Classification of Plantar Pressure and Heel Acceleration Patterns Using Neural Networks

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Abstract— **Postural control in humans relies on information from receptors in the proprioceptive, visual, and vestibular systems of the body. As part of human aging, declines in all three postural control systems occur. Age-related changes impact multiple gait parameters, such as decreased range of motion in plantarflexion, increased hip flexion, and reduced stride length and gait velocity. In addition, excessive weight bearing on the heels during standing or forefoot-dominated walking creates risk factors for falls and injury within this population. Identification of these abnormal patterns by a computerized technique can help in early detection of gait changes and prevention of falls. This paper presents a case study to see if plantar pressure and heel acceleration patterns attributed to different motion activities can be accurately identified by a neural network classifier. The method has been tested on motion patterns collected from a single subject. The results show good sensitivity and specificity of the classifier, confirming the feasibility of further research.**

Keywords—**proprioception, postural control, neural network**

I. Introduction

Postural control in humans relies on information from receptors in the proprioceptive, visual, and vestibular systems of the body. As part of human aging, declines in all three postural control systems occur [1, 2]. The ability of the elderly to learn compensatory tactics to overcome these age-related changes is necessary to avoid a progressive decrease in physical activity, quality of life, and mental well-being. Compensation becomes absolutely critical, however, considering that the proportion of elderly in the United States is expected to increase by over 100% from 2000 to 2030 while the numbers of elderly Americans who will suffer from functional disability is anticipated to increase by 300% by 2049 [3]. One of the most recognized, devastating, and costly consequences of functional decline in the elderly is injury related to impaired balance and falls.

Proprioception is the mechanism involved in the self-regulation of posture and movement through stimuli originating in the receptors imbedded in the joints, tendons, muscles, and labyrinth. Guccione [2] reports that decline in proprioceptive abilities as people age have been speculated to be related to a longer latency and higher threshold from cutaneous and proprioceptive receptors. These proprioceptive receptors send somatosensory input to the brain by sensing pressure and stretching motions in the tissues that surround them. Impulses that come from the bottom of the feet, in particular, are of great importance as they indicate the movement of the body over the base of support. These plantar proprioceptive inputs are the dominant sensory information for balance when the body is standing still on a fixed firm surface or moving through the environment [4].

While the vast majority of research on balance focuses on functional testing [5-7] not necessarily on proprioception, other studies have indeed remarked at the irreversibility of proprioceptive losses and have speculated its direct contribution to falls in the elderly [8-10]. This is furthered by evidence that visual input becomes the primary back-up when the proprioceptive system becomes deficient [11, 12] for balance compensation. While this might appear sufficient, the propensity for age-related declines in the visual and vestibular systems lends to the complexity and difficulty in the treatment of balance disorders within the elderly population. There is a need to devise methods that can assist in the identification of abnormal body positioning.

The focus of existing technologies has been on improving performance in athletes and on indicating potentially debilitating pressure areas in the diabetic foot. Therapeutic interaction for those suffering an age-related loss in proprioception, however, usually does not come until significant functional impairment and/or debilitating injury has occurred. In fact, fewer than 10 percent of patients with balance disorders receive proper treatment [13].

This paper presents a case study looking at the feasibility of using neural networks for early detection of age-related changes and pathologies in standing posture and gait through analysis of the plantar foot pressure and heel acceleration patterns. Application of this methodology would provide an extension of therapeutic services into everyday life as well as offer early intervention for age-related proprioceptive loss interrupting the sequelae of potentially disabling impairment in the elderly.

II. METHODOLOGY

A. Data

The data were collected using a sensor shoe (Fig. 1) designed at Clarkson University. The insole of the shoe was equipped with 34 pressure sensing elements. The tactile feeling of the pressure insole was equivalent to the one supplied with the shoe. A two-dimensional MEMS accelerometer (MEMSIC MXR2999E) was mounted on the heel of the shoe for sensing sagittal and longitudinal accelerations. Data from the pressure and acceleration sensors was sampled at the rate of 400Hz, noise reduction was performed on the shoe by taking an average of 16 samples, and the averages were transmitted to the base computer giving an effective sampling rate of 25Hz. WISAN low-power sensor network was utilized to transmit the data from the shoe to the base computer [14]. The data were visualized and processed by using Matlab and Excel software. The pressure and acceleration levels in this proposal are presented in absolute sensor units on the scale of 0 to 4096. Animations of the pressure and heel acceleration patterns collected by the shoe are available on the Web: http://cias.clarkson.edu/shoe/sensorshoe.htm

Pressure and acceleration patterns have been collected on a subject under the guidance and supervision of a board certified geriatric clinical specialist. Only the right shoe contained insole pressure sensors and heel acceleration sensors, the left shoe was not modified.

Standing data have been collected for two different postures. First is the normal posture with various lateral distances between the feet (Fig. 2). Second is a simulated common geriatric standing posture with heel dominated pressure (Fig. 3).

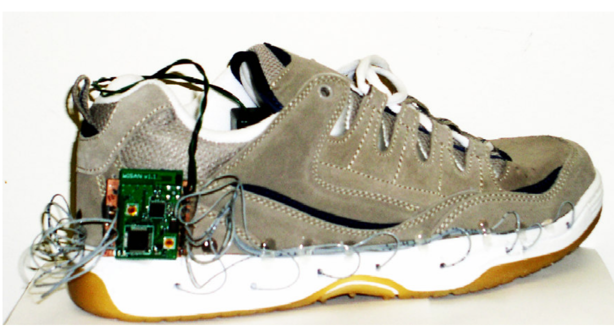
Walking data has been collected on three different gait patterns (Fig. 4). First is the normal gait pattern. Second is a gait pattern simulating normal age-related changes in gait, further referred to as “geriatric” gait pattern. The geriatric pattern is characterized by 5 degrees less motion in plantarflexion, 5 degrees increased hip flexion, and reduced stride length and gait velocity. Third is a gait pattern simulating an abnormal forefoot-dominated gait pattern, further related as “forefoot”. Multiple 10-second recordings of each gait pattern have been taken and used in the analysis.

A single data frame consists of 34 pressure sensors and 2 accelerometer readings. To improve on classification accuracy, the classifiers for normal and the geriatric gait patterns use 8 lagged acceleration readings for each accelerometer. Each reading is 5 samples behind the previous reading. This creates a time history of 16 data points in addition to the 36 data points originally used.

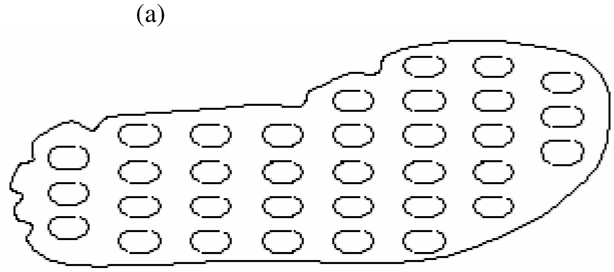
Training set for the data contained two 10-second recordings of each motion pattern. The validation set contained one 10-second recording of a motion pattern.

B. Multilayer Perceptron

A Multilayer Perceptron (MLP) neural network was utilized as the pattern classifier due to good generalization properties. A MLP uses hyperplanes to separate the data into different classes, and consist of three parts: input layer, hidden layers, and output layers [15]. The inputs to the system are 36 and 52 metric vectors described above. The network weights are then adjusted to minimize a cost function by a training algorithm. Initially a traditional backpropagation algorithm with a momentum term [15] was used for network training. However, it was soon



(a)



(b)

Fig. 1. (a) Overall view of the sensor shoe.
(b) Layout of the 34 sensing elements (oval areas).

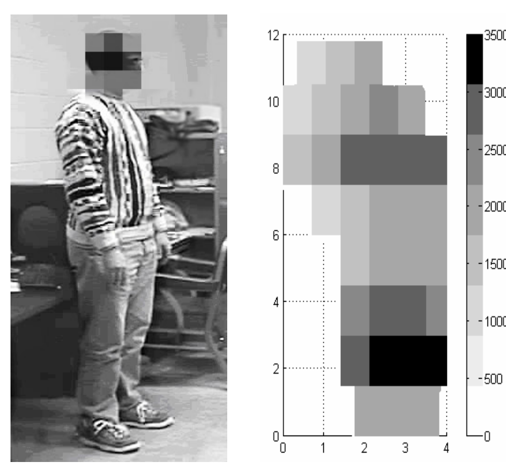


Fig. 2. Average pressure pattern for normal standing. Color map is calibrated in sensor units on the scale 0 to 4096, darker color indicates more pressure.

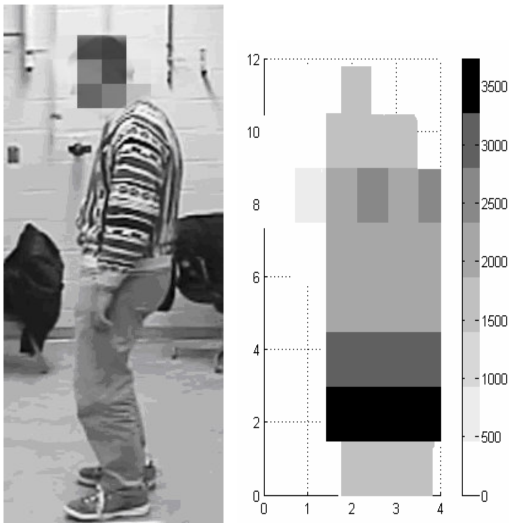


Fig. 3. Average pressure pattern for simulated geriatric standing heel dominated standing pressure. Color map is calibrated in sensor units, darker color indicates more pressure.

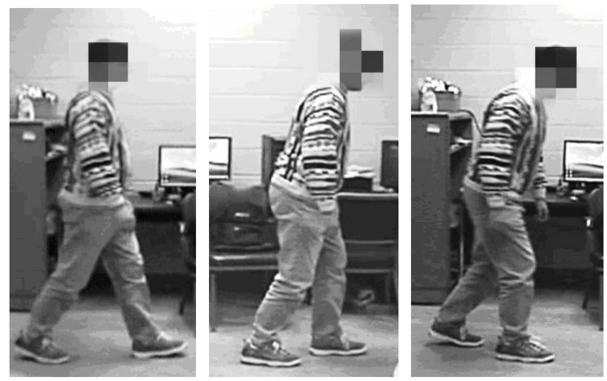
discovered that the backpropagation training is often stuck on a local minimum and cannot produce a viable classifier. To alleviate this problem, the Optimized Levenberg-Marquardt with Adaptive Momentum (OLMAM) training algorithm was used for training. This is the traditional LM algorithm with an additional adaptive momentum term that offers excellent convergence [16]. Application of OLMAM ensured reliable and repeatable convergence of the training procedure.

A separate 2-class classifier has been created for each of the 5 classes (normal standing, heel-dominated standing, normal gait, geriatric gait and forefoot gait) in the problem, that is each MLP had either 36 or 52 inputs and a single output.

The number of epochs required to train the classifier and the number of hidden neurons in the MLP were established in an iterative training process. To determine the number of hidden neurons, each classifier was trained with its number of hidden layer nodes changing from 1 to 20 with 5000 training epochs. After several attempts, the number of nodes needed to train the network was decided by selecting the smallest number that had a high validation accuracy. The number of training epochs was selected to be 5000, since observation of the network training has shown reliable convergence of all training cases after 5000 epochs.

The training process was conducted by assigning a label of 1 to each sample from the training set that belonged to the proper class and a label of 0 to the samples that did not belong.

During the recall and validation, in order to resolve multiple classifications for any pattern, the classifier with the highest output is decided to be the class of the pattern.



(a) **(b)** **(c)**

Fig. 4. Three styles of walking simulated under directions from a physical therapist. (a) Normal gait (b) Simulated age-related geriatric gait (c) Simulated forefoot gait pattern.

Since at each time one and only one classifier is chosen the outputs are transformed into 1 and 0, 1 for active membership and 0 otherwise.

Since the plantar pressure and heel accelerations are sampled at 25Hz and human dynamics do not usually change that fast, the classification results have been improved by a sliding 10-sample majority vote window.

III. Results

The average accuracy of motion pattern classification based on 10 separate experiments is shown in Table I.

True positive is defined as the percentage of the samples of a specific class representing a gait pattern or standing posture being correctly recognized by the binary classifier for that class. False negative is the percentage of the samples in a given class not recognized (rejected) by the classifier for that class. True negative for a classifier of a given class is defined as percentage of the samples of the 4 other classes being correctly rejected by that classifier. False positive for a classifier of a given class is defined as the percentage of the samples of the 4 other classes being incorrectly attributed to that class.

Table I. Average Accuracy of Binary Classifiers.

	Classifier				
	Normal standing	Heel dominated standing	Normal gait pattern	Geriatric gait pattern	Forefoot gait pattern
True positive	99.68%	87.76%	92.05%	79.54%	99.31%
False positive	0.46%	0.84%	0.52%	1.48%	0.52%
True negative	99.54%	99.16%	99.48%	98.52%	99.48%
False negative	0.32%	12.24%	7.95%	20.46%	0.69%

All classes have high accuracy except for lower accuracy exhibited by the geriatric gait classifier. The classification sensitivity is 91.6% on average, while specificity is 99.23%.

Fig. 5 shows an example of applying the obtained classifier to validation data, represented by a brief period of standing, followed by normal gait, followed by a period of standing with normal posture, followed by a period of geriatric walking.

The top graph shows the heel acceleration patterns (the pressure patterns are not shown). Each of the remaining graphs represents a label for a particular class.

IV. Discussion

The results in Table I and in Fig. 5 prove feasibility of the suggested approach. All the classes have been identified with a practically applicable degree of accuracy.

The lower recognition accuracy exhibited by the geriatric gait pattern can be attributed to the closeness of two gait patterns. As an example, a transition from normal gait to normal standing shown in Fig. 5 is misclassified as geriatric. In practical terms, however, such misclassifications do not pose a significant risk, since the laxity of a diagnostic system is much higher and the accuracy will be determined by the average values.

At the same time, pathological patterns (heel-dominated standing and forefoot gait) have been distinctly different from other patterns and have been recognized with a high degree of accuracy.

At this time it is early to definitely conclude the applicability of the suggested methodology to geriatric practice, since these results have been obtained on a simulated data from one subject. At the same time, these results show feasibility for further research in this direction and for conducting this experiment with a large sample of geriatric subjects.

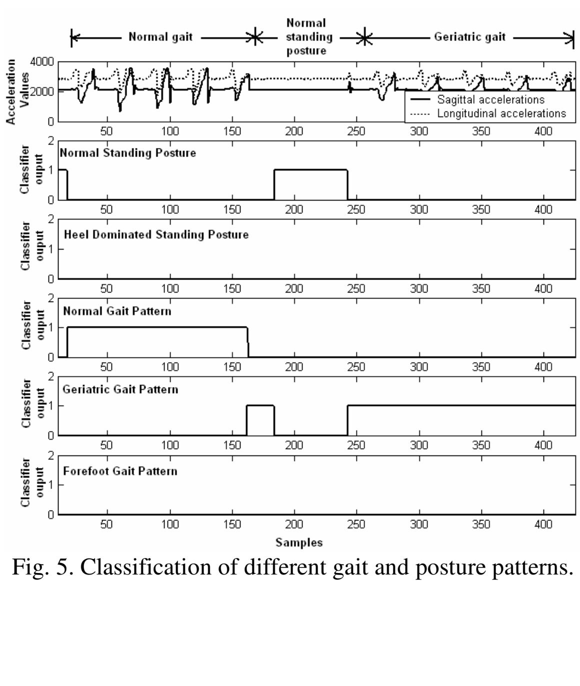


Fig. 5. Classification of different gait and posture patterns.

V. Conclusion

In conclusion, the feasibility of using neural network classifiers for plantar foot pressure and heel acceleration patterns has been established by this study. The results show a potential for the computer diagnostics of age-related non-pathological and pathological changes in the motion patterns of elderly.

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