Journal of Biomechanics 93 (2019) 70–76

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Using smart garments to differentiate among normal and simulated abnormal gaits

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ARTICLE INFO

Article history:
Accepted 14 June 2019

Keywords:
Smart shirt
Smart socks
Smart textile systems
Simulated abnormal gait
Gait classification

ABSTRACT

Detecting and assessing an individual's gait can be important for medical diagnostic purposes and for developing and guiding follow-on rehabilitation protocols. Thus, an accurate, objective gait classification system has the potential to facilitate earlier diagnosis and improved clinical decision-making. Systems using smart garments represent an emerging technology for physical activity assessment and that may be relevant for gait classification. The objective of this study was to assess the accuracy of one such system – comprised of commercial instrumented socks and a custom instrument shirt – for differentiating among normal gait and four distinct simulated gait abnormalities. Eleven participants completed an experiment in which they completed several gait trails on a single day. Gait types were classified using diverse modeling approaches (K-nearest neighbors, linear discriminant analyses, support vector machines, and artificial neural networks). High classification accuracy could be obtained, both when classification models were developed and tested using data from each participant separately and grouped together, particularly using the k-nearest neighbor method (>98% accuracy). Some gaits were more often "confused" with other gaits, especially when they shared underlying kinematic aspects. These results support the potential of using "smart" garments for detecting and identifying abnormal gaits, and for future implementation in diagnosis and rehabilitation.

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1. Introduction

Gait abnormalities stem from a variety of causes (Moon et al., 2016; Salzman, 2010), including neurological disorders and musculoskeletal injuries. To formulate appropriate treatment protocols and improve patient care during rehabilitation, it is important to promptly and accurately identify gait abnormalities (Figueiredo et al., 2018). At present, being observed by a trained physical therapist represents the standard method for identifying gait abnormalities (Bae et al., 2011). This is an inherently subjective approach, dependent on a therapist's experience and training, and thus may not provide consistently reliable assessments (Rathinam et al., 2014). Furthermore, early stages of some gait abnormalities, such as Parkinson's (Zeng et al., 2016), may not be diagnosed easily using neuroimaging methods (Chen et al., 2007a). Finally, there exists a large diversity among abnormal gait patterns that can occur for many reasons, such as among stroke patients (Voigt and Sinkjær, 2000) or children with cerebral palsy (Dobson et al., 2007), making it challenging to differentiate among them using subjective methods and recommend proper treatment. Thus, detecting a specific type of gait abnormality is important for diagnostic purposes, and for devising and carrying out rehabilitation protocols (Bae et al., 2011; Moon et al., 2016). Objective gait classification, or assigning a gait pattern into a specific category, has the potential to facilitate earlier diagnosis and improved clinical decision-making (Dobson et al., 2007).

Several objective approaches to gait classification have been reported, which principally involve: (a) non-wearable systems, such as force platforms (Muro-De-La-Herran et al., 2014), motion capture systems (Taborri et al., 2016), video analysis (Bauckhage et al., 2009), and depth cameras (Stone and Skubic, 2013); or (b) wearable systems, such as instrumented shoes (Crea et al., 2014; Macleod et al., 2014; Meng et al., 2008; Razak et al., 2012), inertial measurement units (Mokhlespour Esfahani et al., 2018; Taborri et al., 2016), and so-called smart garments (Preece et al., 2011; Tirosh et al., 2013). For example, Lakany (2008) used kinematic gait data extracted from a motion capture system (MOCAP) to classify normal gait vs. a pathological gait and to differentiate between pathologies with accuracy levels of 81% and 70%, respectively (Lakany, 2008). Pogorelc et al. (2012) also used MOCAP, and

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https://doi.org/10.1016/j.jbiomech.2019.06.009
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detected gait abnormalities with 100% accuracy. Other researchers have used instrumented treadmills for differentiating gait patterns between healthy subjects and patients (spastic diplegic cerebral palsy and relapsing remitting multiple sclerosis), with accuracy of ~95% reported (Alaqtash et al., 2011). As examples of wearable systems, an in-shoe device with force-sensitive switches differentiated between healthy individuals and those with a neuro-degenerative disease with ~90% accuracy (Joshi et al., 2017), and using an IMU integrated in a shoe was able to discriminate between normal gait and a toe-in-and-toe-out abnormal gaits with ~89% accuracy (Chen et al., 2007b). Non-wearable systems are mainly relevant for lab-based applications, and are less appropriate for ambulatory applications. Moreover, they typically can provide information over relatively short periods. In contrast, wearable systems are suitable for both indoor and outdoor usage and can provide information over longer durations (Muro-De-La-Herran et al., 2014). As such, wearable systems have the potential to be more successful in identifying gait abnormalities (Figueiredo et al., 2018).

Smart garments (SGs) are a promising type of specific wearable system, defined as fabric that has intrinsic sensing materials, and have already been used in several healthcare applications (Cherenack and van Pieterson, 2012; Mokhlespour Esfahani et al., 2013; Mokhlespour Esfahani et al., 2019; Mokhlespour Esfahani et al., 2017). In contrast, only few applications have been reported for gait monitoring. Smart socks have been used to measure select gait parameters (Tirosh et al., 2013), to detect walking and running patterns (Oks et al., 2016), and to detect specific gait events ((Preece et al., 2011). To our knowledge, smart socks are being employed exclusively at present only to monitor or measure gait parameters and gait events, with no studies evaluating their potential to identify gait abnormalities. An abnormal gait can also impact upper-body behaviors, and thus there is potential value in SGs that can monitor these behaviors.

This study was completed to determine the accuracy and most effective components of a smart textile system (STS, including "smart" socks and shirt) in detecting normal vs. simulated abnormal gaits, and in recognizing several specific gait abnormalities. Results of this work were expected to be useful in determining the future viability of using data from SGs for objective healthcare assessments specifically related to gait. A lab-based protocol was used to answer the following two questions: (1) How accurate is a particular smart textile system (STS) in differentiating among normal and simulated abnormal gaits?; and (2) What are the relative merits of the two components of the STS (i.e., socks and shirt), both separately and in combination? As a secondary focus, the relative performance of several classification methods was determined.

2. Methods

2.1. Participants

Eleven participants (six males and five female) completed the study, none of whom had any self-reported history of musculoskeletal disorders over the prior year. Respective means (ranges) for age, body mass, stature, and BMI were 21.3 (18–26) years, 76.2 (64.4–86.0) kg, 174.5 (163–186) cm, and 25.0 (22.4–29.4) kg/m^2. Potential participants were only eligible to take part in the experiment if they could "fit" into the smart shirt (see below). The study procedures were approved by the Virginia Tech Institutional Review Board, and all participants provided initial informed consent.

2.2. Experimental protocol

All participants performed a set of predefined tasks in a laboratory setting. They first walked on a treadmill (SOLE F63, SOLE Fitness, Salt Lake City, UT, USA) at their self-selected (natural and comfortable) walking speed for purposes of familiarization, then donned the STS described below. They subsequently completed walking trails on the treadmill under five different conditions, consisting of "normal" gait and four simulated abnormal gaits. Each of the conditions was performed for at least 120 s to collect sufficient data for assessment, given the sampling rate of 20 Hz (Bersch et al., 2014). The order of the five conditions was assigned using partially-balanced Latin Squares.

Among diverse abnormal gaits, (i.e., neurologic and musculoskeletal disorders), we picked two representatives that relate to neurological disorders, Hemiplegic and Diplegic gaits (Rodda and Graham, 2001), and two related to musculoskeletal injuries, bilaterally asymmetric and hunchback gaits (Nguyen et al., 2016), as shown in Fig. 1. Participants were asked to simulate these four abnormal gaits as described below. (We used *simulations* of gait abnormalities, since recruiting actual patients was considered infeasible and impractical, especially given the exploratory nature of the current work.) In all four cases, we instructed participants on the desired gait by showing a reference video, and also applied several braces.

To help simulate hemiplegic gait, we applied rigid braces to the lower and upper extremities on the dominant side. The former were used to stiffen the knee and ankle on one side, limiting motion at these joints and placing them in extended postures, while the latter were used to stiffen the shoulder, elbow, and wrist and to configure the arm in a certain posture (flexed, adducted, and internally rotated). For diplegic gait, we applied rigid braces on both lower extremities and used flexible braces for both arms. For the purpose of simulated bilaterally asymmetric gait, we used a rigid brace to limit dominant knee flexion. Finally, to simulate hunchback gait, participants were asked to bend forward while walking and to keep their dominant hand placed on their lower back. Participants practiced the four abnormal gaits and were given feedback. We adjusted the treadmill speed according their comfortable walking speed in each of the simulations.

2.3. Smart textile system (STS)

An STS was used that was comprised of two smart garments (smart socks and shirt). We employed smart socks (SSs) since they can directly measure foot pressure. Furthermore, SSs avoid problems associated with the use of flexible plantar pressure sensors within in-shoe systems that can lead to inaccuracies, such as bending (Crea et al., 2014) and slippage within the shoe (Taborri et al., 2016). SSs also have the advantage of being light and flexible, enhancing their potential use for diverse foot shapes, and can be utilized in diverse situations (e.g., with or without shoes). We used a commercial product, Sensoria socks (Sensoria Inc., Redmond, WA, USA), which has three textile pressure sensors integrated under each heel along with the 1st and 5th metatarsals. These socks were available in three sizes, and the appropriate size was used for each participant.

Although measures from the foot-floor interface via SSs could reflect differences between gait conditions, abnormal gaits can also involve distinct upper body postures and motions (e.g., Brandstater et al. (1983), de Bruin et al. (2008), Rodda and Graham (2001), and Nguyen et al. (2016). Further, evidence suggests a user preference for a short-sleeved T-shirt rather than other types of smart garments (Mokhlespour Esfahani and Nussbaum, 2018b). Here, we used a single-size smart undershirt (SUS) described earlier (Mokhlespour Esfahani and Nussbaum, 2018b), which included 11 textile sensors for monitoring both shoulder and low back movements (Fig. 2). We printed five smart textile sensors in the low-back region and six sensors at the shoulders, which were used to capture planar motions of the thorax (relative to the pelvis) and

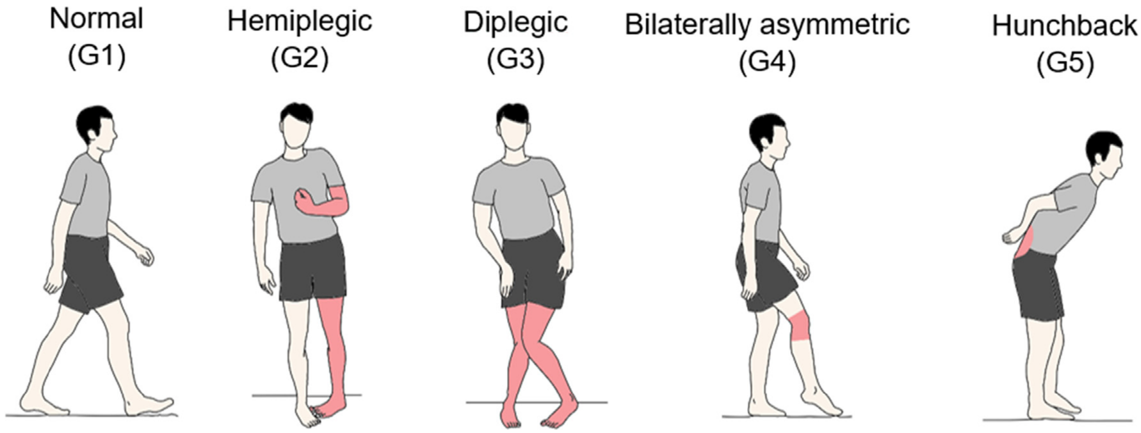

Fig. 1. Illustrations of the five types of gait included in the study.

bilateral shoulders. The placement of these sensors was determined based on previous studies (Mattmann et al., 2008; Mokhlespour Esfahani et al., 2017). Each sensor was 20 × 80 mm and was developed by coating electroactive polymers (i.e., polymerization) on a stretchable fabric. We measured resistance changes between two ends of each sensor using conductive threads that were sewn to both sides of the smart textile (Mokhlespour Esfahani et al., 2016).

Data from the SSs and SUS were sampled at 32 and 1000 Hz, respectively. Both were subsequently low-pass filtered, using 4th-order, bi-directional Butterworth filters, with cutoff frequencies of 5 Hz (Pezzack et al., 1977). We then resampled all data at 20 Hz, and normalized the resampled data based on the two reference postures (see Mokhlespour Esfahani and Nussbaum (2018b).

2.4. Gait classification

A classification approach was used to determine the accuracy of the STS in recognizing several specific gait abnormalities (different gait patterns). Classification models were developed using four methods – K-nearest neighbors (K-NNs), linear discriminant analyses (LDAs), support vector machines (SVMs), and two-layer, feed-forward artificial neural networks (ANNs) – each implemented using MATLAB (2016, The MathWorks, Inc., Natick, Massachusetts, USA). These specific classification methods were selected to represent relatively common approaches for human activity detection (Preece et al., 2009). Inputs for the classification models were obtained from the raw signals of the SSs (6 features) and SUS (11 features), and the output target was the relevant gait pattern (G1 . . . G5).

Fig. 2. (a) Illustration of the placement of 11 smart textile sensors on an undershirt (b) An individual wearing both smart garments (smart socks and smart shirt) and unilateral braces on both extremities (for simulating hemiplegic gait).

Table 1
Global accuracy using different classification models and input data sets.

Model		Individual-Level (%)											Group-Level (%)
		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	
K-NN	SSs	98	98	99	99	98	99	98	99	98	98	99	98
	SUS	96	99	99	99	99	99	96	99	99	98	97	98
	STS	99	99	99	99	99	99	98	99	99	99	99	99
LDA	SSs	91	96	94	87	91	97	93	97	86	87	99	31
	SUS	92	99	99	99	99	98	91	96	96	97	93	52
	STS	99	99	99	99	99	99	96	99	99	99	99	62
SVM	SSs	94	97	99	98	98	98	95	98	95	93	99	33
	SUS	93	99	99	99	99	99	94	98	98	98	95	59
	STS	99	99	99	99	99	99	97	99	99	99	99	73
ANN	SSs	94	96	98	97	97	98	96	98	94	92	99	89
	SUS	96	99	99	100	99	99	97	99	99	99	98	97
	STS	99	100	99	99	99	99	98	99	99	99	100	99

K-NN: k = 10 in k-nearest neighbor, LDA: linear discriminant analysis, SVM: support vector machine, ANN: artificial neural network. P1 … P11 are participant numbers.

Table 2
F-scores obtained when using different classification models at the group level.

Model		G1	G2	G3	G4	G5
K-NN	SSs	0.99	0.99	0.98	0.98	0.98
	SUS	0.99	0.98	0.97	0.97	0.99
	STS	0.99	0.99	0.98	0.98	0.99
LDA	SSs	0.36	0.28	0.38	0.14	0.35
	SUS	0.58	0.54	0.45	0.42	0.60
	STS	0.73	0.59	0.58	0.51	0.66
SVM	SSs	0.36	0.26	0.34	0.28	0.39
	SUS	0.66	0.61	0.52	0.49	0.67
	STS	0.81	0.7	0.72	0.62	0.76
ANN	SSs	0.96	0.89	0.88	0.88	0.85
	SUS	0.98	0.97	0.97	0.97	0.98
	STS	0.99	0.99	0.99	0.99	0.99

K-NN: k = 10 in k-nearest neighbor, LDA: linear discriminant analysis, SVM: support vector machine, ANN: artificial neural network. G1 … G5 are gait types (see Fig. 1).

Using each classification method, we developed two distinct types of models differing in the model training approach. In the first, we trained 11 separate models using data from each participant (i.e., *individual-level*). In the second, a single model was trained using data from all participants (i.e., *group-level*). Separate models were also developed to compare the relative performance of using the SUS only (11 inputs), the SS only (6 inputs), and the combined STS (17 inputs). Thus, a total of 144 classification models were developed: 12 models at the group level (3 input sets $\times$ 4 methods); and 132 models at the individual level (11 participants $\times$ 3 inputs sets $\times$ 4 methods). For the K-NN, LDA, and SVM methods, 5-fold cross validation was used to avoid overfitting. For the ANN method, we randomly divided the dataset into training (70%) and testing (30%) subsets (Siuly et al., 2017). ANN training was done using the scaled conjugate gradient backpropagation method. We used 60 or 200 neurons for assessing classification performance at the individual-level (each participant) and group-level (all participants), respectively. Through trial and error, we selected k = 10 in the K-NN method (Preece et al., 2009). Performance of the various classification models was quantified using global accuracy and the F-score (Preece et al., 2009), which were determined using the testing data subset. Formulas for these metrics are:

$$\text{Global Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Total Sample Number}} \tag{1}$$

$$\text{Sensitivity (Recall)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

$$\text{F-score} = \frac{(2 * \text{Precision} * \text{Recall})}{\text{Precision} + \text{Recall}} \tag{4}$$

where TP, TN, FP, and FN refer to the number of true positives, true negatives, false positives, and false negatives, respectively. Confusion matrices were also created based on results obtained from the entire set of data, to assess the extent to which different classification models confused specific pairs of gaits. Using the entire data set for confusion matrices provided a more complete assessment of mis-classified gaits, especially for identifying the most confused gaits pairs.

3. Results

Table 1 summarizes global accuracy obtained for each classification model at both the group and individual levels. At the group level, global accuracy using k-NN, LDA, SVM, and ANN methods ranged from ~98–99%, ~31–62%, ~33–73%, and 89–99%, respectively. Models developed using LDA and SVM demonstrated relatively poor classification performance using the SSs vs. the SUS at the group level, while the other methods (i.e., k-NN and ANN) had comparable global accuracy using both the SS and SUS. In general, global accuracy at the individual level was higher than at the group level, and exceeded 95% in nearly all cases. Furthermore, accuracy using the STS at the individual level was typically compa-

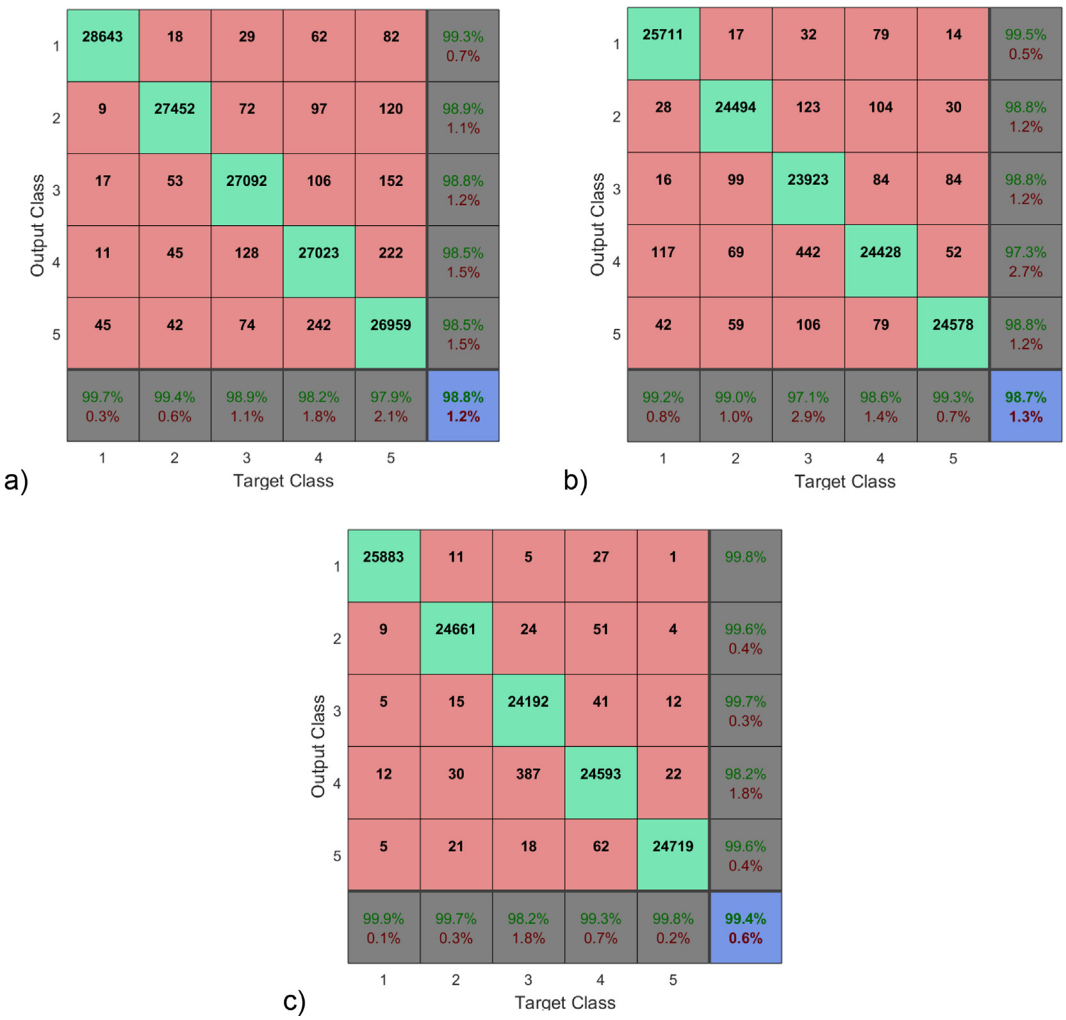

Fig. 3. Confusion matrices using the K-NN classification at the group level, using data from (a) smart socks, (b) smart shirt, and (c) the complete STS. Cells on the main diagonal (green color) and off-diagonals (red color) respectively indicate the number of correctly and incorrectly classified observations of each gait (see Fig. 1). Cells in the right-hand column provide percentages of precision (green font) and false discovery rate (red font) for each gait. Cells in the lowest row provide percentages of both sensitivity (green font) and false negative rate (red font) for each gait. The cell at the bottom-right corner (blue color) provides global accuracy. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

rable to accuracy using either the SS or SUS. In contrast, the STS gave superior accuracy at the group level.

Table 2 provides F-scores for all classification models at the group level. Similar to the results for global accuracy, the LDA and SVM methods led to models with relatively weaker classification performance. K-NN had the best performance, with F-scores for all gaits ranging from 0.97 to 0.99.

Confusion matrices are shown in Fig. 3 for models developed using the K-NN method at the group level. Note that these specific matrices are presented, since the respective models had the best performance based on global accuracy and F-score (confusion matrices for other methods at the group level are shown in supplementary material). As noted earlier, each of the gait activities (i.e., G1 to G5) was done repeatedly for at least 120 s. Therefore, the different gait activities had slightly different durations. At our re-sampled rate of 20 Hz, this means there were ~2200 samples per participant, and ~25,000 total samples for each activity (e.g., Fig. 3c shows 25,883 total samples for G1). The most confused pairs of gaits using the SSs were G4 (bilaterally asymmetric gait) and G5 (Hunchback gait). When using the SUS and STS, the most confused pairs were G3 (diplegic gait) and G4 (bilaterally asymmetric gait).

4. Discussion

Diverse classification models showed that both the SSs and the SUS, and the combination of these two system (STS), were able to differentiate among the five tested gait patterns with accuracy exceeding 98% (for SSs and SUS) and 99% (for STS); and with an F-score greater than 0.98 using the K-NN method (Tables 1 and 2). Furthermore, both the SSs and SUS displayed very similar accuracy, meaning that there was no evidence for superior accuracy of either of these systems. Bilaterally asymmetric and hunchback gaits were the most confused pairs when using the SSs (Fig. 3). We suspect that this occurred because both gaits present with similar foot contact patterns on the ground, and that textile pressure sensors within the SS did not have the sensitivity to differentiate between these two patterns. In contrast, the most confused pair using the SUS was diplegic and bilaterally asymmetric gaits, which likely resulted from both gaits sharing a similar symmetric upper body posture. To reduce the future likelihood of these misclassifications, there may be value in adding specific gait features to the classification model, such as step length and heel strike time extracted from SSs, or improving the SUS ability to monitor shoulder motions, such as by adding additional sensors in this region (Mokhlespour Esfahani and Nussbaum, 2018b).

Several objective methods have been developed and used to identify normal and abnormal gaits using both non-wearable and wearable devices. The accuracy obtained here using smart garments appeared equal to or better than the accuracy reported in these earlier studies. It must be noted, however, that non-wearable approaches, such as using MOCAP or treadmills, cannot be implemented easily in outdoor applications or during activities of daily living, and that smart textiles are more promising in terms of usability (Mokhlespour Esfahani and Nussbaum, 2018a). Furthermore, we did not conduct any type of feature selection, use of which could improve accuracy beyond the levels reported here. For example, Eskofier et al. (2013) showed that the accuracy of MOCAP could be improved from 58 to 95.8% by adding principal component analysis as a feature selection method to the classification approach (Eskofier et al., 2013).

While the current study does support the efficacy and accuracy of using smart garments in identifying simulated abnormal gaits, several limitations must be discussed. First, given the exploratory nature of this investigation, we only considered four specific types of abnormal gait, which limits the generalizability of our findings. Further, our study participants only mimicked four abnormal gaits. In an earlier investigation (Pogorelc et al., 2012), participants also mimicked four abnormal gaits (Parkinson's, hemiplegia, pain in the leg, and pain in the back), though the investigators utilized the help of a physician for training participants. More recently, Nguyen et al. (2016) also included simulations, of two abnormal gaits (knee pain and hunchback). Future work is needed to more specifically evaluate the quality of such simulated abnormal gaits, since the use of such simulations can result in more efficient and safe experimental procedures. Second, the sample here was relatively small and included only healthy, young individuals. It is thus unclear whether similar results will be obtained from actual patients with these gait abnormalities. Third, we conducted this investigation in a laboratory setting; therefore, a similar study should be replicated in a clinical setting with larger samples and while conducting activities of daily life.

In summary, this laboratory-based study explored the potential accuracy of smart garments for detecting five distinct types of gaits (one normal and four simulated abnormal). Our results showed that these gait types could be successfully identified at both the individual and group levels using smart garments, with an accuracy of at least 98%. Based on these preliminary results, we conclude that smart garments have the potential for accurate differentiation among normal and simulated abnormal gaits. Results from this work may have positive implications for identifying the early stages of gait abnormalities in a non-invasive way and beyond a clinic or laboratory. Moreover, smart garments offer the distinct advantage of being able to be worn over more prolonged periods than alternative measurement systems, may thus help provide a better understanding of gait patterns and the day-to-day hazards of gait abnormalities for those with either neurological diseases or musculoskeletal disorders. With such systems, physicians and physical therapists may be better able to devise effective treatment protocols and gauge the progress of their patients. Future work is needed, however, to determine the efficacy of using smart garments for obtaining abnormal gait assessments among actual patients in realistic conditions.

Declaration of Competing Interest

We declare that none of the authors has any financial or personal relationships with other persons or organizations that might have inappropriately influenced the work presented in this manuscript.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2019.06.009.

References

Alaqtash, M., Sarkodie-Gyan, T., Yu, H., Fuentes, O., Brower, R., Abdelgawad, A., 2011. Automatic classification of pathological gait patterns using ground reaction forces and machine learning algorithms. Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE.

Bae, J., Kong, K., Byl, N., Tomizuka, M., 2011. A mobile gait monitoring system for abnormal gait diagnosis and rehabilitation: a pilot study for Parkinson disease patients. J. Biomech. Eng. 133, 041005–041011.

Bauckhage, C., Tsotsos, J.K., Bunn, F.E., 2009. Automatic detection of abnormal gait. Image Vis. Comput. 27, 108–115.

Bersch, S.D., Azzi, D., Khusainov, R., Achumba, I.E., Ries, J., 2014. Sensor data acquisition and processing parameters for human activity classification. Sensors 14, 4239–4270.

Brandstater, M., De Bruin, H., Gowland, C., Clark, B., 1983. Hemiplegic gait: analysis of temporal variables. Arch. Phys. Med. Rehabil. 64, 583–587.

Chen, C., Hong, P., Chen, C., Chou, S.W., Wu, C., Cheng, P., Tang, F., Chen, H., 2007a. Ground reaction force patterns in stroke patients with various degrees of motor recovery determined by plantar dynamic analysis. Chang Gung Med. J. 30, 62–71.

Chen, M., Huang, B., Xu, Y., 2007b. Year Human abnormal gait modeling via hidden Markov model. International Conference on Information Acquisition.

Cherenack, K., van Pieterson, L., 2012. Smart textiles: challenges and opportunities. J. Appl. Phys. 112, 091301–091314.

Crea, S., Donati, M., De Rossi, S., Oddo, C., Vitiello, N., 2014. A wireless flexible sensorized insole for gait analysis. Sensors 14, 1073–1093.

de Bruin, E.D., Hartmann, A., Uebelhart, D., Murer, K., Zijlstra, W., 2008. Wearable systems for monitoring mobility-related activities in older people: a systematic review. Clin. Rehab. 22, 878–895.

Dobson, F., Morris, M.E., Baker, R., Graham, H.K., 2007. Gait classification in children with cerebral palsy: a systematic review. Gait Posture 25, 140–152.

Eskofier, B.M., Federolf, P., Kugler, P.F., Nigg, B.M., 2013. Marker-based classification of young–elderly gait pattern differences via direct PCA feature extraction and SVMs. Comput. Methods Biomech. Biomed. Eng. 16, 435–442.

Figueiredo, J., Santos, C.P., Moreno, J.C., 2018. Automatic recognition of gait patterns in human motor disorders using machine learning: a review. Med. Eng. Phys. 53, 1–12.

Joshi, D., Khajuria, A., Joshi, P., 2017. An automatic non-invasive method for Parkinson's disease classification. Comput. Methods Programs Biomed. 145, 135–145.

Lakany, H., 2008. Extracting a diagnostic gait signature. Pattern Recogn. 41, 1627–1637.

Macleod, C.A., Conway, B.A., Allan, D.B., Galen, S.S., 2014. Development and validation of a low-cost, portable and wireless gait assessment tool. Med. Eng. Phys. 36, 541–546.

Mattmann, C., Clemens, F., Troster, G., 2008. Sensor for measuring strain in textile. Sensors 8, 3719–3732.

Meng, C., Bufu, H., Yangsheng, X., 2008. Year Intelligent shoes for abnormal gait detection. IEEE International Conference on Robotics and Automation.

Mokhlespour Esfahani, M.I., Akbari, A., Zobeiri, O., Rashedi, E., Parnianpour, M., 2018. Sharif-human movement instrumentation system (SHARIF-HMIS): development and validation. Med. Eng. Phys. 61, 87–94.

Mokhlespour Esfahani, M.I., Narimani, R., Ramezanzadehkoldeh, M., 2013. A wearable respiratory plethysmography using flexible sensor. Int. J. Biomed. Eng. Technol. 11, 364–380.

Mokhlespour Esfahani, M.I., Nussbaum, M.A., 2018a. Preferred placement and usability of a smart textile system vs. inertial measurement units for activity monitoring. Sensors (Basel, Switzerland) 18, 2501–2515.

Mokhlespour Esfahani, M.I., Nussbaum, M.A., 2018b. A "smart" undershirt for tracking upper body motions: task classification and angle estimation. IEEE Sens. J. 18, 7650–7658.

Mokhlespour Esfahani, M.I., Nussbaum, M.A., Kong, Z.J., 2019. Using a smart textile system for classifying occupational manual material handling tasks: evidence from lab-based simulations. Ergonomics 62, 823–833.

Mokhlespour Esfahani, M.I., Taghinedjad, S., Mottaghitalab, V., Narimani, R., Parnianpour, M., 2016. Novel printed body worn sensor for measuring the human movement orientation. Sensor Rev. 36, 321–331.

Mokhlespour Esfahani, M.I., Zobeiri, O., Moshiri, B., Narimani, R., Mehravar, M., Rashedi, E., Parnianpour, M., 2017. Trunk motion system (TMS) using printed body worn sensor (BWS) via data fusion approach. Sensors 17, 112–127.

Moon, Y., Sung, J., An, R., Hernandez, M.E., Sosnoff, J.J., 2016. Gait variability in people with neurological disorders: a systematic review and meta-analysis. Hum. Mov. Sci. 47, 197–208.

Muro-De-La-Herran, A., Garcia-Zapirain, B., Mendez-Zorrilla, A., 2014. Gait analysis methods: an overview of wearable and non-wearable systems, highlighting clinical applications. Sensors 14, 3362–3394.

Nguyen, T.-N., Huynh, H.-H., Meunier, J., 2016. Skeleton-based abnormal gait detection. Sensors 16, 1792–1794.

Oks, A., Katashev, A., Zadinans, M., Rancans, M., Litvak, J., 2016. Development of smart sock system for gate analysis and foot pressure control. In: Kyriacou, E., Christofides, S., Pattichis, C.S. (Eds.), XIV Mediterranean Conference on Medical and Biological Engineering and Computing 2016: MEDICON 2016. Springer International Publishing, Paphos, Cyprus, pp. 466–469.

Pezzack, J., Norman, R., Winter, D., 1977. An assessment of derivative determining techniques used for motion analysis. J. Biomech. 10, 377–382.

Pogorelc, B., Bosnić, Z., Gams, M., 2012. Automatic recognition of gait-related health problems in the elderly using machine learning. Multimedia Tools Appl. 58, 333–354.

Preece, S.J., Goulermas, J.Y., Kenney, L.P., Howard, D., Meijer, K., Crompton, R., 2009. Activity identification using body-mounted sensors—a review of classification techniques. Physiol. Measure. 30, 1–33.

Preece, S.J., Kenney, L.P., Major, M.J., Dias, T., Lay, E., Fernandes, B.T., 2011. Automatic identification of gait events using an instrumented sock. J. Neuroeng. Rehabil. 8, 1–10.

Rathinam, C., Bateman, A., Peirson, J., Skinner, J., 2014. Observational gait assessment tools in paediatrics–a systematic review. Gait Posture 40, 279–285.

Razak, A.H.A., Zayegh, A., Begg, R.K., Wahab, Y., 2012. Foot plantar pressure measurement system: a review. Sensors 12, 9884–9912.

Rodda, J., Graham, H., 2001. Classification of gait patterns in spastic hemiplegia and spastic diplegia: a basis for a management algorithm. Eur. J. Neurol. 8, 98–108.

Salzman, B., 2010. Gait and balance disorders in older adults. Am. Fam. Phys. 82, 61–68.

Siuly, S., Li, Y., Zhang, Y., 2017. EEG signal analysis and classification: techniques and applications. Springer.

Stone, E.E., Skubic, M., 2013. Unobtrusive, continuous, in-home gait measurement using the microsoft kinect. Ieee T Bio-Med. Eng. 60, 2925–2932.

Taborri, J., Palermo, E., Rossi, S., Cappa, P., 2016. Gait partitioning methods: a systematic review. Sensors 16, 66–87.

Tirosh, O., Begg, R., Passmore, E., Knopp-Steinberg, N., Year Wearable textile sensor sock for gait analysis. In Sensing Technology (ICST), 2013 Seventh International Conference on.

Voigt, M., Sinkjær, T., 2000. Kinematic and kinetic analysis of the walking pattern in hemiplegic patients with foot-drop using a peroneal nerve stimulator. Clin. Biomech. 15, 340–351.

Zeng, W., Liu, F., Wang, Q., Wang, Y., Ma, L., Zhang, Y., 2016. Parkinson's disease classification using gait analysis via deterministic learning. Neurosci. Lett. 633, 268–278.