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

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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 186 3D optical foot scans of 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

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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.

Keywords: 3D foot scans, statistical shape modelling, personalized medicine, outlier detection

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 [1, 2, 3]. For some people, this pain is linked to foot deformities, with common conditions including hallux valgus [4, 5], collapsed foot arches [6, 7], and club feet [8, 9]. For others, foot pain has been associated with improperly fitting footwear [10, 11], indicating that a more precise characterization of foot shape would be valuable in footwear fitting and design [12, 13, 14, 15]. 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 [2]. 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 [16, 17, 18, 19].

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 [5, 20, 21], with foot arch heights, ankle bone curvatures, and toe angles being key shape cues [5, 7, 22]. Unfortunately, these visual appraisals introduce a measure of subjectivity into the analysis of foot shape, resulting in examinations that can vary significantly between clinicians [23].

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 de-

27 tection algorithms [24]. These include the arch index measure introduced
28 by Cavanagh et al. [25]. Using measurements from 2D footprints and sta-
29 tistical thresholds, arch index can classify feet as being high-, normal-, or
30 flat-arched. Similar statistical thresholds have also been applied to 1D arch
31 height measures [26], center of pressure trajectories [27], and forefoot-rearfoot
32 angles [28] in order to identify abnormal arch heights. A full review of such
33 techniques can be found in the work of Xiong et al. [6]. Similar statisti-
34 cal thresholds have also been defined for hallux valgus based on the hallux
35 abductus angle [29, 30], and for club feet based on calcaneus distances [9].
36 These approaches can be thought of as expert systems where the user inputs
37 a given foot measurement or footprint, the knowledge base is a statistical
38 model, and the inference engine performs outlier detection using significance
39 thresholds. Other expert systems also exist for foot assessment, but they do
40 not consider foot shape [31, 32, 33].

41 Despite the benefits these objective techniques provide, they also have
42 their limitations. Many studies are based purely on scalar measurements or
43 2D images of the foot (e.g. footprints) instead of the full 3D foot shape [25,
44 34]. It has been shown that the full 3D foot shape is not only important
45 for footwear design [4, 19, 35, 36], but it also cannot be fully recovered from
46 lower-dimensional foot measurements [37]. As a result, these expert systems
47 do not provide a complete assessment of foot shape.

48 Additionally, existing expert systems for foot shape provide only coarse
49 groupings, usually only identifying if a foot is normal or abnormal. Several
50 studies [38, 39, 40] reported inter-individual differences for width and height
51 measures of feet within the same class, such as foot size classes. Similarly,
52 different degrees of hallux valgus deformity and toe deformities were associ-
53 ated with different shoe needs [41]. These results suggest that foot shapes
54 within the same class can still vary significantly and that this variance should
55 be further considered in an expert system.

56 We propose that an expert system for foot shape analysis should ideally
57 satisfy four criteria. First, the system’s knowledge base should contain infor-
58 mation on the full 3D foot shape and not simply 2D or 1D foot measurements.
59 This criterion would ensure that assessment of the complete foot is possible.
60 Second, the system’s inference engine should provide more than simply a
61 label of whether a foot is normal or not. If a foot is labelled as abnormally-
62 shaped, the system should explain what part of the foot is abnormal and
63 to what extent it is abnormal. Third, the system’s user interface should be
64 simple enough for a non-expert to use. This criterion aims to eliminate the

65 subjectivity seen in visual assessments as well as ensuring that access to the
66 system is not limited by access to a foot care professional. Finally, the system
67 should employ methods that are familiar to foot care professionals, thereby
68 ensuring that they can confidently recommend such a system and properly
69 follow-up on the system’s results.

70 To address these criteria, we introduce an expert system based on the
71 concepts of outlier detection for the assessment of one’s full 3D foot shape.
72 The user interface requires one to simply enter a 3D optical scan of their
73 foot and basic demographic information (e.g. age, weight, shoe size), making
74 the system usable by an non-expert. The knowledge base of the system is
75 centered on the statistical shape modelling, a technique that has shown to
76 be a useful tool in a variety of applications [42, 43, 44, 45, 46, 47]. The
77 model is constructed from healthy individuals and a regression analysis, like
78 those in [48, 49], is used to link the user-entered demographic information to
79 a baseline foot shape measurement. Finally, statistical testing is employed
80 to compare one’s measurement to this statistical baseline. This testing is
81 performed across the foot surface in order to identify the location and extent
82 of shape abnormalities [50, 51, 52, 53].

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

88 2. Methods

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

95 In order to perform meaningful statistics on such a shape representation,
96 an anatomical correspondence needs to be established between all N foot
97 meshes and these meshes have to be spatially aligned. In section 2.1, the
98 correspondence and alignment procedure is explained after which the model
99 building and personalized analysis parts of our pipeline are presented in sec-
100 tion 2.2 and 2.3, respectively.

101 *2.1. Correspondence establishment and anatomical alignment*

102 Initially, each 3D foot mesh has a different number and order of vertices.
 103 These meshes can also vary in their position within the field of view of the
 104 3D scanner. In order to analyze the shapes represented in 3D foot meshes,
 105 we must first ensure that each mesh has the same vertices located in the
 106 same anatomical locations. Second, we must then align the 3D foot meshes
 107 to remove the influence of pose on the analysis of shape. The first procedure
 108 is referred to as shape correspondence while the second is referred to as
 109 anatomical alignment. Fig. 1 shows the effect of these procedures on two
 randomly-chosen feet.

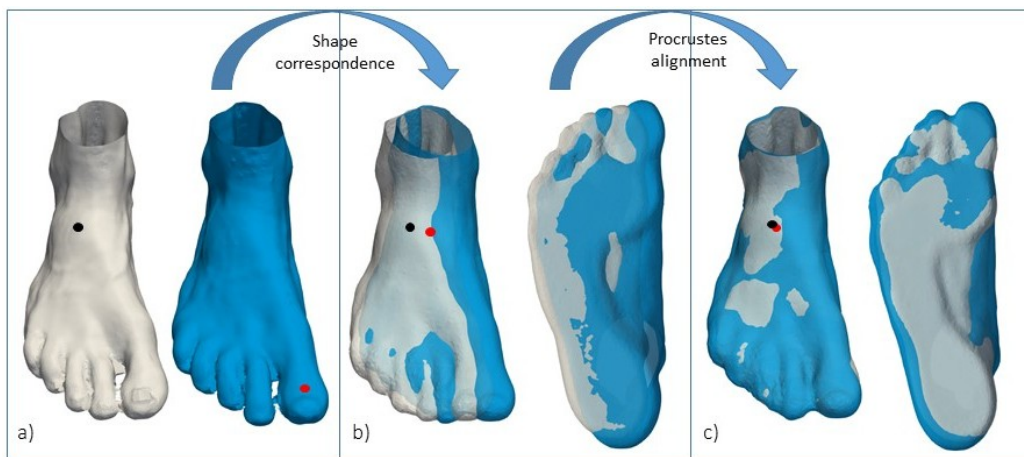


Figure 1: **Correspondence establishment and alignment.** a) Two randomly chosen feet with unmatched vertices before correspondence establishment, b) overlapped feet after correspondence establishment, c) overlapped feet after anatomical alignment.

110

111 *2.1.1. Shape correspondence*

112 To bring two 3D foot meshes into anatomical correspondence, we employ
 113 the pairwise registration of Danckaers et al. [54]. To do so, we choose one
 114 foot mesh, \mathbf{X}_{ref} , as our reference foot mesh and deform it to match the other
 115 foot meshes in our analysis. At a high level, this deformation is described by

$$\mathbf{X}_{target} = \Psi(T(\mathbf{X}_{ref}, \beta)), \quad (1)$$

116 where \mathbf{X}_{target} is a foot mesh being analyzed, T is an affine transformation
 117 and Ψ is a set of displacement vectors. The degree of the deformation op-
 118 eration is controlled by a user-defined elasticity parameter, β . We solve for

119 T and Ψ using the iterative procedure defined in [54]. Briefly, this itera-
 120 tive procedure operates by fixing one of the transformations (e.g. Ψ) and
 121 then solving Eq. (1) for the other transformation (e.g. T). Subsequently, the
 122 procedure solves Eq. (1) for the transformation that was fixed in the former
 123 iteration (Ψ) while now fixing the previously-computed unknown transfor-
 124 mation (T). This process is iterated until the magnitude of the observed
 125 shape changes is below a set threshold (0.01 mm). During the iterations, the
 126 elasticity parameter, β , is increased to gradually introduce more deformation
 127 as the alignment improves. Further details can be found in [54]. The final
 128 result is the reference mesh \mathbf{X}_{ref} deformed to have its shape as similar as
 129 possible to the shape of the target mesh \mathbf{X}_{target} . At this point, \mathbf{X}_{target} is
 130 replaced by $\Psi(T(\mathbf{X}_{ref}))$, ensuring that each foot mesh has the same number
 131 of vertices ordered in the same fashion (Fig. 1b). This pairwise registration
 132 is applied for all N foot shapes in the database to make sure all shapes are
 133 in correspondence with each other.

134 2.1.2. Procrustes Analysis

135 Once the N foot shapes have been brought into correspondence, their
 136 meshes need to be brought into spatial alignment before statistics can be ac-
 137 curately performed. We achieve this alignment through a Procrustes Analysis
 138 as presented by Stegmann and Gomez [55]. This analysis consists of three
 139 steps that estimate the translation, scale, and rotation of one shape that
 140 brings it into alignment with another (Fig. 1c). Since the foot scans are
 141 obtained in a standing position, we further constrain the translation in the
 142 vertical direction to ensure that all 3D foot meshes remain aligned to the
 143 ground plane.

144 For the personalized analysis step of our pipeline, a single Procrustes
 145 Analysis is sufficient to bring the individual’s 3D foot mesh into alignment
 146 with the SSM. However, when building the SSM, all 3D foot meshes need
 147 to be superimposed. We accomplish this task by performing a Generalized
 148 Procrustes Analysis [55]. In a Generalized Procrustes Analysis, a single 3D
 149 foot mesh is chosen as a target and the remaining $N - 1$ meshes are aligned to
 150 it using the traditional Procrustes Analysis. An initial estimate of the mean
 151 shape is then obtained. This mean shape is then chosen as the target mesh
 152 and the process repeats itself until no further changes in the mean shape are
 153 seen. Further details can be found in [55].

154 The shape correspondence and alignment procedures above are followed
 155 for each individual. In the case of the model building task, the shape cor-

156 correspondence is iterated together with Generalized Procrustes Alignment in
 157 order to avoid any bias from the choice of \mathbf{X}_{ref} . In each iteration, the pop-
 158 ulation mean calculated from the previous iteration is used as the reference
 159 foot mesh [56]. Convergence is reached if the average distance between cor-
 160 responding points on the reference mesh from the previous iteration and the
 161 reference mesh from the current iteration is less than $\varepsilon = 0.001$ mm.

162 2.2. Model building

163 From our set of N aligned 3D healthy foot scans, we built a 3D statistical
 164 shape model using Principal Component Analysis (PCA) [57]. This SSM is
 165 then combined with a multivariate linear regression to fine tune the SSM
 166 based on different covariates (such as age, shoe size, BMI, etc.). Using this
 167 fine-tuned model, a maximum-likelihood prediction of one’s foot shape can
 168 be obtained. Then, residuals are calculated between these predicted surfaces
 169 and the aligned, measured, foot surfaces. These model-building steps are
 170 summarized in Fig. 2.

171 2.2.1. Principal Component Analysis

172 Once all foot scans have been brought into correspondence and aligned to
 173 an unbiased reference, a statistical shape model is built from the population.
 174 Let N be the number of 3D foot shapes in our healthy population, with every
 175 shape consisting of n vertices in 3D. This population is represented by $N - 1$
 176 dimensional cloud within $3n$ -space, where each point represents a foot shape.
 177 Principal component analysis (PCA) is then used to represent this cloud
 178 by a mean shape and $N - 1$ eigenmode vectors, where the first eigenmode
 179 describes the largest variance in the population, the second eigenmode the
 180 second largest variance orthogonal to the first, etc. The resulting statistical
 181 shape model consists of the mean shape $\bar{\mathbf{x}} \in \mathbb{R}^{3n}$ and the main shape modes:
 182 the principal components (PC) $\mathbf{P} \in \mathbb{R}^{3n \times (N-1)}$. Under this PCA model
 183 representation, a new shape $\mathbf{y} \in \mathbb{R}^{3n}$ can be formed by a linear combination
 184 of the PCs:

$$\mathbf{y} = \bar{\mathbf{x}} + \mathbf{P}\mathbf{b}, \quad (2)$$

185 with $\mathbf{b} \in \mathbb{R}^{(N-1)}$ being the PC weight vector mapping the shape to the sta-
 186 tistical model parameters [58]. In the context of our work, $\bar{\mathbf{x}}$ is the average
 187 foot shape, the principal components \mathbf{P} can be interpreted as a set of defor-
 188 mations, and the PC weights, \mathbf{b} , are computed to weight each deformation
 189 such that the average foot shape gets warped into the specific foot shape \mathbf{y}
 190 (see the upper-right, yellow, box in Fig. 2)

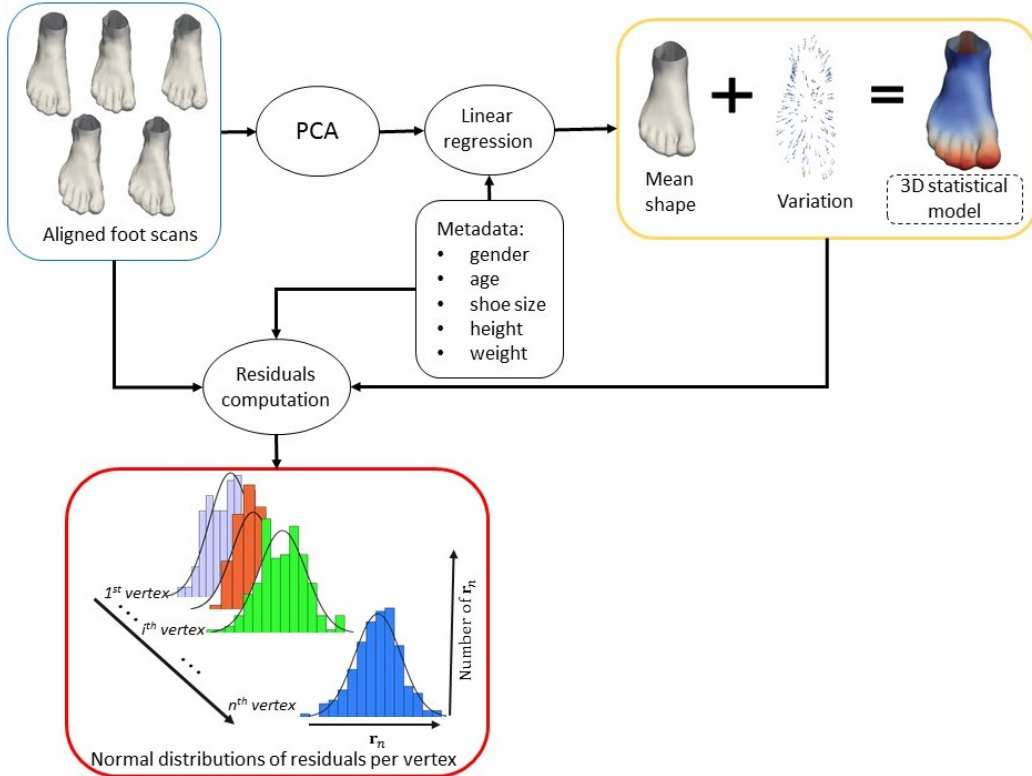


Figure 2: **Model building.** a) Once all feet are brought into correspondence and aligned (blue box), a 3D foot SSM is built using Principal Component Analysis. b) Metadata is combined with the 3D SSM to develop a tunable shape model (yellow box) c) Residuals for each vertex are computed between every aligned foot and its corresponding SSM prediction (red box).

191 2.2.2. Incorporation of subject characteristics

192 While PCA allows us to build a 3D SSM, it has no natural way to han-
 193 dle covariates that can impact foot shape (e.g. weight, sex, shoe size).
 194 To account for these covariates, we link them to the SSM using multi-
 195 variate multiple linear regression [59] Suppose we have a covariate vector
 196 $\mathbf{f} = [f_1, f_2, \dots, f_k, 1]^T \in \mathbb{R}^{k+1}$ that contains information of an individual's
 197 age, shoe size, etc. as well as a 1 at its end to allow for a constant offset in
 198 regression. We can define the relationship between this covariate vector and
 199 the PCA weight vector $\mathbf{b}_i \in \mathbb{R}^{N-1}$ of each shape \mathbf{X}_i from the dataset using a
 200 linear model. A mapping matrix $\mathbf{M} \in \mathbb{R}^{(N-1) \times (k+1)}$, describing the relation-
 201 ship between the PCA weight matrix $\mathbf{B} = [\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_N] \in \mathbb{R}^{(N-1) \times N}$ and

202 the feature matrix $\mathbf{F} = [\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_N] \in \mathbb{R}^{(k+1) \times N}$ is calculated by

$$\mathbf{M} = \mathbf{B}\mathbf{F}^+, \quad (3)$$

203 where \mathbf{F}^+ is the pseudoinverse of \mathbf{F} [60]. With this mapping matrix, a new
 204 PC weight vector \mathbf{b} can be generated from given features \mathbf{f} as follows:

$$\mathbf{b} = \mathbf{M}\mathbf{f}. \quad (4)$$

205 Through this linear regression, we link the shape deformations represented
 206 by the principal components \mathbf{P} to the demographic characteristics of the
 207 individual. In this way, the matrix \mathbf{M} effectively captures how much each
 208 demographic feature influences the foot shape. By substituting Eq. (4) into
 209 Eq. (2), we obtain the statistical shape model which incorporates the shape
 210 variation influenced by an individual’s covariates:

$$\mathbf{y} = \bar{\mathbf{x}} + \mathbf{P}\mathbf{M}\mathbf{f}. \quad (5)$$

211 By providing an individual’s demographic characteristics, the most plausible
 212 corresponding healthy foot shape can then be simulated using Eq. (5).

213 *2.2.3. Residual calculation*

214 Our SSM defined by Eq. (5) provides us with a model of the foot shape as
 215 a whole. To further localize our subsequent analysis, we augment our SSM
 216 with residual distributions at each mesh vertex. For each 3D mesh used in
 217 building our model, we calculated residuals between it and the corresponding
 218 foot shape prediction given by Eq. (5). Each vertex thus obtains the residual
 219 vector \mathbf{r} :

$$\mathbf{r} = \mathbf{v}_r - \mathbf{v}_p, \quad (6)$$

220 where \mathbf{v}_r is the vertex of the measured foot mesh and \mathbf{v}_p is the corresponding
 221 vertex of the predicted foot mesh.

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

$$r_n = \mathbf{r} \cdot \mathbf{n}_p, \quad (7)$$

227 where r_n is the normal component of \mathbf{r} [61, 62].

228 Residuals are calculated using Eq. (7) for each vertex of each 3D mesh
229 used in the model-building procedure. Normal distributions are then fit to
230 the residuals at each vertex to summarize local shape variations that are not
231 otherwise captured by the SSM.

232 *2.3. Personalized foot shape analysis*

233 To evaluate the 3D foot shape of a new individual, we detect shape anom-
234 alies based on the 3D foot SSM built earlier (Fig. 2). To do this, we first predict
235 the healthy foot shape of the new individual using Eq. (5). Then, we estab-
236 lish a correspondence between the predicted foot shape and the individual’s
237 foot shape using the algorithm described in Eq. (1). The individual’s foot
238 mesh is then brought into alignment with the predicted foot mesh using the
239 Procrustes alignment algorithm described earlier. Finally, we compute, and
240 statistically test, residuals between the aligned mesh and the predicted mesh
241 as described below. The full procedure is displayed in Fig. 3.

242 *2.3.1. Statistical inference*

243 To identify outliers in 3D foot shape, we performed single-sample t -tests
244 for each residual projection of the test mesh. To achieve this, we computed
245 the residual between each vertex on the individual’s aligned foot mesh and
246 its corresponding predicted mesh using Eq. (6). Since we are interested in
247 variations present in the mesh along the direction normal to the foot sur-
248 face, we projected vector \mathbf{r} onto the surface normal using Eq. (7). Finally,
249 we tested whether there was a significant difference ($p < 0.05$) for this in-
250 dividual’s shape residuals by comparing them to the corresponding Normal
251 distributions generated in the model-building. We conducted multiple com-
252 parisons correction with False Discovery Rate (FDR) for a given threshold
253 $\alpha = 0.05$ [63].

254 **3. Experiments**

255 *3.1. Dataset*

256 To evaluate our shape analysis technique, we collected 3D optical scans
257 of the feet of 204 Belgian adults: 132 men and 72 women. Participation in
258 the study was entirely voluntary and demographic information (age, BMI,
259 height, weight, and shoe size) was collected for the whole cohort (Table 1).
260 All factors except shoe size were self-reported, while shoe size was measured
261 using a Brannock device. Additional factors such as race and ethnicity were

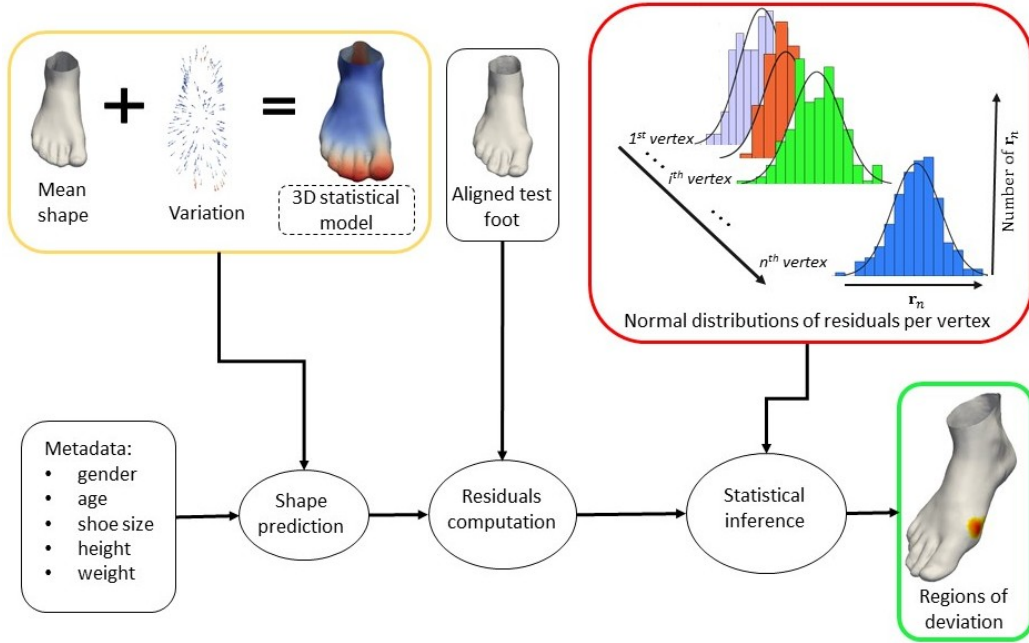


Figure 3: **Procedure for the personalized analysis of an individual’s foot shape.**
 a) The predicted healthy shape for the individual’s foot is obtained using the SSM from the model-building (yellow box) and metadata of the individual b) Residuals for each vertex are computed between the aligned, measured 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).

262 not noted. The Ethics Committee of the Antwerp University Hospital ap-
 263 proved the study and all subjects gave their written informed consent before
 264 participating.

265 The 3D optical scans of the participant’s feet were acquired with an Elin-
 266 vision Tiger 3D laser scanner (rs scan, Paal, Belgium). The accuracy of the
 267 3D scanner was 0.3 mm . A total of two scans were made per person: one of
 268 the left foot and one of the right foot. Both left and right feet were scanned
 269 while standing in a relaxed pose on both feet. Prior to the analysis, the scans
 270 of left feet were flipped along the medial-lateral axis so as to orient them in
 271 the same fashion as the right feet. Also, all 3D scans were cropped 2.0 cm
 272 above the average of the lateral and medial malleolus to decrease the effect
 273 of different lower leg poses on subsequent analysis. The obtained 3D meshes
 274 were used for further analysis.

Table 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 phase 33 females & 60 males	μ	36.5	41.7(265/101)	72.6	176.0	23.4
	σ	12.5	2.8(18.3/7.1)	11.4	8.3	3.1
	min	18	36.0(225/90)	49.0	150.0	17.9
	max	62	47.0(300/114)	100.0	196.0	32.7
Test phase 39 females & 72 males	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
	min	19	36.0(225/90)	47.0	156.0	18.4
	max	68	47.5(304/116)	144.0	198.0	41.6

275 *3.2. Inclusion-Exclusion Criteria*

276 For evaluation purposes, all individuals were categorized into one of four
 277 groups: healthy individuals with a normal foot arch, healthy individuals
 278 with a high foot arch, healthy individuals with flat feet, and individuals with
 279 hallux valgus. Each of these four groups are described further in Table 2.
 280 Individuals were considered healthy if they had no foot or leg complaints
 281 at the time of measurement. For the individuals with hallux valgus, we
 282 measured the hallux abductus angle (HAA) of each individual using the 3D
 283 anatomical annotation approach described in [29]. A foot is considered as
 284 having a hallux valgus if its HAA is larger than 14 degrees, a threshold which
 285 is in line with the previous study of Menz et al. [41]. These feet were also
 286 assessed using the Manchester Scale [5], with the majority of cases being
 287 scored as of mild (45.65%) or moderate (47.8%). Only a few severe hallux
 288 valgus cases were present (6.55%).

289 To classify individuals based on their foot arch height, we employed the
 290 standard approach of thresholding based on the arch index measure of Ca-
 291 vanaugh and Rodgers [25]. This measure was applied to plantar pressure
 292 measurements taken from each participant as they walked at their preferred
 293 walking speed. The plantar pressure measurements were collected using an
 294 rs scan 2 m Hi-End footscan® system (rs scan, Paal, Belgium) with a fre-
 295 quency of 200 Hz and sensor dimensions of 7.62 mm x 5.08 mm. A total of
 296 10 measurements were collected per foot, then spatiotemporally aligned and
 297 averaged using STAPP [64]. The average measurement was then upsampled

Table 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	$< 14^\circ$	0/0	21/40	21/40
Flat arch	> 0.33	$< 14^\circ$	0/0	26/40	26/40
Normal arch	$[0.24, 0.33]$	$< 14^\circ$	93/186	34/40	127/226
Hallux valgus	any	$> 14^\circ$	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.

298 to 3 mm x 3 mm to obtain a correct foot geometry from the pressure plate
 299 with anisotropic sensor dimensions. The arch index was then calculated from
 300 the peak pressure image (i.e. the image that contains the maximum pres-
 301 sure at each pixel over the time of the footstep) and the corresponding foot
 302 was classified as high, normal, or flat arch as described by Cavanaugh and
 303 Rodgers [25]. Note that the larger the arch index, the flatter the foot.

304 3.3. Experimental setup

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

314 In the case of the two arch height groups, we hypothesized that these
 315 groups would show abnormalities in similar areas around the midfoot. In
 316 the case of hallux valgus patients, we hypothesized that shape abnormalities

317 would appear around the hallux (i.e. big toe) and corresponding metatarsal.
318 Additionally, we set aside 40 foot scans of healthy individuals with a normal
319 foot arch in order to validate that our technique shows no abnormalities for
320 feet similar to those in the model. A further description of the groups used
321 in model building and testing are shown in Table 2.

322 4. Results

323 For each individual’s foot, we tested, with FDR correction, how the foot
324 shape deviates from the healthy population. Fig. 4 shows the examples of
325 6 test subjects (2 subjects per test group) where different regions of shape
326 abnormalities are detected on different subjects. These abnormalities are not
327 only localized in different foot areas for different groups, but the degree of
328 shape abnormality for feet within same group also differs between each other.
329 In addition, we calculated the outlier histograms to test whether areas of
330 abnormal shape deviations were grouping in specific foot regions for the feet
331 within the same clinical group. At each vertex, we counted the percentage
332 of feet that detected the vertex as a shape outlier. These histograms are
333 shown in Fig. 5. When we tested each foot, we noticed that the outliers
334 were grouping in different foot regions depending on the clinical group to
335 which the foot belongs. For 30% of flat feet, we detected the medial side
336 of plantar midfoot and the upper part of the midfoot as the main regions
337 of deviation. For 60% of high arched feet, we detected the lateral plantar
338 midfoot as the main region of deviation. For 55% of feet with hallux valgus,
339 we detected the biggest toe and head of the first metatarsal bone as the main
340 regions of deviation, which are expected regions for this deformity. From the
341 normal arched feet we tested, less than 5% showed outliers and these outliers
342 were not concentrated in any specific region. For each foot, we measured
343 the size of detected regions and compared them to the clinical measures
344 used to define the groups: arch index and hallux abductus angle (HAA). In
345 experiments performed with high arched and flat arched feet, we did not find
346 a significant correlation between arch indexes and the size of outlier regions
347 ($\rho = 0.08, p = 0.61$ for flat, $\rho = 0.18, p = 0.25$ for high arched). However, we
348 found a significant correlation ($\rho = 0.76, p < 0.001$) between HAA and size
349 of the outlier regions for the individuals with hallux valgus feet. Fig. 6 shows
350 the size of the outlier regions within the area of shape deviations typical for
351 hallux valgus deformity.

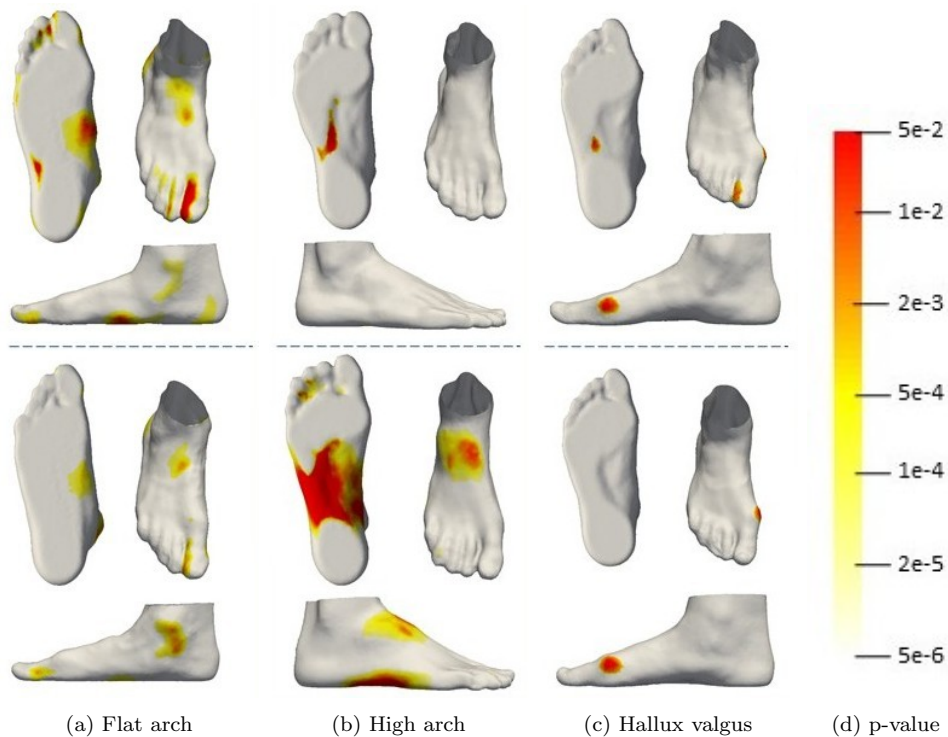


Figure 4: **Example results for 6 individuals within our test groups (2 individuals per group)**. The detected outlier regions for the 6 test subjects differ not only across groups but also within groups.

352 5. Discussion

353 We proposed an expert system for objective and personalized identifica-
 354 tion of 3D foot shape abnormalities through the use of 3D statistical shape
 355 modelling. Our system’s user interface centered around easy-to-input subject
 356 characteristics (e.g. gender, age), allowing for its use by non-experts. Addi-
 357 tionally, our system’s inference engine relies on established statistical testing
 358 procedures, leading to results that are straightforward to interpret. This ap-
 359 proach further enables the identification of local regions on the individual’s
 360 foot that significantly deviate from those of a healthy, normal-arched foot.

361 Considering arch height variability, we hypothesized that groups with
 362 high arched and flat feet would show abnormalities in similar areas around
 363 the midfoot. Our results indeed showed significant shape deviations in the
 364 midfoot, but interestingly, these shape deviations differed between flat- and

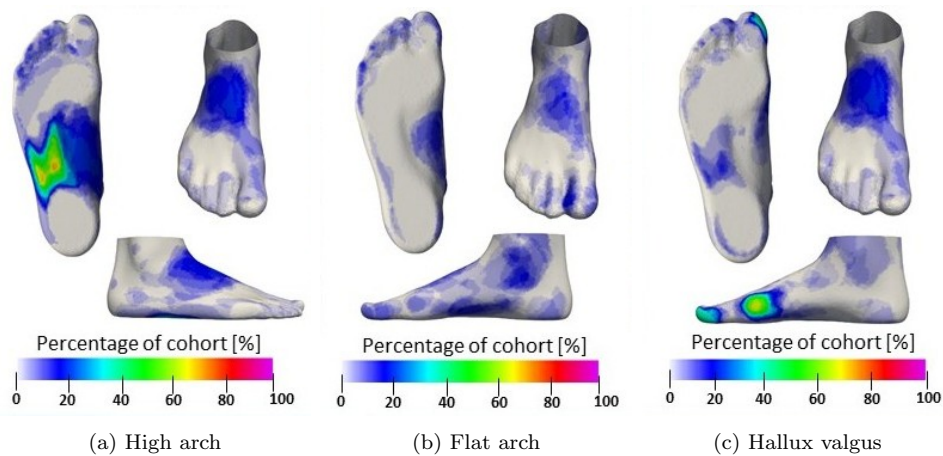


Figure 5: **Histograms of detected outliers** ($p < 0.05$) **obtained for:** a) 40 high arched feet b) 40 flat feet c) 46 feet with hallux valgus.

365 high-arched feet. While high-arched feet had outliers concentrated at the
 366 lateral plantar midfoot, flat feet showed a decreased concentration of outliers,
 367 with abnormalities appearing most prominently at the medial side of the
 368 plantar midfoot and at the upper part of the midfoot (Fig. 5). The location
 369 of detected regions, along all three dimensions, can be beneficial for footwear
 370 manufacturers and can show in which part of the shoe manufacturers should
 371 adapt their design to ensure better fitting and more comfortable footwear.
 372 For example, the shape deviations found in the plantar midfoot for high-
 373 arched individuals could suggest shoe insoles be adapted to enable more
 374 comfortable footwear for this group.

375 Besides the tests related to arch height, we also tested feet with hallux
 376 valgus. We found that the detected shape abnormalities around the hallux
 377 and corresponding metatarsal matched our hypothesis. Here, we observed
 378 a significant correlation between the hallux abductus angle and the size of
 379 the detected regions (Fig. 6). This information can be used to ensure proper
 380 footwear width and guarantee that enough space is provided along all three
 381 dimensions in the forefoot of a patient’s shoe. Given that one of the causes
 382 of hallux valgus is poor-fitting footwear, the insights shown by our method
 383 could help prevent further development of hallux valgus deformity [41].

384 Along with the information on how 3D foot shapes deviate for differ-
 385 ent groups, our method detected and highlighted whether, and where, the
 386 individual’s foot deviates from a given healthy population. These personal-

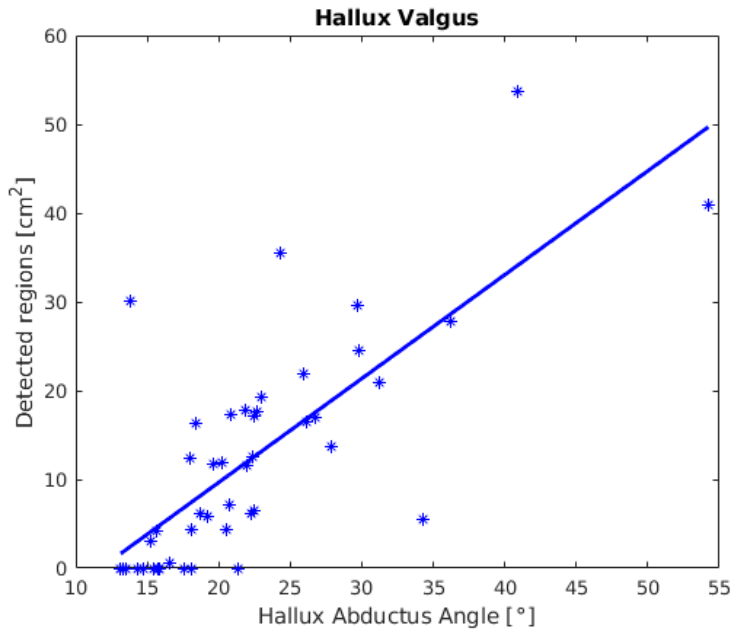


Figure 6: **A significant correlation was found between the size of detected shape abnormalities (in cm^2) and the HAA for the feet with hallux valgus ($\rho = 0.76, p < 0.001$).**

387 ized foot shape tests showed a variety of abnormal shape regions for the feet
 388 within the same clinical group (Fig. 4). This confirms the inter-individual
 389 differences found within feet with similar characteristics [38, 39, 40]. These
 390 results are particularly striking given that existing expert systems were used
 391 to classify the foot scans analyzed in this study [25, 29]. This indicates that
 392 the usual foot examination, based on classifying feet into groups, does not
 393 provide a complete picture of foot shape variability. Instead, our method
 394 for a personalized and objective analysis of 3D foot shapes shows promise
 395 in providing a more complete analysis of foot shape, and analysis that could
 396 prove useful for the evaluation of foot deformities.

397 In comparison to previous expert systems for foot analysis, our approach
 398 also employs statistical techniques, thereby increasing the likelihood that foot
 399 care professionals will be able to work in tandem with such a system. In ad-
 400 dition, our work expands on existing techniques in two key ways. First, our
 401 expert system analyzes the entire 3D foot shape instead of lower-dimensional
 402 shape features. This contribution not only simplifies the user interface but

403 also allows the system to produce a more descriptive explanation for why a
404 foot is identified as abnormally shaped. Second, our expert system incorpo-
405 rates demographic measures such as age and weight, measures that allow us
406 to fine tune the inference to a particular individual. Previous systems relied
407 on statistical thresholds that were constant for all individuals, a limitation
408 that impacts the effect sizes that such systems could identify.

409 At its heart, our proposed foot shape analysis system effectively per-
410 forms outlier detection, and therefore shares similarities with other outlier
411 detection systems in medicine, economics, data mining, and manufactur-
412 ing [24, 65]. Traditionally, outlier detection algorithms have followed one
413 of two approaches. The first, and the one used here, is to build a statistical
414 model of what is considered normal. This model can then be compared to us-
415 ing established statistical tests in order to find outliers [52, 53, 56]. By taking
416 this approach, our system has a strong theoretical foundation for justifying
417 why an exemplar is an outlier [66].

418 An alternative approach to outlier detection is model-free and seeks to
419 identify outliers based on their similarity to existing data points [67], specific
420 prototypes [68], or clusters [69]. A strength of these model-free approaches
421 is that they do not require that the data follow a particular statistical distri-
422 bution, or that a single normative statistical model be considered. Recently,
423 hierarchical approaches have also been proposed for outlier detection in or-
424 der to achieve this same model-free flexibility [70]. In this work, we have
425 attempted to duplicate this flexibility through a regression between the sta-
426 tistical model and subject demographics. This regression allows us to main-
427 tain a strong statistical foundation for our system while also personalizing
428 the model to some degree to the foot under examination.

429 Overall, our expert system produced results consistent with known foot
430 shape abnormalities while also providing more descriptive and personalized
431 results than previous approaches. Nevertheless, some individuals classified as
432 having an abnormal foot arch or a hallux valgus showed no shape abnormali-
433 ties in our system (see Fig. 5 and Fig. 6). These results suggest that there are
434 limitations to this study or its proposed methods. For example, the 3D scans
435 used in testing were initially classified using the established measures of arch
436 index and hallux abductus angle. Since these measures are an incomplete
437 representation of foot shape, it is possible that feet described as abnormal
438 by those measures may not be statistical outliers when considering the shape
439 as a whole. Additionally, the statistical modelling and regression used in our
440 system also has limitations, specifically that the model assumes the data is

441 normally distributed and that the relationship between foot shape and de-
442 mographics is linear. These limitations may introduce additional variance
443 into our modelling, thereby reducing its ability to identify foot shape abnor-
444 malities. Finally, our choice of demographic features may not be complete.
445 It may be possible to reduce variance in the model if additional information
446 like ethnicity [71], leg dominance [72], and footwear choices [73] is included
447 in the regression.

448 Despite the advantages of our approach to detect outliers in 3D foot
449 shapes, it also has some practical limitations. Detection of 3D foot deviations
450 requires the input of 3D foot scans and, thus, the availability of an optical 3D
451 scanner. The high cost of a quality 3D scanner is a notable disadvantage for
452 our approach over traditional foot examination methods. The use of existing,
453 cheaper, low-resolution scanners (e.g. Kinect 2, Fuel3D) can be a possible
454 solution. However, our approach would need further evaluation to see if its
455 behaviour changes with the input of lower quality scans. Additionally, the
456 findings presented herein were observed on high resolution scans collected in
457 a standing pose. Many foot deformities have a more noticeable impact on
458 gait than foot shape [74]. As a result of this constraint, foot deformities that
459 affect only foot motion are unlikely to be detected using our framework. It is
460 for this reason that we tested individuals who have feet with hallux valgus, a
461 deformity which is visible on static 3D foot scans. Despite this limitation, we
462 showed the possibility of automatic, objective, and personalized detection of
463 the hallux valgus deformity, as well as subtle foot arch deviations present in
464 healthy foot shape.

465 6. Conclusion

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

476 *6.1. Implications and Future Work*

477 While our proposed expert system showed promising results, these re-
478 sults also showed that our proposed system would benefit from additional
479 research. First, we observed that the choice of demographics used to fine
480 tune the statistical model can impact the variance within the model and,
481 in turn, its ability to identify abnormalities. It also influences how well the
482 system generalizes to different individuals. Choosing the right demographic
483 features remains an open research question and is effectively the feature se-
484 lection problem commonly seen in other statistical modelling and machine
485 learning problems [75]. Second, the statistical modelling used in our system
486 assumes (a) that foot shapes are normally distributed, and (b) that the rela-
487 tionship between demographics and foot shape is a linear one. While our results
488 seem to agree with those assumptions, it remains to be shown whether those
489 assumptions truly hold. Third, the promise seen in our results may be due
490 in part to our use of a high-quality 3D laser scanner to measure foot shape.
491 It is unclear how this measurement quality impacts our expert system.

492 Based on this study, we clearly see four areas in which future work would
493 be beneficial: feature selection, model flexibility, model sensitivity, and model
494 completeness. With respect to feature selection, it would be beneficial to
495 explore what features - demographic, environmental, or otherwise - impact
496 foot shape. The evaluation and choice of such features would depend not only
497 on their ability to reduce model variance, but also on user privacy and ease-of-
498 use concerns [76, 77]. With respect to model flexibility, conditional generative
499 adversarial networks [78] and permutation testing [79] may provide model-
500 free options for the type of outlier detection we perform here. It remains to
501 be seen if such methods can provide the intuitive explanation of their results
502 that an expert system requires.

503 Additionally, we aim in the future to extend this study to address both
504 model sensitivity and model completeness. With regards to the former point,
505 we intend to evaluate the proposed system on more accessible, but lower
506 quality, 3D optical scanners. Such an extension may require the consideration
507 of mesh denoising [80] or other data enhancement techniques. With regards
508 to the latter point, we further intend to extend this approach to dynamic 4D
509 data [81]. Such an extension could give insights into foot abnormalities that
510 are visible only when an individual is moving.

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520 7. References

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