Activity Detection in Uncontrolled Free-living Conditions Using a Single Accelerometer

Sunghoon Ivan Lee[1], Muzaffer Yalgin Ozsecen[1], Luca Della Toffola[1,2], Jean-Francois Daneault[1], Alessandro Puiatti[2], Shyamal Patel[1], Paolo Bonato[1]

[1]Department of Physical Medicine & Rehabilitation
Harvard Medical School & Spaulding Rehabilitation Hospital
Cambridge, USA
{slee117, mozsecen, jdaneault, pbonato}@partners.org

[2]Institute for Information Systems and Networking
University of Applied Sciences and Arts of Southern Switzerland
Manno, Switzerland
alessandro.puiatti@supsi.ch

***Abstract*—Motivated by a need for accurate assessment and monitoring of patients with knee osteoarthritis in an ambulatory setting, a wearable electrogoniometer composed of a knee angular sensor and a three-axis accelerometer placed on the thigh is developed. Accurate assessment of knee kinematics requires accurate detection of walking amongst dynamic, heterogeneous, and individualized activities of daily living. This paper investigates four different machine learning techniques for detecting occurrences of walking in uncontrolled environments based on a dataset collected from a total of 4 healthy subjects. Multi-class classifier (random forest) based detection method showed the best performance, which supports 90% precision and 75% recall. The in-depth analysis and interpretation of the results show that accurate decision boundaries are necessary between 1) fast walking and descending stairs, 2) slow walking and ascending stairs, as well as 3) slow walking and transitional activities. This work provides a systematic approach to detect occurrences of walking in uncontrolled living conditions, which can also be extended to other activities.**

Keywords—activity recognition; walking detection; wearable sensor; accelerometer; machine learning

I. Introduction

Knee osteoarthritis (OA) is one of the most prevalent joint disorder, whose progression gradually de-conditions the musculoskeletal system [1-2]. This significantly contributes to functional limitations and disability in performing daily activities. [1, 3]. Knee kinematics during walking, which is one of the most essential activities required in daily living, has been widely studied and has shown to be an effective clinical measure of knee OA [4-5]. For the treatment of OA, non-pharmacological physical modalities (*e.g.*, physical therapy and exercise) were shown to alleviate pain and improve functional level [6]. Physical modalities often require prolonged participation and thus, a system that enables longitudinal and continuous monitoring of gait kinematics in patients' home and community settings is in great need [7].

Motivated by these needs, a wearable platform that continuously measures knee kinematics and interacts with patients has been developed as shown in Fig. 1. The platform contains a biomechanically designed electrogoniometer composed of a potentiometer-based angular sensor that measures the knee angles, a three-axis accelerometer that analyzes data context, and a Bluetooth transceiver that delivers the acquired data to a mobile device (*e.g.*, a smart phone). Accurate assessment and monitoring of knee kinematics in an ambulatory setting requires the detection of walking such that knee angles can be extracted and analyzed to produce clinically relevant reports. However, accurate detection of walking amongst free-living activities poses a number of challenges since these daily activities are highly dynamic, heterogeneous, and individualized.

This paper reports unique findings of an exploratory study to develop a detection algorithm for occurrences of walking in uncontrolled free-living conditions using a three-axis accelerometer placed on the thigh. Participants' daily activities were annotated with the help of a wearable camera that captured surrounding images every second. This work discusses the characteristics of walking data by investigating its location within the multi-dimensional feature space, and examines four different detection algorithms formulated based on 1) a multi-class classifier, 2) a binary classifier, 3) an one-class classifier, and 4) a hybrid of one-class and binary classifiers. Note that although this work focuses on detecting walking for the application in knee OA, the presented detection mechanism can be easily extended and applied to other activities and applications.

II. Related Works

There have been many studies on activity recognition using wearable sensors over the past decade. However, most of these studies have been performed within controlled laboratory settings, and only a limited number of studies have investigated the feasibility of performing such analyses in uncontrolled conditions. In [8], authors proposed a classifier combining a rule-based tree and artificial neural networks to recognize nine different activities amongst activities of daily living. A total 12 subjects annotated their own activities using a smart phone application. The average classification accuracy over the nine activities was 72% (with the average walking detection accuracy of 71%). Authors in [9] conducted an experiment involving 24 individuals. Their daily activities were labeled by visual inspection of accelerometer data and annotation sheets. An algorithm that combines principal component analysis (PCA) and Naïve Bayesian classifier recognized five different activities. The average classification accuracy achieved based

978-1-4673-7201-5/15/$31.00 ©2015 IEEE

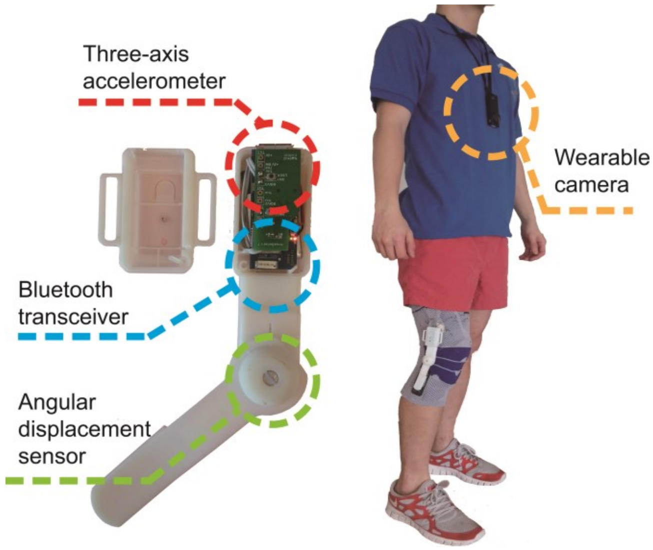

Fig. 1. The wearable platform that continuously monitors the engaged activities and knee kinematics.

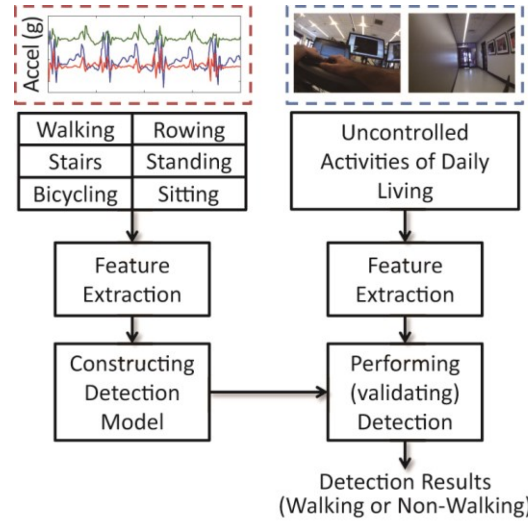

Fig. 2. A graphical summary of the activity detection algorithm. The algorithm utilizes the scripted activities to train a model to detect occurrences of walking amongst activities of daily living.

on a leave-one-subject-out cross-validation (LOSOCV) was 80%. The average walking detection accuracy was also 80%. More recently, the work in [10] introduced a combined algorithm of random forest and hidden Markov model to recognize four different activities of 40 breast cancer survivors. The analysis was performed in a LOSOCV manner and the average classification accuracy was 86%. The average walking detection accuracy was 63%. The aforementioned works yielded reasonably accurate classification results. However, these algorithms are designed to recognize a set of multiple activities. The interest of this work lies specifically in detecting occurrences of walking with higher accuracy (precision), since the knee kinematics will be analyzed from occurrences that are classified as walking. Low precision may lead to the contamination of knee kinematic results by incorporating other activities with similar leg movement characteristics such as ascending or descending stairs. This paper proposes a detection mechanism that constructs a more flexible and refined decision boundary around the walking cluster, and thus improves the precision.

III. Experimental Setup

A total of 17 healthy subjects were recruited from the Motion Analysis Laboratory at Spaulding Rehabilitation Hospital. These subjects performed sitting, standing, walking, going up/down stairs, riding an exercise bicycle, and using a rowing machine while wearing the electrogoniometer. Stairs, bicycling, and rowing activities were selected to provide similar knee movements as walking, and sitting and standing were selected as they are activities with more limited knee movements. Walking, bicycling and rowing were performed at slow, comfortable, and fast speeds. The data collected from this controlled and instructed activities are denoted as *scripted* data. Then, four of these 17 subjects performed everyday activities at Spaulding Rehabilitation Hospital for approximately nine hours. Because this study was performed within the participants' workplace, they spent most of their time sitting. Thus, in order to promote dynamicity of their activities, participants were asked to visit a designated workout room within the hospital twice during the day and perform walking, going up/down stairs, bicycling, and rowing. Participants were given no further instructions on their activities. Participants wore a wearable camera facing the anterior direction of the human body, which captured images at 1 Hz (Fig. 1). Furthermore, patients were given a mobile phone with an application asking the engaged activities every 30 minutes. The images and the responses to the periodic question were then reviewed by two research staff members in order to infer the labels of the performed activities. These data collected from the uncontrolled experiment are denoted as *unscripted* data. In this work, scripted data were used to train the detection model and the unscripted data were used to validate the model.

IV. Activity Detection Algorithm

Fig. 2 summarizes the walking detection algorithm. The raw accelerometer time series were sampled at 51.2 Hz and low-pass filtered at 12 Hz to remove any non-human noise in the signal. The data were then segmented using a five-second window with no overlap, which acted as a single data point. The scripted dataset was labeled as the performed activity if the activity was continuously performed within the time window. This rule ensures to analyze knee kinematics when the subject was fully engaged in walking and thus, produces more robust analytic results.

The same set of features were extracted from the scripted and the unscripted datasets. The features included 1) the mean and the standard deviation of the time series, 2) cross covariance between the first and the second (temporal) halves of the time series to measure consistency of the movements, 3) signal entropy, 4) the range (*i.e.*, difference between maximum and minimum values) of the amplitude, 5) the dominant frequency at which the maximum of the spectrum is located, and the ratio of the spectrum energy at the dominant frequency to the entire signal energy, and 6) correlation coefficients between the time series of the three axes. The above features were computed from each of the x, y, and z-axes except for the correlation coefficients. These resulted in a total of 47 features.

The detection of walking in uncontrolled conditions is not a conventional binary or multi-class classification problem, but rather a problem of detecting a unique kinematic pattern amongst many dynamic and unknown free-living activities where it is impractical to collect all possible non-walking activities of each individual. This creates a unique challenge to which there exists no clear definition of negative class. In order to resolve this problem, four different classification techniques were examined in this work.

A. One-Class Classifier

One-class classifier trains a model using only positive (*i.e.* walking) data, which constructs a minimal spherical decision boundary around the walking (slow, comfortable, and fast speeds) data of the scripted dataset [11]. The hypothesis behind this approach is that the walking data have a unique movement pattern that can be easily distinguished from the movements of other daily activities. In this work, a LibSVM implementation of one-class Support Vector Machine (SVM) was used [12].

B. Binary Classifier Based Detection Algorithm

Binary classifier considers the walking data as positive and all other non-walking data of the scripted dataset as negative. The underlying hypothesis is that the non-walking activities of the scripted dataset would provide sufficient dynamics in leg movements to effectively reflect activities of daily living, and consequently allowing the construction of a more sophisticated decision boundary for the walking cluster. Random forest with 100 trees was used as the classifier [13]. This work employed a WEKA implementation of this algorithm [14] in the MATLAB environment.

C. Multi-Class Classifier Based Detection Algorithm

Random forest with 100 trees was used as the multi-class classifier which is known to provide robust class probabilities [13]. It was trained using the scripted data with labels according to the performed activities. Activities performed at different speeds were labeled differently, *e.g.*, slow walking, comfortable walking, and fast walking. This approach is similar to the binary classifier based detection algorithm, but it is hypothesized to construct more refined and sophisticated decision boundaries between walking and other activities that share similar movements. For instance, it was observed that ascending stairs and walking at slow speed shared very similar feature values since both activities involve fairly slow and less dynamic leg movements. Similarly, descending stairs and walking at fast speed shared analogous feature values. Then, the class probability of the walking class was compared to a threshold (*e.g.*, 90%) to detect occurrences of walking from other activities. Note that changing this threshold acted as adjusting the volume of the decision sphere around the walking cluster.

D. Hybrid of One-class and Multi-class Classifiers.

As discussed in the previous subsection, descending and ascending stairs shared very similar movement patterns with walking. Thus, a one-class classifier was constructed to detect occurrences of walking and stairs amongst daily activities. If the occurrences were noted, then a multi-class classifier was further applied to distinguish walking (slow, comfortable, and fast) from stairs (descending and ascending). One-class SVM and random forest, as discussed previously, were used for the one-class and the multi-class classifiers, respectively.

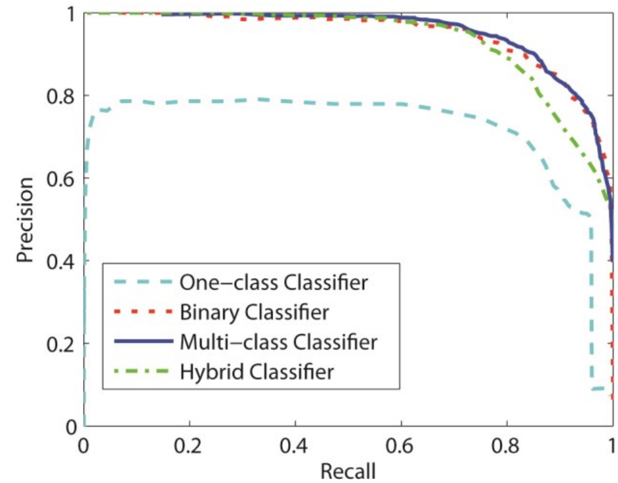

Fig. 3. Precision-recall curves of the four detection algorithms considered in this work. The multi-class classifier based technique outperforms the other techniques.

V. RESULTS

A. Annotation of Unscripted Dataset

As discussed earlier, two research staff members reviewed the captured images of the wearable camera, the accelerometer data, and the responses to the periodic questions to infer the labels of the unscripted dataset. The unscripted dataset was labeled as one of the scripted activities if the activity was continuously performed within the time window. All other activities including transitional activities (*e.g.*, walking-to-standing), activities other than the scripted activities, and any other unrecognizable activities were labeled as *other activities.* The percentage of these *other activities* within the labels of the unscripted dataset was 8.98%.

B. Comparison of Classification Techniques

Fig. 3 illustrates the precision-recall (PR) curves of the four classification techniques that were discussed earlier. Note that all the results were computed in a LOSOCV manner, which eliminated the scripted data of one subject when constructing the classification model, and evaluated the model using the *unscripted* data belonging to the left-out subject. This process was iterated for all subjects. PR curves were used (*e.g.*, rather than receiver operator characteristic curves) to evaluate the performances of the classifiers because the numbers of data points of walking and non-walking classes were quite unbalanced [15]. Precision is the ratio of the number of true positive (*i.e.* walking) data points to the combined number of true positive and false positive data points, which intuitively represents the correctness of the detection algorithm. Recall is the ratio of the number of true positive data points to the

978-1-4673-7201-5/15/$31.00 ©2015 IEEE

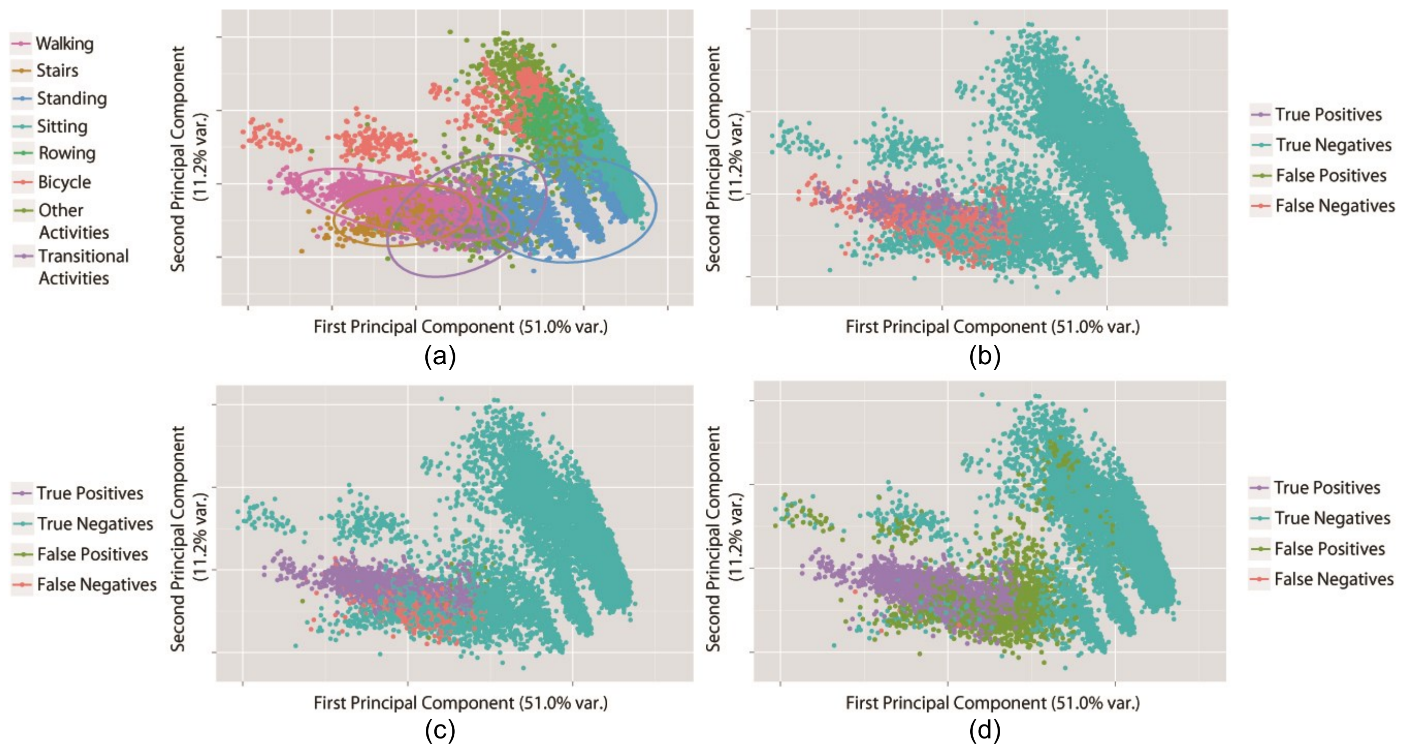

Fig. 4. Principal component analysis plots of (a) the unscripted dataset with the inferred labels, (b) the detection results based on the multi-class classifier, which is operated at precision of 99% and recall of 51%, (c) the detection results of the multi-class classifier at precision of 90% and recall of 75%, (b) the detection results of the multi-class classifier at precision of 50% and recall of 99%,

combined number of true positive and false negative data points, which represent the ability of the algorithm to correctly select walking data amongst the daily activities. As shown in Fig. 3, precision and recall rates are usually inversely proportional since their values are closely related to the size of the decision boundary around the walking cluster. When the volume of the cluster becomes larger, the detection model includes more negatives within its decision boundary and thus, the precision decreases. However, at the same time, the recall increases since an increased number of actual walking data points are included. When the volume of the cluster becomes smaller, the sphere is condensed around the center of the cluster and consequently, the precision is increased and the recall is decreased. These different operating points were obtained by varying the size of the hyperplane for the one-class SVM and the walking class probability for random forest. The hybrid classifier had both of these parameters to adjust the operation points and thus, the envelope of the two dimensional PR pairs created by these two parameters were used as the final PR curve.

Fig. 3 shows that the one-class classifier significantly underperforms compared to the rest of the algorithms. The major reason for its poor detection performance was due to its simple and rigid decision boundary around walking data (of three different speeds), which was not sophisticated enough to distinguish walking activities from ascending/descending stairs (recall that fast walking and descending stairs shared similar movements, and slow walking and ascending stairs shared similar movements). Consequently, the precision remained around 78% when recall was less than 70% because the decision boundary continuously included the stairs data even when the decision boundary was shrinking towards a single dot. When the decision boundary expanded (*i.e.* moving towards the right of the x-axis of Fig. 3), it started to include other non-walking activities and resulted in dramatic degradation in precision. This result signifies the importance of a refined decision boundary between slow walking and ascending stairs, and between fast walking and descending stairs.

Hybrid-classifier performed superior to the one-class classifier when recall was less than 70% because it constructed the decision boundary of its one-class classifier around the combined clusters of walking and stairs, and the multi-class classifier that followed provided a more sophisticated detection of walking. As a result, an accurate decision boundary could be formed between slow walking and ascending stairs, and also between fast walking and descending stairs. However, this technique started to underperform compared to the binary and the multi-class classifiers as the decision boundary expanded. When recall was greater than 70%, the decision sphere of the one-class cluster started to include a large number of transitional activities such as "walking-to-standing" or "standing-to-walking". Because these activities partially contain the movement patterns of walking and standing, they were positioned between walking and standing data (but closer to walking) within the feature space. This is apparent in Fig. 4 (a), which illustrates the PCA plot of the unscripted dataset with the inferred labels. It also includes the 95% confidence ellipses of walking (pink), stairs (gold), standing (blue), and transitional activities (purple), which show that these activities are located very closely in the feature space. The results of the hybrid-classifier support the necessity of an accurate decision boundary not only between walking and stairs, but also between walking and standing.

The binary and multi-class classifiers produced comparable detection performances. Both of these classifiers incorporated the entire scripted activities to train the model, which resulted in constructing accurate decision boundaries that adequately distinguish walking from stairs and transitional activities. Although the transitional activities were not included in the scripted activities, standing data could provide a reasonable boundary between walking and transitional activities. This shows that the scripted activities, especially walking, stairs, and standing, could appropriately define the dynamics of leg movements while walking amongst daily activities. Multi-class classifier slightly outperformed the binary classifier. It is believed that constructing the decision sphere of the walking cluster by combining the decision boundaries (created by the multi-class classifier) of walking at three different speeds produces slightly better detection performance. Fig. 4 (b), (c), and (d) illustrate the detection results of the multi-class classifier, which was operated at three different PR pairs. Fig. 4 (b) shows results when the classifier was operated at an extreme that favors precision: precision of 99% and recall of 51%. This is when the decision boundary is shrunk to provide 99% of precision, but it disregards 49% of the true walking data. As a consequence, a large number of false negatives are illustrated in Fig. 4 (b) (pink). Fig. 4 (d) shows another extreme point that favors recall: precision of 50% and recall of 90%. This implies the decision boundary is expanded to include 90% of the true walking data, but resulted in including a large number of stairs and transitional activities, which resulted in 50% precision. Fig. 4 (c) shows an example of a reasonable operation point: 90% precision and 75% of recall. If the walking detection algorithm is operated at this point, the knee kinematics can be analyzed for 75% of all walking data with 90% of accuracy, which may be reasonable for applications in knee kinematic analysis for OA patients. Most of the false positives (green) were from transitional activities, which were prevalent in daily (indoor) activities. This implies that having transitional data in the training set would improve the PR curve, especially where recall is greater than 70%.

VI. Discussion and Conclusion

This paper reported the findings of an exploratory study that investigated various algorithms to detect walking amongst uncontrolled activities of free-living using an accelerometer placed at the thigh. The results show that the scripted activities considered in this work, especially walking, stairs, and standing, provide sufficient dynamics in knee movement to detect walking amongst activities of daily living. More specifically, the algorithm needs to accurately recognize fast walking from descending stairs, slow walking from ascending stairs, and slow walking from transitional activities. These results provide relevant information regarding the movements patterns of walking compared to other daily activities. The presented techniques can be extended to other activities, which enable new opportunities for in-depth understanding of human context using wearable technologies, especially in patients with knee OA and other related ailments.

Acknowledgment

The authors would like to thank Nicholas Menard, Silvio Iozzia, and Edoardo Bonizzoni for their contributions in system development, data collection, and data preparation. This work was supported in part by the grant entitled “Engineering for Neurologic Rehabilitation”, NIH-NICHD, grant # R24HD050821-07 and by the grant entitled “Development of a Wearable System for Knee Range of Motion Monitoring (KROMM)”, Partners HealthCare Innovation.

References

[1] M. E. van Baar, *et al.*, "Pain and disability in patients with osteoarthritis of hip or knee: the relationship with articular, kinesiological, and psychological characteristics," *J Rheumatol,* vol. 25, pp. 125-33, Jan 1998.

[2] J. Peeler, *et al.*, "Managing Knee Osteoarthritis: The Effects of Body Weight Supported Physical Activity on Joint Pain, Function, and Thigh Muscle Strength," *Clin J Sport Med,* Jan 30 2015.

[3] J. D. Childs, *et al.*, "Alterations in lower extremity movement and muscle activation patterns in individuals with knee osteoarthritis," *Clin Biomech (Bristol, Avon),* vol. 19, pp. 44-9, Jan 2004.

[4] K. S. Al-Zahrani and A. M. Bakheit, "A study of the gait characteristics of patients with chronic osteoarthritis of the knee," *Disabil Rehabil,* vol. 24, pp. 275-80, Mar 20 2002.

[5] M. P. Steultjens, *et al.*, "Range of joint motion and disability in patients with osteoarthritis of the knee or hip," *Rheumatology (Oxford),* vol. 39, pp. 955-61, Sep 2000.

[6] J. Chard, *et al.*, "Osteoarthritis of the knee," *Clin Evid,* pp. 1506-22, Dec 2005.

[7] S. A. Bolink, *et al.*, "Inertial sensor motion analysis of gait, sit-stand transfers and step-up transfers: differentiating knee patients from healthy controls," *Physiol Meas,* vol. 33, pp. 1947-58, Nov 2012.

[8] M. Ermes, *et al.*, "Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions," *IEEE Trans Inf Technol Biomed,* vol. 12, pp. 20-6, Jan 2008.

[9] X. Long, *et al.*, "Single-accelerometer-based daily physical activity classification," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2009, pp. 6107-10, 2009.

[10] K. Ellis, *et al.*, "Multi-sensor physical activity recognition in free-living," presented at the Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication, Seattle, Washington, 2014.

[11] D. J. Tax and R. W. Duin, "Support Vector Data Description," *Machine Learning,* vol. 54, pp. 45-66, 2004/01/01 2004.

[12] C.-C. Chang and C.-J. Lin, "LIBSVM: A library for support vector machines," *ACM Trans. Intell. Syst. Technol.,* vol. 2, pp. 1-27, 2011.

[13] T. Hastie, *et al.*, *The elements of statistical learning : data mining, inference, and prediction*, 2nd ed. New York, NY: Springer, 2009.

[14] I. H. Witten, *et al.*, *Data mining : practical machine learning tools and techniques*, 3rd ed. Burlington, MA: Morgan Kaufmann, 2011.

[15] J. Davis and M. Goadrich, "The relationship between Precision-Recall and ROC curves," presented at the Proceedings of the 23rd international conference on Machine learning, Pittsburgh, Pennsylvania, USA, 2006.

978-1-4673-7201-5/15/$31.00 ©2015 IEEE