Gait analysis by using Smart Socks system

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Abstract. Feet plantar pressure measurement and gait pattern analysis can be utilized for different disease detection as well as post-operation rehabilitation monitoring. Increasingly popular for gait analysis in research have become smart sock systems as an alternative to the more expensive commercial analogs, however, analysis with such systems are complicated due to the limited sensor count and other inherit limitations of textile pressure sensors. This paper proposes a new method for gait pattern recognition for use with smart sock systems. According to this method, steps are classified depending on the sum of Manhattan distances (SMD) between two high-dimension vectors, from which one describes the step to analyze and the other is a predefined vector representing a specific gait pattern. The gait pattern with the lowest SMD value to the particular step vector is assigned to each step. An experiment was performed to verify the proposed method, where three volunteers simulated three gait types, normal, pronation and supination, and the simulated steps were compared to references. The experimental results confirmed that typically the lowest SMD value was obtained by the reference corresponding to the tested gait pattern type. In one of the demonstrated cases, the mean SMD value for the same set of steps with the reference for normal step was 1.26, 1.77, and 1.78, with reference for pronation it was 1.75, 1.57, and 2.59, and reference for supination, 1.75, 2.15 and 1.46, for normal gait, gait with pronation and gait with supination, respectively. It can be seen that the lowest mean SMD value for each gait type is when the correct reference is applied.

1. Introduction
The human gate monitoring by means of foot plantar pressure measurements could have numerous applications, such as post-operation rehabilitation and recovery assessment, abnormal gait condition detection, foot surface pressure monitoring for diabetic patients, and many more [1, 2]. Pressure plates are the typical plantar pressure monitoring systems used in clinics and are considered the golden standard for such measurements. They, however, cannot be used for continuous patient monitoring due to the limited surface area. Pressure-sensitive insoles are, generally, more suitable for out-of-lab measurements, but such devices are sensitive to folds and thus could not be used with orthopedic insoles or shoes. On top of that, both of these systems are rather expensive [3], which limits their usage outside of clinics. In recent years, smart textile based plantar pressure measurement systems have been studied worldwide as a possible alternative [4]. Such smart textile socks are rather inexpensive, they can be made to fit any foot size, can be used for a prolonged period, are washable and do not require a sophisticated data acquisition hardware [5]. Despite the above advantages, smart socks still are not
widely used for gait analysis, as there is no well-established framework for employing the information from a limited number of sensors for detection of differences in gait pattern.

This research proposes a new method for gait pattern evaluation and classification for measurements using a smart sock system. For each step, a high dimension vector is constructed, which is then compared to reference vectors by using sum of Manhattan distances (SMD). The reference vectors were obtained from a set of recordings corresponding to particular step patterns. Such an approach allows evaluating the gait similarity to a certain abnormal gait pattern as well as deviation from a normal gait. The proposed method for step analysis was verified by performing test-walks by three volunteers, wearing custom-designed smart textile socks while walking normally or simulating one of the two analyzed abnormal gait patterns, excessive pronation or excessive supination. The preliminary results demonstrated that the proposed method could be used for gait pattern analysis. A significantly lower SMD value was observed when using the proper reference thus allowing gait type classification.

2. Materials and Methods
A novel gait analysis method for smart sock measurement system is proposed in this paper. According to this method, foot plantar pressure measurement is obtained by textile pressure sensors and then analyzed to evaluate the gait type. The evaluation is performed by extracting a set of step parameters from the measurement and combining them in a single multi-dimensional vector, which is used for step characterization. This vector then is compared to one of the pre-determined vectors by using Manhattan distance, which allows evaluating the difference between two high dimension vectors [6]. Finally, the total sum of Manhattan distances over all vector dimensions is used to determine the difference between a particular step and the reference. Using such approach, any step can be quickly classified by calculating to which of the pre-determined step types it belongs as long as sufficient reference data exists.

2.1. Smart Sock system
The method described in this paper was developed specially for application with a custom-made smart sock system that consists of a five textile pressure sensors incorporated directly in each sock (see figure 1). Smart socks used in this research were knitted from combed cotton yarn platted with elastane/polyamide yarn. Five pressure sensors were directly knitted in each sock, and silver-coated thread Shieldex 117/17 (Statex Produktions und Vertriebs GmbH) was used for electro-conductive lines which were also knitted in the socks during the manufacturing process. The sensors were distributed on the sock sole part in a configuration 2-1-2 with two sensors in the front, one on the lateral side in the middle, and two under the heel (see figure 2). Measurements of sensors output signals were performed with a dedicated circuit attached to electro-conductive lines by snap fasteners. The sampling rate of measurement was 33 SPS. The measurement was transferred to PC through Bluetooth connection, where it was processed as described below.
2.2. Data Processing

The data processing consists of three major parts. First, the signal is filtered and individual steps are recognized. Afterward, step parameters are calculated and a high-dimension vector is constructed for each of the steps. Finally, the constructed vectors are compared to a reference to classify the step.

The individual step recognition is performed by combining together signals of all sensors, which are first inverted and normalized, according to the equations (1):

\[ u_i' = \frac{u_i - \min_{a \leq i \leq b} u_i}{\max_{a \leq i \leq b} u_i - \min_{a \leq i \leq b} u_i} \]

(1)

where \( u_i \) is the corresponding measurement and \( \{a;b\} \) is a window around \( i \)-th measurement to which to normalize the signal. Such local normalization was chosen to solve the issue of creep, which is typical for textile sensors, while at the same time maintaining the local amplitude variations within a few steps. Separate sensor measurements and the combined signal can be seen in figure 3.

The beginning and the end of a step are determined by applying a level threshold of 0.5 to the total signal, where the first measurement above the threshold is considered the beginning of a step, and the first measurement under the threshold and after the start of a step is considered the end of the step. Afterward, detected steps are verified by a minimum length requirement to exclude false detections, where the signal could go above the threshold briefly due to a noise or misstep.

The high-dimension vector consists of 22 different parameters that describe both time and amplitude related characteristics of a step. These parameters are not discussed in this paper in details due to space limitation.
The final step of the algorithm is to use the SMD value to evaluate how close a step is to predefined vector values. The SMD value is calculated according to equation (2):

$$SMD = \sum \frac{|V_{\text{left}}-V'|+|V_{\text{right}}-V'|}{2}$$

where $V_i$ is the high-dimension vector for the step to evaluate, and $V'$ is the predefined reference vector for comparison. The step is considered to belong to the gait pattern with the lowest SMD value.

2.3. Experimental Setup
Following an experiment was performed to verify the applicability of the developed method to gait pattern classification. Three volunteers were requested to walk several times in a straight line for approx. 10 meters in one of the following gait types: normal gait, gait with excessive pronation and gait with excessive supination. Gait with excessive pronation signifies increased pressure on the medial part of the foot, while excessive supination is the opposite with increased pressure on the lateral part of the foot. Measurements were performed with the smart sock system and data was analyzed as described above, and all measurements were compared to the predefined reference vectors to verify variations in SMD value depending on the reference gait type. The mean measurements of one walk per gait type were utilized as references for step type classification.

3. Results and Discussion
An experiment was performed to evaluate the proposed step type classification algorithm for use with smart socks. Three volunteers were requested to walk while simulating one of the gait types, normal gait, gait with excessive supination and gait with excessive pronation. The obtained measurement was processed as described above. In total 616 steps were recognized and used for this study, from those 304 were normal gait steps, 152 steps with pronation and 160 steps with supination. As it can be seen from the summarized data in table 1, the mean SMD between the test data and the reference in most (7/9) cases is lowest when the used reference corresponds to the simulated gait type.

| Table 1. Experimental results |
|-------------------------------|
| Volunteer | Gait pattern | Normal Value | Normal STD | Pronation Value | Pronation STD | Supination Value | Supination STD |
|-----------|--------------|--------------|------------|----------------|--------------|----------------|---------------|
| V1        | Normal       | 1.39         | 0.34       | 1.97           | 0.5          | 1.77           | 0.54          |
|           | Pronation    | 2.33         | 0.59       | 3.34           | 0.62         | 2.4            | 0.48          |
|           | Supination   | 2.73         | 0.49       | 2.14           | 0.51         | 2.19           | 0.55          |
| V2        | Normal       | 1.46         | 0.26       | 2.34           | 0.35         | 1.83           | 0.33          |
|           | Pronation    | 2.92         | 0.55       | 3.12           | 0.61         | 3.75           | 0.69          |
|           | Supination   | 2.18         | 0.61       | 2.14           | 0.51         | 2.15           | 0.36          |
| V3        | Normal       | 1.26         | 0.33       | 1.75           | 0.38         | 1.79           | 0.39          |
|           | Pronation    | 1.77         | 0.27       | 2.59           | 0.51         | 1.46           | 0.3           |
|           | Supination   | 1.78         | 0.38       |                |              |                |               |

Figure 4 demonstrates an example of the effect of different references on SMD. When a normal gait reference is used, most of the normal steps are with a significantly lower SMD value than other gait types (see figure 4a). By changing the reference to pronation gait (figure 4b), the mean SMD for normal gait increased from 1.26 to 1.75 while the mean SMD for pronation decreased from 1.77 to 1.57. The same trend for gait with supination can be seen in figure 4c. Moreover, as supination and pronation are somewhat opposites, so each of them can be identified by using the opposite reference and setting a high threshold instead of low. This can be seen in the example given in figures 4b and 4c, where the mean
SMD for supination increases from 2.19 with supination reference to 3.12 with pronation reference, and for pronation from 2.14 to 3.75.

![Graph showing SMD values for each step for volunteer V3 when (a) normal, (b) pronation, and (c) supination reference is used.]

Significant changes in the mean SMD can be observed in figure 4 despite the variation and overlap in the result of different gait types for individual steps. Although this overlap complicates setting a detection threshold, in practice, however, there is no necessity to classify each step correctly as the overall gait pattern can be concluded from the majority of steps. Table 2 provides the percentage of steps...
with SMD below the threshold of 1.5 for data in figure 4 for each of the gait pattern. As it can be seen, in case of normal gait, using normal gait pattern reference more than 80% of steps have SMD below the threshold, while only 13.51% and 26.32% if pronation and supination references are used respectively. A similar situation can be observed in case of the other two tested gait patterns.

| Gait type / Reference | normal  | pronation | supination |
|-----------------------|---------|-----------|------------|
| normal                | 84.38   | 13.51     | 26.32      |
| pronation             | 25.00   | 43.24     | 2.63       |
| supination            | 28.13   | 2.70      | 50.00      |

4. Conclusions and Future Work
A new gait type detection method for application with smart socks system was proposed, and three gait patterns were observed: normal gait, gait with excessive pronation and gait with excessive supination. The applicability of the proposed method for gait pattern type detection was demonstrated with experimental data.

For future work, additional tests are necessary to further improve the method. Considering that the clinical gait conditions used in this study were simulated by healthy individuals, clinical tests are necessary to acquire a true reference and verify the proposed method with real patients. Additionally, more gait types can be included in the reference list to increase the number of detectable gait types. Finally, the parameters included in the high-dimension vector of the step must be reviewed and optimized to further improve the gait type detection.

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