Clinical Biomechanics 28 (2013) 350–356

Contents lists available at SciVerse ScienceDirect

Clinical Biomechanics

journal homepage: www.elsevier.com/locate/clinbiomech

Classification of forefoot pain based on plantar pressure measurements

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ARTICLE INFO

Article history:
Received 28 March 2011
Accepted 29 January 2013

Keywords:
Plantar pressure
Forefoot pain
Neural networks

ABSTRACT

Background: Plantar pressure is widely used to evaluate foot complaints. However, most plantar pressure studies focus on the symptomatic foot with foot deformities. The purposes of this study were to investigate subjects without clear foot deformities and to identify differences in plantar pressure pattern between subjects with and without forefoot pain. The second aim was to discriminate between subjects with and without forefoot pain based on plantar pressure measurements using neural networks.

Methods: In total, 297 subjects without foot deformities of whom almost 50% had forefoot pain walked barefoot over a pressure plate. Foot complaints and subject characteristics were assessed with a questionnaire and a clinical evaluation. Plantar pressure was analyzed using a recently developed method, which produced pressure images of the time integral, peak pressure, mean pressure, time of activation and deactivation, and total contact time per pixel. After pre-processing the pressure images with principal component analysis, a forward selection procedure with neural networks was used to classify forefoot pain.

Findings: The pressure–time integral and mean pressure were significantly larger under the metatarsals II and III for subjects with forefoot pain. A neural network with 14 input parameters correctly classified forefoot pain in 70.4% of the test feet.

Interpretation: The differences in plantar pressure parameters between subjects with and without forefoot pain were small. The reasonable performance of forefoot pain classification by neural networks suggests that forefoot pain is related more to the distribution of the pressure under the foot than to the absolute values of the pressure at fixed locations.

1. Introduction

Foot complaints can have a major impact on our daily lives and are associated with an increased risk of falling and fractures, limited mobility, pain in other parts of the body, and walking disorders (Gorter et al., 2000; Leveille et al., 1998). Previous studies have reported the high prevalence (10 and 20%) of foot disorders (Garrow et al., 2004; Kuyvenhoven et al., 2002; Spahn et al., 2000). In a cross-sectional survey of 7200 people aged 65 years and older (with a response rate of 79%) conducted in The Netherlands, 20% of the respondents were found to have nontraumatic foot complaints lasting longer than 4 weeks; the forefoot was involved in 60% of these cases, i.e. 12% of the respondents (Gorter et al., 2000). Metatarsalgia, one of the most common forefoot complaints, is defined as pain at the plantar aspect of the distal heads of the metatarsal bones.

Plantar pressure measurements are widely used to evaluate foot function and to investigate foot complaints or foot deformities. In general, high pressure values under the foot can be seen as a good indicator of potential damage, especially in the symptomatic diabetic foot and the rheumatic foot (Frykberg et al., 1998). Many of these diseases lead to forefoot deformities such as claw toe angle, metatarsophalangeal joint extension, and subluxation and dislocation of the metatarsophalangeal joints (Armstrong and Lavery, 1998; Bus et al., 2005; Caselli and George, 2003; Mueller et al., 2003; Waldecker, 2002). Since forefoot deformities are underlying factors for an increase in plantar pressure, elevated plantar pressure in metatarsalgia found in the literature could be a result of foot deformities rather than the primary cause of the forefoot pain. However, many subjects without clear foot deformities also suffer from metatarsalgia. To date, plantar pressure pattern in subjects with foot complaints without clear foot deformities has not been compared to control subjects.

Recently, new methods were developed that spatially normalize plantar pressure images for foot size and foot progression angle (Keijsers et al., 2009; Pataky et al., 2008). The main advantage of these methods is that we can compare different subjects and we can study plantar pressure at the sensor level. Therefore, the first aim of this study is to compare plantar pressure between subjects with and without forefoot pain without clear foot deformities, that is, without neuromuscular disorders, diabetes or a rheumatic disease to compare the differences. Furthermore, by normalizing the plantar pressure to a

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http://dx.doi.org/10.1016/j.clinbiomech.2013.01.012

standard foot, pattern recognition techniques such as neural networks can be used to discriminate between subject groups. It would be clinically relevant if it were possible based on plantar pressure measurement to differentiate between subjects with forefoot pain and without forefoot pain. Hence, the second aim is to investigate whether it is possible to discriminate between subjects with and without forefoot pain based on plantar pressure measurements using neural networks.

2. Methods

2.1. Subjects and experimental setup

In total, 297 subjects with various foot complaints and without foot complaints were measured in this study. The study group was heterogeneous for age (range 16–78), occupation, foot complaint, and wearing insoles. More women (195) compared to men (102) were tested in this study. Demographic data (gender, age, height, weight) were recorded. Foot complaints were assessed using a questionnaire and by physical examination performed by a physical therapist. Subjects with neurological disorders, rheumatoid arthritis, or other disorders were excluded as were subjects who wore insoles for the treatment of back or knee pain. In addition, all feet with hindfoot or forefoot deformities were excluded from the study. For this study, each foot of each subject was classified as having forefoot pain or not having forefoot pain. In addition, other foot complaints such as heel pain, pain along the medial arch, and/or ankle joint pain were also assessed. All subjects with foot complaints wore custom-made insoles because of the foot complaints in question; these were obtained from a podiatrist, a pedorthist, or an orthotist.

Subjects walked barefoot at their preferred walking speed with the third step on the pressure plate (Rsscan, Olen, Belgium). Walking speed was measured by two pairs of infrared photo cells, each located 1 m before or behind the midline of the pressure plate. Subjects walked 10 times starting, alternately, with the left or right foot. Plantar pressure data were collected at 500 Hz using a footscan 0.5 m plate mounted on top of the force plate (Kistler, Winterthur, Switzerland). Both systems were synchronized with the Rsscan 3D-box. Foot contact on the plate was calculated using Rsscan software with a threshold level of 5 N.

For a better understanding of the data analysis, a schematic representation of the different steps in the data analysis is presented in Fig. 1. The main goals were to describe the differences in plantar pressure parameters and to classify forefoot pain.

2.2. Differences in plantar pressure parameters

Plantar pressure data were analyzed at sensor level using the normalization method developed by Keijsers et al. (2009). This method first corrects for foot progression angle and, subsequently, normalizes for foot size. As a result, the plantar pressure pattern has to be interpolated between surrounding sensors. Because the interpolated pressure is not actually measured by a sensor, the term 'pixels' will be used. For each pixel, 6 parameters were calculated: 3 pressure related and 3 temporal ones. As pressure parameters the pressure–time integral (PTI), mean pressure (MP), and peak pressure (PP) values were calculated (see Fig. 2). In addition, three timing parameters were calculated for each pixel, also shown in Fig. 2: the difference in time between first contact for the particular pixel and initial heel contact (referred to as pixel-on), the difference between last contact and initial heel contact (referred to as pixel-off); and the difference between pixel-off and pixel-on, which indicates the contact time for each pixel (referred to as pixel-contact). To determine which pixels to use for the analysis, the following criterion was introduced: only those pixels for which the average mean value for all subjects was greater than 10 kPa were considered, resulting in 289 pixels for each parameter. The image of the 289 pixels will be referred to as plantar pressure images (as shown in the left panel of Fig. 2) and was determined for each of the 6 parameters. Finally, the center of pressure (CoP) was also normalized for foot progression angle and foot size. Because the duration of stance varied among the subjects, the CoP was normalized to stance duration resulting in 100 frames each with a medial/lateral and an anterior/posterior value. In addition to the pressure images and CoP, stance duration, foot progression angle, foot width and foot length were derived from the plantar pressure measurements.

To determine differences between subjects with forefoot pain and subjects without forefoot pain, a *t*-test with corrected *P*-values was used for each of the 6 plantar pressure images. The correction of *P*-values was based on a procedure derived from analysis techniques used in neuroscience for analyzing electroencephalography (EEG) signals (Maris and Oostenveld, 2007) since both data types deal with a large amount of pixels. This technique involves a nonparametric procedure for each parameter to be analyzed, based on grouping all adjacent pixels that exhibit a similar difference in the sign of the difference (i.e. an increase or decrease). Thus, each pixel was categorized as a “decreased” or “increased” pixel. Secondly, all neighboring pixels with the same difference in sign were clustered. Subsequently, the number of

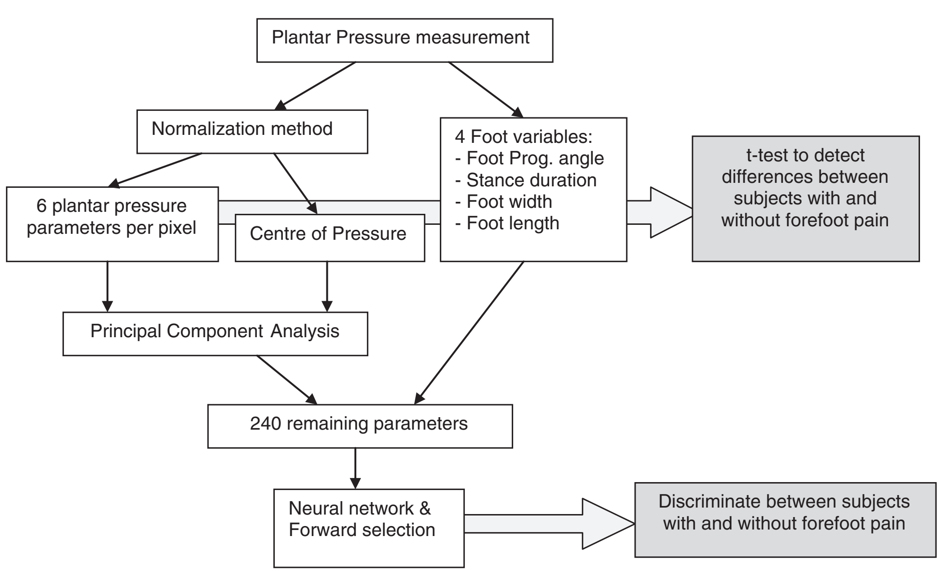

Fig. 1. Schematic representation of the different steps in the data analysis. The gray boxes indicate the 2 main goals of the study.

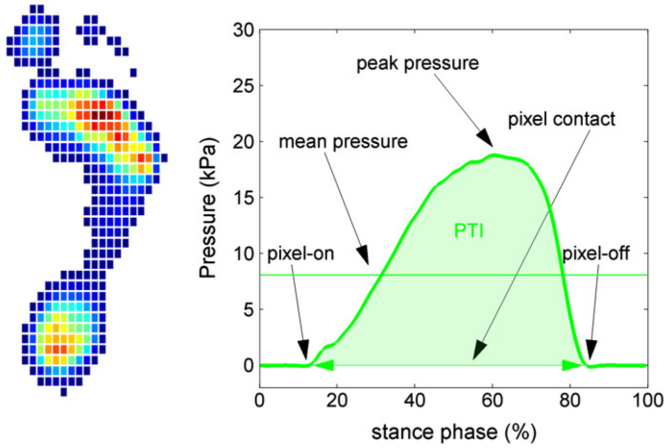

Fig. 2. The left panel shows an example of the mean pressure image for a right foot. Each square box indicates a sensor/pixel. In the right panel, the pressure–time curve is shown for a pixel in the red region of the lateral forefoot. The parameters pressure–time integral (PTI), peak, mean, pixel-on, pixel-off, and pixel-contact are indicated.

clusters was counted and used as the number of comparisons for the Bonferonni correction. The number of clusters ranged from 5 to 15 clusters for the 6 various plantar pressure images. The level of significance was adjusted according to the maximum number of 15 clusters using the Bonferonni correction for all 6 plantar pressure images (P-value for significance = 0.05/number of clusters) to $P<0.0038$.

A t-test was used to indicate differences in demographic data and single pressure parameters between subjects with forefoot pain and subjects without forefoot pain. Gender differences between groups were tested using a chi-square test. The level of significance was set at $P=0.05$.

2.3. Classification of forefoot pain

To determine whether it is possible to discriminate between subjects with and without forefoot pain based on plantar pressure measurements, the choice of the algorithm to be used to classify forefoot pain as well as the choice of input parameters to be used by the algorithm are of crucial importance. In our case, each foot measurement consisted of 289 pixels and for each of these pixels, 6 parameters were calculated; this resulted in a total of 1734 possible input parameters. The center of pressure added another 200 input parameters (100 frames each with a medial/lateral and an anterior/posterior value). The single parameters foot progression angle, stance duration, foot width and foot length added another 4. Hence, almost 2000 input parameters could be used to classify forefoot pain. Since this number was excessive in relation to the 594 (2 feet times 297 subjects) data sample, the pressure images of the 6 parameters and center of pressure were pre-processed using principal component analysis (PCA). Principal component analysis was conducted within each parameter separately on the 289 pixel data (pressure image). The advantage of principal component analysis is that it reduces the number of important variables. Principal component analysis transforms the original variables (289 pixels) into new, uncorrelated variables called principal components. Each principal component is a linear combination of the original variables. The principal component's variance expresses the amount of information contained in that principal component. The principal components are derived in decreasing order of variance. Thus, the first contains the most information, the last the least. Only those principal components which explained more than 0.5% of the variance were used as potential input parameters to make the classification. In general, the first 34 principal components explained more than 0.5% of the variance (see the Results section for a detailed description). After applying the 0.5% criterion to the principal component analysis, the number of input parameters that were used to a make a distinction between subjects with and without forefoot pain was reduced to 231 input parameters. In principal component analysis, the weight (eigenvector) by which each standardized original variable should be multiplied with to get the component score is also important. The eigenvector indicates the relative importance of the component score associated with that variable, in our case the pixel value. Therefore, not only the principal component score but also the eigenvectors of the principal component analysis will be described. In addition to the eigenvectors, the principal component value was used to indicate the effect of a principal component. Based on the principal component value, feet were divided into two groups; one group with a value smaller than the mean value of the principal component of interest and one group with a value larger than the mean principal component value. Subsequently, the differences in pressure images and CoP between these groups were used to indicate the effect of the principal component of interest.

The classification of forefoot pain was carried out using an artificial neural network. The 231 principal component parameters together with 9 subject characteristics (a total of 240) could be used as input for the neural network. However, since it is not clear which of the 240 individual parameters will be useful to classify foot complaints, a forward selection method in combination with an artificial neural network as a classifier was used to choose the optimal parameters to achieve the classification. Artificial neural networks are useful tools for prediction when the form of the relationship is unknown and have been for example successfully applied in mapping the insole pressure patterns and the fore-aft component of the ground reaction force (Savelberg and de Lange, 1999). The neural network used in this study was a multilayer perceptron with an input layer, one hidden layer, and an output layer. Each layer has several units and each unit is connected to all units in the next layer. The number of units in the input layer and hidden layer determine the network's ability to generalize: that is, the network's ability to develop a proper classification for an input pattern which the network has not previously encountered. Neural networks need a data set, which provides examples of how sets of input values are related to the output, which is called the training-set. This data set contains output with a value of 1 or −1, forefoot pain (1) or no forefoot pain (−1). The neural network was trained using backpropagation, which is a common method to teach the network, with a hyperbolic tangent sigmoid transfer function between the units (for more details see Hertz et al., 1991). The neural network uses data examples to adjust the weights between units in the subsequent layers in order to minimize the error between the desired network output and the neural network output for each example. In the present study, 25 sets of data were constructed by randomly selecting cases such that 80% of the cases were used for this training. The remaining 20% formed the test set which is used after training, to evaluate the generalization achieved by the network.

The performance of the network was evaluated using the percentage of feet that was correctly classified. A correct classification was obtained if the difference between the neural network output and the actual output was smaller than 1. In other words, a classification was seen as correct when the neural network output was above 0 for forefoot pain and below 0 for no forefoot pain. The optimal network was the one which gave the largest percentage of correctly classified feet on the test-set.

3. Results

3.1. Differences in plantar pressure parameters

In total 283 feet were classified as having forefoot pain and 311 feet without forefoot pain. Some 207 feet of the 283 feet with forefoot pain also had other foot complaints such as heel pain, ankle pain, or toe pain. Of the 311 feet without forefoot pain, only 58 feet had other foot complaints. The characteristics and differences between the subjects with forefoot pain and subjects without forefoot pain are shown in Table 1. Most characteristics were not significantly different between the groups except for the body height and foot length, which were significantly smaller for subjects with forefoot pain. In addition, the percentage of men in the forefoot pain group was significantly smaller compared to the group without forefoot pain. An analysis of covariance (ANCOVA) with gender as covariate revealed only significant differences in foot length ($P = 0.0005$) and height ($P = 0.007$) between the groups.

Fig. 3 shows the differences in plantar pressure images between subjects with forefoot pain and without forefoot pain for each of the six parameters. Subjects with forefoot pain showed significantly larger pressure–time integrals, mean pressure, and pixel-contact values for pixels under metatarsals II–IV. In addition, the distal and medial part of the bigger toe showed lower values for all plantar pressure parameters. Although stance duration was not significantly different between the two groups (see Table 1), forefoot pain subjects showed larger pixel-contact for the metatarsal regions and larger pixel-off values for the heel region compared to controls.

3.2. Classification of forefoot pain

As can be seen in Table 2, the number and the explained variance of the principal components that explained more than 0.5% were relatively identical for the various plantar pressure images. Most parameters had around 34 principal components with each individually explaining more than 0.5% of the variance. About three-fourths of each parameter's total variance was explained by these principal components. For one parameter, CoP, 94.4% of the variance could be explained with only 13 principal components, while 49 principal components were needed to account for 70.5% of the variance for pixel-off. In all parameters, the first principal component accounted for roughly a third of the total variance. Again exceptions were CoP for which the first principal component accounted for 75.0% of its variance and pixel-off for which the first principal component only accounted for 19.3% of its variance.

Fig. 4 shows the percentage of correctly classified feet for the training-set and test-set as a function of the number of input parameters. Initially, as the number of parameters increased, both training-set and test-set showed an increase in percentage correctly classified for each parameter. However, when the number of input parameters was above 14, the percentage of correctly classified feet increased slightly for the training-set but decreased for the test-set. The decrease in percentage of correctly classified feet for the larger number of input parameters is the result of data overfitting. The network with 14 input parameters and 1 unit in the hidden layer showed the best performance for classifying forefoot pain. That network correctly classified 76.0% of the training-data and 70.4% of the test-data.

To gain more insight into the classification of forefoot pain by the neural network, the relevant input parameters and their relation to forefoot pain were analyzed. Fig. 5 shows the relevant input parameters (parameter name and principal component number), how the optimal neural network weighted them (bars) and the order in which they were selected in the forward selection procedure (the white numbers). The most important parameters, i.e. those receiving the greatest weight in the neural network were, in order of decreasing weight, the parameters mean 24, Peak 4, and CoP 2. Remarkably, the first selected parameter in the forward selection procedure had only a small weight in the optimal neural network. In addition to the weights obtained by the neural network, the eigenvectors used in the principal component analysis are also important. The eigenvectors of the parameter with the second largest weight (Peak 4) revealed what you would expect: relatively high pressure values under metatarsals II and III will increase the risk of forefoot pain. The eigenvectors of the other parameters with the largest weights were less clear but pressure values under the forefoot contributed most to the principal component value. The two principal CoP components derived from parameters related to the CoP had the third and fourth largest weight in the neural network. By grouping subjects with large and small values of these principal components, it was shown that a smaller displacement of the CoP in the anterior/posterior direction and a more lateral displacement of the CoP will increase the risk of forefoot pain. However, it is important to note that the final outcome of the neural network depends on all input parameters because an increased risk in one parameter can produce a decreased risk in another parameter.

Table 1
Mean (SD) of subject characteristics and plantar pressure parameters.

Parameter	Forefoot pain	No forefoot pain	*P*-value for difference
Gender (# of male/female)	81/202	123/188	0.005
Age (years)	53 (14)	50 (16)	0.07
Weight (kg)	76 (14)	77 (15)	0.46
Height (cm)	170 (9)	173 (8)	0.003[a]
BMI (kg/m^2)	26.0 (4.2)	25.7 (4.0)	0.30
Stance duration (s)	0.71 (0.09)	0.70 (0.10)	0.13
Foot progression angle (degrees)	12.5 (6.8)	11.6 (6.8)	0.12
Foot length (cm)	20.8 (1.25)	21.1 (1.21)	0.0002[a]
Foot width (cm)	9.2 (0.70)	9.3 (0.69)	0.13

[a] Indicates significant difference between the groups.

4. Discussion

The purpose of this study was to identify differences in parameters derived from plantar pressure measurements found between subjects with and without forefoot pain who did not suffer from systemic disorders such as neuromuscular disorders, diabetes, and rheumatic disease that provoke foot deformities. The second aim was to investigate whether a neural network could discriminate between subjects with and without forefoot pain. Differences in plantar pressure between subjects with and without forefoot pain were small. However, neural networks with principal components constructed from plantar pressure images and the center of pressure as input could distinguish reasonably well between subjects with and without forefoot pain.

Previous studies have shown that increased plantar pressure in the metatarsalgia patient is generally found in patients with foot deformities such as claw toes or metatarsophalangeal joint subluxations or dislocations (Bus et al., 2005; Mueller et al., 2003; Waldecker, 2002) and that insoles reduce plantar pressure values under the metatarsals and relieve pain in metatarsalgia patients (Kang et al., 2006; Postema et al., 1998). As a result, metatarsalgia can be assumed to be related to repetitive high-pressure loading under the metatarsal head that causes pain. The significantly increased pressure–time integral and mean pressure under metatarsal heads found in the present study confirmed the relation between forefoot pain and increased pressure. However, this increase was not very large. Moreover, no significant differences under the metatarsal heads for peak pressure were found. Therefore, from a clinical point of view, it will be hard to use pressure values to discriminate between subjects with and without forefoot pain. For subjects without foot deformities, peak pressure under the metatarsals might be less important than other factors such as fat pad thickness and pain tolerance. However, the location of the peak pressures will differ between subjects. Due to the averaging over subjects after normalization, these individual differences will partly disappear. On the other hand a causal relation between peak pressure within a region and forefoot pain in people without foot deformities has not been clearly demonstrated in the literature thus far. For the timing parameters, however, subjects with forefoot pain showed a significant longer loading time at their metatarsal heads II and III as well as a delayed heel off. As stance duration was not significantly different between the two groups, it cannot explain the difference. In addition, all subjects' characteristics

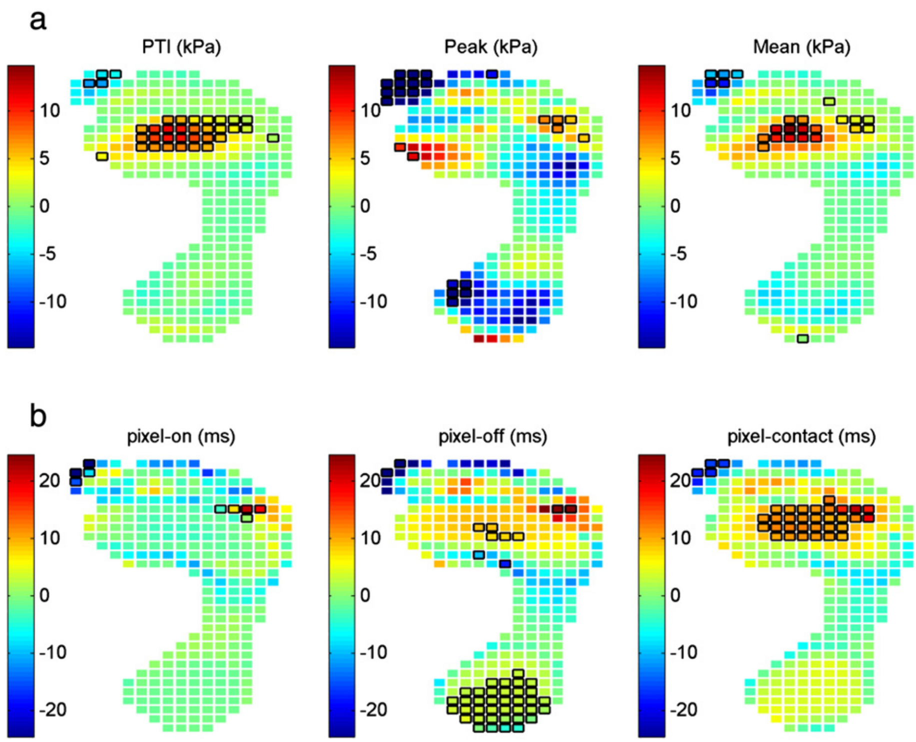

Fig. 3. Differences in plantar pressure images between subjects with and without forefoot pain. The title of each panel indicates the plantar pressure parameter (for definitions of the 6 parameters see Methods and Fig. 1). Pixels with black border are significantly different between subjects with forefoot pain and without forefoot pain ($P<0.0038$).

and single plantar pressure parameters were not significantly different between the groups except for the foot length and body height. Foot length and body height appeared to be significantly larger for subjects without forefoot pain but the differences were very small (see Table 1). Therefore, the relative longer loading of the metatarsal heads and the higher pressure–time integrals under metatarsal heads II and III indicate that forefoot pain is a result of the way the pressure is distributed under the foot.

The importance of the pressure distribution in relation to forefoot pain is further supported by the neural network classification and the input parameters used in the optimal neural network. The parameters that showed the most variation between subjects such as body weight, midfoot loading, medial/lateral loading, and forefoot/heel loading, were not chosen by the forward selection procedure to discriminate between subjects with and without forefoot pain. Only the fourth principal component for the parameter peak pressure and the third principal component for the parameter pixel-off were used by the neural network to classify forefoot pain. The fourth principal component of the peak pressure grouped subjects with high pressure under the metatarsals. Most of the principal components used by the optimal neural network had a component number higher than ten. Hence, these principal components explained less than 2.5% of the total variance and will only indicate subtle differences. Therefore, it seems that forefoot pain results from subtle characteristics in plantar pressure distribution rather than the general characteristics for plantar pressure such as foot type, body weight, and peak pressure under a particular region.

Table 2
The number of principal components per parameter that explained more than 0.5% of the variance, the total variance explained, and the variance explained by the first principal component.

Parameter	PTI	Peak	Mean	Pixel-on	Pixel-off	Pixel-contact	CoP
# of PCs	33	34	34	36	49	32	13
Expl. variance	75.7	74.6	74.9	73.4	70.5	73.9	94.4
Expl. variance first PC	30.4	30.5	29.5	31.2	19.3	33.7	75.0

The third and fourth parameters which received the largest weight from the neural network were the second and fourth principal CoP components. To date, differences in roll-off in relation to forefoot pain have rarely been reported. The CoP also appeared to have an important influence on the development of exercise related foot complaints and lower limb injuries. For example, subjects who showed a CoP displacement in medial direction after four days of extensive marching suffered from foot complaints (Stolwijk et al., 2010). Willems et al. (2006) supported the importance of the roll-off in relation to injuries. Although they did not focus on forefoot pain, they found that subjects with a lateral roll-off had an increased risk of developing exercise related lower limb injuries. In our study, subjects with a small CoP displacement in the anterior/posterior direction and a more lateral roll-off showed an increased risk of forefoot pain. Hence, CoP is a parameter

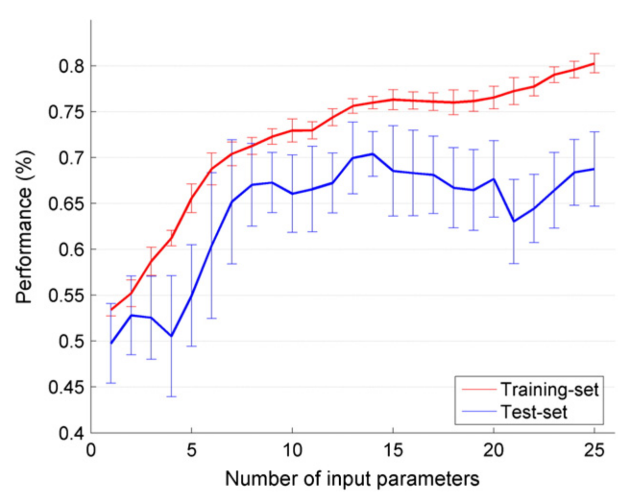

Fig. 4. Percentage of correctly classified feet in the training-set and test-set in relation to the number of input parameters. The optimal network was the network with 14 input parameters, which had a correct performance of 76.0% for the training-data and 70.4% for the test-data.

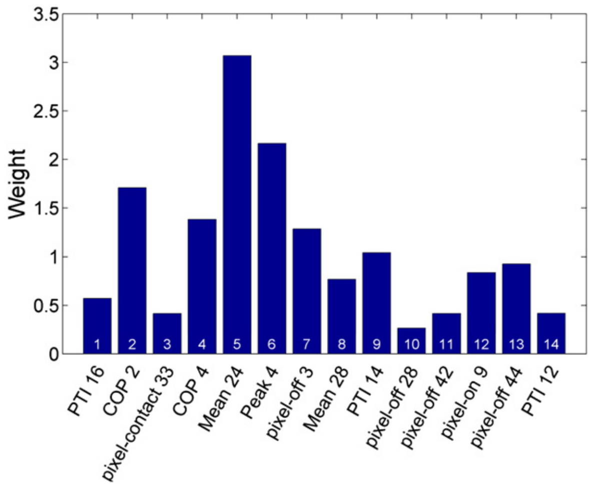

Fig. 5. The weight of the 14 parameters in the optimal neural network, listed according to the order resulting from the forward selection procedure (white numbers in bars). The number after the parameter name indicates which principal component for that parameter had been selected.

that seems to provide essential information regarding forefoot pain and the development of forefoot pain.

A major advantage of the present procedure in classifying metatarsalgia is that it only requires data gathered obtained from the subject walking over a pressure plate. Firstly, principal component analysis reduces the number of important parameters; e.g. in general almost 75% of the variance in pressure images between subjects can be described with only 35 principal components, each accounting for at least 0.5% of the variance for the parameter measured. Secondly, neural networks with a forward selection procedure search for the most valuable principal components using only the information without any prior information and restriction. When even more data would be available, each separate pixel could be used as an input to the neural network. Moreover, other information such as the slope of the pressure–time curve might be of importance in forefoot pain. The correct classification of 70% might increase when more data is available and extra input parameters can be added. Examples of such parameters derived from plantar pressure measurements are maximal and mean loading rates, shear stresses or time and transitional related CoP parameters. Especially, loading rate and shear stresses are of interest since these parameters were greater in subjects with diabetic neuropathy and a history of ulceration (Lott et al., 2008). Although they might have been chosen during the forward selection procedure, the information given by these parameters are related to the potential parameters already used in the classification model. Moreover, plantar pressure alone cannot completely explain forefoot pain. Other factors such as thickness of the fat pad under the metatarsals and heel will be of importance (Abouaesha et al., 2001). In addition, the subjective perceived pain will also be responsible if subjects suffer from forefoot pain. Therefore, the 70% correct classification of forefoot pain based on plantar pressure parameters is a good start and is slightly improved by adding other plantar pressure parameters.

Differences in plantar pressure between subjects with forefoot pain and those without forefoot pain might have been due to pathology and/or avoidance of pain. Several studies have shown that gait kinematics can be affected by acute or chronic pain, for example as has been shown for the knee (Henriksen et al., 2010; Shrader et al., 2004). The effect of pain on the foot walking pattern is less known, but Emborg et al. (2009) showed that painful stimulations near the forefoot resulted in avoidance of forefoot pressure. In the current cross-sectional study, all participants had forefoot pain for a longer period and wore insoles. Many studies have shown that insoles are effective in relieving foot pain in diabetic, rheumatoid arthritis patients, and also for common foot complaints (Burns et al., 2009; Novak et al., 2009; Stolwijk et al., 2011). Furthermore, a questionnaire that had been filled in by those subjects with forefoot pain revealed that insoles significantly reduced forefoot pain. Therefore, only limited gait alterations can be expected due to forefoot pain; most plantar pressure characteristics will be a result of pathology, rather than the result of pain avoidance.

Many steps have been taken for the classification of forefoot pain, which will have their influence on the final results. Firstly, the normalization method was used to standardize each plantar pressure measurement, which only affects foot size and foot progression angle (Keijsers et al., 2009). However, foot size and foot progression angle were presented as potential parameters to the neural network but were not selected during the forward selection procedure. Therefore, foot size and foot progression angle seem to be less important in classifying forefoot pain. After normalization, principal component analysis was conducted on each of the pressure images and the CoP data. Principal component analysis does not affect the data but transforms it into new uncorrelated variables. These principal components are difficult to interpret because their value depends on all pixels of a pressure image. The main reason for using PCA was that we could decrease the number of potential parameters. The most important step in the classification of forefoot pain was the use of an artificial neural network and a forward selection procedure. For artificial neural networks, a known data set is required consisting of input (plantar pressure) and output (forefoot pain). The neural network finds the optimal relation between input and output (training the network) but this relation might be due to chance or cofounding. However, the relative good performance on the test set suggests that it was a causal relationship between plantar pressure pattern and forefoot pain. Hence, it can be concluded that the steps taken for the classification do not affect the data. In addition, it is concluded that the relation between plantar pressure pattern and forefoot pain seems to be causal.

The ultimate goal is to create a classification system which could identify subjects with a high risk of developing forefoot pain. With such a system, it would be possible to prescribe preventive measures. To identify which subjects have a higher risk of developing forefoot pain, a longitudinal study in which the plantar pressure measurements are assessed prior to any sign of foot complaint is recommended. However, such studies are difficult to perform and are time consuming. An alternative would be to study subjects who are at a higher risk of developing foot complaints such as those whose employment entails intense physical labor or those who are long distance walkers.

5. Conclusions

The differences in plantar pressure parameters between subjects with and without forefoot pain were small. Despite of the small differences, forefoot pain was classified with a performance of 70%. Therefore, the present study is the first step towards an expert system that can be used to identify which subjects have a higher risk of developing forefoot pain based on plantar pressure measurements.

Acknowledgment

This study was financially supported by Health Valley, Development Agency East Netherlands (Oost NV) and POM Nijmegen. We thank Mrs. P.G. Anderson for the editorial comments.

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