Assessing Gait Impairments Based on Auto-encoded Patterns of Mahalanobis Distances from Consecutive Steps.

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Abstract. Insole pressure sensors capture the force distribution patterns during the stance phase while walking. By comparing patterns obtained from healthy individuals to patients suffering different medical conditions based on a given similarity measure, automatic impairment indexes can be computed in order to help in applications such as rehabilitation. This paper uses the data sensed from insole pressure sensors for a group of healthy controls to train an auto-encoder using patterns of stochastic distances in series of consecutive steps while walking at normal speeds. Two experiment groups are compared to the healthy control group: a group of patients suffering knee pain and a group of post-stroke survivors. The Mahalanobis distance is computed for every single step by each participant compared to the entire dataset sensed from healthy controls. The computed distances for consecutive steps are fed into the previously trained autoencoder and the average error is used to assess how close the walking segment is to the autogenerated model from healthy controls. The results show that automatic distortion indexes can be used to assess each participant as compared to normal patterns computed from healthy controls. The stochastic distances observed for the group of stroke survivors are bigger than those for the group of people with knee pain.

Keywords. Gait impairment, pattern analysis, modelling, automatic indexes

1. Introduction

Insole pressure sensors are wearable devices that are able to continuously sense the different forces exerted by each foot on the floor while standing up. Their use for the analysis of gait is continuously increasing and they provide supporting tools for better efficiency, flexibility and cost reduction both for researchers and clinicians [1]. By using insole pressure sensors, different pressure distribution patterns while performing different activities can be evaluated. By comparing the differences while assessing pressure patterns from different groups of people suffering different medical conditions with patterns from data of healthy controls distortion indexes can be automatically computed. These indexes could be used as the basis for automatic assessing tools in areas such as rehabilitation, pre-habilitation or sport training [2].

Insole pressure sensors have already been applied in existing literature to different areas. The research in [3] used them for Tai-Chi Chuan learning. Their use in the field

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of ulcer prevention is presented in [4] where a low cost and flexible plantar pressure monitoring system is presented for everyday use to prevent pressure ulcers. Pressure sensors are also used in [5] for monitoring older people with a higher risk of falling and other mobility problems. Smart insoles may also be used to assess long-term chronic conditions that affect the older population such as Dementia, Parkinson's disease, Cancer, Cardiac Disease, Diabetes and Stroke [6].

Self-management applications and tools for assistive health based on insole pressure sensors have also been used in areas such as rehabilitation of osteoarthritis (OA) [7] and post-stroke [8] in order to motivate patients. For example, the use of wearable technology has been explored for the automatic monitoring of the amount of physical activity undertaken, which can be used as a mechanism to provide extrinsic feedback to OA patients within a self-management paradigm [9]. A key factor for wearable technology to be accepted by users is the easiness and non-intrusiveness of the technology [10]. Automatically and continually assessing the progress made by the user in the rehabilitation process and providing personalized feedback based on that progress is a key factor for the user motivation and adherence with the technology [11].

In the particular area of human gait monitoring, different measures and automatic computed features have already been obtained from insole pressure sensors. The authors in [12] used insole pressure sensors in order to predict free torque measures at the shoe–surface interface. Pressure patterns obtained from insoles have also been used for human activity classification in [13]. A novel mechanism for gait assessment in real-life environments based on sensed data from insole pressure sensors is presented in [14].

Using the data sensed from healthy controls from insole pressure devices in order to automatically assess distortion indexes by comparing it with data obtained from patients suffering different medical conditions has been previously used in recent literature studies such as [15]. In this paper, following previous research in this area, a novel methodology is presented in order to assess the differences from knee-osteoarthritis patients and stroke survivors based on the patterns of Mahalanobis distances from several consecutive steps while walking at normal speeds. Data from healthy controls is used to train a single layer auto-encoder. The trained autoencoder is latter used with data from the two experiment groups in order to assess the average reconstruction errors as a measure of how different a walking pattern is from those obtained from healthy controls.

2. Methods

A group of 14 stroke survivors, 14 knee-osteoarthritis patients and 14 healthy subjects walked a distance of approximately 10 meters (repeated 6 consecutive times) wearing two intelligent insoles, one in each shoe. The ethics approval was provided by the Ethics Committee at the University of Sheffield. Different sizes for the insoles were available in order to accommodate the insole to the participants' shoes in an accurate way. Participants were asked to wear outdoor shoes for their visit (to accommodate the insoles). Data collection for each participant began from a seated position. They then stood up, executed the walk, and sat back down after walking around 10 meters (this procedure was repeated 6 times).

Participants were video recorded from the waist down. This allowed us to visually link the physical movement of participants to the data generated by the Intelligent Shoe. These two pieces of information (intelligent insole data and video recordings) were then synchronised.

Each insole contains 8 pressure sensors (Figure 1). The sensors used were manufactured by IEE (a company based in Luxembourg, https://www.iee.lu/en). IEE's Force Sensing Resistor (FSR) are based on an electrical resistance, which varies as a function of the pressure applied to the sensor cell. We used a 100 Hz sampling rate to get the pressure data (one sample each 10 ms). The insoles a LiPo battery (Lithium polymer battery) with 10 hours of continuous usage life. The battery was pre-charged before the start of the measurements. The sensors transmitted the measurements to a central computer using a wireless interface. The central computer ran a software tool provided by a company called Kinematix (www.kinematix.pt) to store the raw data. The raw data was exported to a comma separated values (CSV) file for post-processing and pattern analysis.

Figure 1. Insole pressure device used.

3. Experiment design

3.1. Assessing the stochastic distance for a single step

The different pressure sensors in the insole (figure 1) generate time series of data for each step executed for each participant. We first pre-filter the first and last step in each walking segment since their acceleration particularities make them different from the steady walking steps. The generated time series for intermediate steps for each participant and walking segment are scaled both in time and intensity due to different speeds while walking and different body weights. In order to build a stochastic representation of the sensed data independent of the body weight and speed of walking, the data sensed was re-scaled both in time and in pressure values. We have used a time re-scale factor for the sensed data for all steps to fit them into a 100-sample frame. The pressure values are re-scaled so that the maximum pressure for the combined pressure pattern using the 8 sensors is normalized to "1".

Each point in the re-scaled time series for each step and for each sensor can be seen as a stochastic variable. The probability mass function (pmf) for each group of participants can be assessed based on the normalized data sensed in the data gathering process previously described. The 100 points will generate a joint probability distribution function. The joint pmf assessed for healthy controls will be used in order to compute the Mahalanobis distance for each single step by each participant in each group. The normalized values for sensor i (i=1:8) for a particular step can be represented as shown in equation 1. The Mahalanobis distance for a particular step $\overrightarrow{p_i}$ can be calculated as shown in equation (2), where the mean values for the normalized pressure patterns for healthy controls are represented as $\overrightarrow{\mu_i}$ and S^{-1} is the inverse of the covariance matrix.

$$\forall i_{1:8}\ \overrightarrow{p_i} = (p_{i1}, p_{i2} \dots, p_{i100})$$
$$\max(\overrightarrow{p_i})=1 \tag{1}$$

$$MD(\overrightarrow{p_i}) = \sqrt{(\overrightarrow{p_i} - \overrightarrow{\mu_i})S^{-1}(\overrightarrow{p_i} - \overrightarrow{\mu_i})} \tag{2}$$

The bigger the value for the Mahalanobis distance for a particular step, the less stochastically similar that step is as compared to the data sensed from healthy individuals. The Mahalanobis distance is resilient to sporadic errors in the data sensed from healthy individuals (which will be detected as atypical data as compared to the rest of the data and therefore could be removed from the knowledge database).

3.2. Training a single layer auto-encoder for pressure pattern recognition

Auto-encoders are machine learning tools that can automatically learn the most dominant patterns in training data. When trained with data from a particular group of users, the internal parameters are tuned so that the model is able to reconstruct the samples in that training set with minimal errors. After the auto-encoder is trained for a group of users, it can be fed with data from a different group and the reconstruction errors will show how similar the underlying patterns in the data of both groups are.

In order to assess the gait similarities for a particular member in each of the two experiment groups with the healthy controls, the Mahalanobis distances for 20 consecutive steps are fed into the trained autoencoder. By analysing a consecutive series of steps, different patterns can be associated to each particular group of users (sporadic steps with a high value as computed by equation (2) will generate differentiated patterns from bursts of high values in consecutive steps). The average reconstructed error is calculated following equation (3) where $\epsilon(\overrightarrow{p_s})$ represents the average error for 20 consecutive steps for pressure sensor "s", MD is the input vector of distances (each component denoted as $MD_i(\overrightarrow{p_s})$) and $autoencoded_i(MD(\overrightarrow{p_s}))$ is the output of the autoencoder (component "i").

$$\epsilon(\overrightarrow{p_s}) = \frac{1}{20}\sum_{i=1}^{20}\left|MD_i(\overrightarrow{p_s}) - autoencoded_i\big(MD(\overrightarrow{p_s})\big)\right| \tag{3}$$

4. Results

4.1. Mahalanobis distances calculated for different areas in the insole

In order to assess how similar the pressure patterns for each group of users are to the data obtained from healthy controls, the Mahalanobis distance as described by equation (2) has been computed for each step. The sensors in the insole (figure 1) are numbered as shown in figure 2. The insole has been divided into different areas in order to better assess the most dominant areas contributing to the overall differences among groups. Sensors 7 and 8 are joined in order to cover the heel region. Sensor 6 captures the pressure patterns in the midfoot. Sensors 3, 4 and 5 are combined to assess the walking pressure patterns in the forefoot region.

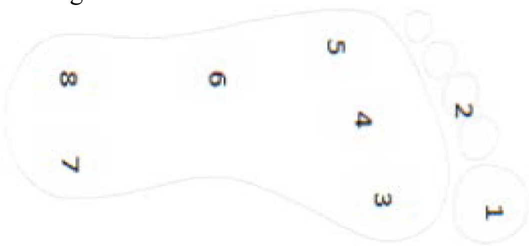

Figure 2. Sensor id numbers.

The average results for the Mahalanobis distaces for all the steps in each group of users divided by foot region are presented in table 1. The average Mahalanobis distances are bigger for the OA group than for the control group. The average Mahalanobis distances are bigger for the stroke survivor group than for the OA group. The region better capturing the average differences is the midfoot region.

Table 1. Average Mahalanobis distances for all the steps in each group of users divided by foot region

	Heel region	Midfoot region	Forefoot region
Controls	0.60	0.81	0.91
Knee pain (OA)	0.91	2.31	1.22
Stroke survivors	0.95	10.00	1.35

Figure 3 captures the 2-D representation of the Mahalanobis distances for the heel and midfoot regions for the 3 groups (each group in a different colour). The results for the control group are close to the origin (0, 0) while the data for patients suffering knee pain (OA group, ”kp” in the key of the figure) cover and intermediate region and the points for the stroke survivor group (“ss” in the key of the figure) tend to be further separated from the origin of the figure. However, using machine learning classification techniques in order to classify single samples (steps) based on this data will misclassify a significant number of samples (steps) as seen in figure 3. Some of the steps executed by participants with knee pain (kp) or stroke survivors (ss) will be similar to those executed by healthy controls (those for example performed by the less affected leg in OA patients or stroke survivors suffering hemiparesis). A pattern analysis combining several consecutive steps is presented in the next subsection in order to overcome this limitation.

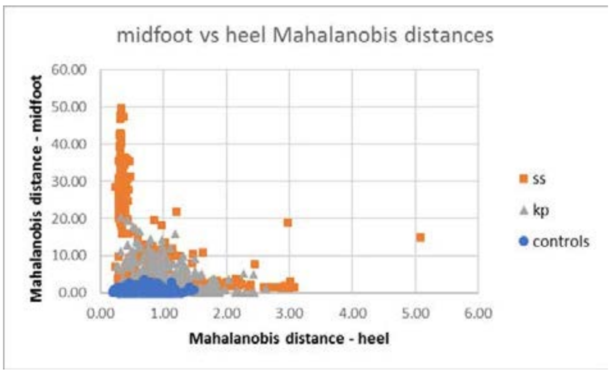

Figure 3. Mahalanobis distances for steps in the 3 groups of participants

4.2. Reconstructed errors in the segments of consecutive steps

Using equation (3) in order to evaluate gait patterns in a series of consecutive steps will provide a second method to complement the results presented in the previous section. Figure 4 captures the results for the entire dataset for healthy controls. Each participant tends to generate bursts of data of similar values in the average computed similarity for 20 consecutive steps. The same results for participants in the OA group are shown in figure 5. In this case, the reconstructed errors are bigger for the majority of participants. Only 2 out of 14 participants end up with values in the range generated by healthy controls and therefore can be easily classified as non-healthy participants. The data for each participant tends to show homogeneous values for each burst of 20 consecutive steps.

Figure 4. Average Mahalanobis distance on reconstructed patterns after the auto-encoder for heathy controls.

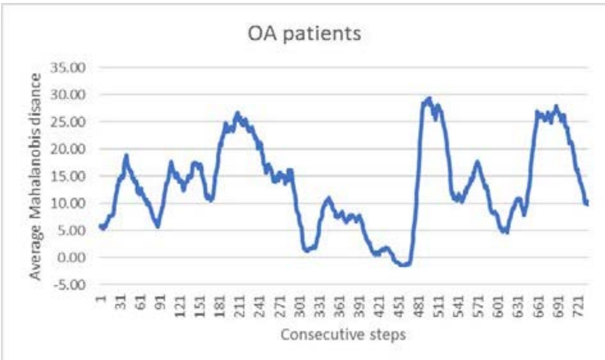

Figure 5. Average Mahalanobis distance on reconstructed patterns after the auto-encoder for OA patients.

The results for stroke survivors are presented in figure 6. In this case, not all the participants were able to finish the 6 repetitions and a smaller number of steps was recorded. The reconstructed errors are significantly higher in this case as compared to the values obtained from the heathy control group. Again, the reconstructed errors are dependent on the particular participant and do not vary significantly for all the bursts of consecutive steps for each participant.

Figure 6. Average Mahalanobis distance on reconstructed patterns after the auto-encoder for stroke survivors.

5. Discussion

Different medical conditions may have a different impact on the way each particular type of patients walk. Insole pressure sensors are valuable tools to assess gait differences from different groups of people [1-15]. Several automatic indexes have been previously presented in order to automatically assess data from insole pressure sensors such as in [8]. A novel data based on auto-degradation features as compared to healthy controls based on previous studies such as [15] based not only on the assessment of single steps but including the underlying patterns in bursts of consecutive steps has been introduced in this paper showing promising results which can be applied in areas such as auto-evaluation in self-rehabilitation programs.

The results show that the stochastic characterization of data from healthy controls is able to find outliers (singular steps) in data from the distributions generated by knee pain (OA) patients and stroke survivor participants. The bigger the distance for each outlier the most affected the individual is according to what is normal for healthy individuals.

The results for single outlier isolation is not always able to assess the condition of each individual since many of the steps may fall inside the normal patterns as stochastically described from data sensed from healthy controls. An analysis taking into account patterns found in consecutive steps has been performed in order to overcome this limitation. The results are very promising and the different individuals show well define degradation measures as compared to healthy individuals.

The results of the paper should now be tested with more participants and the experiment should be extended over time to evaluate if the medically assessed progress for each participant over time is well captured or not by the computed distances presented in this paper. This research will be conducted as future work.

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