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Sensor optimization in smart insoles for post-stroke gait asymmetries using total variation and L_1 distances

Mario Muñoz-Organero, Member, IEEE, Jack Parker, Lauren Powell, Richard Davies and Sue Mawson

Abstract—By deploying pressure sensors on insoles, the forces exerted by the different parts of the foot when performing tasks standing up can be captured. The number and location of sensors to use is an important factor in order to enhance the accuracy of parameters used in assessment while minimizing the cost of the device by reducing the number of deployed sensors. Selecting the best locations and the required number of sensors depends on the application and the features that we want to assess. In this paper we present a computational process to select the optimal set of sensors to characterize gait asymmetries and plantar pressure patterns for stroke survivors based upon the total variation and L_1 distances. The proposed mechanism is ecologically validated in a real environment with 14 stroke survivors and 14 control users. The number of sensors is reduced to 4, minimizing the cost of the device both for commercial users and companies and enhancing the cost to benefit ratio for its uptake from a national healthcare system. The results show that the sensors that better represent the gait asymmetries for healthy controls are the sensors under the big toe and midfoot and the sensors in the forefoot and midfoot for stroke survivors. The results also show all four regions of the foot (toes, forefoot, midfoot and heel) play an important role for plantar pressure pattern reconstruction for stroke survivors while the heel and forefoot region are more prominent for healthy controls.

Index Terms— insole pressure sensors, stroke survivors, optimal sensor selection.

I. INTRODUCTION AND RELATED WORK

The use of insole pressure sensors for the analysis of gait is increasing [1][6][12][14][25][28]. Insole pressure sensors provide researchers and clinicians with a tool to improve efficiency, flexibility and reduce costs (by automating the measurement of gait related features with a limited number of sensors [1]). Different patterns and strategies for executing a range of functional tasks can be assessed by using insole pressure sensors [7]. Extracting and comparing features and time patterns from people with certain medical conditions with data from healthy controls could be the basis for their use in areas such as rehabilitation and pre-

habilitation [7][13]. Assessing gait and movement related features can also be applied to sport training [2]. Insole pressure sensors have been used in a wide range of different areas such as Tai-Chi Chuan learning [3], ulcer prevention [4], monitoring elderly people who have a high risk of falling and other mobility problems [5], assessing long-term chronic conditions that affect the elderly population such as Dementia, Parkinson's disease, Cancer, Cardiac Disease, Diabetes and Stroke [6]. Insole pressure sensors have also been used to assess the walking strategies used by stroke survivors who are following a rehabilitation program [7].

Stroke is of particular importance and relevance since the global incidence of stroke is set to rise from 17 million to 23 million by 2030, and it is one of the largest causes of adult disability [8][9]. Approximately two out of three stroke survivors experience impaired walking ability with subsequent falls risk and associated social isolation [10] [11]. Therefore, the relearning of walking is a major component of stroke rehabilitation with a self-managed rehabilitation paradigm being advocated by many [12]. Assessing walking strategies from data captured from insole pressure sensors, and using automatically computed distortion indexes, could be a valuable tool to help stroke survivors to improve their gait [7]. Furthermore, feedback from the insole can be used to provide motivation through self-managed rehabilitation during post discharge by the health provider [13][31-33].

Various types of insoles with different numbers of sensors have been used in previous studies to detect gait related features from stroke survivors. Lopez-Meyer et al [34] used an insole with 5 force-sensitive resistors (FSR) to compare the differences in the stance and swing faces between stroke survivors and healthy controls. Heel-strike (H) and Toe-off (T) instants were estimated using thresholds. The results obtained showed that the use of FSR sensors on insoles could accurately identify the temporal aspects of the gait cycle in both healthy people and individuals with stroke but no further gait related features were considered neither a sensor location optimization was performed. Qin et al [14] present a tailor-made 3D insole for plantar pressure measurement, comparing it with conventional flat insoles. Howell et al [15] investigate the use of a 32 sensor insole capable to replicate the shape of the ground reaction force and ankle moment in a stroke patient who has regained a more normal gait. The results present some limitations for stroke patients with impaired gait. Howell et al state that several subsets of sensors can be evaluated to ultimately identify an optimum set of sensors for determining

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particular kinetic variables (that are necessary to classify the presence or absence of a particular gait abnormality, or other pathology). However, no optimization is performed. Insole pressure sensors have also been used to measure and characterize pressure patterns over time for post-stroke patients [14]-[16]. In the majority of these previous research studies, the quantity and location of pressure sensors on the insoles is a parameter chosen when designing the experiment and is not normally optimized or evaluated.

Optimizing the quantity and location of the sensors used is a very important factor to help minimize the cost of the devices, and therefore accelerate their mass adoption. Selecting the optimal sensors is a well-studied problem in other areas such as multi-object tracking systems in wireless sensor networks [17][18], in which k sensors are selected in order to solve localization problems within a certain error (choosing k sensors so as to minimize the error in estimating the position of a target). Finding the optimal set of sensors to be used for a particular application tends to be an NP-hard problem, and different approximation techniques have previously been used to find nearly-optimal solutions in other domains. The reduction in the entropy of the target location distribution is used by Wang et al [19]. Shen et al [20] propose the use of information gain in order to select the sensor set. Research by Zois et al [21] uses a selection of sensors mechanism based on state transition probabilities and the number of samples required. The use of a Binary Particle Swarm Optimization (BPSO) algorithm to find the best sensors to estimate a parameter is proposed by Naeem et al [22]. Stochastic distances or divergences have previously been used by Liu et al [23], in which a sensor selection technique for multi-target tracking, where the sensor selection criterion is based on the Cauchy-Schwarz divergence between the predicted and updated densities.

Selecting the optimal set of sensors has also been applied to health applications as published by Santi et al [24]. Within the area of insole pressure sensors, the study by Kanitthika et al [1] uses the correlation coefficients between the positions of 99 sensors (each foot) and 11 subjects walking at a constant speed on a treadmill for around 1 minute to select the optimal sensors. Based on the highest correlation coefficients, 4 regions were selected in the insole. However, the study is limited in terms of its relevance to health and rehabilitation applications since only healthy controls were recruited. Yingxiao et al [25] propose the use of a selective sensing and sparsity-based signal reconstruction method to randomly select some sensors in a pressure insole (for longitudinal gait analysis), to increase the battery life while minimizing the reconstruction errors. From a dense smart insole equipped with 52*20 pressure sensors, a real-time analysis uses a Local Randomized Selective Sensing approach to select some sensors depending on the gait stage. The samples are selected randomly and sparsely. However, the validation of results is limited in terms of including people suffering any medical condition affecting gait. In fact, the proposed algorithm is based on the use of a gait model based on 4 consecutive stages (contact, midstance, propulsive and swing) which cannot be applied for the case of stroke survivors [7]. Sazonov et al. [35] performed a sensor optimization in an 8 sensor (5 pressure-sensors and 3 accelerometers) insole with the objective of

posture and activity detection. Six different postures and activities (sitting, standing, walking/jogging, ascending stairs, descending stairs, cycling) were classified from sensor data using a support vector machine (SVM) with a Gaussian kernel. An iterative process in which a sensor was removed at every step is presented. The proposed systems achieved a 95.2% accuracy when using the 8 sensors and 84.4% when using the optimal sensor (in the heel region). However, only healthy individuals were used in the optimization process and the objective was different from the one in this paper. In our research study presented in this paper, we propose the use of the total variation and the L_1 distances to characterize the influence of each pressure sensor to assess the gait asymmetries and the plantar pressure patterns during the stance phase for stroke survivors and healthy controls. The total variation distance is based on the normalized average activation patterns of each sensor on each foot. The greater the difference for each particular sensor the more significant the asymmetry is while walking. The L_1 distance is applied to the combined 2-D plantar pressure plot using the activation of all the sensors during the stance phase compared to the same activation plot when removing one sensor. A greater distance indicates that the sensor is more fundamental when reconstructing the values of the 2-D pressure plot. This technique is extended to select an optimal subset of 4 sensors in the insole by adding some constraints. Previous metrics to assess gait asymmetries for stroke survivors such as [39] [42] are based on equations that use overall spatiotemporal features in the gait cycle (such as step length, swing time and double support time), in many cases not using the detailed contribution of each part of the foot in the final value. In this research study, we complement previous metrics so that information in the most relevant parts of the foot during the stance phase can be considered.

The remainder of this paper is organized as follows. The methodology is presented in section II. The description of the sensors used is captured in section III. The proposed algorithm is detailed in section IV. Section V details the results of the study which was conducted using healthy controls ($n=14$) and stroke survivors ($n=14$). Finally, section VI presents the authors concluding remarks.

II. METHOD

Stroke survivors ($n=14$) and healthy controls ($n=14$) were recruited from the Sheffield area in the United Kingdom. Each participant performed a 10-meter walk test (repeated 6 times) while resting between repeats. Data was captured to record the pressure signals over time in both insoles. Stroke survivors were undergoing a program of rehabilitation and were able to walk without the assistance of a carer.

The study took place in the Centre for Assistive Technology and Connected Healthcare (CATCH) HomeLab, in the University of Sheffield. The CATCH HomeLab simulates the home environment, allowing participants to experience a setting that represents their daily lives at home. The HomeLab provided a unobtrusive, level, and consistent surface for participants to carry out their walking tests.

Table I and Table II provide a summary of participant

demographics showing their gender, age, insole size, weight, and affected side for stroke survivors.

TABLE I
DEMOGRAPHICS FOR HEALTHY PARTICIPANTS IN THE STUDY

ID	Gender	Age (years)	Insole Size	Weight (kg)
1	F	45	M	63.5
2	M	44	L	69.9
3	F	46	S	64.8
4	F	55	M	64.1
5	F	54	M	75
6	M	45	XL	80
7	F	52	S	64.2
8	F	50	M	72
9	M	46	M	70
10	F	51	S	54
11	M	44	XL	88
12	M	45	L	79
13	M	69	M	72
14	M	58	L	75

TABLE II
DEMOGRAPHICS FOR STROKE SURVIVOR PARTICIPANTS IN THE STUDY

ID	Gender	Age (years)	Affected Side	Insole Size	Weight (kg)
15	F	64	Right	L	105
16	M	61	Right	M	85
17	F	66	Right	M	75
18	M	50	Left	XL	90
19	F	79	Left	S	64.8
20	F	72	Right	M	73
21	M	64	Left	XL	90.8
22	F	75	Right	L	114.3
23	M	75	Left	L	80
24	F	68	Both	M	95.3
25	F	69	Left	M	66
26	M	84	Right	XL	95.3
27	M	39	Both	L	84.1
28	M	64	Right	XL	87.3

The participants wore insoles equipped with pressure sensors distributed as shown in Fig. 1 and a small ankle attachment. The insoles hardware and associated recording software were provided by a company in Portugal called Kinematix[36]. The insole comprises a network of 8 force sensitive resistors per foot/insole (Fig 2).

The first and last steps from each walking segment were omitted from the calculations to analyze steps executed in similar circumstances (the first step tends to have greater forefoot pressure due to the acceleration of the walking speed and the last step the opposite due to deceleration as shown in Fig 3).

All the data was captured using a laptop application provided by Kinematix which was able to generate a comma separated file containing the raw sensor data. The raw data was then further processed and analyzed using Matlab[38].



Fig. 1. Smart Insole Technology: Left - FSRs showing a typical layout, Right - Donning arrangements of ankle strap and accompanying footwear

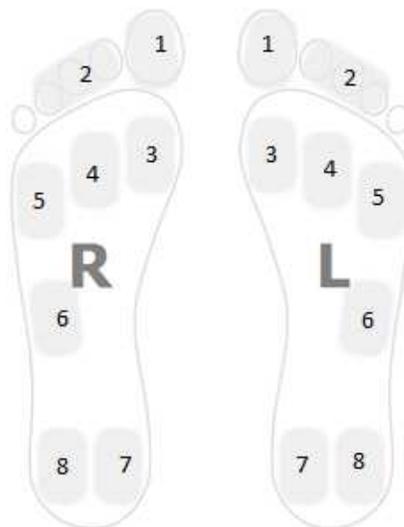


Fig. 2. Initial sensor distribution

The initial design of the location of the 8 insole sensors were distributed to facilitate coverage of the entire foot (two located in the heel region, one in the midfoot, three in the forefoot and two under the toes) as illustrated in Fig. 2. The cost of the insole is one of the major factors in determining its mass dissemination and use in applications such as self-rehabilitation [26]. The aim of this paper is to analyze the relative importance of each sensor in this initial design to assess gait asymmetries and pressure patterns with the goal to select a minimal set of sensors for use with stroke survivors. The influence of the contribution of each sensor as compared to the composed data from the 8 sensors is assessed to evaluate the expected degradation in the system performance when executing the sensor optimization.

III. SENSORS

This section provides further elaboration and about the hardware details of the device used to record plantar foot pressure as well as the sensors used in that device.

A. Sensor technology

The insoles used were provided by Kinematix [36] using sensors from IEE (a Luxembourg based company founded in 1989,[37]). IEE's Force Sensing Resistor (FSR) uses electrical resistance, which varies as a function of the pressure applied to the sensor cell. The sensor can measure punctual plantar

pressure up to 6 Bar. The cell response has a low hysteresis. The sensor cell can withstand more than one million activation cycles[37]. Each sensor weights 5 grams and covers a sensing area of 200 mm². In addition, it houses an accelerometer and magnetometer both of which are not used in this study. Force Sensitive Resistors (FSR) have been previously used in related studies in order to extract temporal parameters such as cadence, step time, stance time and others for gait monitoring using sampling frequencies from 25 to 200 Hz. [27]. IEE's Force Sensing Resistor (FSR) sensors provide an up-to-date tradeoff in terms of battery life, sampling frequency, and accuracy for gait monitoring and plantar pressure measurement [27]. FSR have been previously selected in order to build low-cost smart insoles [28].

B. Smart insole

The smart insole comprises an array of 8 Force Sensing Resistor sensors that provides a novel approach to gait monitoring and can be used in a free-living context which promotes its ecological validity. It is a wearable device that attaches to a users' ankle via a Velcro strap. The device integrates into standard footwear through a network of pressure sensors positioned on a standard insole and connects to the ankle by means of a ribbon cable and terminating connector. The smart insole is capable of capturing data from 8 recording sites on the sole of the foot using the piezo resistive sensors or Force Sensitive Resistors (FSR) as described in the previous sub-section and shown in Fig. 1. Samples are taken at a rate of 100 Hz and at a resolution of 8 bits and are transmitted using Bluetooth to a nearby computer such as a laptop or smart phone. The electronics is powered by a 16 bit mixed signal microcontroller from Texas Instruments (M420 family of processors). It supports a 12 bit 14 channel analogue to digital converter and offers ultra-low power consumption. The device runs from a rechargeable lithium-ion battery which provides 3.7v at a capacity of 890 mAh yielding 200 hours of standby and 40 hours in use.

IV. PROPOSED ALGORITHMS

This section provides details on the proposed algorithms to assess the most significant sensors in terms of discrimination of gait asymmetries and plantar pressure 2D plot reconstruction. An introductory subsection about data gathering and preprocessing follows:

A. Data Gathering and Pre-processing

The insoles are able to sample the 8 pressure sensors at 100Hz. The information was transmitted in real time to a laptop computer using Bluetooth. The laptop stored the received data into a csv file containing the data for each foot on alternate lines one after the other. The csv file was imported into Matlab [38] in order to prepare the data for the chain of processing steps. The pressure data was imported into two N*8 matrixes (one for each foot) in which each column contains the information for a particular sensor and each row represents a particular sample.

Let's assume that we have a total of N samples

(representing N/100 seconds of recorded data, since the data was sampled at 100Hz). The first pre-processing task for the imported data was to select and isolate the steady walking sections from the rest of the data. Our definition of steady walking refers to all the walking data but with the first and last step removed. The first and the last steps in each segment are atypical (accelerating or deaccelerating) as shown in Fig. 3 and therefore should not be compared with the other steps. Fig 3 shows the total pressure captured by the 8 sensors for the left foot of a healthy control during one of the walking segments. The length and the pressure patterns for the first and the last steps are visually different from the middle steps. The stance phase is calculated by marking the start when there is set of 10 samples with a total pressure value greater than a threshold and marking the end when there is a set of 10 samples below that activation threshold (we have used 0.2 kg/cm² as the working threshold). Computing the t-test for the duration of the stance phase for the participant in Fig 3 and isolating the first and last steps from the rest of the steps from the left foot a p-value of 0.00000004 is obtained.

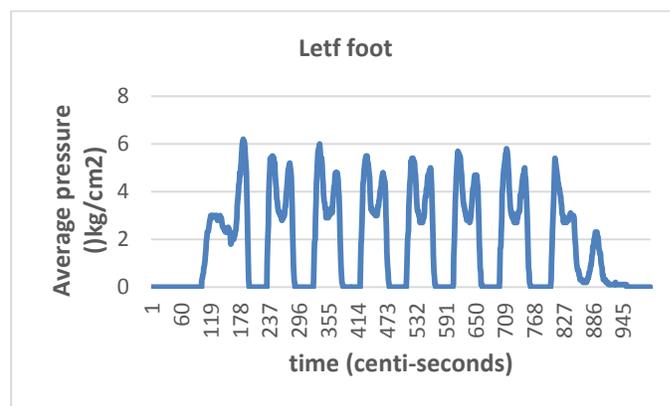


Fig 3. Total pressure captured by the 8 sensors during one way walking.

The second pre-processing task was to discard steps in which the information of one or more sensors was partially or entirely missing due to either a sensing or transmission error.

Finally, the length of each steady and complete step was normalized (resampled) to contain 100 samples. After a stroke, many gait related features are asymmetrical [40]. In order to define assessment metrics for gait asymmetries, some previous studies have normalized the gait cycle into a percentage value (from 0 to 100) [41] or use symmetry indexes or ratios in order to normalize the values [39]. Normalizing the gait asymmetry values facilitates the comparison among individuals using person-independent scales (allowing inter-individual, intersegmental, and inter-parameter comparisons [39]). In our case, the effect of walking at different speeds in each of the walking segments and by different participants has been accommodated by using a normalized stance phase of 100 samples... The resampling process is described by equations (1) to (4). $S_{ji}[1:100](n)$ represents the resampled value n in the range from 1 to 100 for sensor S_j ($j=1:8$) at step i ($i=1:M$ or $1:M'$) and $S_{ji}[1:T](t)$ represents the real value at instant t in the sample of T

elements (in centi-seconds). Two final $100 \times M$ and $100 \times M'$ matrixes containing all the normalized pre-filtered steps for each foot were generated. Each column represents one of the M and M' selected normalized steps.

$$S_{ji}[1:100](n) = C_1 \left(S_{ji}[1:T](t-1) \right) + C_2 \left(S_{ji}[1:T](t) \right) \quad (1)$$

$$\frac{t-1}{T} \leq \frac{n}{100} \leq \frac{t}{T} \quad (2)$$

$$C_1 = T \cdot \left(\frac{t}{T} - \frac{n}{100} \right) \text{ and } C_2 = 1 - C_1 \quad (3)$$

$$S_{ji}[1:100](1) = \left(S_{ji}[1:T](1) \right) \quad (4)$$

B. Assessing Gait Asymmetries

To compute the major gait asymmetries and to assess the relative importance of each sensor to provide an estimation for such gait asymmetries, the average pressure curves are calculated for each sensor on each insole. The signal for the average pressure for sensor S_j is a vector of 100 samples calculated using the following equation (5).

$$S_j[1:100] = \frac{1}{M} \sum_{i=1}^M (S_{ji}[1:100]) \quad (5)$$

In order to compute a stochastic distance for the signal of each sensor at each foot, the S_j is normalized so that the sum of its samples is equal to 1 as shown in equation (6).

$$S'_j(k) = \frac{S_j(k)}{\sum_{i=1}^{100} (S_j(i))} \quad (6)$$

The gait asymmetries can then be estimated by using a stochastic distance or divergence on the S'_j signals (where $j = 1$ to 8). The Kullback–Leibler divergence is widely used in information theory [29] or in variational inference [30]. The Cauchy-Schwarz divergence has previously been applied to solving the problem of sensor selection for multi-object tracking [23]. In this paper, we propose the use of the total variation distance which provides the same value for distances from the left foot to the right foot and vice versa (statistical divergences do not need to be symmetric). The total variation distance for the S'_{R_j} and S'_{L_j} signals can be calculated as captured by equation (7). The R sub-index represents the signal for sensor j in the right foot. The L sub-index represents the signal for sensor j in the left foot. The values for d_j are computed for each sensor.

$$d_j = \frac{1}{2} \sum_{i=1}^{100} |S'_{R_j}(i) - S'_{L_j}(i)| \quad (7)$$

C. Estimating Plantar Pressure Patterns

The center of pressure during the stance phase provides a plot for the evolution over time of the person's weight distribution while walking. Each pressure sensor is located in a particular point in the 2-D space of the insole. The coordinates for sensor j can be expressed as captured in equation (8).

$$L(S_j) = (x_j, y_j) \quad (8)$$

In order to compensate for the effect that different insole sizes may have on the location of each sensor in the insole, and to perform the calculation of distances, we re-scale the locations of each sensor so that the size of the insole is normalized to 1 in both axes as shown in equation (9).

$$L'(S_j) = \left(\frac{x_j}{\max(x)}, \frac{y_j}{\max(y)} \right) \quad (9)$$

The average plantar pressure pattern for each foot will then be calculated as shown in equation (10). $L'(S)$ represents the center of pressure for each sample during the normalized step of 100 samples of duration. M is the number of pre-filtered steps. S_{ji} is the pressure for each sample at sensor j for pre-filtered step i and $L'(S_j)$ the normalized location for sensor j (which does not depend on the sample or step).

$$L'(S)[1:100] = \frac{1}{M} \sum_{i=1}^M \left(\frac{\sum_{j=1}^8 (S_{ji}[1:100] * L'(S_j))}{\sum_{j=1}^8 (S_{ji}[1:100])} \right) \quad (10)$$

In order to assess the influence of each sensor for the plantar pressure pattern estimation, the $L'(S_p)$ is calculated by evaluating the expression in equation (10) leaving apart sensor p . By calculating a certain distance between $L'(S)$ and $L'(S_p)$ the relative importance of each sensor for computing the plantar pressure pattern can be assessed. In our case, and analyzing the stochastic distance used in equation (7) a distance based on the L_1 norm will be used as shown in equation (11). The greater the L_1 distance d_p the more important sensor p will be in reconstructing a pressure plantar plot with similar information as compared to the one calculated using the 8 sensors.

$$d_p = \frac{1}{100} \sum_{i=1}^{100} |L'(S)(i) - L'(S_p)(i)| \quad (11)$$

V. EXPERIMENTAL RESULTS

This section provides the experimental results for assessing gait asymmetries and estimating plantar pressure patterns for the stroke survivor group and the healthy control group. The optimal sensors for each group are presented and the results are compared.

A. Assessing Gait Asymmetries

Gait asymmetries can be assessed by comparing the

pressure captured by each sensor at each foot during the stance phase. In order to compensate different speeds while walking, the length of the stance phase for all the steps has been normalized to contain 100 samples. Normalizing the gait asymmetry values facilitates the comparison among individuals using person-independent scales (allowing inter-individual, intersegmental, and inter-parameter comparisons [39]). After averaging the data from pre-filtered steps (not including the first and the last steps for each walking segment) the pressure per sensor plot is presented in Fig. 4 and Fig. 5 for a healthy control and in Fig. 6 and Fig. 7 for a stroke survivor. By comparing the plots in Fig. 6 and Fig. 7 visually it is obvious that there is a significant difference between the symmetry of left and right foot strikes. At the beginning of the pressure plot in Fig. 6 the left foot of the stroke survivor shows less pressure in the heel region than that of the right foot in Fig. 7. In addition, the sensors activated in the midfoot do so sooner (stroke survivors showing asymmetries caused by hemiparesis may show a similar pattern to healthy controls on the non-affected site and an asymmetrical pattern on the affected site depending on different strategies [7]). The design of the insole in both feet locates the sensors in the same regions in order to assess asymmetries by comparing the same regions (identifying the regions of the insole that capture the most relevant information about gait asymmetries). A generic approach in which different locations could be selected in each insole is left for further study.

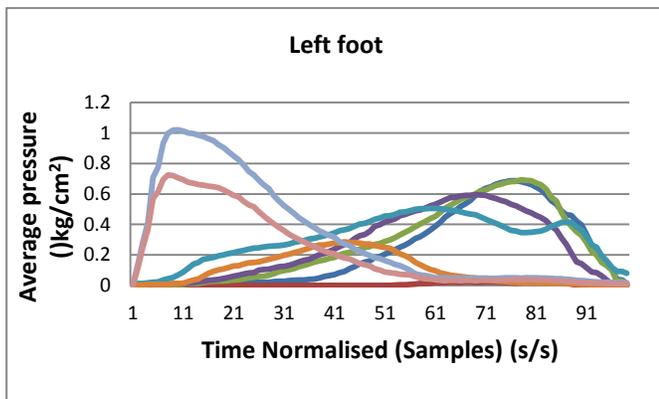


Fig 4. Pressure distribution per sensor during the normalized stance phase for a healthy control (left foot).

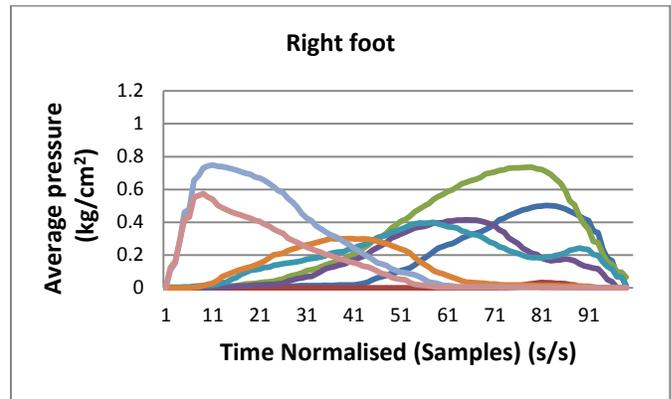


Fig 5. Pressure distribution per sensor during the normalized stance phase for a healthy control (right foot).

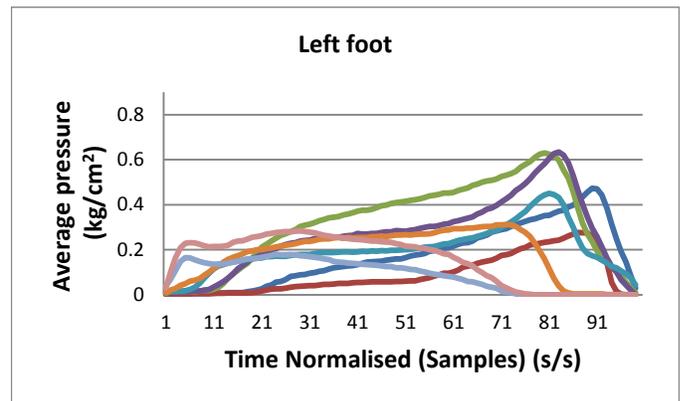


Fig 6. Pressure distribution per sensor during the normalized stance phase for a stroke survivor (left foot).

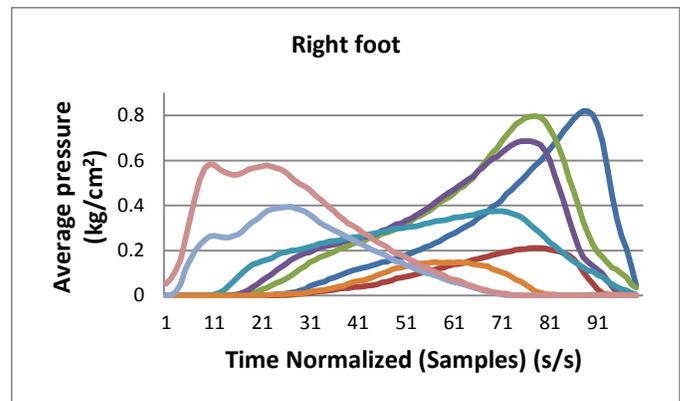


Fig 7. Pressure distribution per sensor during the normalized stance phase for a stroke survivor (right foot).

Normalizing the pressure plots so that the sum of the samples per sensor is equal to 1 and calculating the total variation distance as presented in equation (7) for each sensor and each participant we can try to estimate a quantitative value for gait asymmetries. We can also assess which sensors are better at representing these asymmetries. Fig. 8 shows the mean, maximum and minimum values for the total variation distance for all healthy controls. In this case, the quantitative values should be small for all the sensors since healthy controls do not visually present important gait asymmetries. In Fig. 8, however, there is one sensor, sensor 2, which can be considered atypical, and therefore should not be considered for assessing gait asymmetries. In fact, sensor 2 (as

shown in Fig. 2) is located under the central toes at the end of the shoe. We have observed that in many occasions, due to a moderate mismatch between the size of the shoe and the insole, sensor 2 did not accurately record the pressure under the toes but instead the pressure in the region between the toes and the forefoot. Leaving out sensor 2, the sensors that are best used to represent gait asymmetries are sensors 1 and 6.

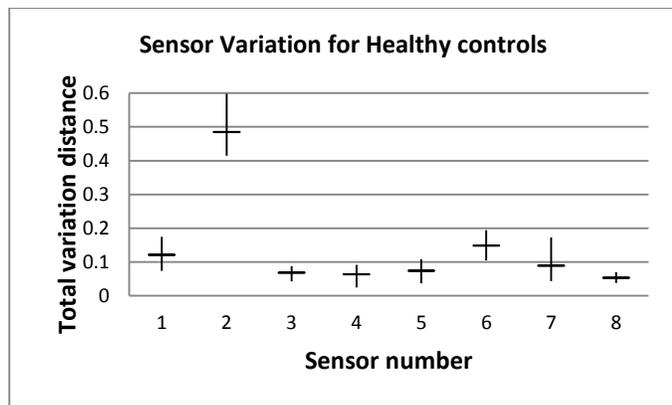


Fig 8. Total variation distance for healthy controls.

Fig. 9 represents a similar figure for stroke survivors. In comparison with the results for healthy controls the total variation distance is greater for all the sensors except for sensors 1 and 2 under the toes. In this case, sensor 6 continues to be the optimal sensor to assess differences in the gait. Sensor 3 in the forefoot region is the second-best sensor in terms of the total variation distance.

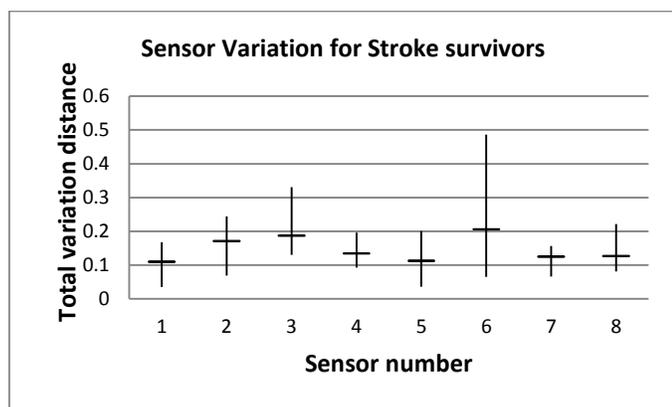


Fig 9. Total variation distance for stroke survivors.

B. Estimating Plantar Pressure Patterns

Plantar pressure patterns can be reconstructed by combining the information of all the sensors as shown in equation (10). In order to assess the importance of each sensor in order to reconstruct the plantar pressure patterns we have applied equation (11) when taking out one sensor at a time and computing the L_1 distance between the plots with all sensors and those with one sensor removed. The total distance has been calculated by adding the L_1 distance for each foot for the same sensors. Fig. 10 shows the results for the mean, maximum and minimum values for healthy controls. Fig. 11

shows the same calculations for stroke survivors group.

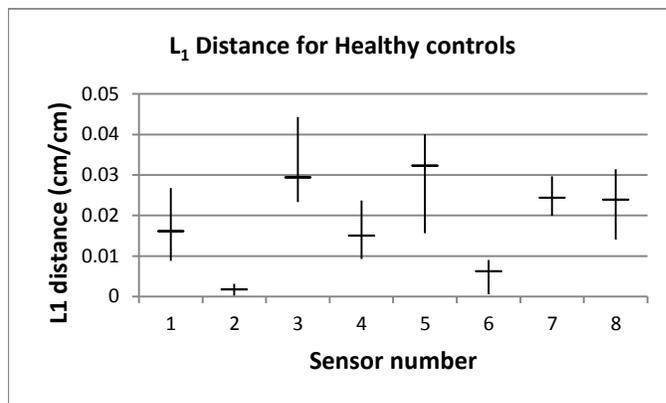


Fig 10. L_1 distance for healthy controls taking out one sensor.

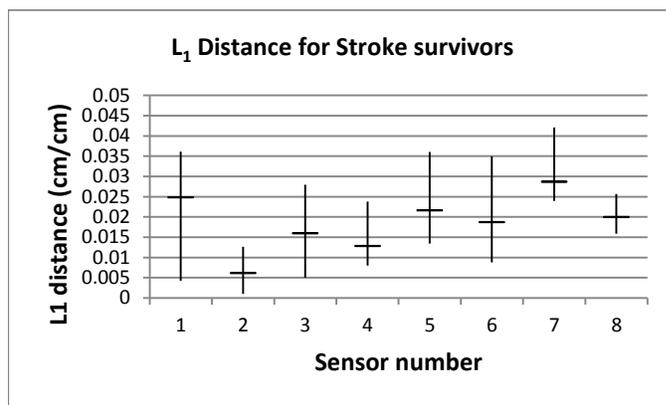


Fig 11. L_1 distance for stroke survivors taking out one sensor.

In the case of healthy controls, sensors 3 and 5 in the forefoot region represent those that, when removed, provide a plantar pressure plot which differs the most compared with the pressure plot including all the sensors. Sensors 7 and 8 in the heel region are also important but the effect of removing one sensor is not as significant since the pressure patterns recorded by both sensors are similar and the absence of one of them is partially compensated by the other. Sensor 2 tends to be of a very limited relevance in terms of reconstructing the plantar pressure patterns.

In the case of stroke survivors, the most important sensors to properly reconstruct the plantar pressure patterns are the sensors in the heel region, in particular sensor 7. In fact, one of the common effects suffered by stroke survivors when walking is the limited heel contact during the stance phase. Assessing this walking strategy is an important aspect in the rehabilitation process. Sensor 6 is of greater importance when compared to the case in the healthy controls group. However, the sensors in the forefoot region tend to be less important for reconstructing the plantar pressure patterns in the case of stroke survivors than in the case of healthy controls. Sensor 2 continues to be of limited significance and sensor 1 has a more significant role in the case of the stroke survivors group.

Finding the optimal sub-set of n sensors to be used in order to minimize the L_1 distance to the average plantar pressure pattern obtained from the complete sensor set will require trying all the possible combinations of n sensors. Several

studies have approximated the search space in order to find a near optimal solution based on the reduction in the entropy [19], the information gain [20], using state transition probabilities [21], using particle swarm optimization techniques [22] or using stochastic distances [23]. In our case, we will simplify the space for searching the optimal solution to include one and only one sensor in each region of the insole (heel, midfoot, forefoot and toes). This implies searching for the optimal set of 4 sensors with the additional constraint of having one and only one sensor in each region of the foot. Having pressure information for the 4 longitudinal parts of the insole is a requirement in order to assess the different walking strategies commonly used by stroke survivors [7]. Having one sensor in each region of the insole will allow us to reproduce the longitudinal transition from heel to toe and the set of 4 sensors will be selected so that the lateral transition is optimally captured with the minimal set of sensors. Instead of trying all possible combinations of one sensor in each region (which will require an evaluation of $2*3*1*2=12$ sensor sets) we could simplify the search space by optimizing a region at a time (simplifying the search space to 3 combinations since the optimization of the heel and toe regions was already done in Fig. 11 since there are only 2 sensors in these regions) and the results will be the same. The optimal solution is obtained for sensors 1, 4, 6 and 7. In fact, sensor 6 is required by the design since it is the only one in the midfoot region and sensors 1 and 7 are expected to be present in the optimal solution since they contribute the most when taken out in their region (each of only 2 sensors) as shown in Fig. 11. However, sensor 4 is the one which less contributes to the error in Fig. 11. However, due to the fact that sensor 4 is in the middle of the forefoot region, it is able to better represent the overall plantar pressure pattern when one only one of the 3 sensors in the forefoot region is used. The location of the selected 4 sensors minimizing the L_1 distance with the plantar pressure pattern provided by the entire set of sensors subject to the constrain of selecting one and only one sensor in each region is shown in Fig. 12. The results are congruent with the plantar pressure plots presented in [7].

The L_1 distance for each normalized sample for the optimal set of 4 sensors to the plantar pressure pattern calculated from the complete set of sensors is shown in Fig. 13. Except for the toe region, the reconstruction error is similar to the error we found when taking out a single sensor.

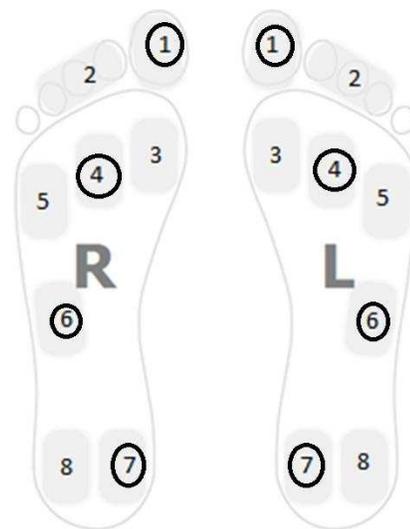
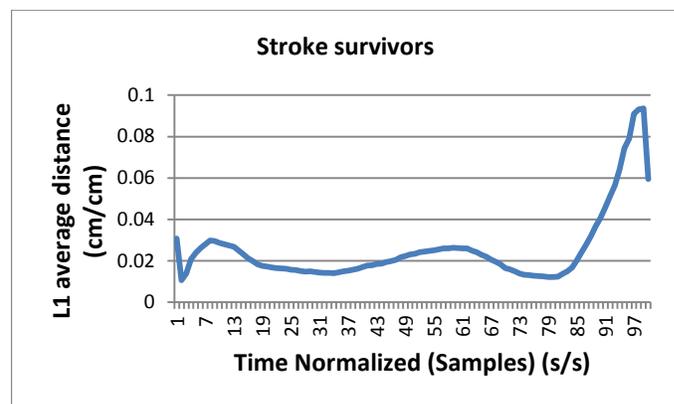


Fig 12. Optimal sensor distribution.



By reducing the set of sensors to sensors 1, 4, 6 and 7, the cost of the insole will be reduced by approximately a half of the original cost. This is an important saving for commercial users and companies in and enhances the cost to benefit ratio for uptake from a national healthcare system. Moreover, the information used to inform a self-rehabilitation tool for stroke survivors based on the reduced insole will remain similar and facilitate patient monitoring in the same manner as before.

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