

Foot Plantar Pressure Estimation Using Artificial Neural Networks

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Abstract. In this paper, we present a novel approach to estimate the maximum pressure over the foot plantar surface exerted by a two-layer shoe sole for three distinct phases of the gait cycle. The proposed method is based on Artificial Neural Networks and can be utilized for the determination of the comfort that is related to the sole construction. Input parameters to the proposed neural network are the material properties and the thicknesses of the sole layers (insole and outsole). A set of simulation experiments has been conducted using analytic finite elements analysis in order to compile the necessary dataset for the training and validation of the neural network. Extensive experiments have shown that the developed method is able to provide an accurate alternative (more than 96 %) compared to the highly expensive, with respect to computational and human resources, approaches based on finite element analysis.

Keywords: Artificial neural network · Foot plantar pressure · Mechanical comfort

1 Introduction

During the last decades, one area that has attracted considerable attention by researchers in biomedical and sport-related applications is the analysis of foot plantar pressure distribution and its relation with mechanical comfort. Mechanical comfort is the interaction of the foot with footwear and the ground, mainly related to the upright stance and gait mechanics [1]. Plantar mechanical comfort is concerned with interactions between footwear sole geometry and materials with the plantar side of the foot and the ground, for different environmental conditions and activities. On the other hand, dorsal mechanical comfort is limited to fitting and stability [2]. A formal definition and a review of measurement methods of footwear plantar mechanical comfort can be found in [3].

In this paper, we focus on measuring the maximum foot plantar pressure, which is the pressure that acts between the foot and the support surface, in our case the shoe's sole. Information derived from such pressure measures is important for diagnosing lower limb problems, improving design for casual and professional footwear, determining sport biomechanics, estimating planar mechanical comfort, etc. [4].

Traditionally, the systems which are used to measure plantar pressure vary in sensor configuration to meet different application requirements. Typically, the sensors' configuration is one of three types: pressure distribution platforms, imaging technologies with specialized image processing software and in-shoe systems. In designing plantar-pressure measurement-devices the key requirements are: spatial resolution, sampling frequency, accuracy and sensitivity [5].

Generally, platform systems can be used for both static and dynamic studies but in the most cases they are restricted to research laboratories. Furthermore, the main disadvantage of these systems is that the patient requires familiarization to ensure natural gait because it is important for the foot to contact the center of the sensing area for an accurate reading.

On the other hand, the in-shoe sensors are flexible and embedded in the shoe such that measurements reflect the interaction between the foot and the shoe. These systems are flexible and allow a wider variety of studies with different gait tasks, footwear designs, and terrains [6]. Their main disadvantage is that the sensors should be suitably secured to prevent slippage and ensure reliable results. A further limitation is that the spatial resolution of the data is low compared to platform systems due to the limited number of sensors.

Recently, new methods are moving towards numerical and simulation techniques in order to determine plantar pressure distribution. Finite Element Analysis (FEA) is one of the most popular techniques for analyzing complex structures by combining different materials, loading and boundary conditions. Accuracy of these methods depends on the quality of the geometric models, initial and boundary conditions, material properties and meshing density. FEA has been used for calculating stress-strain relationships on tissues due to the interaction of the foot with the sole and the floor [7]. Despite the fact that FE analysis using detail biomodels provide high accuracy in estimating various parameters affecting foot planar mechanical comfort, these calculations are very time consuming and require intervention of experienced users.

In this study, an Artificial Neural Network (ANN) is introduced to estimate the maximum plantar pressure on the foot surface exerted by the sole structure for each one of the three main phases of gait cycle (i.e., heel-strike, mid-stance and toe-off). Although, more gait phases can be considered, the above three phases result to high maximum plantar pressures and therefore are of primary importance in biomechanical analysis. The input parameters of the proposed ANN are: (i) the material properties of the insoles, and (ii) the thickness of each insole layer. The output is the maximum plantar pressure.

ANNs are a family of statistical learning algorithms inspired by biological neural networks that have the inclination for storing experimental knowledge and making it available for applications. Usually, an ANN consists of simple processing units, called "neurons", which are linked to other units by connections of different weight. The neurons are typically arranged in a series of layers. The network receives one or more inputs and sums them. The output is generated by passing that sum through an activation function [8].

ANNs have been introduced to biomechanics data-mining as an alternative approach to mapping and simulating the relationship between a set of input and output variables [9]. They have been applied successfully to various areas such as: (i) gait classification [10], where ANNs has been employed to classify people's movement. A typical task is the classification of healthy and pathological gait pattern on the basis of kinematic knee angle

parameters. (ii) Biomechanical modelling [11], where the sequence of input and output variables of ANNs follow common biomechanical ideas about movement control without having deterministic relationships of these variables on hand, like the force relationship. (iii) Estimation of gait variables and parameters [12], where the ANNs are used to estimate gait parameters about the patients' walking ability which are useful in many clinical applications (e.g., to diagnose impairments in balance control or to monitor the progress in rehabilitation) [13]. However, there is a limited number of works focused on the foot-sole system for the purposes of computing footwear comfort during gait.

A recent work related to the use of ANNs in footwear comfort can be found in [14], where an ANN is developed to estimate the dorsal pressures of the foot surface while walking. To accomplish this task, a model based on multilayer perceptron is constructed [15] due to its capacity to model the exerted pressure for most of the materials used for the shoe upper. The input of this ANN includes the properties of the shoe upper material and the positions during a whole step of 14 pressure sensors placed on the foot surface. In [16], an ANN is used as a model to estimate the slip resistance. In [17], the authors compare the effect of two insole materials using neural network analysis. In [18], an ANN is used to estimate the traction forces for any combination of stud variables within the limits of the training data. Although the above works are related to footwear design, none is focused on estimating the foot plantar pressure, which is of significant importance in many types of footwear.

The rest of the paper is outlined as follows. Section 2, describes the data-collection method for the training and validation purposes of our approach. Section 3, presents the proposed ANN, while Sect. 4 presents and discusses the results achieved by the introduced approach. Section 5 provides some conclusions and ideas for future work.

2 Data Collection

For the purposes of this work an extensive dataset of plantar pressure measurements is required in order to comply with the training and validation needs of the proposed ANN. This dataset is developed by running several analysis tests using different combinations of material properties and thicknesses with FEA software. The two thirds of the data are used for training while the rest one third is used for validation purposes.

2.1 The Data-Collection Method

The data used for this study are provided by performing FE analysis using a detailed foot biomodel [20]. Foot data are based on a set of CT scans taken on a foot of a healthy male subject with a resolution of 0.5 mm. The solid models created by the reconstruction process are imported into the ANSYS commercial software. Using the macro-language of ANSYS, a parametric model of a flat sole is developed. The bone and soft-tissue structure as well as the sole are discretized using tetrahedral elements (SOLID285), as shown in Fig. 1. The model is able to handle sole structures consisted of one to three layers, with the thickness and material of each layer being the input parameters.

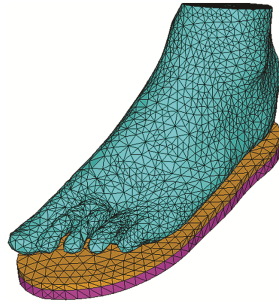


Fig. 1. The foot model and the two-layered sole.

Another parameter of the FE analysis is the gait position of the foot relative to the sole. Since the transfer of forces is done only at the regions of contact between the sole system and the floor, it is easier to assume that the sole system remains unchanged during walking and to rotate the foot according to kinematic data. In this way, three FE models are created to simulate the three major gait phases during walking, i.e., heel-strike, mid-stance and toe-off (Fig. 2).

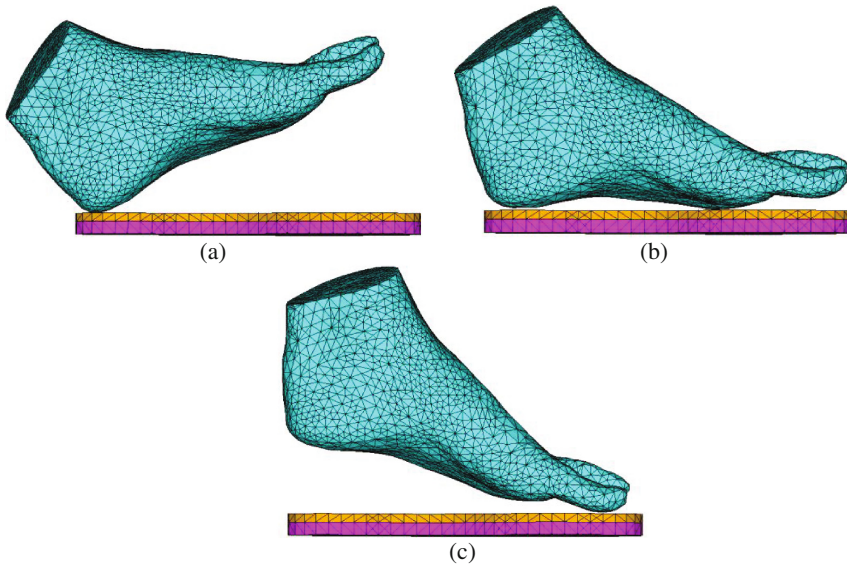


Fig. 2. The three gait phases examined: (a) heel-strike, (b) mid-stance, and (c) toe-off.

In this work, bones are assumed bonded together and to the soft tissue. Constant linear material properties are assumed for the bones (Young's modulus of 7.3 GPa) and the soft tissue (Young's modulus of 1.15 MPa). Contact elements are being used between the foot and the upper sole layer. The upper part of the foot is fixed and a step-wise displacement is applied at the lower sole surface. The two layers of the sole are assumed

perfectly bonded. Young's modulus is a mechanical property of linear elastic solid materials that measures the force (per unit area) required to stretch (or compress) a material sample [19].

The results of the analyses are the applied force (reaction force) and the plantar pressure distribution. Typical plantar pressure results are shown in Fig. 3 for the mid-stance phase. Maximum plantar pressure is observed at the heel and metatarsal regions. Similar distributions are observed for all material and thickness combinations. For the case of the heel-strike phase, maximum plantar pressure is observed at the heel region and is much larger than in the case of the mid-stance phase. The analyses of the toe-off phase shows maximum plantar pressure at the metatarsal region.

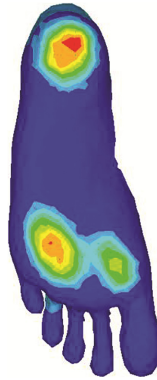


Fig. 3. Typical distribution of plantar pressure.

3 The Proposed Artificial Neural Network

This section summarizes the basic steps that have been followed to model and train the proposed ANN using the aforementioned described dataset.

3.1 Overview

A Multi-Layer Perceptron (MLP) [21] has been adopted to estimate the maximum plantar pressure on the foot surface. The MLP is the most widely used ANN due to its high capacity on relating an input space with an output space. Generally, the MLP is a feed forward artificial neural network model which is composed of successive layers which communicate through synaptic connections.

The structure of a multilayer network contains: (i) an input layer which is made of a number of perceptions equal to the number of data attributes, (ii) intermediate layers which are considered hidden and (iii) an output layer which includes one perceptron in the case of regression or more when it is a task of classification [22].

The inputs of each neuron are multiplied by adaptive coefficients called synaptic weights, which represent the synaptic connectivity between neurons. The output of a

neuron is a function (an activation function) of the linear combination between the inputs and the synaptic weights [22]. Back-propagation has been used for the network training.

3.2 Experimental Setup of ANN

The input parameters of the proposed neural model are Young’s modulus and the thickness of the material of each sole layer. Thus, the overall number of input parameters is 4. The output is the maximum plantar pressure. Input and output parameters are normalized in the range $[-1, 1]$. This resulted to small training sizes and greater accuracy [23].

The proposed ANN is trained using the two thirds of the dataset collected as explained above. The remaining subset has been utilized for validation purposes and for determining the generalization capabilities of the developed model (cross-validation technique) [22]. The goal is to develop a model that works appropriately not only for the cases used to train the model but also for new cases that can involve new materials as long as, their Young’s modulus is within the range of the current training dataset. Otherwise, new materials can be included without changing the ANN architecture as long as there is an appropriate dataset for training.

Furthermore, in this approach, we make use of incremental pruning [24]. This enables the ANN to autonomously select the optimal hidden layer structure based on its capacity to learn best. In this approach, the number of input and output layers is predetermined while a range of minimum to maximum numbers of hidden neurons and layers is provided. The algorithm incrementally increases the size of the neural network and retrains at each increment until it reaches the maximum limits. Then the best trained network is considered as the optimal network configuration.

An important element of the network structure is “the activation function” [25]. In general, the activation function introduces a degree of nonlinearity that is valuable for most ANN applications. Due to the fact that the predicted output of our ANN is in the range $[-1, 1]$ the hyperbolic tangent function is selected as an activation function for the hidden and output layers [26].

A number of training algorithms has been tested including Back Propagation, Resilient Propagation and Levenberg Marquardt Training. Best training times were achieved with “Resilient back propagation” (RPROP). RPROP is based on the traditional back propagation method with just one difference: weight updating is done by evaluating the behavior of the error function. With RPROP, the value of the weight update is calculated by evaluating the partial derivative sign from one iteration to another, improving the learning process, eliminating some problems encountered in the back propagation algorithm and making the proposed method faster than the traditional one [27].

4 Results

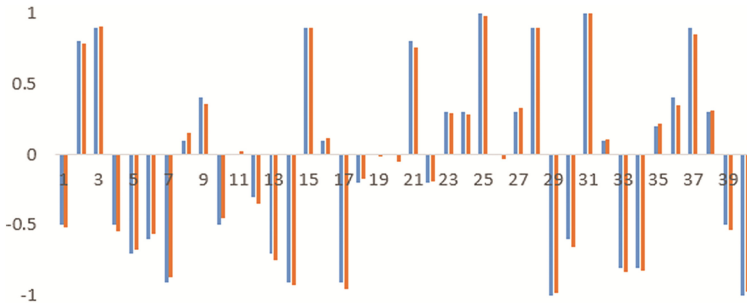
Table 1, shows the Young’s modulus of the sole materials used to train the proposed ANN. We have selected two of the most popular materials used in shoe industry for sole making. Using a varying Young’s modulus it is possible to cover a large range of existing materials. The thickness of each layer takes a value in the interval $[1, 14]$ mm.

Table 1. The materials' Young's modulus

Material	Young's Modulus (MPa)
EVA	10–40
PU double density	4–12

To assess the effectiveness of the proposed approach, we have conducted experiments with data drawn independently from known distributions. For each of the three gait phases, there is a corresponding dataset produced using FE analysis as it is described in Sect. 2. Incremental pruning resulted to a structure with one hidden layer with 6 neurons. After training is completed, each ANN is evaluated by feeding it with the validation data.

For the evaluation of the proposed ANN we have used three different error metrics: (a) the mean error (ME), (b) the mean-absolute error (MAE), (c) the root mean square error (RMSE) and (d) correlation coefficient (r). ME is used as a measure of bias. Positive values mean that the predictor tends to yield maximum pressures lower than the actual ones while negative values stand for an over-biased predictor. Therefore, desired values for ME should be as close to zero as possible. On the other hand, since MAE uses absolute values, negative errors in the prediction do not compensate positive errors, and hence, MAE gives a fair idea of the accuracy of the predictor. In addition, the use of RMSE is often preferred to MAE as an accuracy measure. Finally, the correlation coefficient (r) between the desired plantar pressure and the predicted one is used as a measure of fit, since it gives the linear similarity between the two measurements. A value of r equal to 1 means that the desired plantar pressure and the predicted one contain the same information, whereas a value of r equal to zero means that no information is shared by the desired pressure and the predicted one.

**Fig. 4.** The actual and the estimated results of 40 random runs for the phase heel-strike.

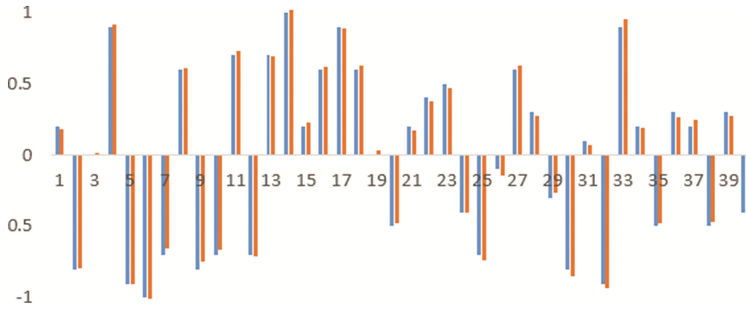


Fig. 5. The actual and the estimated results of 40 random runs for the phase mid-stance.

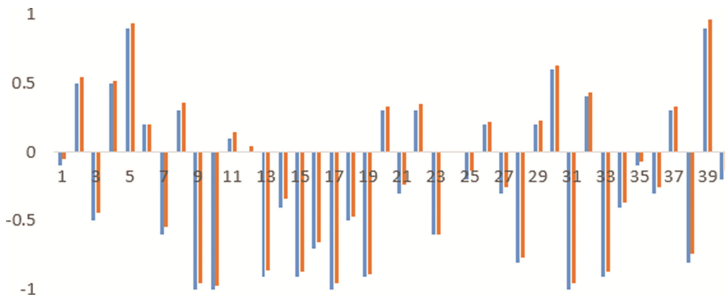


Fig. 6. The actual and the estimated results of 40 random runs for the phase toe-off.

Figures 4, 5 and 6, show three sets of examples of 40 random runs for the heel-strike, mid-stance and toe-off phase, respectively. In all cases, the actual maximum plantar pressure is represented with red color and the estimated result is represented with blue color. For these runs, the thickness of EVA layer takes the discrete values {5, 6} and the thickness of the PU layer takes the discrete values {9, 10}. The obtained results provide more than 96 % accuracy in terms of maximum value deviation compared to the original FEA results. A more detailed analysis of the results obtained for each foot phase is shown in Table 2. All three accuracy indices show a very accurate evaluation of maximum plantar pressure (e.g., MAE ≤ 0.053 ; ME ≤ 0.041 and RMSE ≤ 0.069). In addition, the correlation coefficient is close to unit (e.g., $r \geq 0.953$) confirming that the proposed approach is a reliable predictor of the maximum plantar pressure and can be used as an accurate alternative to the time consuming and tedious process of FE analysis.

Table 2. Error measurement

	MAE	ME	RMSE	r
Heel-strike	0.051	0.037	0.063	0.963
Mid-stance	0.049	0.041	0.061	0.961
Toe-off	0.053	0.028	0.069	0.953

The computational time required for training the proposed ANN was approximately 20 min and it is considered as an offline stage of the proposed approach. The actual run time for the calculation of the maximum plantar pressure for each trained model is about 0.1 s. In contrast, the time needed for FEA to calculate the corresponding value is about 20 min using the same i5 CPU.

All the above results confirm that the proposed ANN is able to estimate the maximum plantar pressure in all three foot phases with high accuracy.

5 Conclusions

This paper has proposed the use of an estimator based on neural networks for use in the selection of shoe's sole materials. Given the properties and the thickness of the material of each sole layer, the maximum plantar pressure can be estimated with high accuracy for each one of the three gait phases. This reduces considerably the time and cost involved in the calculation of this comfort parameter compared to FE analysis approaches.

The research will be further extended to incorporate more input variables to the ANN model in order to address more parameters related to plantar mechanical comfort.

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