MODELING DORSAL PRESSURES ON THE FOOT SURFACE USING ARTIFICIAL NEURAL NETWORKS

[1] María José Rupérez, [2]José David Martín-Guerrero, [1]Carlos Monserrat and [1]Mariano Alcañíz
[1]LabHuman, I3BH, Technical University of Valencia (UPV), email: mjruperez@labhuman.i3bh.es
[2] Department of Electronic Engineering, University of Valencia; email: jose.d.martin@uv.es

INTRODUCTION

Modeling the dorsal pressures over the foot surface is a good way of measuring comfort and functionality in the footwear design, but measuring these pressures for every user wearing different types of shoes might be costly and time consuming. We can reduce both time and cost using prediction techniques based on Artificial Neural Networks (ANNs).

The use of ANNs in Biomechanics is relatively scarce, their main application within this field is related to the classification of people's movement as gait analysis [1], but they have also been used to model the behavior of materials used as shoe uppers [2]. In this work, ANNs are used to predict the pressure over the foot surface exerted by the shoe upper while walking.

METHODS

Four subjects aged 27-31 were required to walk on a platform wearing five different kinds of shoes. The shoes were manufactured from the same design but with five different types of shoe upper material. The pressures exerted by the shoe uppers over the foot surface were measured for each subject while walking using 14 sensors (TEKSCAN Flexiforce®) that are able to gather both static and dynamic pressures and that were connected to a computer through wireless technology. The sensors were placed on 14 anatomical points over the foot surface and under the shoe upper (Figure 1).

Figure 1: Distribution of sensors on the foot surface.

The most widely used ANN, the so-called Multilayer Perceptron (MLP), was used to model dorsal pressures on the foot surface. The classical backpropagation learning algorithm was modified in order to avoid local minima, by means of the Expanded Range Approximation (ERA) algorithm [3]. The MLP is a universal function approximator, which means that it is able to find any relationship between an input space and an output space. Nevertheless, we were not interested in an extremely accurate modeling, but in a model with good capabilities of generalization. Thus, the MLP model could be successfully used with new individuals. Therefore, we stopped the learning process by cross-validation [4].

RESULTS AND DISCUSSION

For each subject, the pressure on 14 foot anatomical points was registered just as the position of the sensors during a complete step. A similar form of the pressure curve measured by the same sensor during the step was obtained for all the materials, but with different values for the pressure due to the different stiffness of each material. This showed that for each subject, the gait cycle was similar wearing any of the shoes. Figure 2 shows the distribution of pressures exerted by the five types of shoe uppers during a complete step measured on the same foot anatomical point for one of the subjects. The higher values of the pressure were obtained for the material with highest Young modulus, 126.085 MPa, and the lower values were measured for the material with the lowest value 8.616 MPa.

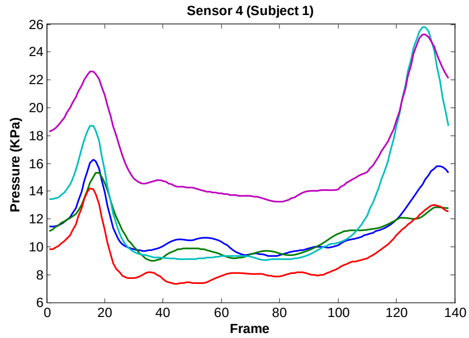

Figure 2: Dorsal pressure distribution.

A model based on the MLP provides a unique model for all the materials by including the characteristics of the material and the position of the sensor as inputs to the neural model. This way, when a new material is used for a subject it is not necessary to carry out new tests to measure the dorsal pressure curve, but the MLP will extrapolate it. Therefore, both time and cost needed for pressure analyses are drastically reduced. The best neural model had an architecture 6x34x1.Two thirds of the patterns (5833) were used to obtain the model (training data set) whereas the remaining third (2917) was kept for validation purposes. The correlation coefficient between the predicted output and the desired signal was 0.977.

CONCLUSIONS

Given the properties of the material and the position of the sensor in any stage of the step, the pressure measured by the sensor for that material can be predicted, thus reducing considerably the time and cost involved in the analysis of this kind of pressures.

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