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Munoz-Organero, M. orcid.org/0000-0003-4199-2002, Littlewood, C., Parker, J. orcid.org/0000-0003-2795-8983 et al. (3 more authors) (2017) Identification of walking strategies of people with osteoarthritis of the knee using insole pressure sensors. IEEE Sensors Journal, 17 (12). pp. 3909-3920. ISSN 1530-437X

https://doi.org/10.1109/JSEN.2017.2696303

Identification of walking strategies of people with osteoarthritis of the knee using insole pressure sensors

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Abstract—Insole pressure sensors capture the different forces exercised over the different parts of the sole when performing tasks standing up. Using data analysis and machine learning techniques, common patterns and strategies from different users to execute different tasks can be extracted. In this paper, we present the evaluation results of the impact that clinically diagnosed osteoarthritis of the knee at early stages has on insole pressure sensors while walking at normal speeds focusing on the effects caused at points where knee forces tend to peak for normal users. From the different parts of the foot affected at high knee force moments, the forefoot pressure distribution and the heel to forefoot weight reallocation strategies have shown to provide better correlations with the user's perceived pain in the knee for OA users with mild knee pain. The paper shows how the time differences and variabilities from 2 sensors located in the metatarsal zone while walking provide a simple mechanism to detect different strategies used by users suffering OA of the knee from control users with no knee pain. The weight dynamic reallocation at the midfoot, when moving forward from heel to forefoot, has also shown to positively correlate with the perceived knee pain. The major asymmetries between pressure patterns in both feet whilst walking at normal speeds are also captured. Based on the described features, automatic evaluation self-management rehabilitation tools could be implemented to continuously monitor and provide personalized feedback for OA patients with mild knee pain to facilitate user adherence to individualized OA rehabilitation.

Index Terms— insole pressure sensors, mild knee pain, osteoarthritis, machine learning, and classification.

I. INTRODUCTION

Motivating physical activity (PA) is a key element for self-managed rehabilitation of osteoarthritis (OA) [1]. The use of wearable technology has been utilized for the automatic monitoring of the amount of PA undertaken as a mechanism to provide extrinsic feedback to OA patients within a self-management paradigm [2]. A key factor for wearable technology to be accepted by users is the easiness and non-intrusiveness of the technology [3]. 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 [4]. Although several self-rehabilitation systems have already been implemented [2][3] the integration of a feedback mechanism based on automatic assessment measures of the rehabilitation progress could increase the users' long-term adherence [4]. A review about previous research on real-time augmented feedback for adults with knee OA can be found in [34] and [35]. This paper proposes, justifies and validates 3 features that can be automatically computed from insole pressure sensors to effectively assess the user's pain induced gait patterns for clinically diagnosed OA patients. The insoles could then be integrated into a self-management rehabilitation tool currently being developed by the research team.

Although many studies have already provided partial correlations between pain in the knee and plantar forces in the different parts of the foot (as described in the related work section), a more holistic approach for OA patients only suffering mild knee pain has been conducted in this study. Patients in the early stages of OA are more likely to benefit from PA based self-rehabilitation interventions potentially preventing further joint damage. However, computing progress assessment features based on wearable technologies becomes more difficult since mild pain implies in many cases only subtle differences in sensed data. The results therefore complement previous studies and summarize the key aspects to take into account in order to build a self-management tool, which monitors and provides motivational feedback to the users. Our approach is based on insole pressure sensors, a wearable technology able to measure gait related patterns and capture differences between healthy controls and OA patients.

The applications of gait analysis using shoe insole pressure sensors are increasing [5]. Using insole pressure sensors, different patterns and strategies for executing different tasks can be assessed and a comparison between control users and non-standard users could be the basis for applications in areas such as rehabilitation or sport training [6].

Insole pressure sensors have already been used in different

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areas for example the authors in [7] used them for learning Tai-Chi Chuan. An application for ulcer prevention is presented in [8] in which a low cost and flexible plantar pressure monitoring system is presented for everyday use to prevent pressure ulcers. Pressure sensors are used in [9] for monitoring elderly people who have high risk of fall and other mobility problems.

Among the different applications, we propose a novel methodology to assess the gait characteristic of users with knee pain in order to explore whether this data could be used as a clinical decision-making tool and potentially a self-managed rehabilitation tool. The authors in [5] examined the optimal position of pressure sensors inside the insole in order to capture gait parameters. The authors found 4 regions which will optimally capture the pressure information while walking at 3 km/h which are: the heel region, the metatarsal region, the toe line, and the outline of the barefoot. In our case, in order to detect mild pain in the knee, the sensors showing a greatest correlation are those in the metatarsal area. This area corresponds to the second knee force peak while walking at normal speeds [10] [11] and we show in this paper that it provides relevant correlations with walking strategies distinguishing people with and without knee pain. From these sensors, the times in which the maximum pressure is exercised and the variability of these times over different consecutive steps while walking are able to capture promising correlations with mild pain in the knee. The distribution of the user's body weight over the different areas of the insole during the first peak region of experienced knee force while walking at normal speeds [10] [11] has also been captured in this paper by assessing the temporal dependencies of the peak pressure moments in the heel, midfoot and forefoot. Finally, we also capture walking asymmetries by assessing the differences in pressure compensation between feet strategies in which the leg less affected by knee pain relieves the pressure in the other leg by using a double feet ground contact at critical high knee pressure moments.

The paper is organized as follows. Section 2 describes some previous related work which is relevant for our study. Section 3 describes the methods and design used to perform the experiment. Section 4 captures the selection of features. The results of the evaluation based on the features described in section 4 are presented in section 5. Section 6 is dedicated to discussion. Section 7 concludes by capturing some major results.

II. Related Work

Insole pressure sensors have been widely used in previous studies for automatic extraction of gait and other activity related parameters [5]. Automation requires the use of direct methods to express the center of pressure (CoP) measured by an insole pressure sensor system (IPSS) into a known coordinate systems [12], optimal sensor location [5] and optimal feature extraction.

Authors in [13] review foot plantar sensors characteristics as reported in previous literature. The authors conclude that in-shoe systems such as insoles with pressure sensors are suitable for gait monitoring. The benefits of using insole pressure sensors for gait monitoring compared with treadmills is captured in [14]. The authors present an instrumented rubber insole for plantar pressure sensing with linear response. The data collected from pressure sensors has shown gait correlated statistical features which can be applied in different applications. Authors in [15] collected a certain amount of normal human foot pressure data and performed a statistical analysis of pressure distribution relations about five stages of swing phase during walking, using the grid closeness degree to identify plantar pressure distribution pattern recognition. Both the algorithm simulation and the experimental results demonstrated this method feasibility. The authors in [16] introduced the design and development of a novel pressure-sensitive foot insole for real-time monitoring of plantar pressure distribution during walking. A prediction model for three-dimensional ground reaction forces (GRFs) and ground reaction moments (GRMs) was proposed in [17], which only used plantar pressure information measured from insole pressure sensors with a wavelet neural network (WNN) and principal component analysis-mutual information (PCA-MI). The results indicated that the proposed model improved performance compared to previous prediction models.

Insole pressure sensors have been used in combination with other sensors for different applications. The authors in [18] combine inertial sensors with insole pressure sensors for gait analysis. Authors in [12] combine a visual system with insole pressure sensors. Piezoresistive pressure sensors are used in combination with a three-axis accelerometer in [19] for gait analysis.

Gait analysis based on plantar pressure sensors have been used in the medical domain for various applications. The work in [20] presents a review of the application of insole plantar pressure sensor systems in recognition and analysis of the hemiplegic gait in stroke patients. The authors in [21] capture insole pressure sensors as a valid technology for assessing gait in rheumatoid arthritis patients. One particular application of insole pressure sensors in the medical and rehabilitation domains is the detection of compensatory walking strategies employed by those with knee pain under different conditions causing the pain. The authors in [22] presented a proof of concept study using augmented auditory feedback from a pressure detecting insole to reduce the knee adduction moment. The work in [23] presents a study focused on the biomechanical implications of knee osteoarthritis (OA) and the association with pain. The authors show that the plantar loading force distribution of the foot was determined and correlated to degenerative knee changes, function, pain intensity, and pain sensitization. The study constitutes a relevant reference for the research we have conducted in this paper in which we have extended the analysis to other pressure related features apart from maximum forces as presented in [23]. The authors in [24] presented a systematic review aimed to identify pertinent methodologies and characteristics measured using plantar pressure devices, and to summarise their associations with running-related injury (RRI). The results in [25] determined whether experimental anterior knee pain independently alters static and dynamic postural control. The study is related to our research in this paper in the use of pressure patterns over time to assess knee pain. However, the scope in [25] was based on the effects of experimental anterior knee pain caused by one 0.75-mL hypertonic saline injection and the authors did not find any effect in static or dynamic postural control. Our research focusses on clinically diagnosed OA patients at an early stage of the disease with several features extracted from insole pressure sensors correlating with the subjects perceived knee pain. Previous studies have found relevant correlations between OA patients and the centre of pressure (COP) as captured from insole pressure sensors which are relevant as a starting point for our study. One major reference is the work in [26] which studied the partial foot pressures as percentages of body weight (%PFP), the anteroposterior length of the center of pressure (COP) path as a percentage of foot length (%Long), the transverse width of the COP path as a percentage of foot width (%Trans) and the knee flexion/extension range of motion (in the OA group) showing correlations between the impact of limited flexion/extension ranges and the COP trajectories. Our study extends previous studies by analyzing the optimal sensors to be used to maximize discriminability between the control and experiment groups, by further finding correlations in time pressure patterns as a comparison of time series from relevant sensors and by assessing gait asymmetries and inter-feet strategies.

In this study, we used the data captured from insole pressure sensors while walking at normal speeds by 2 groups of people (users without experiencing knee pain, the control group, and users with clinically diagnosed osteoarthritis of the knee at early stages, the experiment group) to establish which sensors and which particular features computed from these sensors show better correlations with each group of users. Different classification and clustering techniques are used to show how the proposed features behave for automatic learning applications. The final aim of our study is to be able to automatically monitor OA patients at early stages when performing physical activity (PA) in order to assess their progress in terms of estimated pain suffered when doing the exercises and to be able to automatically provide personalized feedback that will maximize the user adherence to the self-managed rehabilitation [4]. We have focused our study on the analysis of the impact that knee pain has on plantar pressure distributions during the two major periods of time in which the knee force is higher during the stance phase [10] [11]. The different strategies for body weight distribution between feet using double foot stance is also studied and the results presented.

III. METHODS AND EXPERIMENT DESIGN

A. Participants

A total of 28 participants were recruited for conducting the experiment: half of them (14 participants) with knee pain and half of them as controls. All participants were recruited from the Sheffield area in the United Kingdom. To be included in the study, participants were required to be 44 years of age or more. Knee pain participants were recruited from a list of contacts of clinically diagnosed OA patients. Osteoarthritis was diagnosed according to the current NICE guidance [29] which recommends to diagnose osteoarthritis clinically without investigations if a person is 45 or over and has activity-related joint pain and has either no morning joint-related stiffness or morning stiffness that lasts no longer than 30 minutes. Several previous research studies have used a radiographic grading to classify the severity of knee osteoarthritis [30][31]. In our case, we have only recruited participants with no severe pain. As a future work, using a radiographic grading of the severity of the knee OA will help us to select only the recruited participants belonging to the same class as classified by the radiographic grading system (grade 1 participants in a Kellgren and Lawrence system for example). Participants were asked to rate their subjective perceived pain from 1 to 10 (1 representing no pain at all and 10, the worst pain imaginable). As an alternative, pain could be assessed using standard tools like [32] and [33]. We only included participants who had no severe knee pain (declaring a subjective perceived pain of 5 or less in the previous scale) as we were interested in observing the differences in pressure distribution in both feet during the early stages of OA where self-management rehabilitation interventions are more effective. Table 1 captures the summary of the data for the participants in both groups.

TABLE I
DEMOGRAPHICS FOR THE PARTICIPANTS IN THE STUDY.

	Age	Gender	Pain score	Weight	Height
OA group	44-78	6M-8F	2-5	62-92kg	163-188cm
Control	44-69	7M-7F	No pain	60-88kg	165-184cm

Different sizes for the insoles (small, medium, large and extra-large) 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). Insoles where selected so that the anatomical portion of the heel and metatarsus exactly matched the sensors for correct data gathering and comparison.

B. Ethics approval

Ethics approval was provided by the Ethics Committee at the University of Sheffield (number 003487/ date 20/05/2015), under the project title: "Developing an intelligent shoe for use in rehabilitation of knee pain (osteoarthritis of the knee)". The intelligent insoles are thin and would not affect participants' gait. However, during their walks they were supervised throughout. All participants were aware that there were a minimum number of other people in the room present when they were asked to walk.

C. Scenario and sensors

The data was collected in a laboratory environment, participants were asked to stand up walk 10 meters then sit down. This was repeated, 6 times. The participants wore insoles equipped with pressure sensors as shown in Figure 1. The insoles and the recording software were provided by a company in Portugal called Kinematix (http://kinematix.pt/).

The smart insole comprises an array of 8 Force Sensing Resistor (FSR) 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). 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. A related study showed that pressure sensor insoles are a valid and reliable mechanism for measuring temporal gait parameters during walking [36].

Figure 1. Sensor distribution

The first and the last steps from each walking segment were not considered for the calculations to analyze steps executed in similar circumstances (the first step tends to have bigger forefoot pressure due to the acceleration of the walking speed and the last step shows the opposite pattern). Moreover, we have implemented a further pre-filtering of steps not taking into account those in which the information of one or more sensors is not present.

All the data was captured using a Kinematix laptop application able to generate a csv file containing the raw sensed data. The data has been processed using Octave (https://www.gnu.org/software/octave/), Weka (http://www.cs.waikato.ac.nz/ml/weka/) and Excel (https://products.office.com/en-us/excel).

IV. Feature selection

The 8 pressure sensors in each insole capture the progression over time of the distribution of the user's weight over the different parts of each foot during the stance phase. Previous studies such as [23] have shown that there are correlations between the perceived knee pain and abnormal plantar loadings (where medial forefoot and lateral hindfoot applied plantar forces have shown positive and negative correlations with knee pain). The study presented in this paper focuses on further analyzing the time patterns of the pressure distributions on selected parts of the foot and is aimed at complementing the results found in previous studies for mild knee pain in clinically diagnose OA patients in order to pave the way for building self-managed rehabilitation tools based on automatic computed feedback.

The insole used contains 8 sensors distributed to capture the pressure on the different parts of the sole (Figure 1). In order to assess which of these sensors better differentiate the behavior between the control and the experiment group, the Mahalanobis distance [37] between each OA patient and the control group for each sensor has been computed both in terms of the duration and amplitude of the pressure patterns. The results are presented in Figure 2. In terms of durations, sensor 4 achieves the highest distance. The inter-sensor differences are maximized when subtracting times for sensors 3 and 4. This result is aligned with the results in [23] in which the medial forefoot was found to better correlate with knee pain (corresponding to sensors 3 and 4 in Figure 1). In terms of pressure amplitudes, sensors 3 and 4 also show the biggest distance between groups.

A second way to select the sensors in order to extract the particular features that automatically differentiate between the control and the experiment group is based on the experienced knee forces during the stance phase. The fragments in which experienced knee forces are higher are expected to have a bigger impact in the characterization of the different strategies used to distribute the user's weight distribution (which will try to minimize the perceived pain). According to [10] and [11], the stance phase contains two main peaks for knee forces. The first peak of knee forces takes place in the transition from the heel to the forefoot pressure pattern. The second peak is located around the maximum values of the pressure located in the forefoot region. The transition between the 2 segments of high knee forces has been assessed by the analysis of the time series of average pressure in the rear-foot (sensors 7 and 8), midfoot (sensor 6) and forefoot (sensors 3, 4 and 5). The forefoot region is considered by analyzing the time patterns found in sensors 3 and 4. The asymmetries between feet have also been added to the study by considering the regions of double feet contact. Mild knee pain cases have been included to study the subtle differences for both control and experimental groups in early stages of knee degradation so that technology enhanced tools can be developed to help mild knee pain users at early stages.

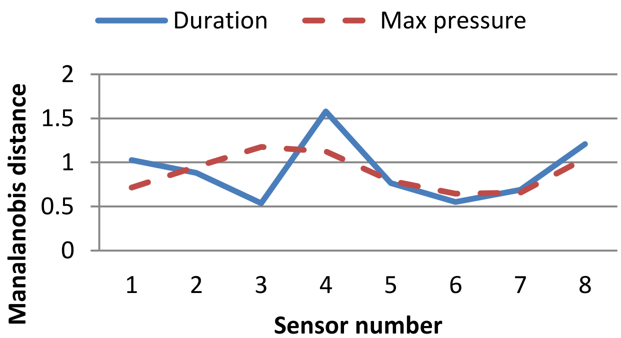


Figure 2. Mahalanobis distance for the duration and maximum pressure

The selected variables for the analysis are explained in the following subsections.

A. Forefoot strategies

The insoles have 3 sensors (3, 4 and 5) located under the forefoot region (in the medial, central and lateral parts of the forefoot). These 3 sensors are able to capture the weight distribution strategies in that part of the foot. We have used several features to characterize these forefoot strategies including the time differences between each pair of the sensors for ground contact, the time differences at the end of the ground contact, the peak values and the time differences at the peak values. The Mahalanobis distance as well as the p-values for the t-test for each variable considering the control and experiment groups have been used to select the best variables in order to better discriminate from the strategies used by each of the groups of participants. The selected variables are:

- V1: Average time differences between maximum values for sensors 3 and 4 taking into account all the recorded steps in the performed test.

$$V_1 = \frac{1}{N}\sum_{i=1}^{N}(\mathrm{tmax}_{3i} - \mathrm{tmax}_{4i}) \tag{1}$$

- V2: Standard deviation of the time differences between maximum values for sensors 3 and 4 (again considering all the recorded steps).

$$V_2 = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left((\mathrm{tmax}_{3i} - \mathrm{tmax}_{4i}) - V_1\right)^2} \tag{2}$$

B. Heel to forefoot strategies

In order to assess the different strategies to migrate the user's body weight from the heel region to the forefoot we have used averaged pressure values from the sensors located in the heel, in the midfoot and in the forefoot regions. In particular the following equations have been used:

- Average heel pressure (average of sensors 7 and 8)

$$\overline{p_{\mathrm{heel}}} = \frac{1}{2}\sum_{i=7}^{8} p_i \tag{3}$$

- Average midfoot pressure (sensor 6)

$$\overline{p_{\mathrm{midfoot}}} = p_6 \tag{4}$$

- Average forefoot pressure (average value for sensors 3, 4 and 5).

$$\overline{p_{\mathrm{forefoot}}} = \frac{1}{3}\sum_{i=3}^{5} p_i \tag{5}$$

C. Inter-feet strategies

In order to assess gait asymmetries caused by pain in the knee we monitored the double feet contact as a measure of one foot helping the other to relieve some of the pain by absorbing more than 50% of the body weight. In particular the following variables have been defined:

- V1: Average time differences between maximum values of pressure in the forefoot region of the foot corresponding to the non-affected leg to the heel region of the affected foot for the N steps.

$$V_1 = \frac{1}{N}\sum_{i=1}^{N}(\mathrm{tmax}_{\mathrm{NAforefoot}i} - \mathrm{tmax}_{\mathrm{Aheel}i}) \tag{6}$$

- V2: Average time differences between maximum values of pressure in the forefoot region of the foot corresponding to the affected leg to the heel region of the non-affected foot for the N steps

$$V_2 = \frac{1}{N}\sum_{i=1}^{N}(\mathrm{tmax}_{\mathrm{Aforefoot}i} - \mathrm{tmax}_{\mathrm{NAheel}i}) \tag{7}$$

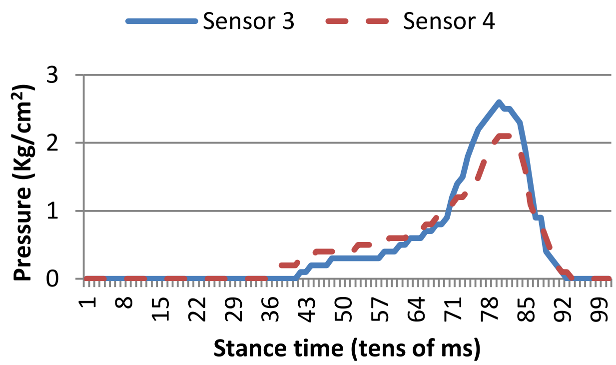
V. RESULTS

A. Forefoot strategies

In order to study the different weight distribution strategies in the forefoot region for mild knee pain in clinically assessed OA patients and healthy control users sensors 3 and 4 have been selected. These two sensors maximize the difference in terms of the Mahalanobis distance with the control group as presented in the previous section. Sensor 4 (as shown in Figure 1) covers the pressure on the center of the forefoot while sensor 3 is located in the medial part of the forefoot

Figure 1. Figure 3 shows, as an example, the pressure distribution over time during the stance phase of both sensors 3 and 4 for both an OA patient and a healthy control in order to visually assess some differences (the computations for all the steps by all the participants are presented next). In both cases, the sensor in the center of the forefoot (sensor 4) gets active before the sensor in the inner part of the forefoot

(sensor 3). However, there is a visual difference in the time patterns if we focus on the maximum value instants of time. For a healthy controls, sensor 4 peaks before sensor 3. However, for OA patients with mild knee pain a slightly inverted pattern in which the peak for sensor 3 takes place a bit in advance can be intuited.



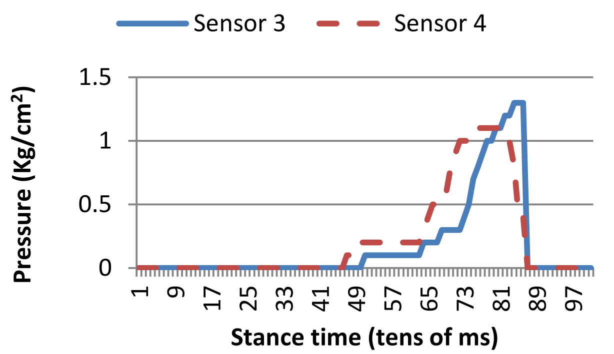


Figure 3. Pressure distribution during the stance phase for sensors in the forefoot for a user with knee pain (above) and pressure distribution during the stance phase for sensors in the forefoot for a user with no knee pain (healthy control) (bellow).

In order to validate the degree of discrimination that the selected features V1 (mean value for the time from the maximum value for sensors 4 to 3 for all the steps by each participant) and V2 (standard deviation of the same values for all the steps by each participant) have in order to detect mild degrees of knee pain in OA patients, a visual representation is captured in Figure 4. The OA group shows smaller mean times and bigger variances while the control group shows bigger mean times and smaller variances. The increase in the value for the variance is natural since the pain in the knee may vary among the different steps and the variability among them therefore increase.

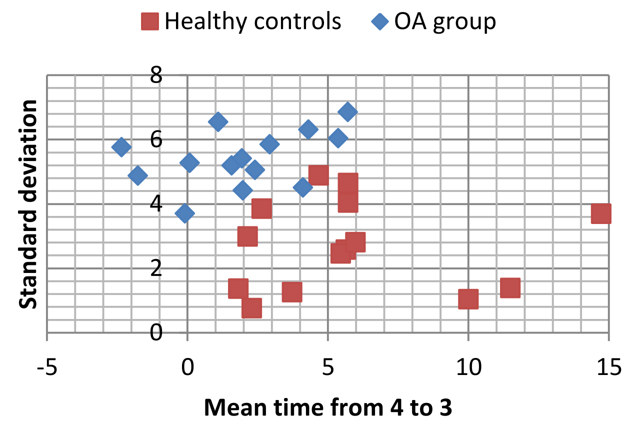


Figure 4. Data for the selected features for all the participants

The results in Figure 4 aggregate the data for all participants (all ages). Disaggregating the results to include age variation is important for OA participants since particular characteristics such as the knee alignment and the tibio-femoral alignment may differ along with age. Table 2 captures the results aggregated per age group (in 5 year intervals). The value of the mean time from sensor 4 to sensor 3 gets smaller as the age grows and the standard deviation increases.

TABLE 2. RESULTS PER AGE GROUP FOR OA PARTICIPANTS.

	<50	50-55	55-60	>60
Mean 4 to 3 time	1.08	-0.65	-0.60	-1.73
STD 4 to 3 time	3.99	5.08	6.64	6.69

The results of applying different machine learning classification techniques to the data in Figure 4 are captured in Table 3 and Table 4. Using Support Vector Machines (SVM), 13 out of 14 cases are classified correctly for users with no knee pain and 12 out of 14 for knee pain users. The results for Logistic regression and multi-layer perceptron (MLP) are able to improve the classification accuracy for knee pain users to 13 out of 14.

TABLE 3. SVM CLASSIFICATION RESULTS.

classified as →	No knee pain	Knee pain
No knee pain	13	1
Knee pain	2	12

TABLE 4. LOGISTIC REGRESSION AND MLP CLASSIFICATION RESULTS.

classified as →	No knee pain	Knee pain
No knee pain	13	1
Knee pain	1	13

Figure 5 captures a cluster analysis using the Expectation Maximization (EM) clustering algorithm [27] for 2 clusters. The x-axis captures the average time differences for the maximum values in sensors 3 and 4 (V1) while the y-axis captures their standard deviations (V2). Healthy controls tend to show bigger values for V1 and smaller values for V1 while the users with knee pain show the opposite scenario. All OA patients are assigned to the right cluster while 10 out of 14 healthy control are assigned to the right cluster. Table 5 captures the results for the mean and standard deviation of the 2 clusters. Using the t-test for populations with different variances to compute the p-values in order to assess if the null hypothesis consisting on having similar populations in both clusters could be rejected we get:

- p-value for the time 4 to 3 means → 0.00456806
- p-value for the time 4 to 3 standard deviations → 0.00012739

In both cases the null hypothesis could be rejected under a 0.05 threshold.

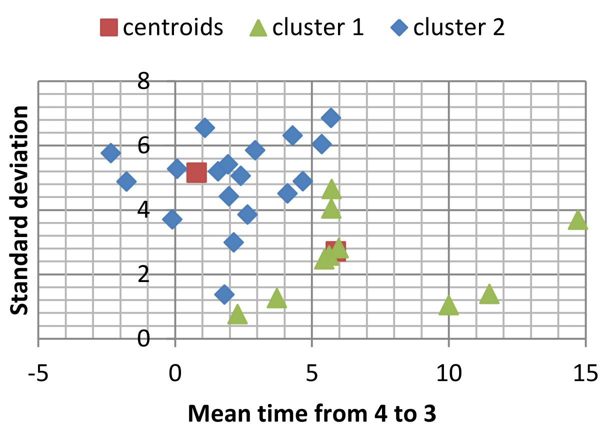


Figure 5. EM clustering

TABLE 5. EM CLUSTERS RESULTS.

	Cluster 0	Cluster 1
time 4 to 3 mean values mean	0.7948	5.8812
time 4 to 3 mean values stddev	4.2928	4.1211
time 4 to 3 stddev values mean	5.158	2.7076
time 4 to 3 stddev values stddev	1.0932	1.5036

B. Heel to forefoot strategies

The distribution of pressure patterns from heel to forefoot are captured in this section. Three variables are considered as described in section 4:

- Average heel pressure (average of sensors 7 and 8)
- Average midfoot pressure (sensor 6)
- Average forefoot pressure (average value for sensors 3, 4 and 5).

Figure 6 and Figure 7 capture the pressure distribution for the heel/midfoot/forefoot averages during the stance phase for both feet in a particular step for a healthy participant as an example to visualize the major characteristics while Figure 8 captures the same variables for the affected foot for an OA participant with mild knee pain (the complete dataset analysis is presented next). A visual inspection shows that the maximum value instant of time for the midfoot pressure shifts towards the maximum value instant for the maximum forefoot pressure.

According to the previous visual analysis we have defined two variables:

- V1: Time elapsed from midfoot to forefoot maxima
- V2: Time elapsed from heel to midfoot maxima

Figure 9 captures the bi-dimensional representation of the samples according the previous variables.

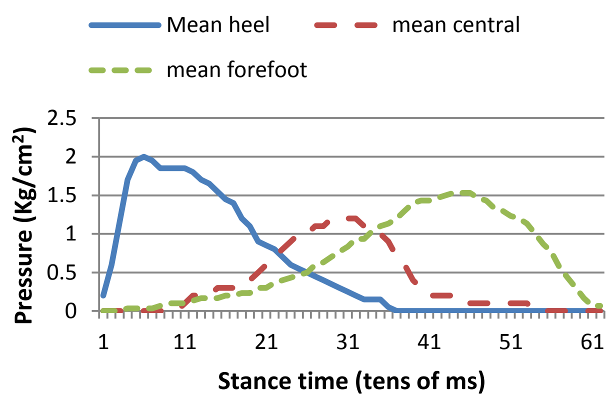


Figure 6. Left foot pressure distribution heel/midfoot/forefoot during the stance phase in a healthy participant

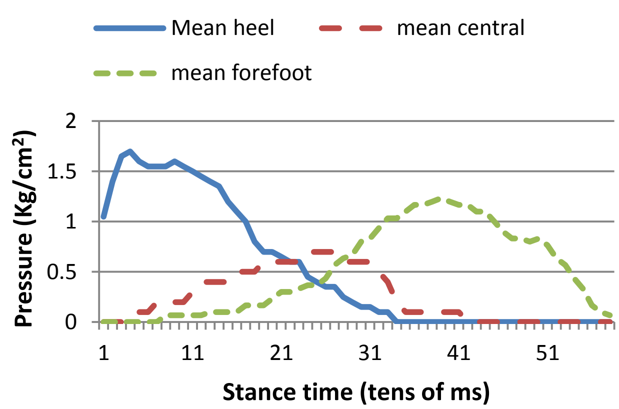


Figure 7. Right foot pressure distribution heel/midfoot/forefoot during the stance phase in a healthy participant

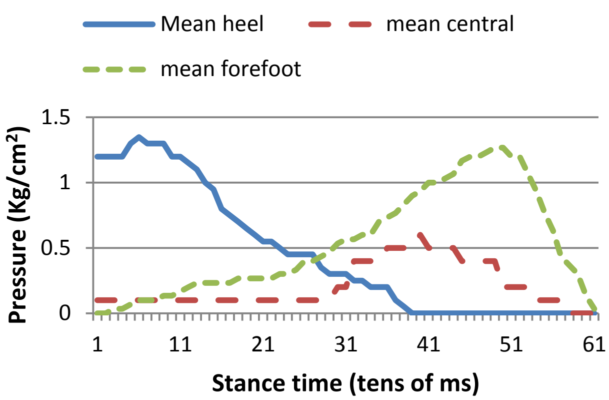


Figure 8. Affected-leg foot pressure distribution heel/midfoot/forefoot during the stance phase in a participant with mild knee pain

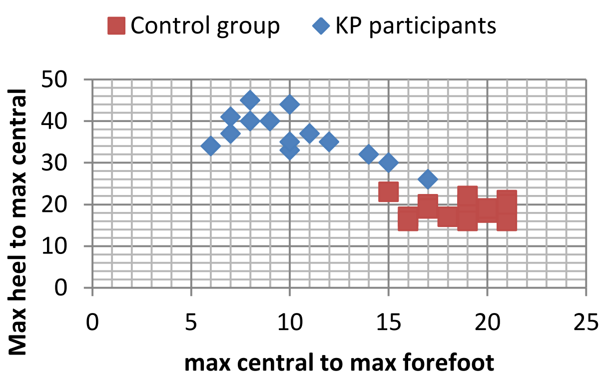


Figure 9. Heel to midfoot (y-axis) midfoot to forefoot (x-axis)

Disaggregating the results in Figure 9 to include age variation provides the results captured in Table 6. In particular, Table 6 captures the values of the mean and the standard deviation values for the ratio (max central to max forefoot) / (max heel to max central) for OA participants in 5 year groups. The value for the mean value is close to 1 for healthy controls and gets smaller as the age grows for OA participants.

TABLE 6. RESULTS PER AGE GROUP FOR OA PARTICIPANTS.

	<50	50-55	55-60	>60
Mean max-to-max time	0.71	0.61	0.63	0.29
STD max-to-max time	0.22	0.30	0.39	0.10

Applying several machine learning classification algorithms (considering only the affected leg for participants with knee pain and average values for both feet for healthy controls), SVM provides a good classification technique for classifying mild knee pain users but shows a 35% of bad-classifications for healthy controls (Table 7). Logistic regression and MLP classification improve the classification for healthy controls but degrades the performance for mild knee pain users (Table 8). The best classification results in this case are obtained applying tree based classifiers. The results for the J48 classification are captured on Table 9.

Applying the EM clustering algorithms the results for the means and standard deviations are captured on Table 10. Using the t-test to assess the null hypothesis of having similar populations we obtain (the null hypothesis can be rejected under the 0.05 significance value):

- p-value for the heel to midfoot variable (V2) → 0.000004711
- p-value for the midfoot to forefoot (V1) → 0.0002326656

TABLE 7. SVM CLASSIFICATION RESULTS.

classified as →	No knee pain	Knee pain
No knee pain	9	5
Knee pain	0	14

TABLE 8. LOGISTIC REGRESSION AND MLP CLASSIFICATION RESULTS.

classified as →	No knee pain	Knee pain
No knee pain	12	2
Knee pain	1	13

TABLE 9. J.48 CLASSIFICATION RESULTS.

classified as →	No knee pain	Knee pain
No knee pain	12	2
Knee pain	0	14

TABLE 10. EM CLUSTERS RESULTS.

	Cluster 0	Cluster 1
heel to centre mean values mean	18.6893	35.4402
heel to centre mean values stddev	2.7056	5.2336
center to forefoot mean values mean	17.9888	10.4752
center to forefoot mean values stddev	2.2505	3.3439

C. Inter-feet strategies

The final analysis has been performed considering the strategies used to support the affected leg by OA participants with mild knee pain. In order to get a visual intuition of the differences let's present first some particular examples. Figure 10 captures the foot pressure distribution heel/midfoot/forefoot for both feet for a participant with mild knee pain. Figure 11 represents a second example for a different participant with knee pain. Figure 12 captures the equivalent information for a healthy participant. The x-axis shows the same time values for both feet (captured one on top of the other so that time execution patterns can be visually compared). The left foot is shown on top and the right foot below it. Observing Figure 10 a visual asymmetry could be seen in terms of double feet contact. In this case, the left heel is capturing its maximum pressure value on the heel region at the same time the forefoot for the right forefoot is peaking. This double contact allows transferring part of the user's body weight from the affected leg to the healthy leg. Figure 11 captures a similar example for a second knee pain participant. In both cases, in order to relieve the knee force moments suffered by the affected knee (the right knee in both cases) during the maximum forefoot pressure region, the other foot is used in a double contact strategy. Figures 10 and 11 also show the behavior for transferring the body weight from heel to forefoot as described in the previous section. Figure 12 shows a more balanced feet pressure distribution in which high heel pressure values from each foot are achieved after the forefoot pressure on the other foot is decreasing.

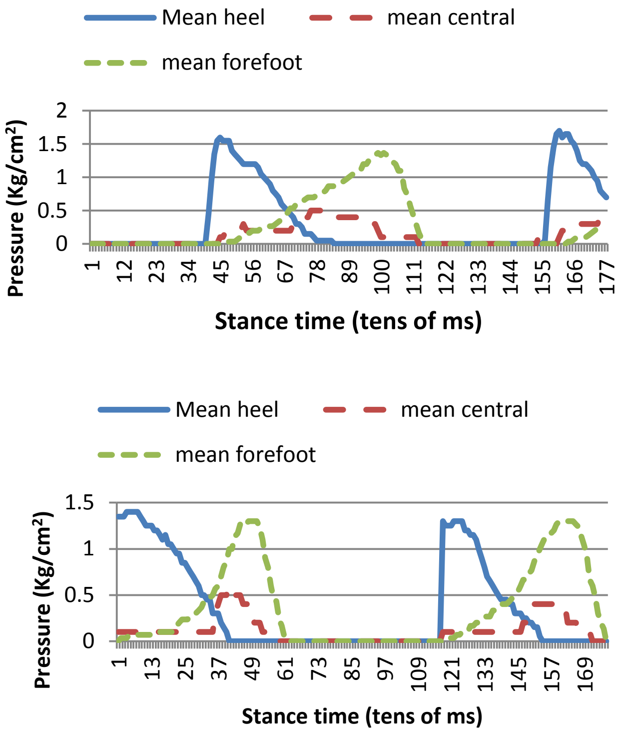


Figure 10. Foot pressure distribution heel/central/forefoot for both feet for a participant with mild knee pain (the bottom image corresponds to the affected knee).

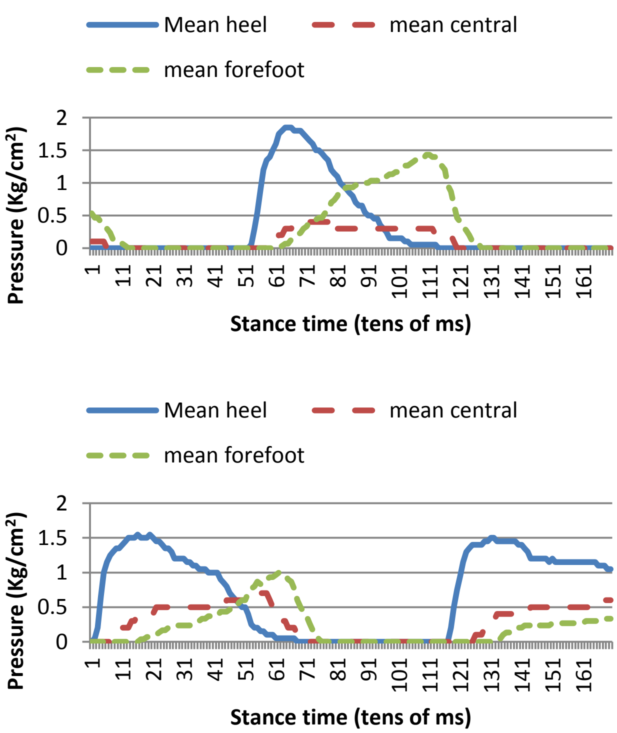


Figure 11. Foot pressure distribution heel/central/forefoot for both feet for a second participant with mild knee pain (the bottom image corresponds to the affected knee).

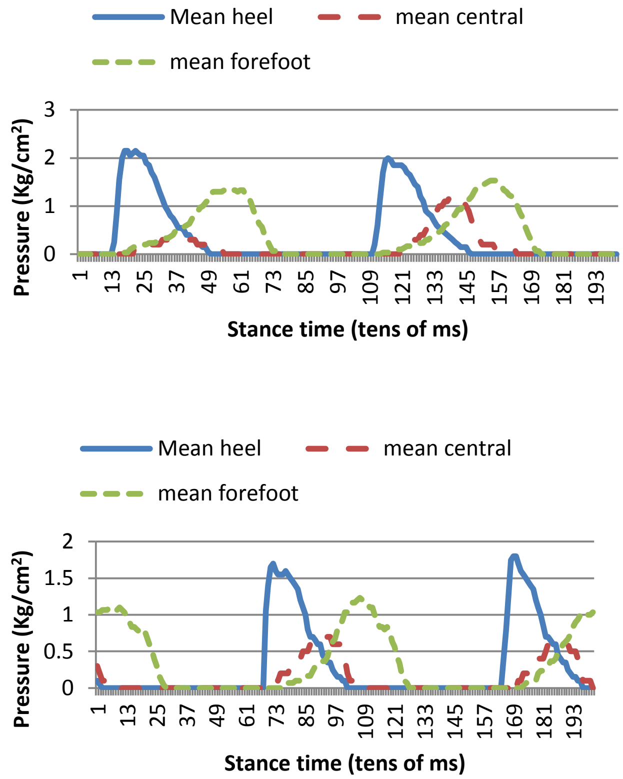


Figure 12. Foot pressure distribution heel/central/forefoot for both feet for a healthy control participant

A more detailed representation for data captured from all participants is presented in Figure 13. The figure captures the time differences (in milliseconds) from the forefoot maximum pressure to the heel maximum pressure of the next step for samples for all participants in both groups. For OA patients, the x-axis corresponds to the transition from the leg without pain to the affected leg while the y-axis captures the transition from the affected leg to the non-affected one. While the x-axis shows positive values higher than 100 ms for the experiment group (there is no double feet contact in that case), the y-axis shows values close to 0 (both positive and negative) showing a double feet contact in which the body weight is distributed between both feet to decrease the force in the affected knee. In the case of healthy controls, the data in both axes are closer to inter-feet symmetry and all the transition times are positive around 100 ms. Data in both groups can in this case be automatically separated. Table 11 captures the results for the SVM classifier applied to the 28 participants. All healthy participants are classified in the correct group. 3 of the participants in the experiment group did not use this strategy.

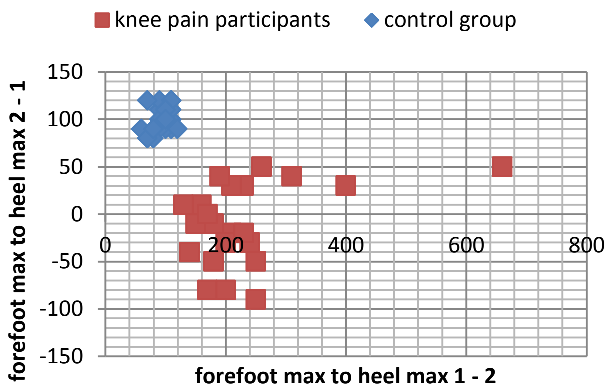


Figure 13. Forefoot max to heel max time differences for both groups.

TABLE 11. SVM CLASSIFICATION RESULTS.

classified as →	No knee pain	Knee pain
No knee pain	14	0
Knee pain	3	11

D. Medial and lateral pressure patterns

The distribution of the sensors in the insole (figure 1) allows us to compute pressure patterns for the medial (sensors 1, 3 and 7) and lateral (sensors 2, 5, 6 and 8) parts of the foot. In order to complement the results in the previous sub-sections, the average medial and lateral pressure patterns for both feet for a healthy control and an OA participant are captured in figures 14 and 15. The stance phase has been normalized to 100 samples in order to be able to accommodate steps executed at different speeds and provide a normalized representation for visual comparison. Average values for all steps for the same participants are computed. Figure 14 shows that pressure patterns for both feet for a healthy control are visually similar. The medial patterns show two major peaks of pressure in the heel contact and toe off moments. The lateral patterns have a similar peak in the heel region but the peak softens in the toes region. Figure 15 shows some relevant differences for an OA participant. There is a less symmetrical weight distribution pattern between both feet. Moreover, the heel pressure peak is less prominent than for healthy controls. Using a double foot contact strategy, as captured in the previous sub-section, will relieve part of the heel pressure from the more severely affected leg.

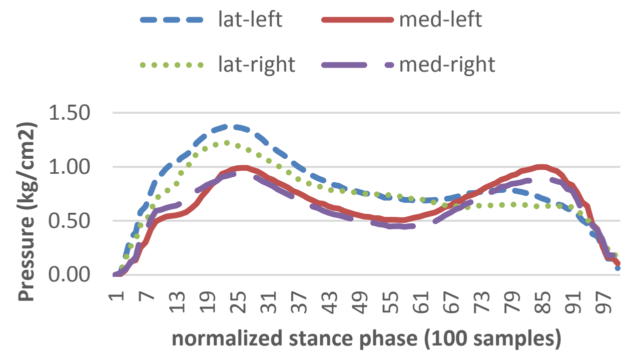


Figure 14. Lateral-medial pressure plots for a healthy control.

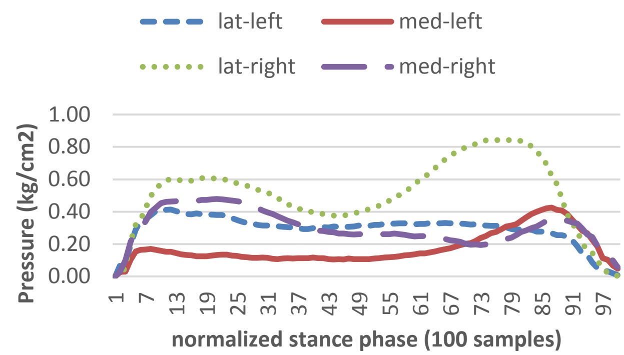


Figure 15. Lateral-medial pressure plots for an OA participant.

VI. DISCUSSIONS

Current evidence suggests that pain in the knee affects walking and that using wearable sensors such as pressure insoles can be beneficial to detect pain [23]. It is also accepted that based on automatically assessed data from sensors, personalized feedback can be generated to help the user in their rehabilitation process [22]. However, there are different conditions and mechanisms that can cause knee pain and particular methods are required for particular conditions. In this paper, we have concentrated on clinically diagnosed OA patients in the early stages of the disease trajectory and furthermore identified a number of metrics based on the impact of the pressure dependent features as automatically recorded from the users' insoles. We further suggest that this data could be feedback to the user as the basis for a self-management rehabilitation system [28]. Patients with early stage OA were those with a score of 5 or less on a subjective pain scale scored 0-10. Detecting when a pressure pattern as recorded from the insoles deviates from a normal one (as characterized based on the data from the control group) can be done in different ways. A first approach is based on using the particular pressure sensors that provide maximum distances using particular measures. In stochastic terms, a commonly used measure for distances is the Mahalanobis distance. Based on the data we have collected, sensors 3 and 4 are the optimal sensors for this. These sensors are located in the forefoot and are able to detect the progression of the pressure from the center of the foot to the medial part of the foot in the forefoot area. Normal pressure patterns move the body weight from sensor 4 to 3. For the experiment group however, a more planar pressure pattern has been detected. This strategy alone has been valid for 13 out of the 14 participants in the experiment group.

A second assessment measure was used to detect time differences in the way body weight moves from heel to toes. A gradual transition was detected for users in the control group. OA patients with mild knee pain however, showed a more abrupt transition in which the time from the maximum loadings from the center to the forefoot tends to collapse. This strategy has shown to be valid for all users in the experiment group but generates false positives for participants in the control group.

Knee pain in one participant generated asymmetries in gait. In particular, double feet contact strategies can be used to detect the severity of the pain suffered by a user. Using an automatic detection of double feet contact strategies has allowed us to correctly classify all the users executing the double feet contact strategy in this study in the experiment group.

Finally these findings suggest that based on these automatic assessment features, a personal monitoring system can be created that continuously guides patients with an early stage OA diagnosis when performing physical activities as part of a personal, self-managed rehabilitation system.

VII. CONCLUSIONS

This paper presents the impact that mild knee pain in clinically diagnosed OA patients has on several features computed from pressure sensors placed in the insoles of both feet. The results extend previous studies and provide further insight about different parameters that can be used to build applications to help the users self-manage their condition. Three main parameters have been selected to detect different strategies used by people suffering knee pain to dynamically move the body weight during the stance phase: forefoot pressure distribution from the center to the medial part of the foot, pressure transition from heel to forefoot and double feet contact asymmetries between feet.

Strategies at the forefoot show that OA patients with mild knee pain tend to spread the body weight (when the maximum pressure is located on the forefoot) between the medial and the center of the forefoot while healthy controls first load the central part and then move the body weight to the medial part of the forefoot.

In the sample used for this study, OA patients with mild knee pain tend to delay the transition from the heel to midfoot loading and move the maximum pressure time in the midfoot region closer to the maximum pressure time in the forefoot. In comparison healthy controls tend to perform a more smooth transition from the heel to the midfoot and from the midfoot to the forefoot.

Gait asymmetries based on the time differences of maximum forefoot pressure to maximum heel pressure for the next foot values show that OA related mild knee pain tends to generate double feet contact strategies. This allows them to share the body weight in both legs relieving the force in the affected knee.

As a work in progress, the 3 features presented in this paper are being included in a rehabilitation tool. The tool will allow the authors of the paper to validate user acceptance, adherence and motivation. It will also assess the increase in long term benefits for the experiment group in a self-managed rehabilitation process.

ACKNOWLEDGMENTS

The research leading to these results has received funding from the "HERMES-SMART DRIVER" project TIN2013-46801-C4-2-R (MINECO), funded by the Spanish Agencia Estatal de Investigación (AEI), and the "ANALYTICS USING SENSOR DATA FOR FLATCITY" project TIN2016-77158-C4-1-R (MINECO/ ERDF, EU) funded by the Spanish Agencia Estatal de Investigación (AEI) and the European Regional Development Fund (ERDF). The research was also funded from the grant PRX15/00036 from the Ministerio de Educación Cultura y Deporte and from a sabbatical leave by the Carlos III of Madrid University. The research was funded and supported by the NIHR CLAHRC Yorkshire and Humber. www.clahrc-yh.nihr.ac.uk. The views expressed are those of the author(s), and not necessarily those of the NHS, the NIHR or the Department of Health

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