vertex, a full Gaussian distribution over the residuals computed between aligned foot shape and estimated normal equivalent. These residuals distributions act as our normative statistical model and can be compared to identify significant shape deviations. An overview of this process is shown in Figure 1.8.

Second, we use this statistical model to analyze an individual's measured 3D foot shape, belonging to one of the groups: normal high arched, normal low arched or hallux valgus. Initially, we align the new mesh to the estimated normal equivalent. Then a single-sample statistical test is applied at each mesh vertex to identify significant shape deviations. We employed False Discovery Rate (FDR) correction to prevent inflation of false positive rates that occur with multiple statistical tests. Non-significant

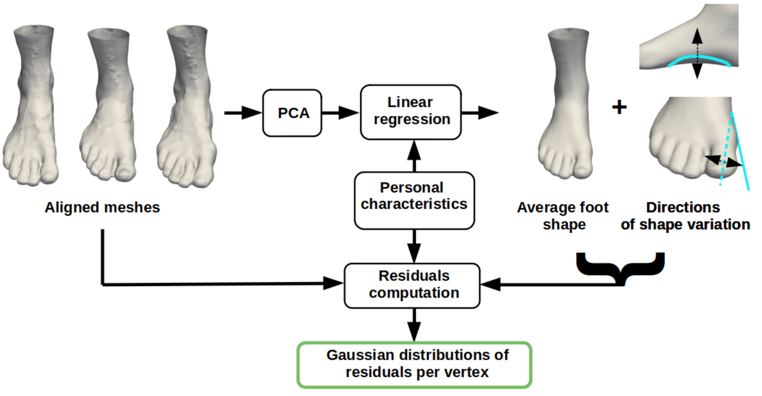

Figure 1.8: **A normative statistical model of training population.** First, the person's factors are incorporated through linear regression to generate a 3D tunable model. This model is used to estimate a normal foot shape based on person's factors. Then residuals are computed between this estimated normal equivalent and the aligned foot shape. The outcome is a normative statistical model that contains Gaussian distributions of residuals on vertex level.

shape deviations are then ignored via FDR correction. This process is visualized in Figure 1.9 The result of this analysis pipeline is a 'map of shape deviations': A map that identifies all vertices that are significantly different from the modeled normative population.

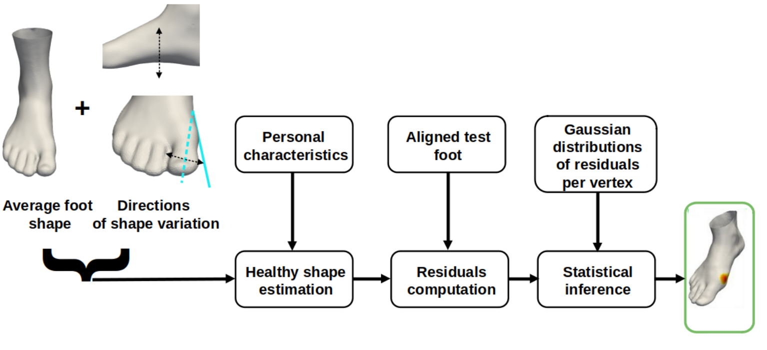

Figure 1.9: **Personalized analysis of 3D foot shape** First, the normal estimate of the test foot shape is generated from the 3D tunable model (obtained in the previous phase). Then, we compute the residuals between the aligned test foot and its estimated normal equivalent. At last, these residuals are compared to the residuals obtained in the previous phase. The final result is a map over the foot shape with highlighted shape deviations.

Summary of Results

We found significant deviations in foot shape of three test groups: high arched feet, low arched feet, and feet with hallux valgus. These shape deviations are localized in different foot areas for different groups. In addition, we found a significant correlation between the angle of the first toe and the detected regions of deviation for the subjects with hallux valgus feet. Similarly, for the foot arch groups, we identified the midfoot region as the main region of shape deviations. While the areas of abnormal shape deviations were limited to specific foot regions for the feet within the same test group, the degree of these shape deviations varied between feet within the same test group. Our methods results consistent with known shape deformities present within feet with hallux valgus, while also providing descriptive and personalized results for the normal foot shape with subtle foot arch deviations.

1.4 Thesis contribution and organization

We respond to the current challenges in the field by introducing the novel contributions through a review of existing techniques for foot assessment, 3D statistical foot shape analysis, and identification of subject-specific foot shape deviations. In particular, those contributions are:

- An overview of the various foot measurements and techniques for foot shape assessment in the context of orthotics and footwear design. Here, we highlighted the importance of 3D foot shape for assessing the entire foot automatically and objectively. This contribution makes up Chapter 2 of this thesis.
- Development of a technique for quantitative statistical description of the 3D foot population. This technique incorporates 3D shape registration, which establishes correspondence within the entire data set and allows for shape alignment. As a result, further statistical analysis is feasible and applicable on the entire population of feet. Additionally, we provided a technique that investigate how person's factors (age, sex, BMI) influence the 3D foot shape. This contribution makes up Chapter 3 of this thesis.
- The construction of a statistical analysis pipeline for subject-specific identification and localization of 3D foot shape deviations. This pipeline is the first to allow a user to take a single 3D foot scan, compare it to a normative foot population, and highlight vertices on a mesh that are significantly different than that of population. This contribution constructs Chapter 4 of this thesis.

In the subsequent chapters of this thesis, we introduce each contribution and discuss their connection to the quantitative description of a 3D foot shape. Finally, a fifth and final chapter summarizes this research and discusses future work.

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Part II

Contributions

2

Foot shape data collection and analysis techniques: a review

Contents

Abstract

Foot shape assessment is important for understanding the complex shape of a foot and for providing detailed information about foot shape diversity. Extensive knowledge about an individual's foot shape could lead to a more accurate design of foot orthoses and more comfortable footwear. Numerous approaches have been applied over the past few decades to evaluate 3D foot shape for orthotic and footwear purposes as well as for investigating how one's habits and personal characteristics influence the foot shape. This paper presents the developments reported in the literature for the assessment of the external foot shape and summarizes them using the narrative review. In particular, we focus on three main dimensions of foot assessment: (a) the choice of measurements to collect, (b) how automated and objective the foot assessment is, and (c) how these foot measurements are employed in orthotic and footwear applications. We present how different choices along these three dimensions impact the resulting foot assessment and, finally, discuss possible improvements in the field of foot shape assessment.

The work in this chapter has been submitted as:

Stanković K., Huysmans T., Booth B. G., Sijbers J. (2021). Foot shape assessment techniques for orthotic and footwear applications: a review. *Foot and Ankle Research*.

2.1 Introduction

People spend a great deal of their lives on their feet, so much so that famous Greek philosopher Socrates once said “When our feet hurt, we hurt all over”. Therefore, it is important to enable maximal comfort of the feet to achieve a person’s overall satisfaction and healthier life. The adequate foot shape assessment could lead to improved comfort. A better understanding of how an individual’s physical characteristics or everyday habits influence foot shape may lead to improvements in the overall comfort and functionality of the footwear and orthotic devices that are being produced [54, 57]. Hence, quantitative description of 3D foot shape is an important task for a number of different applications relating to the ergonomic design of footwear, foot orthotics and insoles, and for research into and clinical assessment of foot deformities.

As a result of the foot’s complex anatomical structure, flexibility, and variety of geometric features, a number of measurement procedures have been developed to represent external 3D foot shape. Traditionally, foot surface is examined visually by an experienced and well-trained expert [18–20, 29, 52, 76]. In this way, the foot could be examined in different environments in standing pose (half-weight bearing), sitting pose (non-weight bearing), by placing the foot on plexiglass, or similar. One important characteristic of this type of foot assessment is that it entirely relies on the knowledge and experience of the examiner. In essence, it enables the palpation of the foot and possible determination of painful regions.

Additionally, there are studies in which experts assess 3D foot shape using different measurement equipment and devices such as sliding calipers, tapes, 3D scanners [2, 4–7, 9, 10, 14, 17–20, 23, 31, 32, 34–37, 47–51, 55, 58, 60, 65, 68, 75, 78, 80, 82, 84, 85]. Yet, foot shape assessment can often be dependent on who collects these measurements [39]. In order to eliminate human influence and objectify foot measurement, automated measurement procedures have been introduced for foot assessment. These procedures are accompanied by specialized devices (e.g., 3D scanners) that enable partially or completely automatic measurements of the foot shape. The use of these new technological inventions (e.g., laser 3D scanners, structured-light 3D scanners, plantar pressure measurement plates) have, in turn, given way to new types of measurement data and new analysis techniques.

The variety of techniques for foot shape assessment is exceedingly large. Common foot assessment methods compare foot shape between distinct populations, such as females and males [27, 66]. These methods mostly employ statistical testing on key geometrical features (such as foot dimensions) of distinctive populations [27] to emphasize their shape differences. Other, more advanced, techniques for foot assessment, such as principal component analysis, analyse the entire foot shape based on its geometry, not just separate measurements of different foot dimensions [71, 73]. In addition, personal physical characteristics (e.g. sex, height) or lifestyle habits (e.g. wearing high heels) can be linked to the foot shape and their impact on foot shape can be measured. Knowledge about the relation between these factors and foot shape is often used to determine the predictive significance and generate prediction models [73]. This is frequently achieved through regression analysis where foot shape is examined through the estimation of specific foot shape characteristics (such as the prediction of arch height based on foot width) [27, 71]. At last, techniques have been proposed to examine the complex shape of a foot by categorizing it into distinctive groups [33, 46]. This variety, coupled with recent improvements in measurement equipment, measurements procedures, and the analysis techniques necessary for foot assessment, suggested that this review is needed.

The aim of this paper is to summarize the numerous ways the foot surface has been assessed for orthotic and footwear design. In particular, 3D foot shape assessment is organized through a procedure where the foot shape is described through various measurements. These measurements are obtained from various measurement equipment. Depending on the available measurement equipment different levels of automation for 3D foot shape assessment are present. As a final result, the obtained measurements could be analyzed in different manners. Here, we attempt to synthesize the existing knowledge on these topics in the literature: a) the overview of the different representations of the foot surface, b) their link to the automation level of the foot shape assessment, c) and possible techniques to analyze these shape representations. To our knowledge, this is the first review of 3D foot shape analysis.

2.2 Methods

Although we provide a narrative review, we make use of a flow diagram for new systematic reviews of the PRISMA guidelines for the literature search part of our review. In this way, we ensure a structured and transparent search increasing the odds that all relevant articles are extracted. The PRISMA review protocol [PRISMA] is divided into four main steps (summarized in Fig. 2.1): study identification, study screening, study eligibility, and study inclusion.

The initial literature search for this review was carried out in January 2021 in the PubMed and Scopus databases. Inclusion criteria were the studies that analyse the adult the foot surface in orthopaedic and footwear applications. The year range was set to exclude the articles which are focused on out-dated technology which is less likely to be still in use. In the identification phase of the PRISMA flow, we searched for the following terms (and its variations): foot, form, shape, posture, surface, analysis, model, index, score, scale, orthopedics, orthotics, orthosis, footwear, shoe. We used ANDs to search for relevant terms for this review, while ORs are used to include plurals, different forms of a word (verb vs noun) or similar. In the screening phase of the PRISMA flow diagram, all abstracts were reviewed. The first author read and assessed the full-text articles extracted from the screening phase. Only the articles whose main focus is the analysis of foot shape were then considered for inclusion. Full inclusion and exclusion criteria are summarized in Fig 2.1.

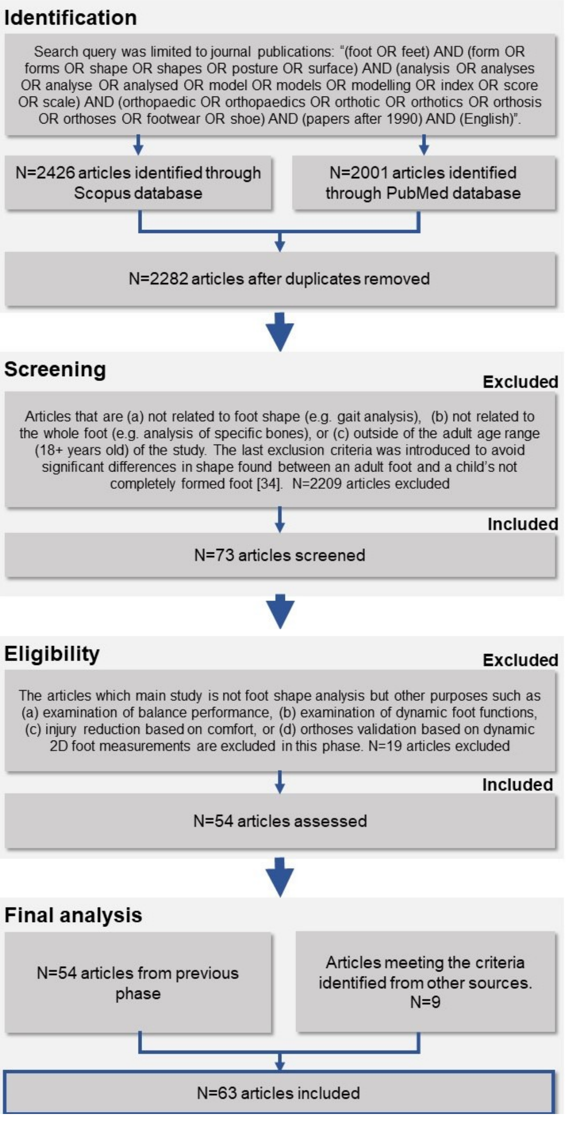


Figure 2.1: **Flow of information:** Different phases of a review.

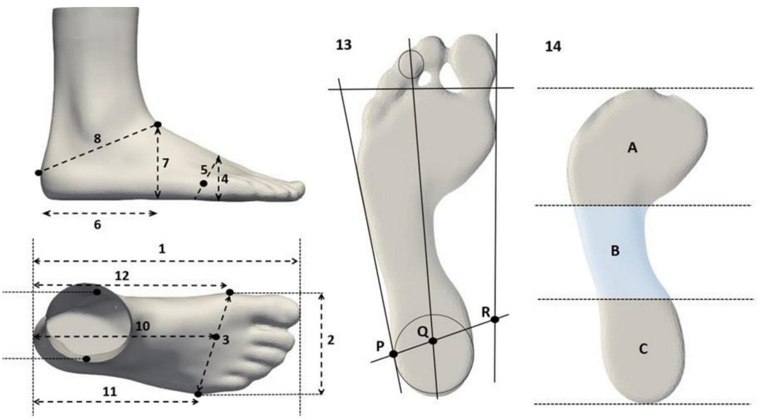
2.3 Results

2.3.1 Search results

Following the PRISMA flow [PRISMA] from the original database searches, 73 unique articles were screened, 54 of which met the eligibility criteria (Fig. 2.1). Nine additional articles meeting the criteria were identified from other sources.

2.3.2 Choice of Foot Measurements

Numerous studies examined foot shape for different purposes, such as variability of foot shape, comparison of distinct populations, establishment of new measurement system, design of custom products. [2–10, 12–15, 17–23, 27, 29, 31–38, 41, 42, 44–53, 55, 58, 60, 62, 64–66, 68, 69, 71, 73–76, 78, 80, 82, 84–86, 88]. In general, foot shape is assessed by extracting important geometrical features using various measurement procedures. Although several requirements must be met for a good study design, perhaps the most important is the choice of foot measurements to be collected.



1	Foot length	Distance between the back most point of the heel and the furthest toe point parallel to the foot axis and along the plantar surface plane.
2	Foot width	Distance between the medial and lateral points that define the ball of foot measured perpendicular to foot axis.
3	Ball width	Distance the most medial and lateral points, projected on the ground plane.
4	Ball height	Maximum height of the perimeter of the ball section (joining the most medial and most lateral metatarsal points) from the ground plane.
5	Ball circumference	Total perimeter of the ball section joining the most medial and most metatarsal points.
6	Instep length	Distance between the most point of the heel and the maximum height of the intersection of ta vertical cross-section of the foot along the foot axis with the dorsal foot surface, projected on ground plane.
7	Instep height	Maximum height of the intersection of a vertical cross-section of the foot along the foot axis with the dorsal foot surface.
8	Heel circumference	Shortest perimeter that contains the back most point of the heel and the maximum height of the intersection of a vertical cross-section of foot along the foot axis with the dorsal foot surface.
9	Heel width	Distance between the two widest points of the heel at 15% of the foot length from the heel to the toe.
10	Arch length	Distance between back most point of the heel and the intersection of the ball circumference with the foot axis, measured along the ground plane.
11	Lateral metatarsal length	Distance between the back most point of the heel and the lateral point of ball of the foot, parallel to the foot axis.
12	Medial metatarsal length	Distance between the back most point of the heel and the medial point of ball of the foot, parallel to the foot axis.
13	Hallux valgus index	$\frac{\left(\frac{PR}{2}-PQ\right)}{PR} * 100\%$
14	Arch index	$\frac{B}{(A+B+C)}$

Figure 2.2: Foot characteristics that are commonly measured to assess foot shape. More details on characteristics in 13 and 14 can be found in [11, 79], respectively.

We observed that there are three main approaches to the collection of foot measurements: purely qualitative (e.g., foot posture index, plantar surface visual assessment), anthropometric (e.g., lengths, angles, circumferences, indexes), and geometric (e.g. marker locations, boundary curves, surfaces). These measurements, together with their applications to foot assessment are summarized in Table 2.1.

A qualitative foot assessment is a purely visual appraisal. It relies entirely on the expertise of the examiner. Nevertheless, these visual appraisals can also be summarized using numerical scales like the foot posture index (FPI) [25], plantar surface visual assessment as an estimate of foot arch height [76], foot arch index [52], and hallux valgus scale [29]. The FPI measure consists of summing the values of 6 assessment criteria, where each criterion is scored visually from –2,-1,0,1,2. This leads to a numerical foot shape score ranging from –12 (indicating maximal supination) to +12 (indicating maximal pronation) [5, 17–20, 47, 88]. Thus, although this scoring system is not a quantitative foot measurement, its numerical value has the potential to be analyzed using quantitative algorithms. Another qualitative foot assessment is through arch height estimation by plantar surface assessment [76]. Here the plantar foot surface is assessed visually as low, normal, or high by the examiners. However, there is much inter-clinician variability in this type of assessment, even for extremes of foot type [16]. These findings demonstrate the need for objective standards and quantitative methods of evaluating foot morphology using foot arch height. Similarly, in the study of Menz [52], plantar foot surfaces of elderly people were reliably categorised as high, normal, or low using an arch index based on a visual categorization tool. This tool shows 2D footprints' shape of upper and lower boundaries for each of the foot arch categories. Then, the examiner visually categorizes the 3D foot shape into one of the groups. Alternatively, foot morphology can be assessed through the hallux valgus scale [29]. This scale categorizes the first toe angle by the level of deformity: none, mild, moderate, or severe. This grading method showed excellent interobserver repeatability, making it a suitable instrument for clinical and research purposes.

The second and most popular approach to foot measurement is represented in studies that use anthropometric measurements. This approach collects one or more numerical measurements obtained as distinctive foot dimensions (Fig. 2.2) such as lengths, widths, angles, girths, heights, circumferences [3–5, 7, 12, 14, 18–20, 23, 27, 31, 33, 35, 38, 41, 42, 44–47, 51, 53, 58, 62, 64, 66, 69, 71, 82, 84, 85] or specific foot parameters such as arch index [14, 18–20, 31, 47, 74], or valgus index [78]. These foot dimensions are measured using widely-available measurement equipment such as measuring tapes and sliding calipers. Meanwhile, arch index is obtained from the toeless footprints as the ratio between the middle area of footprint to the entire toeless footprint area. Footprints are generated manually using clay moulds [18–20, 31, 47, 68], or automatically using foot-arch analysis platforms [14, 74]. The valgus index is defined as a measurement of the medial malleolar shift of the intermalleolar diameter in relation to the posterior foot support area [78]. It is calculated numerically from the footprints as shown in Fig. 2.2. The valgus index is a useful criterion to determine hindfoot position since it is less subjective and possibly more sensitive in detecting small amounts of hindfoot deviation compared to the relaxed calcaneal stance position and the neutral calcaneal stance position [78]. By collecting these foot dimensions and/or foot parameters, a complicated foot shape is simplified into a small number of numerical values convenient for further analysis.

Throughout the literature, various foot parameters and characteristics have been measured and examined. In addition, an inconsistency in the number of foot characteristics is present within studies of similar purposes (Table 2.1). Although there are ISO norms (e.g. ISO 19408 [64-]) of the relevant foot dimensions for shoe design, the selection of the specific subset of foot characteristics for analysis is still inconsistent between different studies from the literature. It is important to note that, for reliable foot assessment, the anthropometric measurements should be selected in order to match the salient dimensions of variability of the foot shape.

In studies that use a geometrical representation of the foot, some parts of the foot shape (such as footprint outline), or the whole 3D foot shape, is analyzed at once. These geometrical forms are digitally represented as a set of 2D or 3D points generated using clay moulds or 3D scanners, respectively. Usually, geometrically-significant discrete points are manually marked as a set of markers located on important anatomical locations of the foot shape [2, 7, 15, 21, 22, 55, 60, 71, 80]. In [7, 21, 22], footprint and foot outline were represented by 85 markers and automatically derived pseudo-markers, while in the study of [60], the entire 3D foot shape was represented by 240 pseudo-markers. Compared to the studies [2, 7, 21, 22, 60] which employ a specific number of markers, in [8, 15, 37, 49, 50, 71, 73] the foot surface is represented by all points obtained from the 3D scanner. In general, the type of the measurement device dictates the type of the data that can be obtained. For instance, from plantar pressure plates a lower level of data representation such as foot length and foot width could be extracted, while this does not stand for the higher level of data representation such as 3D foot scan.

Table 2.1: **Different types of foot measurements.**V-visual, G-geometrical, A-anthropometric measurements used for different orthotic and footwear applications.

	Foot variability	**Subject features**	**Subject behaviour or health condition**	**Custom products**	**Definition of product sizes**	**New measure. system**	**Other**
Arch height (V)		[52, 76]					
Hallux valgus scale (V)						[29]	
Foot posture index (V)		[10, 20]	[18, 19, 88], [17, 47]				
Footprint (G)	[68, 80]	[22, 31, 74], [36, 68]			[75]	[65]	[7]
3D foot shape (G)	[71, 73], [15, 60]	[13, 37]		[8, 49, 82]	[35, 37, 55]	[64, 84]	
Ankle circumf. (A)		[10]	[19]		[3]		
Arch angle (A)	[80]	[27]	[5]				
Arch circumf. (A)		[23]			[3]		
Arch height (A)	[80]	[27, 31, 85]	[18, 19]	[46]	[3]	[14]	
Arch index (A)	[80]	[20, 27, 31], [10, 74]	[18, 19, 47]			[14]	
Arch length (A)	[60]	[62]			[3]	[84]	
Arch width (A)	[60]	[27]			[3]	[14]	[7]
Ball angle (A)		[27, 33, 44], [42, 48]			[3]		[7]
Ball circumf. (A)	[2, 9, 60]	[62], [45, 66], [23, 38, 53], [20, 48, 86], [4, 10, 85]	[12, 18, 19], [51]	[12, 46]	[3]	[84]	[7, 64]
Ball height (A)		[38, 53, 62], [10, 20, 85], [4]	[18, 19]				
Ball length (A)		[38, 44, 48], [85]		[46]			[7]
Ball-to-heel length (A)		[85]					[7]
Ball width (A)	[2, 9]	[62, 66, PRISMA], [23, 44, 53], [10, 20, 48], [4]	[18, 19]		[3]		[7]
Dorsal arch circumf. (A)					[3]		[7]
Dorsal arch height (A)		[20, 85]	[5]		[3, 32]		[7]
Fibulare instep length (A)		[45]		[12]			[64]
Foot breadth (A)	[41]	[6, 45, 85], [58]	[12]	[12, 46]			

Foot circumf. (A)	[41]						
Foot length (A)	[41, 80, 86], [9, 60]	[45, 62, 66], [33, 38, 42], [23, 64, PRISMA], [4, 58]	[12, 64, 69], [51]	[12, 46, 82]	[3, 32]	[84]	[7, 64]
Foot slope (A)							[7]
Foot width (A)	[60, 80]	[33, 62, 86]	[69]		[3]	[84]	[64]
Footprint angle (A)					[3]		
Footprint index (A)					[3]		
Hallux valgus index (A)							[78]
Heel breadth (A)		[45, 85]	[12]	[12, 46]			
Heel circumf. (A)		[23, 45, 62], [85]	[19]				[7]
Heel length (A)					[3]		
Heel width (A)	[60]	[27, 62, 66], [33, 44, 53], [20, 42, 48], [4]	[19, 51]		[3]	[84]	[7]
Height of top of ball circumf. (A)		[85]		[12]			
Instep breadth (A)	[41]						
Instep circumf. (A)	[2]	[45, 53, 66], [20, 38, 85], [4, 10]	[18, 19, 51]	[12, 46]	[3]	[84]	
Instep height (A)	[2, 9, 41]	[4, 45, 62], [33, 44, 66], [38, 42, 53], [48]	[19, 51]	[12, 46]	[32]		
Instep length (A)		[44, 45, 62], [33, 42, 85]	[12]	[12]	[32]		[64]
Instep size (A)							[7]
Instep width (A)		[4, 48]					
Medial malleolus height (A)	[34]	[33, 48, 53], [85]	[19]			[84]	
Medial metatarsal length (A)		[27, 33, 62], [42, 53]			[3]	[84]	
Midfoot circumf. (A)					[3]		
Midfoot height (A)						[84]	
Midfoot width (A)	[60]					[84]	
Minimal distance between hallux and the interphalangeal joint of the second toes (A)			[69]				
Lateral malleolus heigth (A)		[33, 48, 53], [85]				[84]	
Lateral metatarsal length (A)		[27, 33, 62], [42, 53]			[3]	[84]	
Navicular height (A)	[9]	[53, 66]	[5, 17, 47], [51]	[12]	[32]		
Plantar circumf. (A)				[82]			
Sphyrion height (A)		[33, 45]					
Toe #1 angle (A)		[45, 53, 66], [10, 20]	[18, 19, 69]	[12]			
Toe #5 angle (A)		[45, 53, 66], [10, 20]	[18]	[12]			
Toe #1 height (A)		[33, 53, 66], [20, 38, 42], [10, 48, 85]	[18, 19]	[46]			
Toe #5 height (A)		[33, 53, 66]					
Toe #1-#5 circumf. (A)		[10, 20]	[18, 19]				
Toe #1-#5 width (A)		[10, 20]	[18, 19]				
Toes height (A)	[2]	[85]					[7]

Truncated foot length (A)	[34]	[66]			[32]		

2.3.3 Measurement Objectivity and Automation

In this section, we examine to what level the various foot shape measurement procedures are automated. To this end, the measurement procedures were classified as manual, semi-automatic, or automatic (Table 2.2). Table 2.2contains the information of a certain measurement (e.g. foot length) that in one study is obtained manually, while in some other studies it is obtained automatically. Hence Table 2.1 also reveals the purpose of using this foot measurement, for example, by taking the row of a specific foot measurement and checking the column name of the cell where the study is located.

2.3.3.1 Manual

Manual foot shape quantification has been reported in numerous studies [5, 6, 10, 14, 17–20, 23, 31, 47, 82, 85, 88]. Manual assessment requires at least one experienced and well-trained professional to perform the measurements. In some cases the experts visually examine the foot shape, for example by visual categorization of foot shape based on arch height [10, 18–20, 29, 47, 52, 76, 88]. However, the common way to examine the foot shape is through numerical representation of foot shape characteristics (e.g. foot dimensions). Usually, the numerical foot measurements are obtained using devices such as a ruler for measuring the foot arch height [5, 14, 47]; a Brannock device for measuring the foot length [23]; sliding caliper for measuring ball width [23], foot length/width [6, 18–20, 58], and arch height [31]; measuring tape for various foot circumferences (ball, low-instep, high-instep, heel instep etc.) [10, 18–20, 23]; goniometer for angle measurements [5, 10, 18–20]; analog pachymeter for foot widths and lengths [10], or an analog height rod for foot heights [10]. Since manual assessment is labor intensive, often only one foot dimension is measured at a time. Although a manual procedure can lead to examiner fatigue and loss of concentration, Fryer et al. [28] showed that examiner fatigue was not responsible for the low reliability when foot markers are assessed. However,using a measuring device for assessing joint range of motion (e.g. goniometer) can easily be affected by, among other things, the skill of the operator [29]. Even when angle measurements are taken from standard radiographs, measurement errors of 5 degrees have been recorded. In addition, inter-observer variation is an issue with manually-collected measurements [39]. Knippels et al. [39] reported significant difference in the manual assessment of 4 static parameters (calcaneus in relaxed stance, forefoot position (relative to hindfoot), hallux valgus, longitudinal arch) between the different examiners. Moreover, in clinical practice foot can be assessed completely visually, such as in the case of foot posture index. Another example for visual examination is the foot arch characterization[87]. In the study of Xiong et al[87] subjective ranking of foot arch showed significant correlation with arch index. However, different expertise of the examiners (podiatrists, physical therapists, surgeons) adds to variance in foot assessment[30]. In summary, while manual foot shape assessment is subjective and error prone and has a low precision, it is deemed reliable enough for many studies, they are still widely-used due to their simplicity and low equipment cost.

2.3.3.2 Semi-automatic

Most of the reported foot shape examination methods are semi-automatic (Table 2.2). These methods extract numerical measurements from a digital representation of the foot such as a 2D image or a 3D optical scan. Prior to automated numerical measurements, important features of the foot are manually annotated by placing markers at significant anatomical locations, either directly on the foot (physical markers) [2, 12, 32, 33, 38, 41, 42, 45, 46, 48, 51, 53, 55, 66, 69, 80, 86] or after the digital version of foot shape is obtained (virtual markers) [27, 34, 44, 64]. Virtual markers are placed at the corresponding significant locations but on the digital foot representation using some software tools (e.g., ScanWorX in the study of [44], Geomagic Qualify8 in the study of [27], or D+ in the study of [64]). The markers on the digital representation of foot shape are used to calculate important foot dimensions (e.g., foot length, foot width) and important foot parameters (e.g., arch index). Once markers are present on the digital foot representation, all subsequent measurements are obtained automatically.

Both physical and virtual markers are placed by experienced and well-trained professionals. Compared to physical markers, virtual markers usually reduce the measurement time for each subject [44]. However, physical markers allow palpation of the underlying bones on specific anatomical locations, while virtual markers are solely based on the visual interpretation of the local shape features of the external surface. Consequently, physical markers are more accurate in annotating important features of the foot. An important remark is that physical markers should be placed onto the subject's feet in a half-weight-bearing condition to limit skin movements between marker placement and scanning [32].

2.3.3.3 Fully automated

In fully automated procedures, the foot is assessed without human interaction and key anatomical points are automatically identified as foot shape markers (pseudo-markers). In [13, 60, 62, 66], only a certain number of pseudo-markers on the digital foot (such as markings of navicular tuberosity) are necessary to automatically obtain foot dimensions. In [15, 21, 22, 37, 71, 73], where the foot shape variations are assessed for given populations, the entire point cloud in 3D space represents the significant pseudo-markers. In order to analyse these types of data, it is necessary to establish geometrical correspondence between 3D foot shapes (e.g. using markers). That is, the point clouds need to be brought into correspondence so that all points are ordered in the same manner and refer to the same anatomical locations.

Both semi-automatic and automatic procedures require 2D imaging systems [33, 36, 38, 41, 68, 69, 71, 74], 3D scanners [2, 3, 8, 9, 12, 13, 15, 21, 22, 27, 34, 35, 37, 42, 44–46, 49–51, 53, 60, 62, 64–66, 73, 75, 84, 86] or dynamic 4D scanners [27]. Compared to the manual procedure, semi-automatic and automatic procedures are fast and highly accurate. 2D imaging systems can be split into single-camera and multi-camera approaches. These systems are broadly used to acquire the plantar surface [36, 38, 68, 69, 71, 74], or to generate a static geometric foot representation [33, 41]. Although the accuracy of data obtained by semi-automatic and automatic procedures is relatively high compared to manual procedures [77], significant differences in foot length and foot width have been reported between manual foot measurements and measurements obtained using 3D foot scanners [86]. It has been shown that these differences are due to toe separation and toe flexion during scanning [86]. Moreover, automation of measurement procedure enables measurements of several foot dimensions at once, or even capturing the whole foot shape in a fully numerical representation. Moreover, the digital representation of foot shape can be transmitted and recorded which removes the constraints of time, distance and/or use of second opinion. In terms of equipment costs, the manual procedure is cheaper compared to semi-automatic and automatic procedures since the latter two require expensive 3D scanners. However, there have been attempts to investigate low cost equipment for the purposes of 3D scanning [50, 65, 84]. Although semi-automatic and automatic procedures are expensive in terms of equipment, they potentially have lower measurement costs due to less manual labour.

Table 2.2: **Studies that are using different automation levels of measurement procedure related to the number of measured foot shape characteristics (* virtual markers, ' physical markers).**

	Manual	Semi-automatic	Automatic
Foot lengths	[7], [82], [23], [48], [85], [6], [10], [58]	[12]', [64]*, [66]', [45]', [46]', [27]*, [44]*, [33]', [53]', [42]', [41]', [38]', [69]', [86]', [80]', [32]', [2]', [51]', [34]*	[62], [3], [84], [9]
Foot widths	[7], [14], [23], [20], [18], [19], [48], [85], [6], [10], [58]	[12]', [64]*, [66]', [45]', [46]', [27]*, [44]*, [33]', [53]', [42]', [41]', [69]', [86]', [80]', [2]', [51]'	[62], [3], [84], [9]
Foot heights	[7], [31], [14], [20], [18], [19], [48], [76], [52], [85], [10], [5], [47], [17]	[12]', [66]', [45]', [27]*, [44]*, [33]', [53]', [42]', [41]', [38]', [80]', [32]', [2]', [51]', [34]*	[62], [3], [84], [9]
Foot circumferences	[7], [82], [23], [20], [18], [19], [48], [85] [10]	[12]', [64]*, [66]', [45]', [46]', [53]', [41]', [38]', [86]', [2]', [51]'	[62], [3], [84], [9]
Foot angles	[7], [20], [18], [19], [48], [10], [5]	[12]', [66]', [45]', [27]*, [44]*, [33]', [53]', [42]', [69]', [80]'	[3]
Foot indexes	[31], [14], [20], [18], [19], [88], [10], [5], [47], [17]	[27]*, [80]'	[3], [74]
Plantar surface			[21], [22], [7], [31], [14], [74], [36], [68], [75], [65]
3D foot shape			[71], [15], [82], [13], [73], [8], [37], [60], [84], [50], [49], [35]

2.3.4 Techniques for foot shape analysis

Different approaches have been developed to analyse foot shape. Based on the data type and the purpose of the study, the following types of foot shape analysis can be distinguished: shape variation, comparison between groups, prediction of specific parameters, shape classification (Fig. 2.3). A huge variety of available techniques for foot shape assessment leads to the numerous diverse applications within the field of orthotics and footwear (Table 2.3). Tables 2.4- 2.9 summarize techniques for foot assessment and provide the information about studies where they are employed. It is straightforward to link these to the foot measurements (Table 2.1). For example, if a study [60] which employs t-tests for several groups (Table 2.5) is taken, then it is possible to extract for which foot dimensions this technique is employed by simply looking into cells within (Table 2.1).

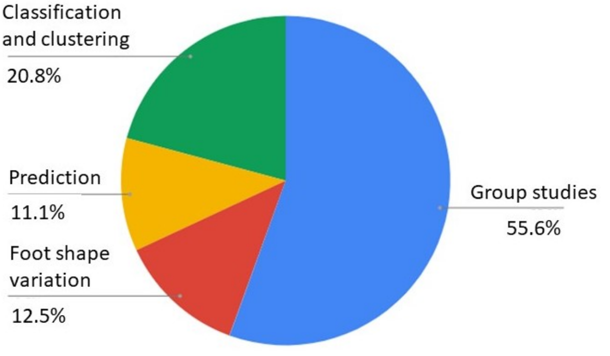


Figure 2.3: Distribution of various techniques used for foot shape assessment.

Table 2.3: **Techniques for foot shape analysis for different orthotic and footwear applications.**

	Foot shape variation	Group studies	Prediction	Classification and clustering
Describe foot variation	[21], [71], [15], [41], [73], [60], [68]	[80]	[86]	[2], [9], [34]
Linking to subject characteristics	[22], [36]	[62], [66], [45], [27], [44], [33], [53], [42], [13], [20], [48], [86], [74], [85], [6], [37], [68], [58], [4]	[31], [23], [13], [85]	[33], [42], [38], [76], [52]
Linking to subject behaviour and health condition		[12], [53], [69], [18], [19], [88], [10], [5], [47], [17], [51]		
Custom products		[82], [49]	[8]	[12], [46]
Definition of product sizes		[37]	[32]	[3], [55], [75], [35]
New measurement system		[14], [84], [50], [65]		[29]
Other		[7], [64]	[78]	

2.3.4.1 Groups studies of foot shape

Foot shape is usually assessed through group comparison techniques as reviewed literature has revealed. These techniques are commonly used when it comes to proposing new measurement procedures. Besides, they are broadly used when examining differences in shapes of two groups (such as foot shape differences between females and males).

(a) Comparison of measurement procedures

Usually, two measurement procedures are evaluated by comparing the foot measurements obtained from both procedures over the same set of feet (Table 2.4). We noted several foot shape comparison techniques in order to evaluate a new measurement procedure [7, 14, 64, 82]. Usually, the measurement procedures are compared numerically by examining differences in foot shape. This covers comparisons in (root) mean squared error (MSE) between data [50, 65, 82, 84], comparisons between estimated data and ground truth [14], data distribution parameters [64], mean Euclidean distance between shapes [84], and mean shortest distance from predicted to actual shape [49]. Beside comparing the pure data between two sets, the data distributions are often compared as well in terms of their mean and standard deviation, where normality of the distributions is assumed. Comparison between estimated results and the ground truth has been performed through Spearman's rank order correlation [14]. This method is useful when data are at least ordinal and the scores on one variable must be monotonically related to the other variable. A common way to compare differences between two shapes is mean Euclidean distance [84]. This method requires the correspondence between points of two different shapes. Another way to compare the data is by comparing their predictive significance. This could be achieved through linear regression [45].

From the above, it is not clear which foot shape characteristics should be compared to establish a new measurement system. Also, it is not easily noticeable which comparison techniques should be applied on foot shape characteristics to examine whether a measurement procedure is compatible with existing approaches.

(b) Group studies for distinct populations

Group studies have also been used to compare foot shape characteristics between distinct populations such as females and males, or older and younger people (Table 2.5). Usually differences between groups are examined through t-tests on foot dimensions [5, 6, 12, 13, 18–20, 27, 33, 37, 42, 44–46, 48, 53, 58, 66, 68, 74, 80, 85, 86, 88], Hotelling's T-squared test [51], Pearson's chi-squared test [47], analysis of variance (ANOVA) [4, 17, 27, 62, 69], or analysis of probability [26] in [10, 18, 19]. The most common technique, the t-test, compares the differences between the means of two populations to determine if the null hypothesis (equal means) should be rejected. Yet, a few assumptions need to be considered when t-test is applied. First, the data should be collected from a representative, randomly selected portion of the total population. In addition, the data should be continuous and normally distributed. The final assumption is the homogeneity of variance. Hotelling's T-squared is the multivariate counterpart of the t-test used when the number of response variables is two or more.

Another technique used for comparing means between three or more groups is ANOVA. When assumptions underlying t-tests are invalid, such as large differences between the numbers of subjects in the compared groups, a convenient method for comparison is the analysis of probability. The t-test also requires continuous variables as inputs, so in case of categorical variables (e.g. FPI) it is not possible to apply it. The convenient analysis for this scenario is Pearson's chi-squared test [47]. Moreover, if there is a small number of samples which are categorical, a promising technique is the Fisher exact test. However, having

Table 2.4: **List of studies that apply comparison techniques for evaluation of measurement system based on extracted foot measurements.**

Technique	Measurement	Application	Study
MSE	Several foot dimensions	Comparison of proposed low cost 3D scanning procedure to the measurement procedure which uses anthropometric data	[82]
	Several foot dimensions	Comparison of scanned and predicted foot shape for the purposes of the shape reconstruction	[84]
	Foot outline, foot profile, several sections	Comparison of scanned and predicted foot shape for the purposes of using low cost scanning	[50]
RMSE	Plantar foot shape	Comparison of 3D foot high resolution scan and low cost 3D foot scan for the purposes of using low cost scanning	[65]
Data distribution measurements	Several foot dimensions	Comparison of 3D Fourier descriptor foot model to the homologous model	[64]
Spearman's rank order correlation	Foot parameter (arch index) and arch dimensions	Comparison of estimated results to the ground truth	[14]
Linear regression	Single foot dimension (arch width)	Comparison between two different measurement systems based on the arch width as a common variable for both data sets	[45]
Mean Euclidean distance	3D foot shape	Comparison of scanned and predicted foot shape for the purposes of the shape reconstruction	[84]
Mean shortest distance between shapes	3D foot shape	Comparison of actual scan and predicted foot parameterized using foot length, foot width, foot height, and a measure of foot curvature so that foot shape for the generation of personalized last	[49]

small sample size irrevocably leads to another problem with its use - namely that, irrespective of the result of a statistical test, one cannot have much confidence in results based on very small sample sizes. Another approach used to examine differences between groups is through the changes of shape volume [36].

Table 2.5: **List of studies that compare foot shape of distinct groups using several different techniques for comparison.**

Technique	Distinct groups	Study
t-test	Gender	[66], [46], [27], [44], [33], [53], [42], [20], [48], [86], [85], [6], [37]
	Sport activity	[12]
	Age	[66], [45], [46], [27]
	BMI	[62], [27], [13]
	Ethnic groups	[45], [74]
	Females with and without foot problems	[18]
	Foot problems and healthy foot	[53]
	Different geographical regions	[37]
	Different bearing conditions	[80], [58]
	With and without patellofemoral pain syndrome	[5]
Hottelings T-squared test	Foot shape before and after long distance military marching	[51]
ANOVA	Gender	[27]
	Age	[27]
	BMI	[62], [27]
	Running (shod and unshod)	[69]
	Weight bearing, Within-day measurements, Between-day measurements	[4]
	Participants before and after running a half marathon	[17]
Analysis of probability	Foot arch groups (normal, pes planus or pes cavus)	[18]
	Incorrectly sized shoes and the presence of pain or diabetes	[19]
	Older females with and without arthritis	[10]
Pearson's chi-squared test	People with and without medial compartment knee osteoarthritis	[47]
Fisher exact test	Subjects with Charcot foot and without any diabetic complication on foot shape	[88]
Volume calculation	Early pregnancy, before delivery and in the period of puerperium	[36]

The above implies that comparison groups need to be carefully formed for different comparison techniques. For example, when comparing groups with different body-mass indexes, it is likely that if one participant was obese since childhood, their foot structure would be different to someone who became obese three years prior to the study, although both subjects could be within the same group.

2.3.4.2 Foot shape variation

(a) Descriptive statistics

Several studies [15, 21, 22, 60, 68, 71] describe anatomical variation of the foot shape for a given population based on geometrical measurements (Table 2.6). A convenient way to analyse these measurements is Principal Component Analysis (PCA). In order to apply PCA, it is necessary to have shape data that have identical representations. In other words, the geometrical markers or measurements need to be brought into correspondence and, potentially, superimposed. A common way to do so is by using Generalized Procrustes Analysis [15, 21, 22, 71]. When PCA is applied to geometrical measurements, an average shape for a given population and the main modes of variation from the mean shape are obtained. Geometrically speaking, the main modes of variation, also referred to as principal components (PCs), represent the most common changes in foot shape and can be interpreted as shape deformations. Each foot shape can then be represented as the average foot shape plus the sum of weighted PCs. In this way, it is possible to see how much - and in which regions - foot shape varies the most.

Another convenient approach to describe variability of a footprint outline is Fourier analysis [68]. This method allows a quantitative analysis of a shape and of its changes independent from size. The Fourier coefficients can be standardized for size, position and orientation and do not need external reference planes. The resulting coefficients are often referred to as Fourier descriptors.

Table 2.6: **List of studies that examine foot variation of 3D foot shape and footprint outline using PCA and Fourier analysis, respectively.**

Technique	Measurements	Application	Study
PCA	3D foot shape	3D shape variation of foot	[21], [22], [71], [15], [60]
Fourier analysis	Footprint outline	Variation of footprint outline	[68]

(b) Demographic Co-variations

Additionally, several studies suggested examining how personal characteristics (e.g. age, body-mass index) influence foot shape variation [21–23, 27, 71] (Table 2.7). A common technique used for prediction of a dependent variable is multiple linear regression (MLR). In general, MLR examines how multiple independent variables are related to one or more dependent variables. Once each of the independent factors has been determined to predict each dependent variable, the information of multiple variables is used to create an accurate prediction on the level of effect they have on the outcome variable. MLR is based on the assumption that there is a linear relationship between both the dependent and independent variables.

Another approach to examine the influence of personal characteristics on the foot shape is principal component regression [73]. The same assumptions are used as those used in regular multiple regression: linearity, constant variance (no outliers), and independence. Other advanced regression techniques also exist which could be applied for this task [81].

Table 2.7: **List of studies that evaluate foot shape changes due to factors influence.**

Technique	Factor	Study
Regression	Age	[71], [23]
	Gender	[22], [71]
	BMI	[22], [71], [27], [23]
	High-heeled shoes	[21]
	Amount of physical activity	[71]
Principal component regression	Age	[73]
	Gender	[73]
	BMI	[73]

The outcome of these studies showed that the variation in foot shape caused by the personal characteristics should be considered to enable better shoe fit and, therefore, more comfortable footwear.

2.3.4.3 Prediction

A useful asset during the foot assessment would be to estimate the foot shape based on a number of specific personal characteristics or foot shape characteristics (Table 2.8). The most commonly-used technique to determine the predictive significance of specific personal characteristics on foot shape is multiple linear regression. Several studies employed this technique to develop prediction models [13, 23, 31, 32]. Other prediction methods employ machine learning algorithms [8], which may yield notable improvement in terms of accuracy and efficiency. As the amount of data increases, the algorithms learn to make increasingly accurate predictions. Although regression models are quite common in the literature, appropriate data normalisations are necessary for the relationships to be strong.

Considering the shape dimensions of feet that are not always proportional to each other, another technique could be employed, such as allometry [86]. Allometry is the study of the relative size of different parts of a body as a consequence of growth. In the context of foot shape analysis, the allometric model is used to investigate how foot shape dimensions change as foot size changes.

Further investigation of personal characteristics as predictors of a foot shape could lead to the better foot shape estimation and contribute to the more accurate foot assessment.

2.3.4.4 Classification and clustering

(a) Classification

Classification techniques are used to examine foot shape by assigning feet into predefined classes (Table 2.9). Once a foot is assigned to a class, the knowledge of the shape characteristics of the whole class could be used in further analysis. Different classification techniques have been used in literature when assessing the foot shape [2, 12, 29, 52, 53, 55, 76]. A promising classification technique for establishing typologies of foot shape is an archetypoid analysis (ADA) [2]. In general, ADA is an extended variant of archetype analysis applied to the

Table 2.8: **List of studies that employ prediction techniques to estimate predictive significance of specific predictor.**

Technique	Predictor	Study
Regression	Age	[23]
	BMI	[13]
	Arch height	[31]
	Hallux valgus index	[78]
	Foot length	[32]
Principal component regression	Age	[73]
	Gender	[73]
	BMI	[73]
Machine learning	10 foot dimensions	[8]
Allometry	Foot length	[86]

shapes with landmarks. This technique is an unsupervised statistical learning tool [24]. The objective of ADA is to represent the cases by means of a mixture of representative archetypoids. This makes the results returned by ADA easily interpretable, even for non-experts. Archetype analysis has also been combined with the k-Nearest Neighbor algorithm to detect extreme shape anomalies [9]. Furthermore, free form deformations have been used in classification to capture the dissimilarity between two 3-D foot shapes [55]. Another available technique which is used for classification is discriminant analysis [12, 85]. In many ways, discriminant analysis parallels multiple regression analysis. The main difference between these two techniques is that regression analysis deals with continuous dependent variables, while discriminant analysis must have discrete dependent variables. Another classification technique is based on the calculation of location of central tendency [75]. The simpler classification technique uses the mean and standard deviation of the foot parameters as the limits between the classes [34]. The simplest classification technique relies on pure visual appraisal of the examiner [29, 52, 76]. There are numerous classification techniques beyond those listed here [40], but each should be applied to specific tasks according to the requirements and limitations of the techniques.

(b) Clustering

In general, clustering identifies similarities between objects, and groups them according to common characteristics while also differentiating them from other groups of objects. The most common clustering technique is K-means clustering analysis. The goal of this technique is to group data points into distinct non-overlapping subgroups. In general, the K-means algorithm identifies k number of centroids, and then in an iterative procedure, allocates every data point to the nearest cluster while also optimizing the positions of the centroids. This approach is used in two-stage cluster analysis for foot type classification in multiple studies [33, 35, 38, 42, 46]. Prior to K-means analysis the number of clusters (k) for subsequent cluster analysis needs to be determined. This is obtained using Ward's minimum variance method [83], in which the total within-cluster variance is minimized using a recursive algorithm. Then, the obtained clusters are optimized in the next stage using K-means clustering analysis [33, 38, 42, 46].

Table 2.9: **List of studies that employ classification techniques to distinct foot shape groups.**

Technique	Classification groups	Study
Achetypoid analysis	The first archetypoid is a very short and narrow foot; the second archetypoid is very wide foot; and the third archetypoid is a very long foot	[2]
Archetype analysis + knn	Normal shape or outlier	[9]
Discriminant analysis	Recreational sprinters and non-habitual exercisers	[12]
	Gender	[85]
Free form deformation method	Four groups: (a) short toes and large leg depth; (b) long toes and small leg depth; (c) low dorsal and plantar arch; (d) high dorsal arch	[55]
Calculation of central tendencies based of 4 plantar shape parameters: foot width, heel width, three-quarters of the length of the foot; the arch height	S, M, L types based on their central tendencies	[75]
Mean and standard deviation of truncated normalized navicular height are used as the limits for group ranges	Arch height (normal, pes cavus, pes planus)	[34]
Visual appraisal	Arch height (normal, pes cavus, pes planus)	[76], [52]
	Hallux valgus (no, mild, moderate, severe)	[29]

Another approach for clustering is presented in the study of Baek [3]. Here, hierarchical clustering is used to categorize feet using geometrical foot shape dissimilarities. The differences in foot shape between obtained clusters were validated visually as well as numerically by calculating mean, std, min, max of foot dimensions obtained from mean group shapes. This clustering approach is much more advanced than conventional foot-shape classification methods, in that it takes into account the comprehensive geometry of the entire foot shape.

Classification of a foot shape into distinctive classes, or foot shape clustering, could improve foot shape examination. The shape features of a foot belonging to a certain class can be obtained as the representative characteristics of that class instead of having to apply techniques that extract unique shape characteristics of a single foot.

2.3.5 Reported foot shape changes as the influence of subject characteristics or subject behaviour

Different lifestyle choices (e.g., amount of physical activity, shoe wearing habits) and personal characteristics (e.g., sex, body mass index, age, ethnicity) have been shown to have a significant influence on adult foot morphology [5–7, 12, 13, 20–23, 27, 33, 37, 42, 44–46, 48, 53, 58, 62, 66, 71, 74, 80, 85, 86]. Most of the studies employ t-tests [5–7, 12, 13, 20–22, 27, 33, 37, 42, 44–46, 48, 53, 58, 66, 71, 74, 80, 85, 86] to examine these factors' influence on the changes in foot shape. ANOVA was also used for the same purposes in multiple studies [27, 62, 69]. Additional studies used different approaches such as analysis of probability [10], Pearson's chi-squared test [47], Fisher exact test [88], MLR [23], principal component regression [73], to estimate the influence of different factors on foot shape variety. These factors are important to consider when assessing the foot shape in several disciplines such as orthopaedics and footwear production. Several studies have evaluated their influence on foot shape (Table 2.10).

Table 2.10: **Papers showing which factors influence specific foot regions.**

	Age	BMI	Ethnicity	Foot problems	Sex	Others
Toes	[71], [20]		[6]	Hallux valgus- [73]; Hallux valgus, Toe deformity, Swollen foot - [53]	[22], [71], [66], [20], [85]	High-heeled shoes - [21]; Amount of physical activity- [71], [12]; Different bearing weight- [58]; Shod and unshod runners- [69]
Forefoot	[20]	[71], [7], [62], [27], [13]	[45], [46], [6]	Hallux valgus - [73]; Hallux valgus, Toe deformity, Swollen foot - [53]	[46], [44], [33], [53], [42], [48], [86], [6]	High-heeled shoes - [21]; Geographic region- [37]; Amount of physical activity- [12]; Different bearing weight- [58]; Shod and unshod runners- [69]
Midfoot	[23]	[21], [22], [7], [62], [27], [23], [13]	[74], [6]	Hallux valgus, Toe deformity- [53]; Patellofemoral pain syndrome- [5]; Osteoarthritis- [47]	[22], [71], [66], [46], [44], [33], [53], [42], [20], [85], [37]	Amount of physical activity- [71]; Geographic region- [37]
Heel	[71]	[71], [7], [62]	[6]	Swollen foot- [53] Patellofemoral pain syndrome- [5]; Arthritis- [10]; Osteoarthritis- [47]; Diabetic foot- [88]	[71], [46], [20], [37]	
Ankle	[71]	[71], [7]	[6]	Toe deformity, Swollen foot- [53] Patellofemoral pain syndrome- [5]; Arthritis- [10]; Osteoarthritis- [47]; Diabetic foot- [88]	[71], [20], [85]	Amount of physical activity- [71]

Age: Several studies examined the influence of age on foot shape. No significant relationship was found when the effect of the age was evaluated on footprint shape [21] and on 4D dynamic foot scans [27]. In contrast to these findings, other studies reported changes in older populations: a wider heel, a less noticeable Achilles tendon, but also a hallux valgus, and more curled toes [71]; flatter wider feet [23]. These insights should be considered when designing shoes for older populations.

Body-Mass Index (BMI): Many studies examined the influence of BMI on foot shape. Increased BMI is associated to many foot shape changes: wide and flat feet [21, 22]; thicker forefoot along the dorsoplantar axis, a wider Achilles tendon, a wider heel, and a wider ankle [71]; wider foot, wider ball, bigger ball circumference, lower ball height, wider heel, bigger heel circumference [62]; more pronounced changes of medial ball length and ball width during stance phase, wider midfoot [27]; bigger instep circumference [23]; longer foot, wider foot, decrease of arch height [13]. Based on the findings reported in the above studies, it can be concluded that foot shape changes significantly as BMI changes.

Ethnicity: The influence of ethnicity on foot shape was evaluated in studies by Lee [45, 46] and Stolwijk [74]. A significant difference in forefoot shape between Taiwanese and Japanese females was reported in [45]. Wider foot breadth was noted in Taiwanese adults compared to Mainland Chinese and Europeans [46]. Stolwijk et al. [74] reported a lower arch index for most Malawian subjects, compared to Dutch subjects. The foot dimensions of Nigerian population in the study of [6] are comparatively larger than Caucasian ones. The findings from [6] match with the theoretical expectation that populations living in warm climates would have longer arms and legs than populations living in cold environments [67]. Large foot dimensions are an adaptation to tropical environments as they increase the surface area available for heat loss [67]. Since some shoemakers refer to the shoe lasts of specific ethnicity and make slight modifications, the shoe fit problem may be encountered if the differences in foot shape between the two groups are not recognized. Therefore, there is a need for further studies on how ethnicity affects foot shape.

Foot problems: Several studies examined how the foot shape of people without foot problems differs from the foot shape of those with problems (e.g. hallux valgus). Stankovic et al. [73] reported that the biggest toe and head of the first metatarsal bone were the main regions of deviation for hallux valgus subjects, compared to the healthy foot shape. The study by [53] indicated that subjects who have moderate to severe hallux valgus feet had a significantly increased ball girth, ball width, medial and lateral ball lengths, heel bone angle and first toe angle. They also reported that the individuals with swollen feet had a significantly increased ball girth, ball width and heel width, likely due to the excess fluid present in the foot region. It was stated that individuals with lesser toe deformities displayed an increased first and fifth toe height, first toe angle and medial ball length in addition to a decreased ball height, medial malleoli height, navicular height and instep height compared to those without lesser toe deformities [53]. The study by [5] reported that those with Patellofemoral Pain Syndrome (PFPS) showed significant differences in FPI, normalized navicular drop, and calcaneal angle relative to the subtalar joint compared to control groups. Significant differences in the FPI were also found in the study by [10] where they examined the differences in foot shape of women with and without arthritis. The study by [47] indicated significant differences between the control and the medial compartment knee osteoarthritis (OA) groups in relation to the FPI, navicular drop and the arch index. The study by [88] reported significant differences in FPI between people having Charcot foot and subjects without any diabetic complication.

Sex: Many studies discuss gender related differences in foot morphology [20, 22, 27, 33, 42, 44–46, 53, 66, 71]. It has been reported that female foot shape is characterized as having: relatively narrow footprint (lower width-to-height ratio), smaller distal toe elements, and a higher arch [22]; a narrower ankle width, a hallux valgus, a narrower Achilles tendon, a higher arch, and a narrower heel compared to the male foot [71]; greater the first toe angle [66]; the first and fifth metatarsophalangeal angles were greater [20]; smaller ball girth [46, 66, 86]; smaller instep girth [46, 66, 85]; lower instep height [37, 46, 66]; lower navicular height [66, 85]; narrower foot breadth [6, 37, 46, 48, 86]; narrower heel breadth [37, 46]; larger ankle girth [85]; shallower first toe [85]; shorter ankle length [85]; ball length [48]; greater ball circumference [46]; narrower widths [33, 42, 44, 53]; smaller girths [33, 53]; lower heights [33, 42, 44, 53], compared to men's feet. The study of Saghazadeh [66] reported a greater foot arch height for males, which is contrary to findings in [22, 71, 85]. There were no significant differences reported between gender when examining dynamic foot shape [27], or arch index and foot posture index [20]. Within the literature that studies differences between females and males we could not find information on BMI correction. Moreover, it could be a standard procedure which is always performed in such an analysis, although not reported within the studies. We suggest correcting for BMI when examining differences between female and male foot shape, as significant differences in sex for BMI have been reported in the literature [43]. In conclusion, female feet cannot be regarded as a smaller version of male feet, and the differences in foot shape between sexes should be examined in the studies which assess foot shape.

Other factors: Additionally, the factors that reflect some lifestyle habits on the foot shape have been evaluated. Wearing high-heeled shoes is associated with a larger forefoot area of the footprint and a relatively long hallux [21]. Amount of physical activity is not influencing the footprint shape [21], while it has been reported that more physically active people tend to have a more narrow Achilles tendon, a more narrow midfoot, and more curled toes [71]; narrow foot [12]; longer toes [12] then less physically active people. The study of Shu [69] reported significant differences in foot shape of shod and unshod runners for foot length, width, hallux angle and the minimal distance from hallux to second toe. The study of [17] showed that arch height tended to decrease after running a half marathon. The study of [37] revealed that the geographic region from where an individual is coming from is influencing the foot shape, indicating that shoes for the Asian market should be made wider compared to the shoes for the North American and the European market, and shoes for the European market should be made higher in the instep compared to the shoes for the Asian and the North American market. The study of [58] reported significant increase in foot breadth and foot length for both females and males under increased weight bearing. The study of [51] showed there were no relevant changes in foot shape measures before and after long distance military marching. The influence of these factors should be carefully explored and included in the studies which investigate design of the shoes influenced by the above factors.

2.4 Conclusions

We provide a narrative review of techniques to analyze the 3D foot shape. To ensure a higher level of objectivity in the study selection, we partially followed PRISMA guidelines. However, there are a few limitations. First, only one author reviewed the literature, having a higher possibility of missing relevant papers. Next, we provide a specific search string while screening the relevant papers. Although in our case the search string was quite broad, in general the use of a specific search string could lead to missing the sources deviating from the terminology which is unfortunately unavoidable. In the end, our paper was focused on the orthotic field. As a consequence, the articles from some other fields that examine foot (e.g. podiatry) may have been missed during our literature screening. Important to note is that our review did not exclude articles focusing on other application areas. Despite these limitations, we believe to report useful findings from the literature along with future suggestions that may be considered when assessing the 3D foot shape for orthotic and footwear applications. In addition, review presents the most common techniques to measure and analyze 3D foot shape, which could be implemented for other application purposes. For example, a variety of techniques could be used to access foot arch as a common reason for foot problems. In podiatry, an accurate geometrical characterization of the foot shape is critical to designing custom orthoses and footwear for different categories of people, from athletes [56], to patients with foot or lower limb issues [70] , such as patients with diabetes [59, 61]. However, the techniques should be applied according to their requirements and possibilities.

Studies have demonstrated numerous different techniques applied for various purposes in footwear and orthotics. Many of these techniques are quite simple (such as t-test, regression) due to the underlying 1D variables (e.g. Anthropometric dimensions or foot indices), compared to the research fields that study other parts of the human body. However, novel devices that capture the entire foot geometry require the development of novel analysis methods in order to explore and possibly benefit from their full potential. In addition, the available literature has shown that the selection of foot assessment techniques is coupled with foot measurement types. The less information of foot geometry is captured within the measurement (such as 1D foot dimension), the simpler the analysis techniques that have been employed. In addition, the more information of foot geometry is captured, the more automated the measurement procedure needs to be and the more complex the needed analysis techniques are. We recognized four different groups of techniques for studying foot shape. Techniques employed for differentiating between two or more groups have been well known and commonly used for the analysis in other fields (e.g. MSE, t-test, ANOVA etc.). These techniques are often used for their simplicity, common availability in statistics software and straightforward results interpretation. In addition, the data for which the methods are applied should be carefully formed. For example, when comparing groups with some foot deformity, it is likely that if one participant has a foot deformity since childhood, their foot structure would be different to someone who got the same foot deformity three years prior to the study, although both subjects could be within the same group. We showed that the choice for classification and clustering techniques used for foot assessment might be too narrow compared to the techniques used for this purpose in other fields. Moreover, we suggest that the classification and clustering techniques should be applied to specific tasks according to the requirements and limitations of the techniques, for example nature and size of data or definition of the problem to solve. Although these techniques are used to categorize the foot shape into distinctive groups based on some shape similarity measure, they are suboptimal as they are disregarding the full set of the individual's unique shape characteristics as they are rather focused on the shape characteristics relevant for the class. Promising results were reported in the studies which employ 3D foot shape analysis. Here, the methods employed from the studies that investigate other parts of the human body have been replicated.

Plenty of different subject's physical characteristics or subject's lifestyle choices have been investigated to check how these influence foot shape (Table 2.10). For some of them (e.g. BMI and frequent wearing of high-heeled shoes) reports show [7, 62, 72] the shape differences are localized in specific foot regions (forefoot-midfoot for BMI and toes-forefoot for high-heeled shoes). However, for the other (e.g. sex) [20, 22, 44, 62] the reports reveal no specific region of the foot where the shape differences appear the most, but rather the entire 3D foot shape. Many studies emphasized the significant differences in foot shape in different ethnicities, suggesting the shoe fit may not be optimal for a specific ethnicity if the differences in foot shape between two groups are not recognized.

Therefore, we recommend further extensive investigation on mentioned factors that can influence foot geometry as well as the other factors (such as type of sport, or intensity of physical activity) that have not been investigated thoroughly in the literature. We endorse the usage of the 3D foot shape that potentially leads to further investigation of applicable techniques for foot assessment. Bringing researchers in the field, orthotic and footwear companies, end users together to further explore the possibilities of techniques for foot shape assessment may result in multi disciplinary activity to resolve current needs and issues.

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3

Three-dimensional quantitative analysis of healthy foot shape: a proof of concept study

Contents

Abstract

Foot morphology has received increasing attention from both biomechanics researches and footwear manufacturers. Usually, the morphology of the foot is quantified by 2D footprints. However, footprint quantification ignores the foot's vertical dimension and hence, does not allow accurate quantification of complex 3D foot shape. The shape variation of normal 3D feet in a population of 31 adult women and 31 adult men who live in Belgium was studied using geometric morphometric methods. The effect of different factors such as sex, age, shoe size, the amount of physical activity, Body Mass Index (BMI), foot asymmetry, and foot loading on foot shape was investigated. Correlation between these factors and foot shape was examined using multivariate linear regression. The complex nature of a foot's 3D shape leads to high variability in normal populations. After normalizing for scale, the major axes of variation in foot morphology are (in order of decreasing variance): arch height, combined ball width and inter-toe distance, global foot width, hallux bone orientation (valgus-varus), foot type (e.g. Egyptian, Greek), and midfoot width. These first six modes of variation capture 92.59% of the total shape variation. Higher BMI results in increased ankle width, Achilles tendon width, heel width and a thicker forefoot along the dorsoplantar axis. Age was found to be associated with heel width, Achilles tendon width, toe height and hallux orientation. A bigger shoe size was found to be associated with a narrow Achilles tendon, a hallux varus, a narrow heel, heel expansion along the posterior direction, and a lower arch compared to smaller shoe size. Sex was found to be associated with differences in ankle width, Achilles tendon width, and heel width. The amount of physical activity was associated with Achilles tendon width and toe height. A detailed analysis of the 3D foot shape, allowed by geometric morphometrics, provides insights in foot variations in three dimensions that can not be obtained from 2D footprints. These insights could be applied in various scientific disciplines, including orthotics and shoe design.

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3.1 Introduction

Human foot morphology is an important subject for physical anatomical analysis in several biomedical disciplines, including orthopedics, orthotic design and sports sciences [3, 5, 10, 12, 17–20, 26, 27, 37, 39, 42]. Different environments and everyday habits (e.g., the amount of physical activity, shoe wearing habits), as well as physical characteristics such as sex, body mass index, and age, have been shown to have a significant influence on adult foot morphology [3, 12, 17, 19, 20, 26, 37, 39, 42]. Human foot shape also differs among ethnic groups [3] and changes in the course of postnatal development [27]. As a result, footprint shape has been used in a variety of disciplines such as orthopedics [5, 10], and footwear research [18].

A common approach to study foot morphology is to analyze the two-dimensional footprint, despite the potential loss of information along the vertical dimension [12, 16, 31, 43]. The reason for the ubiquitous use of footprints is that they can be relatively easily obtained, measured, and preserved by using wax, plaster, foam or dynamic pressure plates [1, 7, 13, 40]. To fill the missing 3D shape information along the vertical dimension, feet tend to be classified into discrete types, such as pes planus (flat foot) and pes cavus (high-arched foot), by visual inspection of footprint shape [16, 27, 31]. A wide range of different quantitative measures and indices of footprint shape, mainly based on the geometry of the medial longitudinal arch, have also been proposed [31]. Based on these parameters, various foot typologies have been defined [27, 31, 43]. Most of these quantifications are based on a small number of footprint shape characteristics, such as the sizes of different footprint regions, the curvature of the medial longitudinal arch, or the orientation of the forefoot relative to the rearfoot [16, 31].

Nonetheless, these quantitative measures are insufficient to describe the entire 3D foot shape. The study of Luximon et al. [25] showed that generating 3D foot shape from 2D information for custom footwear design introduces error in the 3D foot shape, revealing that there is additional information in 3D shape compared to 2D footprint. Overall, a 3D foot scanner is recommended for collecting foot anthropometric data because it has relatively high precision, accuracy and robustness [23]. A promising technique to examine this full 3D shape information is statistical shape modelling. This technique is used in dysmorphology training [15] and various product design applications [4]. Statistical shape modelling has also been successfully employed in foot classification [38] based on metatarsal bones geometry, but only a partial 3D foot shape is described (i.e. the position of the metatarsal bones).

To date, statistical modelling of the full 3D foot shape has yet to be achieved. Such a model could be beneficial in various applications. In clinical examinations, a statistical model of normal healthy 3D foot shape could be used as a baseline to which a patient's 3D foot scan can be compared. In footwear design, a 3D foot shape model could help produce footwear with a better accommodation for foot girth.

In the present paper, we propose a methodology to quantify the 3D shape of whole feet based on geometric morphometrics, which is a standard technique used for the analysis of 3D shapes in biological datasets [6, 29, 38]. We employ geometric morphometrics on anatomically matched 3D meshes of feet from a normal population. The aligned meshes preserve foot topology, and therefore statistical results, such as group means or principal components, describe actual foot shapes and foot shape deformations. Using geometric morphometrics, we examine the normal 3D foot shape, the bilateral asymmetry of foot shape, and the difference in shape between different foot loadings. The influence of person's physical characteristics and lifestyle habits (e.g. body mass index, sex, age, the amount of physical activity, represented as hours of physical activity per week) on the foot shape are also investigated.

3.2 Materials and Methods

3.2.1 Data collection

Our cohort contains 62 adults equally split between males and females. The Ethics Committee of the Antwerp University Hospital approved the study and all subjects gave their written informed consent before participating.

All individuals were considered to have normal healthy feet if they had never been diagnosed with foot pathology or injury requiring medical intervention, had no foot complaints (i.e. no foot pain), and no incidental findings were found at the time of data collection, as evaluated by a physical therapist. In particular, the height of the foot arch was not an excluding factor for our cohort. We calculated arch index of each foot shape based on plantar surfaces as described in [9] The arch index was calculated from the peak pressure image (i.e. the image that contains the maximum pressure at each pixel over the time of the footstep) and the corresponding foot was classified as high, normal, or flat arched foot. The individuals with certain ranges of the height of the arch, which are considered to be normal, were selected for our cohort. In fact, 13 (20.97%) individuals were considered to have high arched feet, 7 (11.30%) individuals were considered to have flat feet, while 42 (67.73%) individuals were considered to have normal foot arch.

Foot breadth diagonal and foot length [23] were determined by applying the Principal Component Analysis (PCA) to vertices which belong to plantar surface of each foot. In this way, we obtained 3 main axes of variation for each plantar surface. Once we have the main axes of variation, we determined the foot length as the difference between the maximum and minimum value along the first axis. Similarly, the foot breadth was computed as the difference between the maximum and minimum value along the second axis. The shoe sizes for each sex are distributed as follows and are given using both the European and Mondopoint scales. Mondopoint scale: The range for female shoe size was [224/90, 278/105], with average shoe size 246/93 ($\pm$14/5), while the range for male shoe size was [248/93, 291/109], with average shoe size 271/103 ($\pm$8/4). European scale: The range for female shoe size was [36.8, 45.7], with average shoe size 39.8 ($\pm$2.2), while the range for male shoe size was [40.6, 47.6], with average shoe size 43.9 ($\pm$1.6).

Additionally, demographic information was collected for the cohort (Table 3.1). All non-binary factors except shoe size were self-reported. Beside these, we also have an information on binary factors such as sex (1=male, 0=female), foot loading (1=half loaded, 0=full loaded), and foot side (1=right foot, 0=left foot). We note that significant group differences were found for shoe size between sex (t = -17.138, $p <$ 0.001). Also, a significant correlation was found between body mass index and age (ρ = 0.35, $p < 0.001$). To check how representative our cohort is we compared the values we obtained in Table 3.1 to the average values found for the entire Belgian population: age 41.9 [age], height 173.4cm, [weight and height] weight 72.85kg [weight and height], the amount of physical activity: at least 2.5h/week [physical activity]. This shows that the small differences between our cohort and the entire Belgian population should not influence the proposed methodology.

Table 3.1: Cohort demographics

	Age[years]	Shoe size [European(Mondopoint)]	Weight[kg]	Height[cm]	BMI	The amount of physical activity [hours/week]
μ	38.9	40.9 (258/98)	72.6	175.0	23.7	3.7
σ	13.5	2.2 (17/6.8)	12.0	9.3	3.5	4.1
min	18.0	36.0 (224/90)	53.0	156.0	18.6	0.0
max	60.0	46.0 (291/109)	107.0	196.0	35.8	15.0

The 3D foot scans were acquired with an Elinvision FootIn3D laser 3D foot scanner (rs scan, Belgium). The 3D accuracy of the scanner is $0.3mm$, while the mesh resolution is $3.02mm$. A total of four scans were made for each person, two of the left foot (half loaded: bearing 50% of body weight, and full loaded: bearing 100% of body weight) and two of the right foot (half loaded and full loaded). Before scanning of the full loaded foot starts, the participant is allowed to establish their balance by holding a side wall and setting their free leg in the most comfortable position. This position is held during approximately 15 seconds required to obtain the scan. The scans of left feet were mirrored to the coordinate system of the right feet. Prior to the analysis, all 3D scans were cropped just above the ankle (lateral malleolus) to decrease the effect of different ankle poses obtained from half loaded and full loaded scans. Once cropped, a 3D mesh was triangulated [22] and the obtained 3D mesh was used for further analysis.

3.2.2 Methods

3.2.2.1 Geometric morphometry

Before the shape variation in the population can be statistically analyzed, the 3D foot meshes need to be brought into correspondence and superimposed (Figure 3.1a). This is done in two steps. First, mesh vertices are matched across subjects based on their anatomical similarity. Then, those matches are used to bring all feet into anatomical alignment (Figure 3.1).

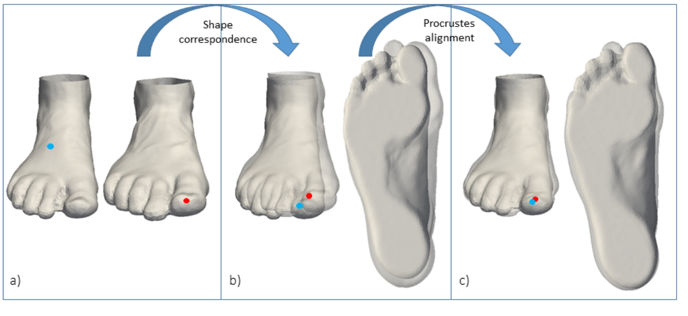

Figure 3.1: **Example of shape correspondence and Procrustes alignment.** (a) Two randomly chosen foot meshes. Initially, the vertices (e.g. blue and red points) on these meshes do not correspond; (b) Foot meshes after shape correspondence. Their vertices (e.g. blue and red points) are matched and located on the same anatomical position; (c) Foot meshes after Procrustes alignment. The geometric distance between corresponding vertices (e.g. blue and red points) is minimized.

Shape Correspondence: Initially, the vertices in our 3D meshes are randomly ordered, meaning that, say, vertex 511 in one foot mesh does not anatomically correspond to vertex 511 in another foot mesh (Figure 3.1a). The number of vertices may also be different for every mesh. Before performing statistical analysis on these meshes, we must first establish an anatomical correspondence between them. To do so, we choose one foot mesh, $X_{reference}$, as our reference foot and deform it to match the other feet in the database. This deformation is described by

$$X_{target} = \Psi(T(X_{reference}), \beta) \tag{3.1}$$

where X_{target} is a foot mesh in the database, T is an affine transformation (which rotates, shifts, and scales the whole foot mesh), and Ψ is an elastic deformation operation. The degree of the deformation operation is controlled by a user-defined elasticity parameter β. We solve for T and Ψ using the iterative procedure defined in [11]. Briefly, this iterative procedure operates by keeping one of the unknowns fixed (e.g. Ψ) and then solving equation3.1 for the other unknown (e.g. T). Subsequently, the procedure solves equation3.1 for the other unknown (Ψ) by keeping the previously-computed unknown (T) fixed. This iterative process repeats until no changes are observed in either Ψ or T. During these repetitions, the elasticity, β, is increased to gradually introduce more deformation as the alignment improves. Further details can be found in [11]. The final result was that the reference surface $X_{reference}$ is deformed to have its shape as similar as possible to the shape of the target surface X_{target}. At this point, X_{target} is replaced by $\Psi(T(X_{reference}), \beta)$, ensuring that each foot mesh has the same number of vertices ordered in the same fashion. This consistent vertex order ensures that every foot mesh has the same vertices in the same anatomical positions (Figure 3.1b).

Procrustes Alignment: Once shape correspondence has been established across all 3D foot meshes, the meshes still need to be brought into spatial alignment before statistics can be accurately performed. To obtain this alignment, all meshes are superimposed by a Generalized Procrustes Analysis [32]. This analysis consists of three steps that normalize the 3D foot meshes for position, size, and orientation (Figure 3.1c). In the first step, all meshes are translated to have the same centroid (average vertex position). Next, the meshes are scaled to have the same size. In the last step, the meshes are rotated to minimize the summed squared distances between the vertices and their corresponding sample average. The above procedure is followed for each individual. To avoid reference bias, the whole approach is iterated three times, where in each iteration, the population average calculated from the previous iteration is used as the reference foot [36].

We performed a PCA of the aligned mesh vertices to investigate the major components of variation in 3D foot shape and to determine the mean 3D shape. PCA models each 3D mesh as follows:

$$\boldsymbol{X} = \boldsymbol{M} + \sum_{i=1}^{n} \boldsymbol{P_i} \boldsymbol{w_i} \tag{3.2}$$

where $\boldsymbol{X}$ is the 3D shape, $\boldsymbol{M}$ is the mean 3D shape, $\boldsymbol{P_i}$ is the i^{th} principal component (PC) and $\boldsymbol{w_i}$ represents the contribution of that PC in the shape. The first PC captures most of the population's shape variance. For each individual, a score ($\boldsymbol{w_i}$) along the PC can be computed. The following PCs are computed to be uncorrelated to previous PCs, while also explaining as much of the remaining subject variation as possible. A single PCA was performed on the whole cohort, including left and right feet, males and females, and different foot loadings.

Statistical analysis

To assess the influence of different subject factors on 3D foot shape, we applied multivariate linear regression between the factors and their most relevant PCs:

$$\boldsymbol{F} = \boldsymbol{W}\boldsymbol{B} + \boldsymbol{E} \tag{3.3}$$

where $\boldsymbol{F}$ is the factors matrix, $\boldsymbol{W}$ is the matrix of the principal component contributions of each population member for the most relevant PCs (i.e. the $\boldsymbol{w_i}$ values from equation 3.1), $\boldsymbol{B}$ is the matrix of regression coefficients, and $\boldsymbol{E} \sim N(0, \sigma^2 I)$. The recorded cohort demographics of sex (1=male, 0=female), age, shoe size, BMI, the amount of physical activity, foot loading (1=half loaded, 0=full loaded), and foot side (1=right foot, 0=left foot) were selected as factors. The subset of relevant PCs, $\boldsymbol{W}$, was determined through dimensionality reduction by sequential forward selection [14]. Bayesian information criterion (BIC) was used to select PCs and to determine when to stop the dimensionality reduction. In this way, only the PCs that best predict the subject factors are used for the statistical analysis. A statistical power analysis (*post hoc*) was applied to the obtained results.

3.2.2.2 Subject characteristics impact on foot asymmetry or loading

Finally, we also employed geometric morphometrics and multivariate linear regression to investigate how subject characteristics impact foot asymmetry and loading. To examine the correlation between foot asymmetry and other factors, a non-binary asymmetry measure was included. First, both right and reflected left foot were brought into correspondence and aligned. Then, we defined the foot asymmetry measure as the Euclidean distance between each vertex on the right foot and the corresponding vertex on the left foot. Next, we performed PCA on the obtained foot asymmetry measure (vectors containing all vertex distances) and applied multivariate linear regression of the PCs on the remaining factors. We further employed a non-binary loading measure between half and full loaded feet, in the same manner as for determining the asymmetry measure (i.e. using the Euclidean distance between feet under different loads). Finally, to examine the correlation between different foot loading and other factors, we performed the above PCA and linear regression procedures in the same manner as for the asymmetry measure.

3.3 Results

3.3.1 Principal component analysis

Figure 3.2 shows the first six PCs, in order of decreasing variance, explaining 92.59% of the total foot shape variation. The shape variations identified by the first 6 PCs are shown in Figure 3.3. Note that the input to our PCA calculation are 3D meshes of feet. These meshes are represented as a collection of roughly 50,000 3D points per mesh. That means that the initial dimensionality of the 3D foot mesh is roughly 50,000 x 3 = 150,000 (with the 3 coming from the fact that each point on the mesh is represented by 3 numbers: the x,y,z coordinates). After applying PCA to these foot meshes, we get an average foot shape and 61 principal components (PC). Thus, PCA reduces dimensionality from 150,000 to 62. Each PC is interpreted as a deformation of the mean foot shape, and is shown by adding (+3σ) and subtracting (-3σ) it from the mean foot shape (Figure 3.3). The given size of each PC (32,272 numbers per PC) represents a limitation when displaying them. To illustrate the variation captured by each PC, we display its effect on the mean shape in Figure 3.3 and marked what we observed. We noted that PC 1 principally captures the variation between high arched feet (pes cavus: low PC 1 score) and flat feet (pes planus:high PC 1 score) as well as the extent of Achilles tendon protrusion. We observed that PC 2 mainly captures the variation between feet with a narrow ball width (low PC 2 score) and feet with a wide ball width (high PC 2 score). Moreover, a low PC 2 score appears to characterize feet with small distance between toes, while a high PC 2 score appears to characterize feet with spread out toes. We detected that PC 3 mostly captures the variation in global foot width, including the ankle width, as well as variation in ball/waist/instep girth. We noted that PC 4 chiefly reflects the variation in the position of the hallux bone; individuals with high scores along PC 4 had feet with the hallux valgus, while individuals with low scores had feet with a hallux varus. We observed that PC 5 mostly represents variation in the shape of the toes and in the ankle angle. Individuals with a low score on this component are referred to as having Egyptian feet compared to individuals with high score who are referred to as having Greek feet. Individuals with Egyptian feet have the hallux as the longest toe, while individuals with Greek feet have a longer second toe [21]. We detected that PC 6 mainly reflects variation in midfoot width and direction of toes. Proportionally, the differences in variation of the latter PCs (PC 4, PC 6) are not that large since the shape variations they represent are more localized and limited in range in normal populations. A larger variation along these PCs might be observed in a population including patients with, for example, a pathological degree of hallux valgus.

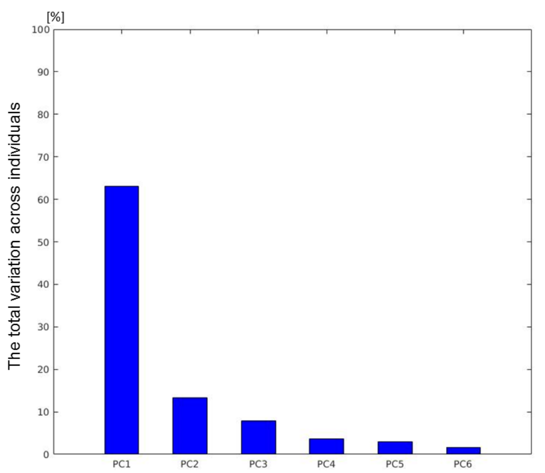

Figure 3.2: The amount of between-subject variance in 3D foot shape described by the first 6 principal components (PCs)

3.3.2 The influence of factors on the foot shape

We investigated the influence of each subject factor separately on foot shape by regressing the principal component weights on the respective variables. For all factors, after dimensionality reduction, the 28 PCs, that correlated with factors, were retained.

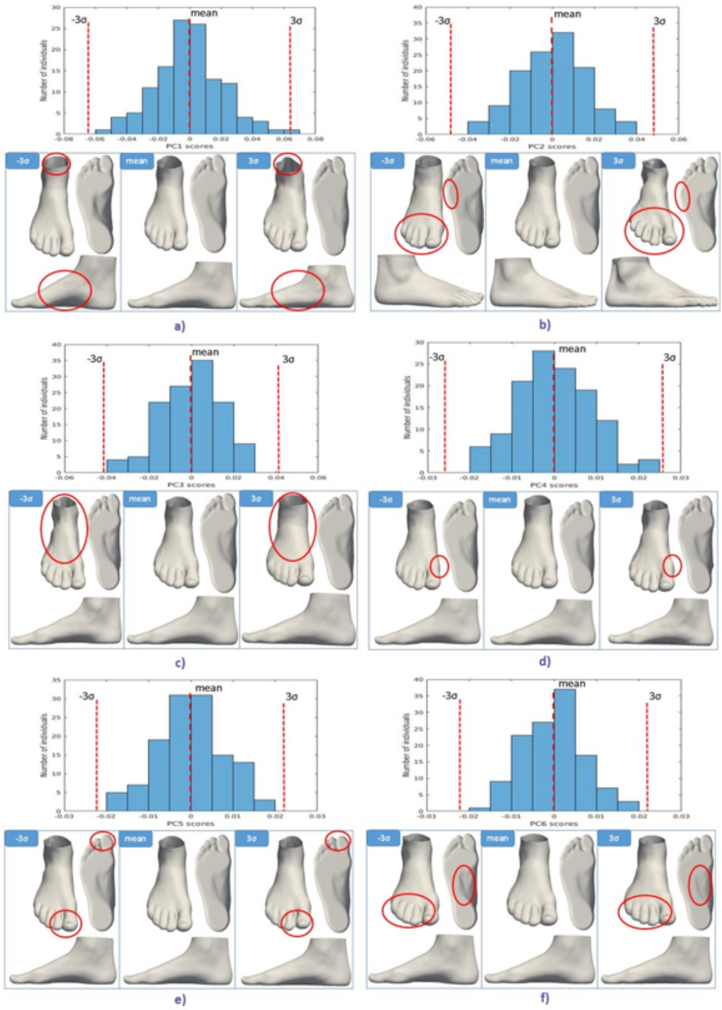

Figure 3.3: **Histograms and views of the first six PCs of the 3D foot shape in a normal population.** a) The first principal component (visualized by the foot shapes along the PC 1 axis) is a contrast between high arched feet (low PC 1 sores) and flat feet (high PC 1 scores). b) The second principal component (visualized by the foot shapes along the PC 2 axis) represents the differences between narrow ball width with touching toes (low PC 2 scores) and wide ball width with spread out toes (high PC 2 scores). c) The third principal component (visualized by the foot shapes along the PC 3 axis) is a contrast between narrow feet (low PC 3 sores) and wide feet (high PC 3 scores). d) The fourth principal component (visualized by the foot shapes along the PC 4 axis) represents the differences between feet with normal hallux bone (low PC 4 scores) and feet whose hallux bone is angled towards the other toes-hallux valgus (high PC 4 scores). e) The fifth principal component (visualized by the foot shapes along the PC 5 axis) is a contrast between "Egyptian" foot type (low PC 5 sores) and "Greek" foot type (high PC 5 scores). f) The sixth principal component (visualized by the foot shapes along the PC 6 axis) represents the differences between feet with a narrow midfoot with toes angled laterally (low PC 6 scores) and feet with a wide midfoot with toes angled medially (high PC 6 scores).

Table 3.2 shows the statistical significance ($\alpha = 0.05$) of the factors. The obtained R-squared values (Table 3.2) sum to a value greater than one, which shows that each factor describes a high percentage of variation within the model, and that the same shape variations occur as a result of multiple factors. This was expected as we had already found significant correlation between factors. We noted a significant correlation between age and BMI ($\rho = 0.35$, $p < 0.001$, and significant differences in shoe size due to sex (t = -17.138, $p < 0.001$). For example, sex explains around 90% of variation present within the model Table 3.2. However, sex is correlated to shoe size, meaning that this value might be lower if these factors were not correlated. A *post hoc* statistical power analysis was also performed on each subject factor. The results of this analysis are given for each factor in Table 3.2. The factors of sex, age, shoe size, the amount of physical activity, and BMI all had significant influence on 3D foot shape ($p < 0.05$) and high statistical power (>0.8).

We examined the correlation between each factor and first six PCs. The obtained results are shown in Table 3.3, which contains correlation coefficients per each of the factors, while significant correlations are bolded. As a result of our linear regression analysis, a factor's strong positive correlation with a certain PC could be balanced out by its possible strong negative correlation with another PC. Therefore, each individual correlation cannot be interpreted independently. Instead, the impact of a subject factor on the foot shape should be examined as a whole.

To visualize the impact of subject factors on foot shape, we used our linear regression model to predict foot shapes when varying each factor in isolation. The representative feet shown in Figure 3.4 to Figure 3.8 were quantitatively derived from the linear model in equation 3.2. Since we used PCA to investigate the shape variations of feet, all we can report is which shape changes appear together in our cohort. We could not say anything else about any cause-and-effect relationship, any underlying mechanism, or whether it was just a coincidence. Our methods simply do not provide these answers. The changes in foot shape were observed when varying the corresponding subject factor in equation 3.2, while other factors remained fixed (to their averages, or in the case of correlations between factors, to the values shown in the figures). Our evaluation of these shape variations are described below.

First, we examined the relationship between BMI and foot shape (Figure 3.4) by fixing the age for two groups: younger and older people (both age groups are examined due to the correlation between age and BMI). We observed that a low BMI was associated with a narrow ankle, a narrow Achilles tendon region, a narrow heel, a narrow midfoot, a straight heel in the sagittal plane, and a thinner forefoot along the dorsoplantar axis. We found that midfoot width, ball girth, waist girth and instep girth all increase with BMI. Similarly, we investigated the influence of age on foot shape (Figure 3.5) by fixing the BMI for two groups: underweight and overweight. We noted that younger individuals were associated with a more noticeable Achilles tendon, a hallux varus , a more noticeable cuboid bone, a wider midfoot, and a narrow heel.

Next, we investigated the relation between shoe size and foot shape (Figure 3.6) for males and females (both sex were examined separately due to their significant difference in shoe size). We observed that a smaller shoe size was associated with a wider Achilles tendon, hallux valgus, a wider heel, a straight heel in the sagittal plane, and a higher arch. We found a significant influence of sex on foot shape (Figure 3.7). We noted that female foot has a narrower ankle width, a hallux valgus, a narrower Achilles tendon, a higher arch, and a narrower heel compared to the male foot.

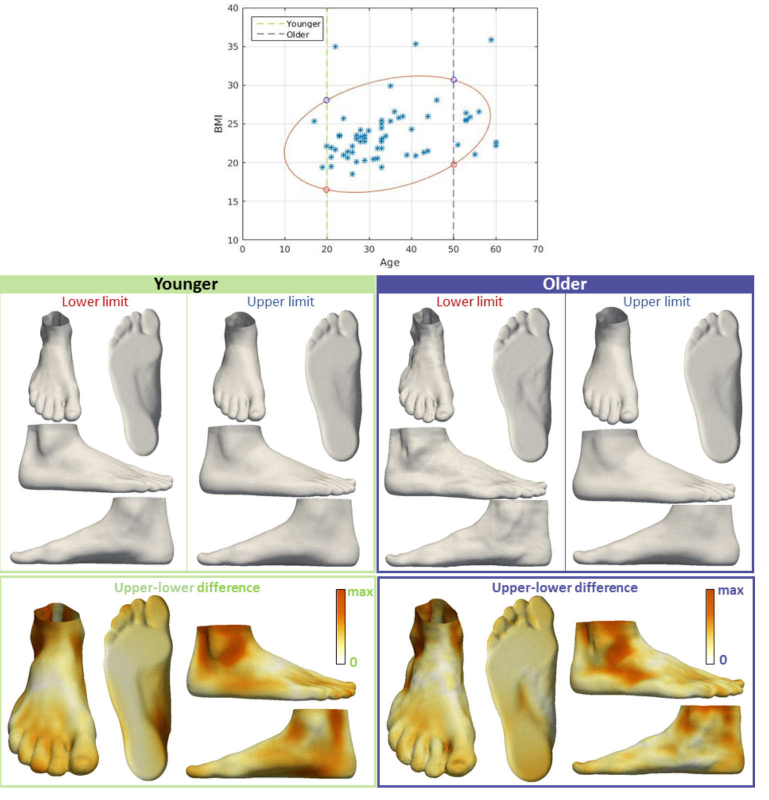

Figure 3.4: **Visualization of the effect of BMI on foot shape.** The influence of BMI on foot shape of younger people (20 years old, green box), and the influence of BMI on foot shape of older people (50 years old, purple box). Upper and lower limits are determined for each group as intersections with contour that covers the range that 90% of the values fall into. For each group, the influence of BMI is represented by color-mapped Euclidean distance computed between the foot shape obtained for upper limit and the foot shape obtained for lower limit.

Finally, we studied the influence of the amount of physical activity (represented as the exercising in hours per week) on foot shape. We found that a low amount of physical activity is associated with a wider Achilles tendon, a wider midfoot, and smaller toes along vertical direction (Figure 3.8). All above shape changes come together as the result of the analysis. Therefore, we could not notice some existing process, such as underlying mechanism from PCs.

Additionally, we have investigated the influence of foot side and foot loading on foot shape, by involving the binary factors for left/right feet and full/half loaded feet. Although the obtained p for foot side and foot loading are less than 0.05, the statistical power of those results are smaller than 0.8. Due to these low statistical powers, we cannot conclude that foot side and loading have a significant influence on foot shape (Table 3.2).

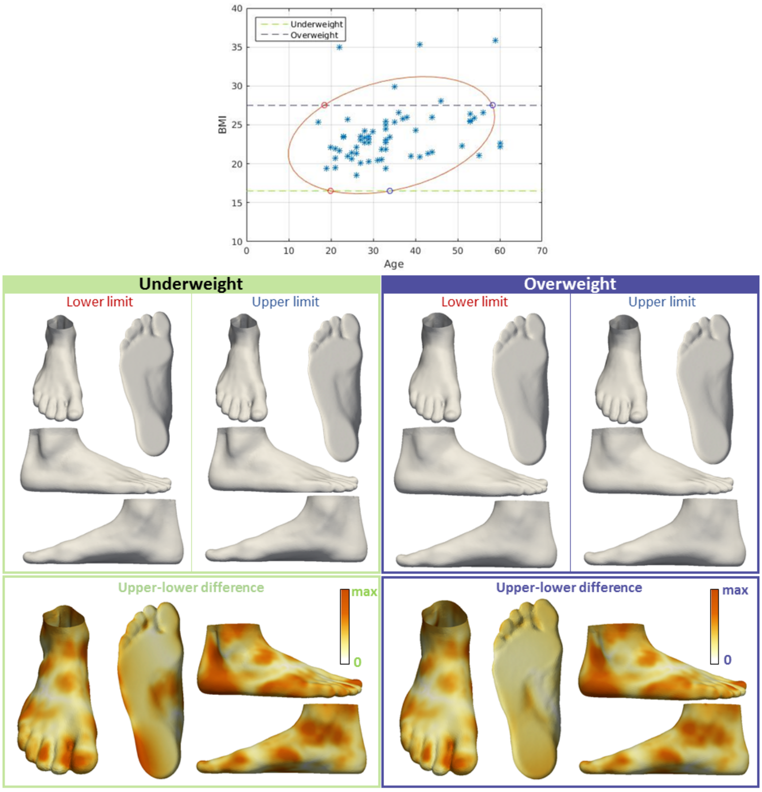

Figure 3.5: **Visualization of the effect of age on foot shape.** The influence of age on foot shape of underweight people (16.5 BMI, green box), and the influence of age on foot shape of overweight people (27.5 BMI, purple box). Upper and lower limits are determined for each group as intersections with contour that covers the range that 90% of the values fall into. For each group, the influence of age is represented by color-mapped Euclidean distance computed between the foot shape obtained for upper limit and the foot shape obtained for lower limit.

3.3.3 Correlation between factors and non-binary foot asymmetry/foot loading

Finally, we examined the correlation between foot asymmetry and other factors, and foot loading and other factors. Neither foot asymmetry nor foot loading were associated to any of the remaining factors.

3.4 Discussion and Conclusion

We applied geometric morphometric methods to study 3D variations in foot shape on a database of 3D foot scans collected from adults defined as normal. Geometric morphometricics was previously used to study the variation of foot shape based on footprints [12]. We expanded on that research by capturing shape variation in the vertical dimension. We further investigated the influence of several factors on foot shape.

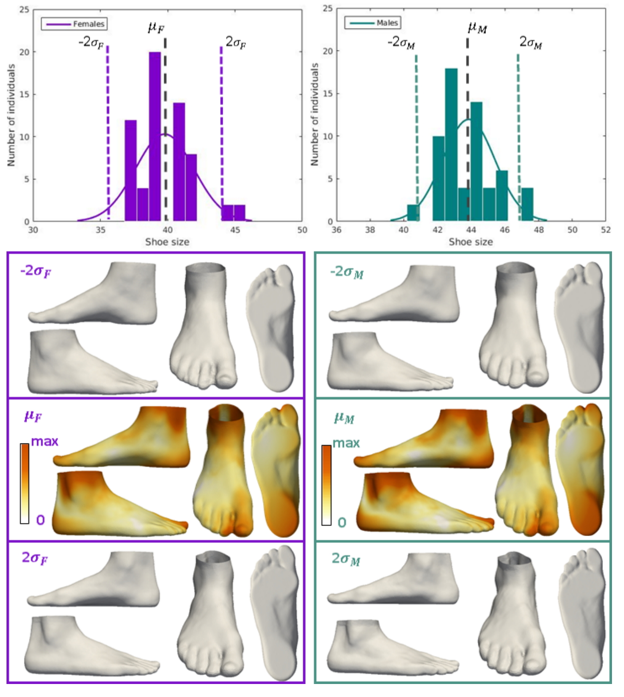

Figure 3.6: **Visualization of the effect of shoe size on foot shape.** The influence of shoe size on foot shape for females (purple box), and the influence of shoe size on foot shape for males (green box). For each group, the influence of shoe size is represented by color-mapped Euclidean distance computed between the foot shape obtained for μ+2σ and the foot shape obtained for μ-2σ

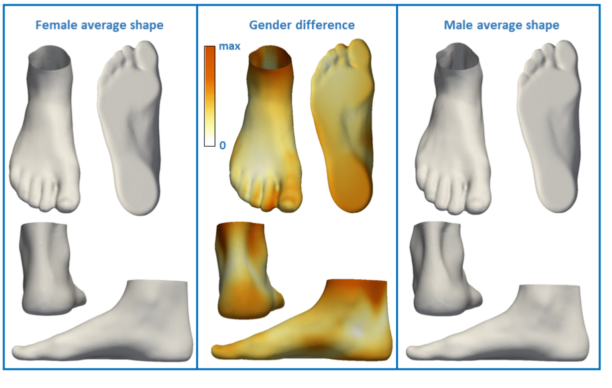

Figure 3.7: **Visualization of the effect of gender on foot shape.** The influence of gender is represented by color-mapped Euclidean distance computed between average male foot shape and average female foot shape.

Our results showed similar foot shape phenomena as has been reported in previous studies of 2D footprints. These findings include a high BMI being associated with wide and flat feet [3, 12, 26], shoe size having a significant influence on foot shape [12], and significant differences being found between sex in arch height, Achilles tendon

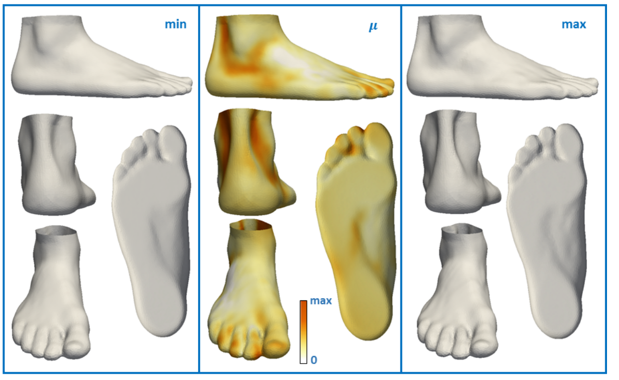

Figure 3.8: **Visualization of the effect of the amount of physical activity on foot shape.** The influence of the amount of physical activity on foot shape (middle), the expected foot shape for 0 hours/week (left), the expected foot shape for 15 hours/week (right). The middle picture represents color-mapped Euclidean distance computed between the foot shape obtained for maximum amount of physical activity and the foot shape obtained for minimum amount of physical activity.

Table 3.2: Statistical significance of the linear relation between subjects factors and foot shape

	Sex	**Age**	**Shoe size**	**The amount of physical activity**	**BMI**	**Foot side**	**Foot loading**
R-squared	0.9034	0.5959	0.8490	0.4042	0.7363	0.3566	0.3689
p	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
post hoc statistical power	1.0	0.9992	1.0	0.8640	1.0	0.7614	0.7905

width, and hallux angle [42]. Our reported variations in foot shape with age also match previous literature [34, 39], and our lack of significant relationships regarding foot asymmetry, and foot loading match what has been previously reported on 2D footprints [33, 35].

The performed analysis on 3D foot shape revealed the advantages in using 3D shape compared to 2D, showing the foot shape variation in three dimensions. PCA is a mathematical procedure used to summarize data, meaning that there is no concept of inference in the use of PCA. As such there is no statistical power concept associated with PCA. Moreover we could not conclude anything else about any cause-and-effect relationship, any underlying mechanism, or whether it was just a coincidence. Therefore, the PCA could be applied to any subset of data, regardless of the number of subjects. However, if the computed PCA weights are used in statistical tests, then the statistical power would be relevant. We followed this rule as explained in Section 3.2.2.1 (Statistical analysis).For example, the first PC of 3D foot shape (representing the major axes of variation) captured low-arched versus high-arched feet, as well as showing significant variation in the mediolateral position of the foot arch (Figure 3.3a). High-arched feet tend to have the midfoot moved medially compared to low-arched feet. The heel and Achilles tendon become more noticeable for flat feet

Table 3.3: Correlation between subjects factors and first six PCs

	Sex ρ (p)	**Age** ρ (p)	**Shoe size** ρ (p)	**The amount of physical activity** ρ (p)	**BMI** ρ (p)	**Foot side** ρ (p)	**Foot loading** ρ (p)
PC1	**0.72** (< 0.001)	-0.019 (0.761)	**0.60** (< 0.001)	**0.19** (0.002)	0.0574 (0.368)	-0.0253 (0.691)	**-0.26** (< 0.001)
PC2	**-0.33** (< 0.001)	**0.2246** (< 0.001)	**-0.23** (0.002)	-0.0452 (0.478)	**0.16** (0.011)	0.045 (0.480)	**0.14** (0.024)
PC3	0.0113 (0.860)	-0.122 (0.054)	**0.17** (0.008)	**0.24** (< 0.001)	**-0.53** (< 0.001)	0.0871 (0.171)	0.06578 (0.302)
PC4	-0.067 (0.291)	-0.1164 (0.067)	0.00789 (0.901)	0.0174 (0.785)	**-0.13** (0.033)	0.08831 (0.166)	**0.26** (< 0.001)
PC5	0.01847 (0.772)	-0.0192 (0.764)	-0.0363 (0.570)	-0.0887 (0.164)	**0.17** (0.007)	**0.14** (0.025)	0.06364 (0.318)
PC6	0.0018 (0.978)	-0.0068 (0.915)	-0.06156 (0.334)	**-0.23** (< 0.001)	0.01258 (0.844)	**-0.24** (< 0.001)	0.05232 (0.412)

(Figure 3.3a). The distances between toes and the ball width change along PC2. PC2 showed that feet with spread out toes have a wider ball width, compared to the feet that have smaller distance between toes (Figure 3.3b). A notable difference in ankle and heel width between narrow and wide feet (Figure 3.3c), as well as the difference in ball/waist/instep girth size are revealed along PC3. The variation in orientation of the hallux bone (PC4) showed that the cuboid bone becomes more noticeable when the hallux bone is angled medially (hallux varus). These results could not have been found with previous 2D footprint analysis.

The analysis that examines the influence of the factors on foot shape, revealed some information about the vertical variations visible only for 3D foot shape. Higher BMI results in a thicker forefoot along the dorsoplantar axis, a wider Achilles tendon, a wider heel, and a wider ankle which can be seen only in the 3D foot scan (Figure 3.4). In particular, the 3D foot shape revealed that older people tend to have a wider heel, a less noticeable Achilles tendon, but also the hallux valgus, and more curled toes compared to younger people (Figure 3.5). The difference in ankle width, Achilles tendon width, and heel width between males and females is also distinct in the 3D foot shape (Figure 3.6 and 3.7). The influence of shoe size on foot shape showed that a bigger shoe size was associated with narrow Achilles tendon, hallux varus, a narrow heel, extended heel in posterior direction, and a lower arch. People that are more physically active tend to have a more narrow Achilles tendon, a more narrow midfoot, and more curled toes (Figure 3.8). To the best of our knowledge, these results were not previously observed. We reported foot loading and foot asymmetry are correlated with PC1, PC2, PC4 and PC5, PC6, respectively (Table 3.3). However, shape differences between half and full loaded feet appeared to be less prominent as the computed statistical power was so low that we could make conclusions on the influence of foot loading to foot shape.

Despite the advantages of 3D methods over 2D, our approach has some limitations.

Three-dimensional analysis of the foot shape, requires the input of 3D foot scans and hence, the availability of a 3D scanner. This is a notable disadvantage over 2D footprint analysis methods. Additionally, the findings presented herein were observed on a cohort of only 62 individuals. These individuals were also all adults and therefore did not cover the full range of mature foot shapes [8]. Finally, it should be noted that ethnicity was not considered as part of this study. As a result of these constraints, it is possible that the shape variability described here is not a complete representation of the possible 3D foot shapes present in an entire normal population. Despite this limitation, we do show that our 3D foot shape model captures morphological information not present in a 2D footprint model. Furthermore, the theoretical properties of geometric morphometrics have been well-studied and the results we have shown fall well within the range of what is reliable for this analysis technique [24, 28].

In this study, the data collection was performed in the running shoe stores. As a consequence, the statistical shape model built for this cohort could be biased towards people who regularly run. For the purpose of proving the methods for foot shape analysis, the potentially biased statistical model does not represent a major concern as we are simply describing the foot shape variations that are present. Nevertheless, it should be stressed that the observations we made here may not extend to other populations.

Additionally, we could not provide a detailed analysis on how the intensity of physical activity or the type of physical activity influenced the 3D static foot shape as this information was not present. It is quite possible that the type and intensity of physical activity can impact foot shape and this impact would be mixed into the results related to the amount of physical activity. Therefore, any conclusions we made on the relationship between foot shape and the amount of physical activity should be taken with a grain of salt.

Our findings could prove valuable in various areas of application. For example, they could allow footwear manufacturers to adapt the 3D design of a shoe based on how a customer's factors influence their 3D foot shape. Our results show that the current approach of creating the shoes based only on 2D footprints [27] does not fully capture the wide variability in foot morphology. As a result, the quality of a shoe fit could be improved upon by using the comprehensive 3D foot shape in shoe design.

Our findings on 3D foot shape might also prove useful in routine clinical examinations. Our statistical analyses on a population of individuals could possibly aid in further standardizing and automating clinical evaluation. A recent study by Knapik on injury risk based on the plantar surface shape came to a similar conclusion [18]. In the study of Knapik, there tended to be a bimodal relationship between BMI and injury risk among the men. Our findings showed that the 3D foot shape changes as BMI changes. Therefore, taking this relationship into consideration during future research could potentially result in decreasing the foot injury risk. Relatedly, the study of Billis et al. [5] emphasizes the importance in everyday clinical practice to use more than one assessment technique of foot posture. Usage of the 3D foot shape during such a clinical examination might give more insight into the relationships between different foot parts, thereby improving diagnosis. These are just a few areas that could benefit from the reported findings.

In summary, normal 3D foot shape, which we quantified using geometric morphometrics, gives more insight of the complex shape of the foot as compared to 2D footprint analysis. We found that the person's physical characteristics and lifestyle habits of sex, age, BMI, the amount of physical activity and shoe size, all significantly influence the 3D foot shape. This information about 3D foot shape variation has the potential to be used for various purposes within several biomedical disciplines, including in the design of more accurate footwear and in the facilitation of more objective clinical diagnosis techniques. Our future work will be focused on extending our results from this study to these two areas of application.

Acknowledgments

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4

Subject-specific identification of three dimensional foot shape deviations using statistical shape analysis

Contents

Abstract

The high prevalence of foot pain, and its relation to foot shape, indicates the need for an expert system to identify foot shape abnormalities. Yet, to date, no such expert system exists that examines the full 3D foot shape and produces an intuitive explanation of why a foot is abnormal. In this work, we present the first such expert system that satisfies those goals. The system is based on the concept of model-based outlier detection: a statistical shape model (SSM) is generated from a normative population of 186 3D optical foot scans of normal healthy feet. This model acts as a knowledge base which is then parameterized by one's demographic characteristics (e.g., age, weight, height, shoe size) through a multivariate regression. This regression introduces model flexibility as it allows the model to be fine tuned to a specific individual. This fine tuned model is then used as a baseline to which the individual's 3D foot scan can be compared using standard statistical tests (e.g. t-tests). These statistical tests are performed at each vertex along the foot surface to identify the degree and location of shape outliers. Our expert system was validated on foot scans from patients with hallux valgus and abnormal foot arches. As expected, our results varied per patient, confirming that feet with the same clinical classification still show high shape variability. Additionally, the foot shape abnormalities identified by our system not only agreed with the expected location and severity of the tested foot deformities, but our analysis of the full 3D foot shape was able to completely characterize the extent of those abnormalities for the first time. These results show that the combination of statistical shape modelling, multivariate regression, and statistical testing is powerful enough to perform outlier detection for 3D foot shapes. The resulting insights provided by this system could prove useful in both shoe design and clinical diagnosis.

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Stanković K., Huysmans, T., Danckaers, F., Sijbers, J., Booth, B. G. (2020). Subject-specific identification of three dimensional foot shape deviations using statistical shape analysis. *Expert Systems with Applications*, 151, 113372.

4.1 Introduction

It is estimated that anywhere between 17-41% of the general population experience foot pain and, in roughly half of these cases, the foot pain is disabling [34, 41, 43]. For some people, this pain is linked to foot deformities, with common conditions including hallux valgus [33, 59], collapsed foot arches [78, 79], and club feet [1, 32]. For others, foot pain has been associated with improperly fitting footwear [22, 25], indicating that a more precise characterization of foot shape would be valuable in footwear fitting and design [24, 65, 66, 76]. Despite a clear link between foot shape and foot pain, one study has reported that more than half of its participants who experienced debilitating foot pain did not seek professional help [34]. These results suggest that either foot shape abnormalities are difficult for a non-expert to assess, or that access to professional foot care is limited. Either way, this indicates a need for an expert system that can assess whether one's foot shape is abnormal or not. Such a system could reduce one's future foot pain by either identifying foot deformities requiring professional care, or by recommending better footwear choices [26, 40, 55, 58].

The development of expert systems for foot assessment remains an open research question. Traditionally, experts such as physical therapists and podiatrists have classified feet based on visual appraisal [17, 33, 52], with foot arch heights, ankle bone curvatures, and toe angles being key shape cues [33, 64, 79]. Unfortunately, these visual appraisals introduce a measure of subjectivity into the analysis of foot shape, resulting in examinations that can vary significantly between clinicians [46].

In recent years, attempts have been made to develop expert systems based on objective measures of foot shape, most notably in the form of outlier detection algorithms [80]. These include the arch index measure introduced by Cavanagh et al. [13]. Using measurements from 2D footprints and statistical thresholds, arch index can classify feet as being high-, normal-, or flat-arched. Similar statistical thresholds have also been applied to 1D arch height measures [57], center of pressure trajectories [69], and forefoot-rearfoot angles [31] in order to identify abnormal arch heights. A full review of such techniques can be found in the work of Xiong et al. [78]. Similar statistical thresholds have also been defined for hallux valgus based on the hallux abductus angle [14, 62], and for club feet based on calcaneus distances [1]. These approaches can be thought of as expert systems where the user inputs a given foot measurement or footprint, the knowledge base is a statistical model, and the inference engine performs outlier detection using significance thresholds. Other expert systems also exist for foot assessment, but they do not consider foot shape [4, 56, 61].

Despite the benefits these objective techniques provide, they also have their limitations. Many studies are based purely on scalar measurements or 2D images of the foot (e.g. footprints) instead of the full 3D foot shape [12, 13]. It has been shown that the full 3D foot shape is not only important for footwear design [37, 51, 55, 59], but it also cannot be fully recovered from lower-dimensional foot measurements [77]. As a result, these expert systems do not provide a complete assessment of foot shape.

Additionally, existing expert systems for foot shape provide only coarse groupings, usually only identifying if a foot is normal or abnormal. Several studies [3, 23, 48] reported inter-individual differences for width and height measures of feet within the same class, such as foot size classes. Similarly, different degrees of hallux valgus deformity and toe deformities were associated with different shoe needs [53]. These results suggest that foot shapes within the same class can still vary significantly and that this variance should be further considered in an expert system.

We propose that an expert system for foot shape analysis should ideally satisfy four criteria. First, the system's knowledge base should contain information on the full 3D foot shape and not simply 2D or 1D foot measurements. This criterion would ensure that assessment of the complete foot is possible. Second, the system's inference engine should provide more than simply a label of whether a foot is normal or not. If a foot is labelled as abnormally-shaped, the system should explain what part of the foot is abnormal and to what extent it is abnormal. Third, the system's user interface should be simple enough for a non-expert to use. This criterion aims to eliminate the subjectivity seen in visual assessments as well as ensuring that access to the system is not limited by access to a foot care professional. Finally, the system should employ methods that are familiar to foot care professionals, thereby ensuring that they can confidently recommend such a system and properly follow-up on the system's results.

To address these criteria, we introduce an expert system based on the concepts of outlier detection for the assessment of one's full 3D foot shape. The user interface requires one to simply enter a 3D optical scan of their foot and basic demographic information (e.g. age, weight, shoe size), making the system usable by an non-expert. The knowledge base of the system is centered on the statistical shape modelling, a technique that has shown to be a useful tool in a variety of applications [2, 16, 29, 30, 67, 81]. The model is constructed from normal healthy individuals and a regression analysis, like those in [45, 75], is used to link the user-entered demographic information to a baseline foot shape measurement. Finally, statistical testing is employed to compare one's measurement to this statistical baseline. This testing is performed across the foot surface in order to identify the location and extent of shape abnormalities [5, 7, 39, 44].

Our proposed expert system merges together established shape analysis and outlier detection techniques, thereby making it a natural extension to methods currently used by foot care professionals. We hypothesize the use of such techniques can provide sufficient analytical power to become the first expert system to simultaneously satisfy the four criteria mentioned earlier.

4.2 Methods

Our proposed expert system for foot shape assessment consists of two main parts: the building of a statistical shape model (i.e. the knowledge base), and the comparison of an individual's foot to that model (i.e. the inference engine). In both parts of the system, we represent a foot shape, $\boldsymbol{X}$, as a triangulated 3D mesh of the foot surface. Also, let $\{\boldsymbol{X}_1, \boldsymbol{X}_2, \cdots, \boldsymbol{X}_N\}$ be the N foot scans from which a statistical shape model will be computed.

In order to perform meaningful statistics on such a shape representation, an anatomical correspondence needs to be established between all N foot meshes and these meshes have to be spatially aligned. In section 4.2.1, the correspondence and alignment procedure is explained after which the model building and personalized analysis parts of our pipeline are presented in section 4.2.2 and 4.2.3, respectively.

4.2.1 Correspondence establishment and anatomical alignment

Initially, each 3D foot mesh has a different number and order of vertices. These meshes can also vary in their position within the field of view of the 3D scanner. In order to analyze the shapes represented in 3D foot meshes, we must first ensure that each mesh has the same vertices located in the same anatomical locations. Second, we must then align the 3D foot meshes to remove the influence of pose on the analysis of shape. The first procedure is referred to as shape correspondence while the second is referred to as anatomical alignment. Fig. 4.1 shows the effect of these procedures on two randomly-chosen feet.

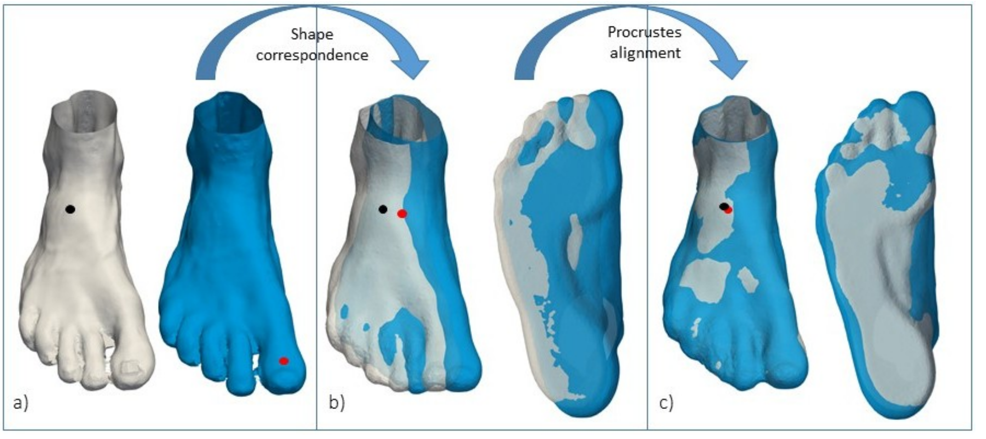


Figure 4.1: **Correspondence establishment and alignment.** a) Two randomly chosen feet with unmatched vertices before correspondence establishment, b) overlapped feet after correspondence establishment, c) overlapped feet after anatomical alignment.

4.2.1.1 Shape correspondence

To bring two 3D foot meshes into anatomical correspondence, we employ the pairwise registration of Danckaers et al. [18]. To do so, we choose one foot mesh, $\boldsymbol{X_{ref}}$, as our reference foot mesh and deform it to match the other foot meshes in our analysis. At a high level, this deformation is described by

$$\boldsymbol{X_{target}} = \Psi(T(\boldsymbol{X_{ref}}, \beta)), \tag{4.1}$$

where $\boldsymbol{X_{target}}$ is a foot mesh being analyzed, T is an affine transformation and Ψ is a set of displacement vectors. The degree of the deformation operation is controlled by a user-defined elasticity parameter, β. We solve for T and Ψ using the iterative procedure defined in [18]. Briefly, this iterative procedure operates by fixing one of the transformations (e.g. Ψ) and then solving equation 4.1 for the other transformation (e.g. T). Subsequently, the procedure solves equation 4.1 for the transformation that was fixed in the former iteration (Ψ) while now fixing the previously-computed unknown transformation (T). This process is iterated until the magnitude of the observed shape changes is below a set threshold (0.01 mm). During the iterations, the elasticity parameter, β, is increased to gradually introduce more deformation as the alignment improves. Further details can be found in [18]. The final result is the reference mesh $\boldsymbol{X_{ref}}$ deformed to have its shape as similar as possible to the shape of the target mesh $\boldsymbol{X_{target}}$. At this point, $\boldsymbol{X_{target}}$ is replaced by $\Psi(T(\boldsymbol{X_{ref}}))$, ensuring that each foot mesh has the same number of vertices ordered in the same fashion (Fig. 4.1b). This means we do actually change shape's geometry but these errors are so small that they do not impact subsequent analysis [18]. The pairwise registration is applied for all N foot shapes in the database to make sure all shapes are in correspondence with each other.

4.2.1.2 Procrustes Analysis

Once the N foot shapes have been brought into correspondence, their meshes need to be brought into spatial alignment before statistics can be accurately performed. We achieve this alignment through a Procrustes Analysis as presented by Stegmann and Gomez [72]. This analysis consists of three steps that estimate the translation, scale, and rotation of one shape that brings it into alignment with another (Fig. 4.1c). Since the foot scans are obtained in a standing position, we further constrain the translation in the vertical direction to ensure that all 3D foot meshes remain aligned to the ground plane.

For the personalized analysis step of our pipeline, a single Procrustes Analysis is sufficient to bring the individual's 3D foot mesh into alignment with the SSM. However, when building the SSM, all 3D foot meshes need to be superimposed. We accomplish this task by performing a Generalized Procrustes Analysis [72]. In a Generalized Procrustes Analysis, a single 3D foot mesh is chosen as a target and the remaining $N-1$ meshes are aligned to it using the traditional Procrustes Analysis. An initial estimate of the mean shape is then obtained. This mean shape is then chosen as the target mesh and the process repeats itself until no further changes in the mean shape are seen. Further details can be found in [72].

The shape correspondence and alignment procedures above are followed for each individual. In the case of the model building task, the shape correspondence is iterated together with Generalized Procrustes Alignment in order to avoid any bias from the choice of $\boldsymbol{X_{ref}}$. In each iteration, the population mean calculated from the previous iteration is used as the reference foot mesh [71]. Convergence is reached if the average distance between corresponding points on the reference mesh from the previous iteration and the reference mesh from the current iteration is less than $\varepsilon = 0.001$ mm.

4.2.2 Model building

From our set of N aligned 3D normal healthy foot scans, we built a 3D statistical shape model using Principal Component Analysis (PCA) [70]. This SSM is then combined with a multivariate linear regression to fine tune the SSM based on different covariates (such as age, shoe size, BMI, etc.). Using this fine-tuned model, a maximum-likelihood prediction of one's foot shape can be obtained. Then, residuals are calculated between these predicted surfaces and the aligned, measured, foot surfaces. These model-building steps are summarized in Fig. 4.2.

4.2.2.1 Principal Component Analysis

Once all foot scans have been brought into correspondence and aligned to an unbiased reference, a statistical shape model is built from the population. Let N be the number of 3D foot shapes in our normal population, with every shape consisting of n vertices in 3D. This population is represented by $N-1$ dimensional cloud within $3n$-space, where each point represents a foot shape. Principal component analysis (PCA) is then used to represent this cloud by a mean shape and $N-1$ eigenmode vectors, where the first eigenmode describes the largest variance in the population, the second eigenmode

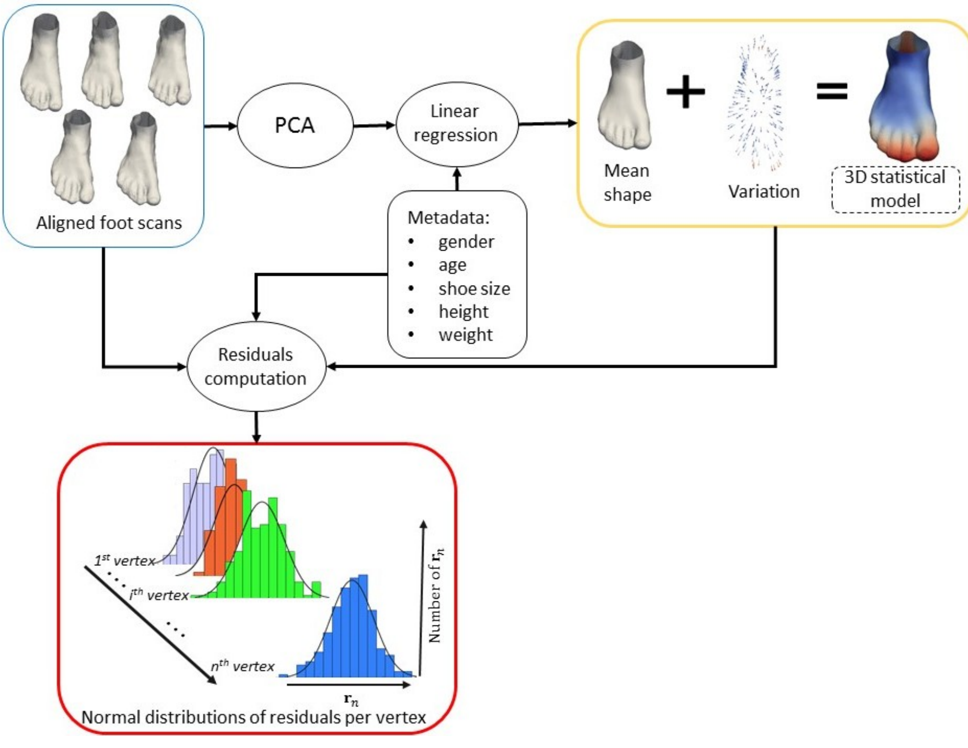


Figure 4.2: **Model building.** a) Once all feet are brought into correspondence and aligned (blue box), a 3D foot SSM is built using Principal Component Analysis. b) Metadata is combined with the 3D SSM to develop a tunable shape model (yellow box) c) Residuals for each vertex are computed between every aligned foot and its corresponding SSM prediction (red box).

the second largest variance orthogonal to the first, etc. The resulting statistical shape model consists of the mean shape $\bar{\boldsymbol{x}} \in \mathbb{R}^{3n}$ and the main shape modes: the principal components (PC) $\boldsymbol{P} \in \mathbb{R}^{3n\times(N-1)}$. Under this PCA model representation, a new shape $\boldsymbol{y} \in \mathbb{R}^{3n}$ can be formed by a linear combination of the PCs:

$$\boldsymbol{y} = \bar{\boldsymbol{x}} + \boldsymbol{P}\boldsymbol{b}, \tag{4.2}$$

with $\boldsymbol{b} \in \mathbb{R}^{(N-1)}$ being the PC weight vector mapping the shape to the statistical model parameters [68]. In the context of our work, $\bar{\boldsymbol{x}}$ is the average foot shape, the principal components $\boldsymbol{P}$ can be interpreted as a set of deformations, and the PC weights, $\boldsymbol{b}$, are computed to weight each deformation such that the average foot shape gets warped into the specific foot shape $\boldsymbol{y}$ (see the upper-right, yellow, box in Fig. 4.2).

4.2.2.2 Incorporation of subject characteristics

While PCA allows us to build a 3D SSM, it has no natural way to handle covariates that can impact foot shape (e.g. weight, sex, shoe size). To account for these covariates, we link them to the SSM using multivariate multiple linear regression [21]. Suppose we have a covariate vector $\boldsymbol{f} = [f_1, f_2, \cdots, f_k, 1]^T \in \mathbb{R}^{k+1}$ that contains information of an individual's age, shoe size, etc. as well as a 1 at its end to allow for a constant offset in regression. We can define the relationship between this covariate vector and the PCA weight vector $\boldsymbol{b}_i \in \mathbb{R}^{N-1}$ of each shape $\boldsymbol{X}_i$ from the dataset using a linear model. A mapping matrix $\boldsymbol{M} \in \mathbb{R}^{(N-1)\times(k+1)}$, describing the relationship between the PCA weight matrix $\boldsymbol{B} = [\boldsymbol{b}_1, \boldsymbol{b}_2, \cdots, \boldsymbol{b}_N] \in \mathbb{R}^{(N-1)\times N}$ and the feature matrix $\boldsymbol{F} = [\boldsymbol{f}_1, \boldsymbol{f}_2, \cdots, \boldsymbol{f}_N] \in \mathbb{R}^{(k+1)\times N}$ is calculated by

$$\boldsymbol{M} = \boldsymbol{B}\boldsymbol{F}^{+}, \tag{4.3}$$

where $\boldsymbol{F}^{+}$ is the pseudoinverse of $\boldsymbol{F}$ [19]. With this mapping matrix, a new PC weight vector $\boldsymbol{b}$ can be generated from given features $\boldsymbol{f}$ as follows:

$$\boldsymbol{b} = \boldsymbol{M}\boldsymbol{f}. \tag{4.4}$$

Through this linear regression, we link the shape deformations represented by the principal components $\boldsymbol{P}$ to the demographic characteristics of the individual. In this way, the matrix $\boldsymbol{M}$ effectively captures how much each demographic feature influences the foot shape. By substituting equation 4.4 into equation 4.2, we obtain the statistical shape model which incorporates the shape variation influenced by an individual's covariates:

$$\boldsymbol{y} = \bar{\boldsymbol{x}} + \boldsymbol{P}\boldsymbol{M}\boldsymbol{f}. \tag{4.5}$$

By providing an individual's demographic characteristics, the most plausible corresponding normal foot shape can then be simulated using equation 4.5.

4.2.2.3 Residual calculation

Our SSM defined by equation 4.5 provides us with a model of the foot shape as a whole. To further localize our subsequent analysis, we augment our SSM with residual distributions at each mesh vertex. For each 3D mesh used in building our model, we calculated residuals between it and the corresponding foot shape prediction given by equation 4.5. Each vertex thus obtains the residual vector $\boldsymbol{r}$:

$$\boldsymbol{r} = \boldsymbol{v}_{\boldsymbol{r}} - \boldsymbol{v}_{\boldsymbol{p}}, \tag{4.6}$$

where $\boldsymbol{v}_{\boldsymbol{r}}$ is the vertex of the measured foot mesh and $\boldsymbol{v}_{\boldsymbol{p}}$ is the corresponding vertex of the predicted foot mesh.

Since the variations in vertex position along tangential directions do not induce shape variations, and since we are only interested in shape variations, we further restrict our analysis to variations in vertex position along the direction normal to the foot surface. For this reason, the vector $\boldsymbol{r}$ is projected onto the vertex normal $\boldsymbol{n}_{\boldsymbol{p}}$ of the predicted foot mesh as follows:

$$r_n = \boldsymbol{r} \cdot \boldsymbol{n}_{\boldsymbol{p}}, \tag{4.7}$$

where r_n is the normal component of $\boldsymbol{r}$ [35, 42].

Residuals are calculated using equation 4.7 for each vertex of each 3D mesh used in the model-building procedure. Normal distributions are then fit to the residuals at each vertex to summarize local shape variations that are not otherwise captured by the SSM.

4.2.3 Personalized foot shape analysis

To evaluate the 3D foot shape of a new individual, we detect shape anomalies based on the 3D foot SSM built earlier (Fig. 4.2). To do this, we first predict the normal foot shape of the new individual using equation 4.5. Then, we establish a correspondence between the predicted foot shape and the individual's foot shape using the algorithm described in equation 4.1. The individual's foot mesh is then brought into alignment with the predicted foot mesh using the Procrustes alignment algorithm described earlier. Finally, we compute, and statistically test, residuals between the aligned mesh and the predicted mesh as described below. The full procedure is displayed in Fig. 4.3.

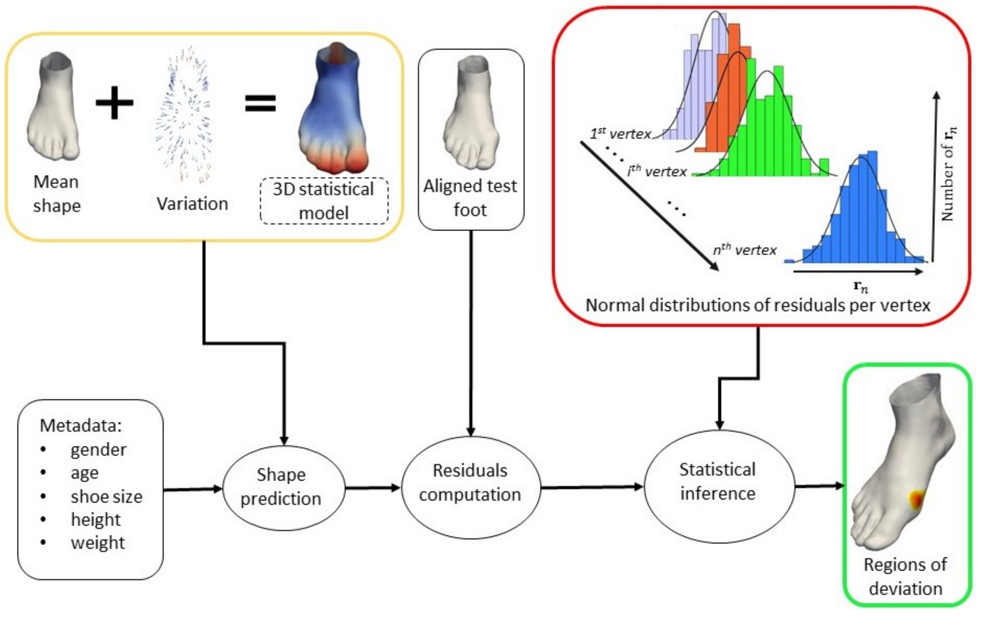


Figure 4.3: **Procedure for the personalized analysis of an individual's foot shape.** a) The predicted normal shape for the individual's foot is obtained using the SSM from the model-building (yellow box) and metadata of the individual b) Residuals for each vertex are computed between the aligned, measured foot shape and its corresponding prediction c) Calculated residuals are compared to residuals obtained in the model-building (red box) using statistical significance tests (green box).

4.2.3.1 Statistical inference

To identify outliers in 3D foot shape, we performed single-sample t-tests for each residual projection of the test mesh, as the appropriate test to use when the mean and standard deviation are estimated from the built model. To achieve this, we computed the residual between each vertex on the individual's aligned foot mesh and its corresponding predicted mesh using equation 4.6. Since we are interested in variations present in the mesh along the direction normal to the foot surface, we projected vector $\boldsymbol{r}$ onto the surface normal using equation 4.7. Finally, we tested whether there was a significant difference ($p < 0.05$) for this individual's shape residuals by comparing them to the corresponding Normal distributions generated in the model-building. We conducted multiple comparisons correction with False Discovery Rate (FDR) for a given threshold $\alpha = 0.05$ [73].

4.3 Experiments

4.3.1 Dataset

To evaluate our shape analysis technique, we collected 3D optical scans of the feet of 204 Belgian adults: 132 men and 72 women. Participation in the study was entirely voluntary and demographic information (age, BMI, height, weight, and shoe size) was collected for the whole cohort (Table 4.1). All factors except shoe size were self-reported, while shoe size was measured using a Brannock device. Additional factors such as race and ethnicity were not noted. As the participants were recruited by the running shoe stores, a bias towards the people who run regularly could be present within our cohort. Detailed information on the recruitment procedure can be found in Section 1.3. The Ethics Committee of the Antwerp University Hospital approved the study and all subjects gave their written informed consent before participating.

Table 4.1: **Metadata for the whole cohort, divided between the model-building and testing phases**

		Age [years]	Shoe size [European (Mondopoint)]	Weight [kg]	Height [cm]	BMI [$\frac{kg}{m^2}$]
Model-building	μ	36.5	41.7(265/101)	72.6	176.0	23.4
phase	σ	12.5	2.8(18.3/7.1)	11.4	8.3	3.1
33 females &	min	18	36.0(225/90)	49.0	150.0	17.9
60 males	max	62	47.0(300/114)	100.0	196.0	32.7
Test phase	μ	43.0	41.4(263/100)	77.3	174.8	25.2
	σ	12.8	2.5(18/7)	15.1	9.1	4.3
39 females &	min	19	36.0(225/90)	47.0	156.0	18.4
72 males	max	68	47.5(304/116)	144.0	198.0	41.6

The 3D optical scans of the participant's feet were acquired with an Elinvision Tiger 3D laser scanner (rs scan, Paal, Belgium). The accuracy of the 3D scanner was 0.3 mm. A total of two scans were made per person: one of the left foot and one of the right foot. Both left and right feet were scanned while standing in a relaxed pose on both feet. Prior to the analysis, the scans of left feet were flipped along the medial-lateral axis so as to orient them in the same fashion as the right feet. Also, all 3D scans were cropped 2.0 cm above the average of the lateral and medial malleolus to decrease the effect of different lower leg poses on subsequent analysis. The obtained 3D meshes were used for further analysis.

4.3.2 Inclusion-Exclusion Criteria

For evaluation purposes, all individuals were categorized into one of four groups: individuals with a normal foot arch, individuals with a high foot arch, individuals with flat feet, and individuals with hallux valgus. Each of these four groups are described further in Table 4.2. Individuals were considered to have normal foot shape if they had no foot or leg complaints at the time of measurement. For the individuals with hallux valgus, we measured the hallux abductus angle (HAA) of each individual using the 3D anatomical annotation approach described in [14]. A foot is considered as having a hallux valgus if its HAA is larger than 14 degrees, a threshold which is in line with the previous study of Menz et al. [53]. These feet were also assessed using the Manchester Scale [33], with the majority of cases being scored as of mild (45.65%) or moderate (47.8%). Only a few severe hallux valgus cases were present (6.55%).

Table 4.2: **Exclusion and inclusion criteria for each group as well as the number of 3D foot meshes used for model-building and testing phases.**

	AI	HAA	Number of individuals/feet (training)	Number of individuals/feet (testing)	Total number of individuals/feet
High arch	< 0.24	$< 14°$	0/0	21/40	21/40
Flat arch	> 0.33	$< 14°$	0/0	26/40	26/40
Normal arch	$[0.24, 0.33]$	$< 14°$	93/186	34/40	127/226
Hallux valgus	any	$> 14°$	0/0	30/46	30/46

The number of feet is not always equal to twice the number of individuals, due to differences in AI and HAA between left and right feet.

To classify individuals based on their foot arch height, we employed the standard approach of thresholding based on the arch index measure of Cavanaugh and Rodgers [13]. This measure was applied to plantar pressure measurements taken from each participant as they walked at their preferred walking speed. The plantar pressure measurements were collected using an rs scan 2 *m* Hi-End footscan® system (rs scan, Paal, Belgium) with a frequency of 200 Hz and sensor dimensions of 7.62 *mm* x 5.08 *mm*. A total of 10 measurements were collected per foot, then spatiotemporally aligned and averaged using STAPP [6]. The average measurement was then upsampled to 3 *mm* x 3 *mm* to obtain a correct foot geometry from the pressure plate with anisotropic sensor dimensions. The arch index was then calculated from the peak pressure image (i.e. the image that contains the maximum pressure at each pixel over the time of the footstep) and the corresponding foot was classified as high, normal, or flat arch as described by Cavanaugh and Rodgers [13]. Note that the larger the arch index, the flatter the foot.

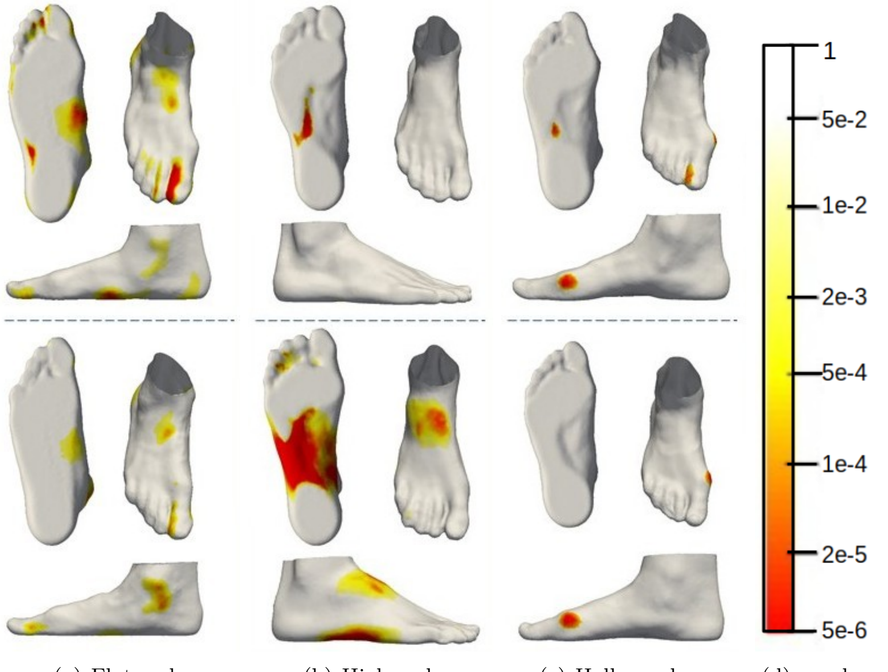
4.3.3 Experimental setup

To evaluate our technique, we built a model from a normative population consisting of 93 individuals with a normal foot arch (186 normal feet). Individuals in the remaining three groups - high arch, flat foot, and hallux valgus - were used for testing purposes. Each test consisted of taking a 3D foot scan from one of the test groups and comparing it to the shape distribution in the SSM. Given the number of scans in our model, and a 5% tolerance of an incorrect test result, we calculated that a comparison with our SSM should be able to detect effects with a Cohen's d value of 0.24. This result corresponds to effects in the small-to-moderate range ($0.2 < d < 0.5$).

In the case of the two arch height groups, we hypothesized that these groups would show abnormalities in similar areas around the midfoot. In the case of hallux valgus patients, we hypothesized that shape abnormalities would appear around the hallux (i.e. big toe) and corresponding metatarsal. Additionally, we set aside 40 normal foot scans of individuals with a normal foot arch in order to validate that our technique shows no abnormalities for feet similar to those in the model. A further description of the groups used in model building and testing are shown in Table 4.2.

4.4 Results

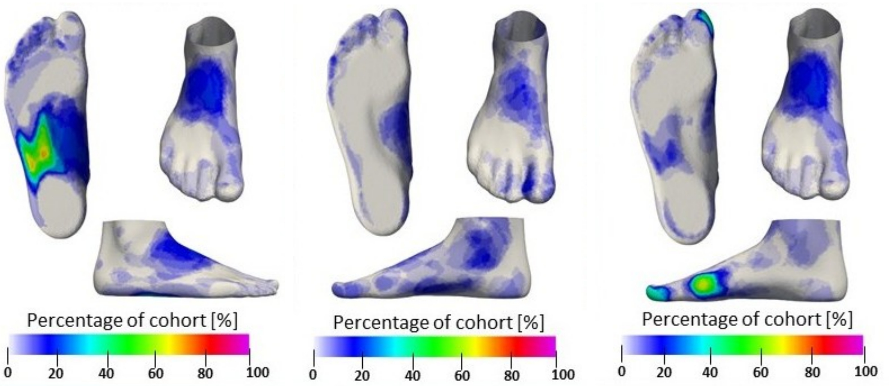
For each individual's foot, we tested, with FDR correction, how the foot shape deviates from the normative population. Fig. 4.4 shows the examples of 6 test subjects (2 subjects per test group) where different regions of shape abnormalities are detected on different subjects. These abnormalities are not only localized in different foot areas for different groups, but the degree of shape abnormality for feet within same group also differs between each other.



(a) Flat arch (b) High arch (c) Hallux valgus (d) p-value

Figure 4.4: **Example results for 6 individuals within our test groups (2 individuals per group).** The detected outlier regions for the 6 test subjects differ not only across groups but also within groups. We provide the above views to highlighted regions that were hard to see in some other view.

In addition, we calculated the outlier histograms to test whether areas of abnormal shape deviations were grouping in specific foot regions for the feet within the same test group. At each vertex, we counted the percentage of feet that detected the vertex as a shape outlier. These histograms are shown in Fig. 4.5. When we tested each foot, we noticed that the outliers were grouping in different foot regions depending on the test group to which the foot belongs. For 30% of flat feet, we detected the medial side of plantar midfoot and the upper part of the midfoot as the main regions of deviation. For 60% of high arched feet, we detected the lateral plantar midfoot as the main region of deviation. For 55% of feet with hallux valgus, we detected the biggest toe and head of the first metatarsal bone as the main regions of deviation, which are expected regions for this deformity. From the normal arched feet we tested, less than 5% showed outliers and these outliers were not concentrated in any specific region.



(a) High arch (b) Flat arch (c) Hallux valgus

Figure 4.5: **Histograms of detected outliers ($p < 0.05$) obtained for:** a) 40 high arched feet b) 40 flat feet c) 46 feet with hallux valgus.

For each foot, we measured the size of detected regions and compared them to the clinical measures used to define the groups: arch index and hallux abductus angle (HAA). In experiments performed with high arched and flat arched feet, we did not find a significant correlation between arch indexes and the size of outlier regions ($\rho = 0.08, p = 0.61$ for flat, $\rho = 0.18, p = 0.25$ for high arched). However, we found a significant correlation ($\rho = 0.76, p < 0.001$) between HAA and size of the outlier regions for the individuals with hallux valgus feet. Fig. 4.6 shows the size of the outlier regions within the area of shape deviations typical for hallux valgus deformity.

4.5 Discussion

We proposed an expert system for objective and personalized identification of 3D foot shape abnormalities through the use of 3D statistical shape modelling. Ideally, a "healthy" foot shape model would be a baseline for detection and identification of foot shape anomalies. A comparison of a test foot to this model would quantify whether the foot is "healthy" or if some particular regions are appearing to be abnormal and would require further examination. Our system's user interface centered around easy-to-input subject characteristics (e.g. gender, age), allowing for its use by non-experts. Additionally, our system's inference engine relies on established statistical testing procedures, leading to results that are straightforward to interpret. This

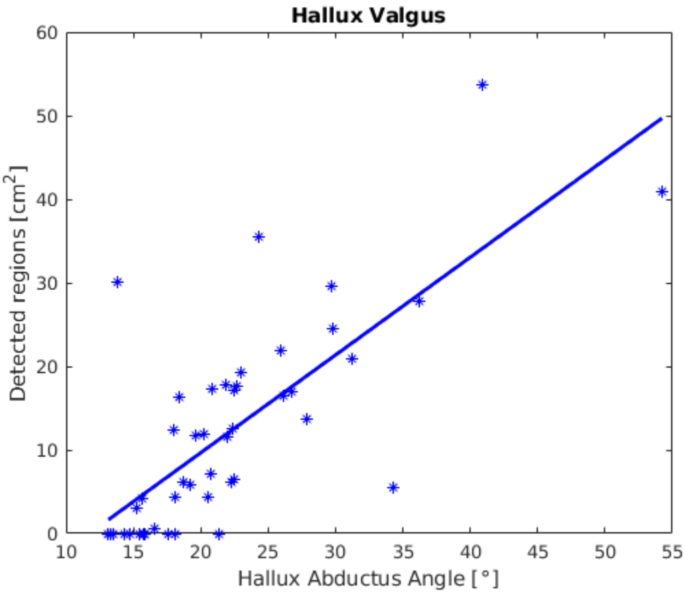


Figure 4.6: **A significant correlation was found between the size of detected shape abnormalities (in cm^2) and the HAA for the feet with hallux valgus ($\rho = 0.76, p < 0.001$).**

approach further enables the identification of local regions on the individual's foot that significantly deviate from those of a normal-arched foot.

Considering arch height variability, we hypothesized that groups with high arched and flat feet would show abnormalities in similar areas around the midfoot. Our results indeed showed significant shape deviations in the midfoot, but interestingly, these shape deviations differed between flat- and high-arched feet. While high-arched feet had outliers concentrated at the lateral plantar midfoot, flat feet showed a decreased concentration of outliers, with abnormalities appearing most prominently at the medial side of the plantar midfoot and at the upper part of the midfoot (Fig. 4.5). The location of detected regions, along all three dimensions, can be beneficial for footwear manufacturers and can show in which part of the shoe manufacturers should adapt their design to ensure better fitting and more comfortable footwear. For example, the shape deviations found in the plantar midfoot for high-arched individuals could suggest shoe insoles be adapted to enable more comfortable footwear for this group.

Besides the tests related to arch height, we also tested feet with hallux valgus. We found that the detected shape abnormalities around the hallux and corresponding metatarsal matched our hypothesis. Here, we observed a significant correlation between the hallux abductus angle and the size of the detected regions (Fig. 4.6). This information can be used to ensure proper footwear width and guarantee that enough space is provided along all three dimensions in the forefoot of a patient's shoe. Given that one of the causes of hallux valgus is poor-fitting footwear, the insights shown by our method could help prevent further development of hallux valgus deformity [53].

Along with the information on how 3D foot shapes deviate for different groups, our method detected and highlighted whether, and where, the individual's foot deviates from a given normative population. These personalized foot shape tests showed a variety of abnormal shape regions for the feet within the same test group (Fig. 4.4). This confirms the inter-individual differences found within feet with similar characteristics [3, 23, 48]. These results are particularly striking given that existing expert systems were used to classify the foot scans analyzed in this study [13, 14]. This indicates that the usual foot examination, based on classifying feet into groups, does not provide a complete picture of foot shape variability. Instead, our method for a personalized and objective analysis of 3D foot shapes shows promise in providing a more complete analysis of foot shape, and analysis that could prove useful for the evaluation of foot deformities.

In comparison to previous expert systems for foot analysis, our approach also employs statistical techniques, thereby increasing the likelihood that foot care professionals will be able to work in tandem with such a system. In addition, our work expands on existing techniques in two key ways. First, our expert system analyzes the entire 3D foot shape instead of lower-dimensional shape features. This contribution not only simplifies the user interface but also allows the system to produce a more descriptive explanation for why a foot is identified as abnormally shaped. Second, our expert system incorporates demographic measures such as age and weight, measures that allow us to fine tune the inference to a particular individual. Previous systems relied on statistical thresholds that were constant for all individuals, a limitation that impacts the effect sizes that such systems could identify.

At its heart, our proposed foot shape analysis system effectively performs outlier detection, and therefore shares similarities with other outlier detection systems in medicine, economics, data mining, and manufacturing [27, 80]. Traditionally, outlier detection algorithms have followed one of two approaches. The first, and the one used here, is to build a statistical model, a baseline model, of what is considered normal. This baseline model can then be compared to using established statistical tests in order to find outliers [5, 7, 71]. If we have a clinical question in mind, then the question would dictate what the baseline should be. In general, the baseline model could be formed from, for example, high-arched subjects and then tested whether the test shape is deviating significantly from high-arched population. By taking this approach, our system has a strong theoretical foundation for justifying why an exemplar is an outlier [9]. For the purpose of validating our methodology, we had enough variation for validating our methods present in our normative population, although the variation of this particular population might not be sufficient to make clinical conclusions.

An alternative approach to outlier detection is model-free and seeks to identify outliers based on their similarity to existing data points [10], specific prototypes [47], or clusters [28]. A strength of these model-free approaches is that they do not require that the data follow a particular statistical distribution, or that a single normative statistical model be considered. Recently, hierarchical approaches have also been proposed for outlier detection in order to achieve this same model-free flexibility [11]. In this work, we have attempted to duplicate this flexibility through a regression between the statistical model and subject demographics. This regression allows us to maintain a strong statistical foundation for our system while also personalizing the model to some degree to the foot under examination.

Overall, our expert system produced results consistent with known foot shape abnormalities while also providing more descriptive and personalized results than previous approaches. Nevertheless, some individuals classified as having an abnormal foot arch or a hallux valgus showed no shape abnormalities in our system (see

Fig. 4.5 and Fig. 4.6. These results suggest that there are limitations to this study or its proposed methods. For example, the 3D scans used in testing were initially classified using the established measures of arch index and hallux abductus angle. Since these measures are an incomplete representation of foot shape, it is possible that feet described as abnormal by those measures may not be statistical outliers when considering the shape as a whole. Additionally, the statistical modelling and regression used in our system also has limitations, specifically that the baseline model assumes the data is normally distributed and that the relationship between foot shape and demographics is linear. These limitations may introduce additional variance into our modelling, thereby reducing its ability to identify foot shape abnormalities. Another limitation is the limited number of subjects used to build a baseline model. However, we provide a proof of concept for the developed methodologies which should not be affected by a small number of subjects within the model. In addition, our subjects for the model were limited to normal-arched foot shapes only to prove the methodology, while the high-arched and flat-arched foot shapes were used for testing purposes. Finally, our choice of demographic features may not be complete. It may be possible to reduce variance in the model if additional information like ethnicity [63], leg dominance [60], and footwear choices [20] is included in the regression.

Despite the advantages of our approach to detect outliers in 3D foot shapes, it also has some practical limitations. Detection of 3D foot deviations requires the input of 3D foot scans and, thus, the availability of an optical 3D scanner. The high cost of a quality 3D scanner is a notable disadvantage for our approach over traditional foot examination methods. The use of existing, cheaper, low-resolution scanners (e.g. Kinect 2, Fuel3D) can be a possible solution. However, our approach would need further evaluation to see if its behaviour changes with the input of lower quality scans. Additionally, the findings presented herein were observed on high resolution scans collected in a standing pose. Many foot deformities have a more noticeable impact on gait than foot shape [49]. As a result of this constraint, foot deformities that affect only foot motion are unlikely to be detected using our framework. It is for this reason that we tested individuals who have feet with hallux valgus, a deformity which is visible on static 3D foot scans. We showed the shape changes were clearly identified in high arched feet, but less so for flat feet. This result may be because we analyzed half loaded feet. This loading may flatten the foot arch to the point where fewer prominent shape differences can be seen between flat and normal arched feet. We also assumed normal distribution of our foot shapes. Since a normal distribution is characterized as symmetrical, it could be the case that our assumption on normality of distribution does not stand. For example, we could have more flat feet that are closer in shape to normal-arched feet than we have in our high-arched group. This asymmetry in the data would be lost in the normal distribution, making it difficult to detect flat feet as outliers from the distribution. Despite these limitations we showed the possibility of automatic, objective, and personalized detection of the hallux valgus deformity, as well as subtle foot arch deviations present in normal foot shape.

4.6 Conclusion

In summary, our expert system for assessing 3D foot shape provides an automatic and objective procedure to examine whether, and where, a single foot shape differs from a normative foot population. We validated our technique on four groups of feet with different known shape deviations and the results generally matched our hypotheses. However, our analysis technique provided additional insights into how arch height influences foot shape as well as capturing individual variability within each foot group. This information has the potential to be used for various purposes within several biomedical disciplines, including facilitation of more objective clinical diagnosis techniques as well as more accurate footwear design.

4.6.1 Implications and Future Work

While our proposed expert system showed promising results, these results also showed that our proposed system would benefit from additional research. First, we observed that the choice of demographics used to fine tune the statistical model can impact the variance within the model and, in turn, its ability to identify abnormalities. It also influences how well the system generalizes to different individuals. Choosing the right demographic features remains an open research question and is effectively the feature selection problem commonly seen in other statistical modelling and machine learning problems [50]. Second, the statistical modelling used in our system assumes (a) that foot shapes are normally distributed, and (b) that the relationship between demographics and foot shape is a linear one. While our results seem to support those assumptions, it remains to be shown whether those assumptions truly hold. Third, the promise seen in our results may be partly due to our use of a high-quality 3D laser scanner to measure foot shape. It is unclear how this measurement quality impacts our expert system.

Based on this study, we clearly see four areas in which future work would be beneficial: feature selection, model flexibility, model sensitivity, and model completeness. With respect to feature selection, it would be beneficial to explore what features - demographic, environmental, or otherwise - impact foot shape. The evaluation and choice of such features would depend not only on their ability to reduce model variance, but also on user privacy and ease-of-use concerns [36, 38]. With respect to model flexibility, conditional generative adversarial networks [54] and permutation testing [15] may provide model-free options for the type of outlier detection we perform here. It remains to be seen if such methods can provide the intuitive explanation of their results that an expert system requires.

Additionally, we aim to extend this study in the future to address both model sensitivity and model completeness. With regards to the former point, we intend to evaluate the proposed system on more accessible, but lower quality, 3D optical scanners. Such an extension may require the consideration of mesh denoising [74] or other data enhancement techniques. With regards to the latter point, we further intend to extend this approach to dynamic 4D data [8]. Such an extension could give insights into foot abnormalities that are visible only when an individual is moving.

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Part III

Conclusions

Conclusions and Future Work

Conclusions

The morphology of the human foot has been a subject of research in the biomedical disciplines. A deep understanding of foot shape, along with the understanding of the foot anatomy and biomechanics, is essential for the effective diagnosis and the treatment of the subjects with foot and ankle problems. This suggests that the objective assessment of the entire foot shape may play a beneficial role in foot assessment and diagnosis. To date, the human foot is represented through measurements that vary from the simple visual examinations, 1D or 2D measurements, and recently represented through 3D optical scans. The methods for foot shape analysis are tightly coupled to these measurement types. Although there are plenty of different methods that analyze 1D and 2D foot shape representation, the novel techniques for 3D foot shape analysis have been lacking. Usually, complex foot morphology is studied through the analysis of two-dimensional footprints. Such a foot representation is frequently used since it is relatively easy to obtain, measure, and preserve. Moreover, different measures and indices of footprint shape are proposed to describe the variation of the medial longitudinal arch. Although footprints could be used for quantitative foot assessment through classification techniques, they are insufficient to describe the external 3D shape of the foot [14]. Moreover, retrieving the 3D foot shape from the 2D footprint introduces the error in the 3D foot shape which confirms the presence of the additional information in 3D foot representation[26].

To date, different studies classified feet through statistical techniques. In addition, geometric morphometric methods were employed to describe the variation present in 2D footprints. However, a method to describe the 3D shape variation present in a population of feet was yet to be achieved. Many studies have also investigated how different factors such as age, sex, and ethnicity influence the variation of a foot shape. Although these analyses are based on quantitative techniques, they are usually applied on single 1D or 2D foot representations. The analysis on how and whether different physical characteristics and lifestyle habits influence the 3D foot shape is still missing.

The insight into the shape variation of a population of feet could enable 3D foot shape analysis through an expert system. In such a system, a new test foot would be assessed through the comparison to a statistical baseline. Usually, the new test foot shape is compared by categorizing it to a predefined class, such as via visual appraisal. This introduces the subjectivity into the analysis of foot shape, leading to the assessments that can vary significantly between the examiners [11]. Recently, expert systems for the foot assessment have been investigated, in the form of outlier detection algorithms [7, 27]. These systems are based on objective measures, such as arch index calculated from 2D footprints [15], the center of pressure trajectories [17], or forefoot-rearfoot angles [22], or forefoot-rearfoot angles [8]. Similar statistical thresholds have also been defined for hallux valgus based on the hallux abductus angle [4, 18], and for club feet based on calcaneus distances [1]. Although the previous examples of expert systems provide objective foot assessments, it has been shown that the analysis of 1D or 2D foot representation does not provide a complete assessment of foot shape [26]. Moreover, existing expert systems do not provide personalized foot assessment but rather coarse groupings, usually only identifying whether the foot is abnormal or not. For example, different studies reported inter-individual differences for width and height measures of feet within the same class, or different degrees of hallux valgus deformity and toes deformities were associated with different shoe needs. The previous examples of expert systems show that the foot shapes within the same class can still vary significantly, suggesting the need for personalized foot assessment.

The above discussion concludes the main knowledge gaps present in the field:

- The incompleteness in the selection of the measurements to capture the salient 3D foot geometry,
- The lack of quantification techniques for the 3D shape variations present in population of feet, and
- A lack of framework for the statistical analysis of the 3D foot shape on a subject level.

In this research, we provide the methodology to improve and automate 3D foot shape assessment. The main research objectives are:

- The critical assessment of currently existing 3D foot shape representations along with the techniques that are used for their analysis,
- The development of the methods for statistical and quantitative description of the variation present in the 3D foot shape along with the analysis of the additional factors that can influence the 3D foot shape, and
- The development of an expert system for identifying outlier local geometry of the 3D foot shape on a subject level.

These objectives correspond to the main gaps present in the field. At first the standardized representation of the foot that captures the external 3D foot geometry could be provided in the form of 3D foot scans. Next, a statistical analysis on a population of the 3D foot shape could provide insights into the shape variation present in a population. In the end, such a population could be used as a statistical baseline to be compared to using outlier detection when assessing the new foot shape.

Despite the advantages of the proposed methods, we also take a critical point of view on this study. First, we had a relatively small number of subjects in the cohort, for whose data we assumed a normal distribution. As a result of this constraint, it is possible that the shape variability described in this thesis is not a complete representation of the possible 3D foot shapes present in an entire normal population. For example, we observed that the gap between the shapes of flat and normal arched feet could be closer than the gap between normal and high-arched feet which would violate our assumption of a symmetrical normal distribution. In addition, we assumed the linear relationship between foot shape and demographics. The small number of subjects in the cohort may lead to the less accurate estimate of the model variance. Additionally, exclusion of some factors (such as race, sport type) may introduce additional variance into our modeling, thereby resulting in high variance within the built models and reducing the ability to identify foot shape abnormalities. As a consequence, high variance within the model means that the model performs very well on the training data, while it does not generalize on the data it has not seen before, leading to high error rates on test data. Much bigger sample sizes, along with possible non-linear relationship between foot shape and demographics, would reduce above mentioned high variance within our built models.

Next, our models are optimized for the information that was available from the data collection. This leads to potentially incomplete models, as some additional information such as type of sport practiced, shoe wearing habits, ethnicity, race, etc. could significantly influence the variation present in the model built for the normal population. It would be beneficial to further explore these additional factors that could impact the 3D foot shape. Moreover, their correlation with each other could be investigated further.

It is also known that many foot deformities have a more noticeable impact on gait than foot shape[12]. As a result of this constraint, foot deformities that are only observable during foot motion are unlikely to be detected using our developed framework. It is for this reason that our proof-of-concept tests were limited to individuals who have feet with hallux valgus or abnormal arch heights, shape anomalies that are known to be visible on static 3D foot scans. An extension of the proposed methods towards the technique that analyzes the 3D foot shape in motion may provide more insights into the shape changes that occur when the foot is moving. Such an extension may lead into the analysis of foot disorders that are more noticeable during movement.

In the end, the implementation of the proposed analysis in a clinical practice would require the presence of the 3D foot scanner, resulting in a significant cost compared to the traditional equipment for the foot assessment. Moreover, such equipment provides high resolution data for which we validated our methods. Further evaluation of the proposed methods on more accessible systems, such as lower quality 3D scanners, would be desired. Such an extension would require some additional data enhancement techniques, such as mesh denoising.

The developed techniques are thoroughly discussed across the Chapters consisting of the main contributions of the thesis.

First, Chapter 2 provides an overview of existing techniques for the foot assessment. We discuss the available selection of foot measurements and automatic procedures for foot assessment are highlighted. We emphasize the need for the techniques that employ the analysis of an entire foot, represented through 3D foot shape. In Chapter 3, we present a technique that quantifies a population of normal 3D foot shapes. Here we describe which subjects we consider to have normal foot shape. In addition, we found that body-mass index, age, sex, and sport activity contribute to the vertical variations visible only for 3D foot scans. The shape variations present in a normal healthy population could be used to examine the abnormal regions of foot shape. In Chapter 4, we propose an automatic technique that identifies abnormal 3D regions of the foot by statistically comparing them to the normative population. We further capture to what extent the foot shape is abnormal. We validated our technique on four groups of feet with known shape deviations. We demonstrated the automatic localization of foot pathologies (hallux valgus), as well as of subtle deviations present in feet with different arch height. This research provided several contributions to the field of foot assessment, which we list further.

Contributions

3D foot shape We showed that the 3D representation of foot shape provides more valuable insights into complex foot morphology than compared to 2D footprints. Moreover, it fully captures the geometrical characteristics along all three dimensions of the foot.

Objective 3D foot shape description We identified that quantitative analysis of 3D foot shape might be beneficial to shoe and orthotic manufacturers for generation and validation of their designs by providing additional insights into shape variation along vertical dimension. A perfectly fitted shoe leads to optimal comfort, thus reducing foot pain. As we proposed automatic foot shape assessment techniques, they remove the subjective human influence present during common foot measurement collection techniques.

Statistical foot analysis We showed that statistical foot shape analysis explains the shape variation present in a population. This knowledge can be used to compare the average shapes between different foot populations, such as normal and not-normal, or to find statistically significant differences between foot shapes. Moreover, we showed that the influence of various factors can be examined by linking them to the statistical shape analysis.

Personalized assessment We introduced a technique for the automated personalized assessment of 3D foot shape. We showed that it is valuable as it both compares an individual foot shape to a normative population, and incorporates the influence of the individual's personal characteristics within the analysis. This technique provides additional insights into whether, where, and to what extent the single foot shape deviates from a normative population.

Future work

Although we proposed approaches for improved foot assessment, some factors can be considered as the limitations to our approaches. To conclude this thesis, we suggest possible steps for further improvement of the proposed methods for foot assessment.

Assumption linearity Although many scientific and engineering processes can be described well using linear models, or other relatively simple types of models, there are many other processes that are inherently nonlinear. The PCA approach is a linear technique that is used to reduce the high-dimensional foot scan data to a number of dimensions that is easier to work with and interpret. That being said, it is possible that the 3D foot scan data lies on a non-linear manifold in this high-dimensional space, making the use of PCA a sub-optimal decision. Possibly, non-linear modeling techniques can better describe this high-dimensional data [16] and fit more variance into less dimensions [17] . We also assumed a linear relationship between the demographics and foot shape, although we have not tested whether this relationship is indeed linear. This assumption either needs to be proved or an alternative non-linear regression could better reflect the actual relationship between demographics and foot shape [9].

The biggest advantage of nonlinear regression over many other techniques is the broad range of regression functions that can be computed. One common advantage is efficient use of data. Non-linear regression can produce good estimates of the unknown parameters in the model with relatively big data sets. Since our studies had a relatively small data set, we could only rely on linear techniques. The advantage that nonlinear techniques share with linear one is a fairly well-established theory [9, 19] for computing confidence, prediction and calibration intervals to answer scientific and engineering questions. In most cases, the probabilistic interpretation of the intervals produced by nonlinear regression are only approximately correct, but these intervals still work very well in practice.

Model sensitivity As mentioned, all our methods are evaluated for high-resolution meshes. However, the equipment that generates these scans is rather expensive compared to the equipment used for the conventional 1D or 2D foot assessment. Lately, alternative equipment in the form of cheaper low-resolution scanners are being investigated to make 3D foot shape assessment affordable for broader use [23]. In addition, deep learning methods are becoming more popular to synthesize high-resolution 3D shapes from low-resolution measurements [24, 25]. Considering the loss of information between high- and low-resolution measurements, it would be useful to validate the methodology proposed in this thesis on low-resolution meshes.

Additionally, the proposed methods generate a 3D statistical foot shape model that quantitatively assesses normal feet. However, this model is generated for a relatively small population, thus may not capture the full range of variations present in mature foot shape. To reduce model variance and to completely describe the population of normal foot shapes, it would be valuable to collect a larger number of 3D normal foot shapes within the larger population [10].

Feature selection We also examined the influence of different factors, demographic, environmental, or otherwise, available from the measurement collection. The selection of the right features is an issue commonly seen in other statistical modeling and machine learning problems [13]. Thus, the future step would be to explore which factors, demographic, environmental, or otherwise, impact 3D foot shape. We explored how some of the factors, available to us at that time, influence the foot shape variation. Additional factors, such as ethnicity, race, type of sport, intensity of sport, shoe-wearing habits, or dominant leg should be investigated further. As a suggestion, the factors could be selected according to the application. For example, distinct factors could be fed to the foot shape analysis in order to make a custom shoe and/or to make a custom insole.

Analysis of the static measurements This thesis provides methods to describe the population of feet, and to identify the abnormal shapes on a single foot, based on static 3D foot measurements. The extension to dynamic 3D foot measurements could give insights into shape variation when the foot is moving [3]. This could be beneficial for the detection of foot abnormalities that are less visible when the foot is static, but possibly more prominent when the foot is moving. For example, some injuries or disorders could appear to have the same pattern in shape changes during motion (e.g. shape changes in the specific region in terminal stance of gait).

Use cases The main challenge in the application of the developed methods for clinical foot assessment is the software deployment in a clinical setting. In this case, the strong medical regulatory environment requires the ability to diagnose, monitor, interpret the results obtained using these methods. For example, the software informs a clinician about location, size, and degree of abnormality, but not about the pain it causes or severity of the abnormality, two common parameters required to decide further treatment. Another example is how the software would interpret rehabilitated cases in which some level of abnormality remains and how these cases are different from feet which have a present abnormality without prior rehabilitation. A different perspective on foot assessment can be found between clinical practice and footwear manufacturers. During foot assessment, footwear manufacturers mainly attempt to provide maximal comfort and prevent injuries. Therefore, they are mainly interested in the relation of the foot shape outward to the footwear. Thus, footwear manufacturers tend to accommodate foot shape. In contrast, clinicians usually require insight into the foot changes during movement. They are mostly interested in linking foot shape towards inner anatomical structures, allowing them to evaluate underlying processes caused by the irregularly functioning of anatomical structures. As such they may be attempting to adjust the foot shape, perhaps to reduce loading of certain inner structures. To implement the developed methods in clinical practice, a step towards analyzing the moving 3D foot shape is needed. Such an assessment would replace standard anthropometric measurements with the novel advanced techniques for foot measurements.

In general, clinical examination can be performed in several ways [2]. Usually the foot assessment in clinical practice is linked to the type of pain experiences [20, 21]. Such an assessment can consist of physical examination performed by the well-trained examiner; static scanning in form of 3D scanning of the external foot shape; gait analysis in form of 3D scanning of moving feet combined with 2D plantar pressure imaging; the underlying anatomy visible in plain x-rays of the feet; and a personal report of pain, discomfort or injuries through self-complete questionnaire. While all of the above possibilities are not necessary to apply when assessing the foot in real world cases, the presence of 3D foot shape analysis can play a useful role. Lately, 3D scanning equipment along with techniques for foot shape assessment are developing. The proposed method analyzes the static 3D foot shape by comparing it to a statistical foot shape model previously built for a normative population. In this way, the main regions of deviation present in foot shape are marked and highlighted. This could provide support for the clinicians' diagnosis. In addition, the proposed method provides the extent to which the foot shape varies compared to the normative population. This could be beneficial for a clinical practice in the providing monitoring of the severity of foot disorders, or the impact of treatment, over time. In a concrete clinical implementation, the method for checking anomalies of 3D foot shape could be applied to monitor the development of hallux valgus pathology in a specific group of people, for example people who regularly wear high-heeled shoes. Moreover, digitizing the procedure of foot assessment in clinical practice could be beneficial for several reasons: a) the external foot surface is accurately captured and simply stored in a digital file, b) the digital file could be easily shared between clinicians, c) it allows the analysis of the entire 3D foot geometry, d) the digital foot representation could be used for creation of digital models of orthotics (such as insoles), e) it results in examining more patients in less time, compared to the traditional procedures for foot assessment.

The assessment of 3D foot shape is constantly improving by incorporating innovative measurement equipment and novel techniques for analysis. As this research progresses, one day we will be able to automatically examine the foot shape while standing or walking, leading to suggestions or designs of shoes that perfectly match our foot shape. The well-fitted shoe provides the optimal comfort. This improved footwear fit can then improve human health by reducing foot pain and foot disorders [5, 6].

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Curriculum Vitae

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