CoachMe: Activity Recognition using Wearable Devices for Human Augmentation

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Abstract

Wearable devices have paved the way for several context-aware applications in the field of health-care, sports and entertainment to improve the well-being of users. During rehabilitation patients need accurate feedback on their physiotherapy and preferably in near real-time. This feedback to users can empower and improve the speed of recovery. We present here a system that analyzes activities of patients to provide real-time feedback. Specifically, we analyze exercises performed during knee rehabilitation where patients undergoing therapy often have to visit doctors for feedback. Moreover, they receive little or no feedback when performing these exercises away from the clinic. To overcome this, we propose a novel two-stage methodology that provides accurate feedback on the exercises performed. We collected data from six patients during their rehabilitation to evaluate our models. Furthermore, the proposed technique can be applied in wide-variety of exercises and also in sports.

Categories and Subject Descriptors

I.5 [**Pattern Recognition**]: Models, Applications

General Terms

Classification algorithms, Experimentation

Keywords Human augmentation, Wearables

1 Introduction

The ability to observe, measure and track how individuals function in their daily living is *easily possible now* with the help of Internet of Things (IoT) [1, 2]. Specifically, recognition of human activities has enabled the development of several context-aware applications to improve well-being of humans. For example, patients with heart diseases or diabetes are often required to a follow particular routine of exercises, therefore identifying activities such as walking, standing, or sitting enables caregivers to provide feedback accordingly. Furthermore, patients who underwent surgery or suffering from chronic impairments require physical therapy as part of their rehabilitation. Identifying and providing accurate, real-time feedback on the exercises performed can improve the recovery process significantly.

Human activity recognition systems can be broadly classified into two *viz.,* (i) external and (ii) wearable [2]. External system requires deployment of sensors in a pre-defined location e.g., training room, laboratory, etc. Inference of activities performed is based on the interaction between these devices and users. In contrast, wearable systems include sensors attached to the user to identify the activities performed. Wireless/wearable inertial measurement units (WIMUs) are capable of measuring human biological data, e.g., physiological and motion data.

We employ WIMUs to assist human augmentation for enhancing human productivity and restoring capabilities of the human body. Specifically, we address the problems involved in physical therapy during knee rehabilitation. There are around 10.4M patients visiting doctors for common knee injuries such as fractures, dislocations, sprains and ligament tears every year [3]. Most of the knee injuries can be successfully treated through rehabilitation exercises and some may require surgeries. Patients attend regular sessions with their therapist during the early rehabilitation stages. The therapist monitors the progress of patients in the clinic; however patients have no feedback when performing the exercises in their homes. This might lead to longer recovery process or in some cases it may cause further injury if sufficient care is not taken. This process is labour intensive and has several limitations *viz.,* (i) the therapist is not aware of how accurately the exercises were performed by the patients; (ii) patients have no feedback on the exercises performed and thus require frequent visits to the therapist; (iii) patients may lose motivation when performing exercises at home due to lack of feedback; and (iv) therapists need to keep track of the exercises and specific details of each patient to guarantee the individual attention for fine-tuning the rehabilitation.

Recent research efforts have used wearable devices on humans to monitor different exercises performed. These solutions collect data from various WIMUs such as accelerometer, gyroscope and magnetometer to determine the knee joint angle, movement techniques, and other temporal aspects of gait [5]. Feedback provided using these mechanisms can be broadly classified into the following: (i) *knee angle based–*

International Conference on Embedded Wireless
Systems and Networks (EWSN) 2017
20–22 February, Uppsala, Sweden

ISBN: 978-0-9949886-1-4

this indicates the deviation of knee movements compared to the correct positions; and (ii) *activity label based*– this classifies the exercise to one of the labels defined by the therapist and appropriate feedback is provided based on the identification. Even though the above approaches aim to provide information on the exercises performed, patients often cannot relate directly to the exercises. For example, feedback on the knee joint angle cannot be understood by the patients to take corrective measures in their exercises. Similarly, labels obtained by the therapist are generally a rough approximation. Feedback based on the identified label may not be accurate as there could be multiple labels associated with the same exercise performed [3]. The labels are defined by the therapist using visual inspections and are generally not well-defined.

To address the above issues in this paper, we present CoachMe that provides accurate feedback on the exercises performed by the patients during knee rehabilitation. We designed and developed a knee band, which is low-cost and wearable comprising of WIMUs to collect data related to the rehabilitation exercise. Furthermore, we propose a two-stage methodology; first, we identify the composite activities performed and its corresponding micro-activities. Second, we classify the micro-activities into a set of labels that represent the exercises performed. Since there are many exercises during rehabilitation, in this work we focus on the lunge exercise. Lunges are one of the common knee rehabilitation exercise performed to increase the knee strength and control. Finally, based on the identified labels, appropriate feedback is provided to the patients on the lunge exercise.

Current research on activity recognition considered an exercise as a single macro-activity, while this may work with simple activities such as walking, running and jumping, it fails for complex/composite activities such as lunges, which typically includes a set of micro-activities. For understanding and to provide feedback on such complex activities, recognition of underlying micro-activities is important. CoachMe is the first step towards developing a system that can classify micro-activities accurately. The key idea proposed in this paper is to segment activities into micro-activities and determine the best feature set that can classify these micro-activities. We first evaluate the performance of standard machine learning algorithms (classifiers) to classify the micro-activities. We then fine-tune these algorithms to accurately detect micro-activities.

The main contributions of this paper are:

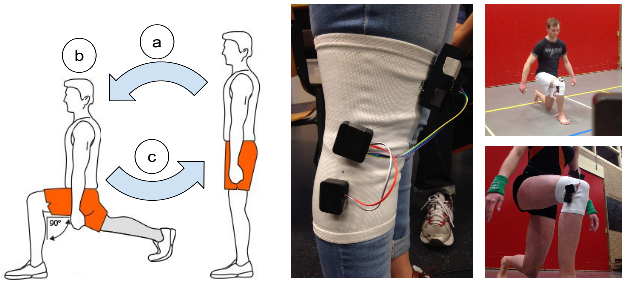
- We propose a two-stage methodology that provides accurate feedback on the exercises performed by the patients during knee rehabilitation.
- We describe our system design and a low-cost knee band used to collect activity information of patients.
- We present our experimental evaluation from six patients in rehabilitation and compare classification accuracy across classifiers.

2 Related Work

In this paper, the focus is to identify the lunge exercise and provide feedback to patients on how well they performed the exercise. The standard approach to measure the performance of a patient involves the measurement of the knee angle with a tool called Goniometer [6]. Most often, this is done by observation since electronic goniometers are capable of measuring the knee angle only in motion. Other techniques employ expensive hardware like Kinect health [7] or video processing to track patient activities and provide feedback [4]. To this end, recent works aim to determine the knee angle using low-cost sensors. Dejnabadi et al. [8] and Tomaru et al. [9] make use of IMUs like magnetometers, gyroscopes and accelerometers to determine the knee angle. They employ Kalman filters to estimate the angle towards ground in a 3D space. Another approach employs artificial neural networks along with IMUs for measuring the knee angle [5]. Most of the proposed techniques to classify lunges aim to understand the knee angle using the IMUs. However patients have little knowledge on knee angle based feedback. Hence, this paper takes an orthogonal approach that analyzes the micro-activities in an exercise to determine the position of the knee and use pre-defined labels to classify how accurately an exercise was performed.

In the past decade numerous activity recognition algorithms have been proposed by researchers [2]. Most activity recognition algorithms [2, 10, 11] are generally evaluated on simple activities such as walking, running, and jumping by using machine learning approaches. In scenarios such as sports or rehabilitation, activities could be a complex routine, for example, consider recognizing a user cycling, which involves micro-activities such as accelerating, turning, standing still, bending, etc. with certain logical sequence and duration. Current studies have not focused on recognizing these micro-activities which surely enriches the context and provide better feedback. CoachMe aims to identify these micro-activities by segmenting a macro-activity. Recent research efforts have shown that accelerometer data can be used to identify micro-activities and monitor athlete performance [2, 11].

Activity label based feedback systems have two major challenges: (i) *Composite activity* – an exercise in rehabilitation is composed of several instances of simple activities, i.e., micro-activities. For example, a lunge exercise involves stepping forward, steady position and stepping back. (ii) *Overlapping labels* – most of the labels defined are based on the visual inspection by the therapist. These labels are generally overlapping due to the approximation and inconsistency in defining labels across therapists. Hence label based feedback systems need to identify multiple related labels rather than a single label to provide feedback. CoachMe overcomes the above problems by developing a two-stage methodology, (i) segment a macro-activity into micro-activities and (ii) enhance the standard machine learning algorithms to accurately detect micro-activities. Recent activity recognition algorithms have tried to identify the optimal set of features to identify an activity, which is computationally simple and also energy efficient [10]. In this paper we present a ranking model, which determines the best feature set to identify individual micro-activity labels in contrast with a complete macro-activity. This is challenging since micro-activities are shorter in length and the number of unique features are much lesser as compared to a macro-activity.



(a) Lunge exercise (b) Knee band with WIMUs

Figure 1. Lunge exercise and the designed knee band.

3 System Design

We now present the details of the considered exercise to provide feedback during knee rehabilitation.

Exercise: Lunges are one of the most common knee rehabilitation exercise. Each lunge exercise is a composite activity, which includes several micro-activities, (a) step forward, (b) steady position and (c) step backward (Fig. 1(a)).

Data acquisition: The data acquisition setup includes a knee band, which contains two WIMUs and an Arduino board for data processing. The placement of WIMUs depends on the positions that can provide the maximum information of the performed lunge exercise. We identified two positions, one on the upper leg and the other on the lower leg, which captures the position and movement of the corresponding leg [5]. Each WIMU consists of 3-axis accelerometer, gyroscope and a magnetometer. Fig. 1(b) shows the knee band worn by the patient. Furthermore, sampling rate of 50 Hz was used for data collection. The sensed data is then transmitted to the Arduino board using Bluetooth Low Energy (BLE). Note that, the sensed data can be sent directly to a smartphone for processing, eliminating the Arduino board.

The knee band developed is portable and can be used by the patients anywhere. Unlike other wearables, CoachMe is used only when patients are performing exercises (few hours/day). In our experiments, the battery powering up the knee band lasts for 3 to 4 days. We collected data from six participants, four males and two females in a physiotherapy clinic. Participants from different age groups (20-65 years) were chosen for this study. Each participant was asked to perform their normal routine during rehabilitation, which includes a 10 m warm-up followed by several lunges. In total around 200 lunges were performed by each participant. Furthermore, video footage from the data collection session was recorded for ground truth. A therapist analyzed the lunge exercises performed by the participants to label each lunge along with the help of video footage. Eight labels were defined *viz.,* **(i)** ***Over*** indicates the over flexion of the knee. In this case, the knee cap is beyond the position of the foot due to over-leaning in the forward direction. **(ii)** ***Knee In*** (KI) indicates that the knee flexes were inside the body. This is due to bad rotation of knee or wrong leg angles while performing the lunge. **(iii)** ***Knee Out*** (KO) indicates that the knee flex is outside the body. **(iv)** ***Unstable*** (Ins) indicates the instability in the end position of legs due to excessive movement or vibration. **(v)** ***OverIns*** refers to Over Unstable, which is a combination of Over and Unstable. **(vi)** ***Good*** indicates that the lunge exercise was performed properly. **(vii)** ***Small*** indicates a small step was used during the lunge and is due to lack of knee flexes. **(viii)** ***Fast*** indicates that the lunge is done faster than the average, leading to a short time in the steady phase.

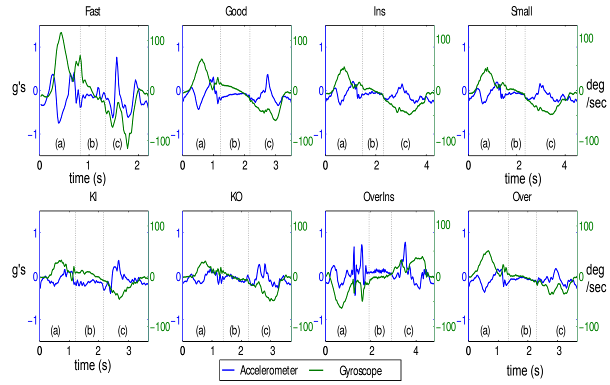


Figure 2. Accelerometer and gyroscope raw data from WIMUs for different labels.

A simple automated segmentation method that identifies the starting position (standing still) was employed to segment the data collected into repetitions. Fig. 2 shows the raw accelerometer (z-axis) and gyroscope (z-axis) data averaged from 10 repetitions for different labels. The *x*-axis indicates the time in seconds and *y*-axis indicates the units of accelerometer (g) and gyroscope data (deg/sec). The micro-activities are labeled as (a), (b) and (c) corresponding to stepping forward, steady position and stepping backward respectively. It can be seen that, the time duration of the micro-activity (b) i.e., steady state, varies for each label.

4 Automatic classification of micro-activities

In this paper, we employ algorithms that are previously evaluated for macro-activity recognition. We first describe a traditional approach and then present two methodologies, (i) Average Signal Model (ASM) and (ii) Ranking Model (RM) to classify lunges by considering micro-activities.

4.1 Traditional classifier

Fig. 3(a) shows the traditional classifier model used to classify lunges. As mentioned previously the collected data from WIMUs are segmented to repetitions, where each repetition represents a lunge. The data is split according to 10-fold cross-validation. Several features were extracted from each repetition and a classifier model is developed using the features extracted. We employed three well-known classifiers [12] such as NaïveBayes (NB), decision trees (J48), and K-nearest neighbor (IBk) for classifying each repetition. During evaluation, each repetition was evaluated to the closest label. The traditional classifier has several drawbacks. First, since the entire lunge is used for classification, micro-activity recognition is not possible. This results in considering activities, which may not be significant. For example, in a lunge stepping forward and stepping backward are not crucial. However, the lunge steady position is the significant micro-activity that can provide more information on how good the lunge was performed. Second, the traditional

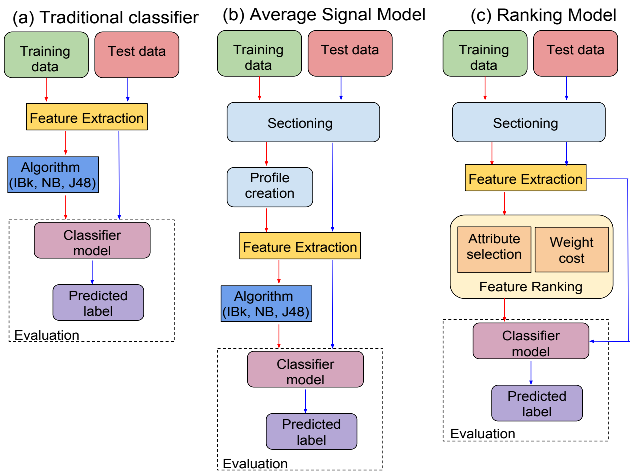


Figure 3. Different micro-activity classification models.

classifiers are generally binary. However, most of the labels defined in rehabilitation and other human augmentation applications have multiple overlapping labels.

4.2 Average Signal Model (ASM)

To overcome the above issues, we propose average signal model (ASM) that first segments (bifurcates) a composite activity into micro-activities and then classifies the test data by comparing it to the average signal for each label. Fig. 3(b) shows the proposed ASM model. The major components are: sectioning, creating profiles and extracting features.

Sectioning: The objective of sectioning is to determine the micro-activities from the composite activity. We employed an unsupervised clustering approach to determine different sections from repetition. Clustering approaches [12] such as Expectation Maximization (EM) and *k*-means with different configurations were empirically evaluated across all labels and repetitions. EM clustering with 3 clusters was able to accurately identify the micro-activities across all repetitions.

Creating Profiles: This component determines an average signal for each label, which can be used during the classification of a new repetition. Since the steady position of the lunge is the crucial micro-activity, we focus only on this micro-activity. Profile creation first determines the average length of the steady state for each label. Since, each repetition may have varying period, we apply dynamic time wrapping (DTW) to stretch or shrink the micro-activity such that all the repetitions of a label have the same length. We then merge all the corresponding signals for that label to obtain an average signal. For example, we determine the average length of steady state for all good lunges and then merge all accelerometer *x*-axis signals of the good repetitions into one *x*-axis signal. Please note, we merge only same axis (same sensor) data for each repetition. Finally, the merged signal represents the golden profile for that label.

Extracting Features: Several features from golden profile of each label are then extracted for classification. The extracted features include fundamental frequencies, mean crossing, standard deviation, root mean square, max, minimum, mean, size (*n* samples), and signal difference between two signals. We employed three classifiers, NB, J48, and IBk [12] for classifying each repetition. Test repetitions are evaluated with the average signal of each label. The label that is similar to the repetition is then selected. However, ASM model still cannot identify labels that are similar. Consequently, any misclassification will result in providing inaccurate feedback.

4.3 Ranking model (RM)

Ranking model (RM) aims at determining the set of labels rather than a single label that represent the test data (Fig. 3(c)). The hypothesis here is that, by providing feedback from a set of similar labels increases the accuracy compared to feedback based on a single label. The functionality of sectioning and feature extraction block remains the same as ASM. A feature ranking block is added to identify the most influential features for each label.

Feature Ranking: In ASM all the features were used to classify the test data. This results in inclusion of features that are similar or noisy. Feature ranking block identifies the most influential features for each label. This saves computing time and considers only features that are important. In order to identify features that are influential for a particular label, we apply weighted cost along with attribute selection ranking tool from WEKA [13] [14]. The attribute selection ranking provides a set of features that are most influential across all labels. However, since we want the features that are influential for each label, a weight cost is applied that penalizes a feature during misclassification. This ensures we derive the most influential features for each label. Finally, we use this ranked features for each label to build a classifier model. The resulting model includes the probability density function (PDF) of a feature across labels.

The test data is first sectioned and the top-*k* feature vectors that are obtained from the feature ranking block are used for evaluation. The RM model identifies not only the closest label the test data belong to, but also the similar labels (if any). To this end, the set of labels whose feature values are below standard deviation threshold (δ) were selected as similar labels. The intuition is that similar labels have similar feature values. Furthermore, by calculating the probability density function (PDF) for each top feature, one can select the set of labels that are similar. Feedback systems can now exploit this to provide feedback based on the set of labels determined for each repetition.

5 Results

Classification accuracy: The first step in providing feedback to participants on how accurately they performed a lunge is by determining if a lunge was performed or not. To this end, we applied *K*-nearest neighbor (IBk) classifier to distinguish a lunge from other activities such as walking and running. The classifier accuracy of identifying a lunge was close to 96%. The high classification accuracy is mainly due to the unique characteristic of lunges. We applied the traditional classifier to classify the test data into one of the labels. We tested with three classifiers *viz.,* IBk, J48 and NB. IBk performs better than the other classifiers with an average classification accuracy of 24.8% across all labels. The poor classification accuracy is due to the inability of identifying the micro-activities involved in a lunge.

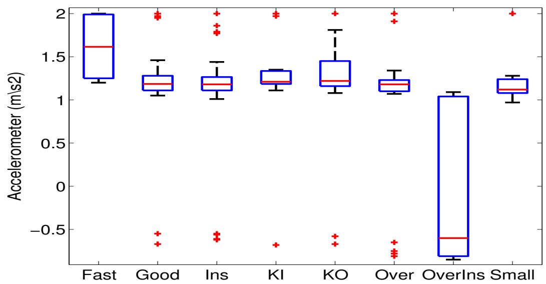


Figure 4. Probability distribution of a feature.

ASM model first sections the composite activity into micro-activities. We employed a clustering approach to determine the different micro-activities. The semi-supervised method first identifies the clusters that correspond to the micro-activities. These clusters are then labeled with the help of a domain expert. In our case, the identified clusters represent the stepping forward, steady position, and stepping back activities. Furthermore, we merged the signals from the WIMUs (corresponding to their axis) of a particular label to derive its golden profile. The test data was evaluated with the golden profile across multiple classifiers. The average classification accuracy of identifying the corresponding label for NB, J48 and IBk were 39.6%, 45.2% and 51.8%, respectively. The metrics employed to study the efficacy of the classifiers are: (i) *Precision (P)* is the number of true positives divided by the total number of repetitions labeled as belonging to a particular label; (ii) *Recall (R)* is the number of true positives divided by the total number of repetitions that actually belong to a label; (iii) *F-measure* (F_1) indicates the accuracy of the classifier and it is the harmonic mean of precision and recall. Table. 1 shows the precision, recall and F-measure for each label using IBk classifier. It can be seen that for some labels the accuracy is high (100% for *Fast*) and for others the accuracy is as low as 32%.

Ranking model improves ASM by first identifying the best set of features and then using standard deviation to determine similar labels. If the best set is not determined there could exist numerous features which might be similar across labels. Ranking model employs attribute selection ranking with weighted cost matrix in WEKA tool to obtain the top features that are important for each label. The attribute selection ranking performs an exhaustive search over all features to identify the top features. Then a weighted cost matrix is applied to ensure misclassifications are highly penalized. Furthermore, to select the closest set of labels, we compute the probability distribution function for each feature across labels. This allows to identify the set of labels that are closest. Fig. 4 shows the probability distribution values for a feature 3_*mean* (corresponding to the accelerometer x-axis on the lower leg WIMU) across all labels. It can be seen that for *OverIns* label this feature has unique median value. This enables the classifier to accurately determine the corresponding label. Fig. 5 shows the probability distribution for 5 test repetitions across different labels with average signal and ranking models. It can be clearly seen that ASM is highly biased towards one of the labels. However, for ranking model using the PDF we can identify the set of labels that are similar.

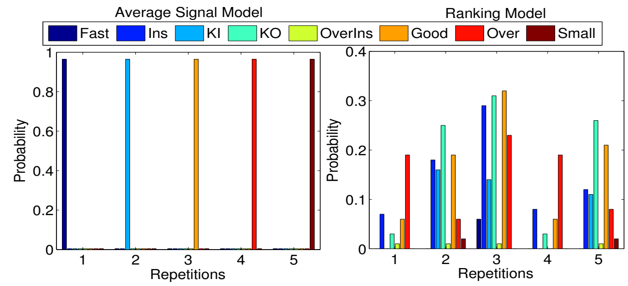


Figure 5. Evaluation of 5 repetitions across labels.

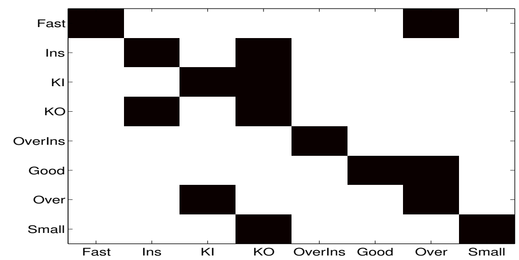


Figure 6. Overlapping set of labels derived using RM.

This can be seen in Fig. 5 where for some repetitions only one label has high probability and for other repetitions more than one label have similar probabilities. For example, Repetition 1, 4 can be clearly identified as a *Over* lunge, whereas, in Repetition 3, the probability of being *Unstable* or *KO* or *Good* is similar. Hence labels that have similar probabilities are selected as the predicted set of labels. In our evaluation, the time required to correctly classify a test repetition to a label is in order of few ms. Furthermore, feedback for most rehabilitation exercises can accept delay in the order of minutes [15]. Finally, Fig. 6 shows the set of labels that are overlapping in the entire dataset. The colored column indicates that the label is similar to the corresponding row label. Note that this mapping between labels may vary depending on the training data. This allows our proposed methodology to be adaptive and learn new patterns in the collected data over time. Table. 1 shows the precision, recall and F-measure obtained using the ranking model with top three features. The average accuracy across all labels is around 70% with a precision of 74%. Note that, the accuracy of the system can be further improved by adding more training data and having balanced data across labels. Further experiments were conducted to test the robustness of classification: (i) Excluding a patient data: leave-one-out approach (training data set did not include any repetition from one patient) and (ii) Excluding a class-label data: we excluded a particular label data (either Over/KI/KO/INS) of the patient. In both experiments overall classification accuracy was around 70 to 90%.

Feedback mechanisms: Providing real-time feedback is non-trivial, especially when micro-activities are performed. In this work, we proposed a micro-activity classifier that identifies a set of labels representing the activity performed. Feedback is provided based on the labels that are highly similar. For example, if the predicted label of a test repetition is *Over and Unstable* label, then the system selects feedback corresponding to these two labels. This could be the com-

Table 1. Classification accuracy across labels.

	ASM			RM		
Labels	P	R	F_1	P	R	F_1
Fast	1.00	1.00	1.00	1.00	1.00	1.00
Ins	0.60	0.60	0.60	1.00	0.57	0.73
KI	0.50	0.50	0.50	1.00	0.60	0.75
KO	0.35	0.30	0.32	1.00	1.00	1.00
OverIns	0.50	0.50	0.50	0.33	1.00	0.50
Good	0.40	0.57	0.47	0.62	1.00	0.77
Over	0.80	0.80	0.80	0.90	0.90	0.90
Small	0.67	0.67	0.67	1.00	0.67	0.80

bination of feedback from *Over* and *Unstable* such as keep your upper body straight and do the exercise slower to get more control, respectively. The developed classifier models run on user smart phones. Hence, the corresponding feedback is provided to the users on their phone or in-home displays. Further, this feedback can also be sent to the therapist who can then adapt the feedback to provide more personalized recommendations or incorporate corrections.

Discussions: In this section, we discuss the lessons learnt in developing a portable knee band and highlight challenges that exist to make the system applicable to other rehabilitation exercises. First, the selection of WIMUs and their placement is highly dependent on the application [16]. In our experiments, one of the major hurdles was to ensure the mounted WIMUs are properly aligned. The video data collected helped us to eliminate instances where the band was not worn properly. To this end, we employed iPi motion capture tool[1] to map the video data to a 3D model which could be used to eliminate data instances and to assist in labeling. Second, domain knowledge plays a key role in developing human augmentation technologies. In CoachMe, we arrived at the labels by consulting five physiotherapists. Eventhough physiotherapists had a similar notion on labeling the lunge repetitions, most of them were overlapping and there is no clear boundary to differentiate them. Further, to generalize the proposed methodology to other rehabilitation exercises, there still exist some challenges *viz.,* (i) Energy constraint and time complexity: A key requirement for current wearables is to have a low-power, low-complexity, higher lifetime system. Power-aware feature selection, online classification models and energy budgeting will certainly help to provide real-time feedback and increase the robustness of the system. (ii) Datasets: Currently there exists a few datasets for general activities like walking and running, which is used to improve activity recognition models. Similarly, for robust and generic micro-activity recognition, there is a need to develop similar open datasets. (iii) Feedback: While there are few studies on the techniques to be employed for providing feedback such as a smartphone, in-home displays and Google glass, it is important to study the acceptance of this feedback by the patients. Hence large-scale studies on how patients adapt their routine with this feedback are crucial in developing a persuasive human augmentation system.

6 Conclusions

We designed a system that helps in faster rehabilitation of patients with knee injury using a knee band comprising of WIMUs. We described a novel two-stage methodology to accurately classify the exercises performed by identifying the set of labels for each exercise. Unlike the existing systems, the techniques presented here can identify the microactivities involved in a particular exercise. The proposed ranking model determines the most influential features that can accurately identify the set of labels that are similar to the test repetition. The predicted set of labels is then used to provide feedback on the quality of exercises performed. The proposed models perform significantly better than the traditional classifiers. The classification accuracy of identifying the correct set of labels using ranking model is close to 70%. We believe that our novel methodology and analysis presented in this paper will make the rehabilitation easy, simple, faster and accurate.

7 Acknowledgments

The authors would like to thank Daniel Steginga (Dutch Coast) and Rick Oppedijk (Oppedijk Sports Engineering) for their support towards developing the knee band.

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