

# Monitoring Patient Recovery Using Wireless Physiotherapy Devices

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**Abstract.** We aim to improve physiotherapy patients' recovery time by monitoring various prescribed tasks and displaying a score associated with how well the patient has performed said task. This kind of feedback would be desirable in situations where physical proximity between the physiotherapist and his patient is not always convenient or achievable. Having a way to remotely perform and receive feedback on prescribed tasks remedies that problem. We used a wireless device that contains accelerometer (acceleration) and gyroscope (angular velocity) sensors to collect motion information from the patient. After this information has been collected, it is processed in order to provide a more accurate representation of the performed task. The processed data is then broken up into micro-exercises, parts that make up the specified exercise, to evaluate qualitatively how accurately the exercise was performed and quantitatively how many times the task was performed. Finally, a task score is provided to the user that is based on the Functional Ability Scale and a weighted linear algorithm of the sum of the micro-exercise scores. This allows a patient to receive instant feedback on a performed task without the need to physically interact with a physiotherapist.

## 1 Introduction

In a day and age where mobile technology is ubiquitous, there still are not that many medical applications that take advantage of such a technology. Medical technology that incorporates smart phone technology for use in their program stand to gain ease of use and compatibility, since so many people already own the platform required. Our goal is to create a mobile app that tracks the recovery progress of physiotherapy patients with motor deficits - such as stroke patients - by collecting real time data from wireless sensors about various prescribed exercises and then providing both qualitative and quantitative feedback to the patient without the need for the physiotherapist to be present [1, 2].

As a remedy to the possible schedule conflicts or difficulty in transporting patients with motor deficits, physiotherapists often prescribe exercise regimens in order to help the patient regain his or her motor ability that was lost.

Oftentimes however, these regimens are either followed incorrectly or not as often as prescribed, as the only way of verifying if a regimen is being followed is through patient self-reporting - the accuracy of which cannot be guaranteed.

Our app would remedy this problem. By using a mobile phone to analyze the exercise data sent by the SHIMMER sensor [4], the patient would be able to receive qualitative and quantitative feedback on the regimen exercise he or she performed, thus helping he or she determine how to best remedy the problem. Qualitative feedback would be based on the Functional Ability Scale, FAS [3], while quantitative feedback would display the number of times the patient performed the exercise.

The SHIMMER sensor monitors real-time accelerometer (acceleration) and gyroscope (orientation) data and sends it over a Bluetooth connection. On the receiving end, raw accelerometer and gyrometer data is exported to a comma separated value file (.csv) for storage. As shown in Fig. 1, not everything in the file is accelerometer or gyrometer data. In order to begin processing the raw sensor data, we removed the SensorID, DataType, SeqNo, and TimeStamp values from the file. After that is completed, we process the data. This provides two benefits: the first being that the size of the dataset is reduced, which allows for a faster classification time later on, and second, it allows for a more accurate classification of the data.

	A	B	C	D	E	F	G	H	I	J
1	SensorID	DataType	SeqNo	TimeStamp	AccX	AccY	AccZ	GyroX	GyroY	GyroZ
2	0	255	50	42077	1885	1990	2774	1845	1847	1797
3	0	255	51	42237	1875	1998	2786	1845	1845	1797
4	0	255	52	42397	1885	1979	2782	1845	1848	1796
5	0	255	53	42557	1875	1993	2804	1844	1849	1799
6	0	255	55	42877	1866	2005	2778	1843	1849	1798
7	0	255	56	43037	1886	1961	2790	1843	1850	1796
8	0	255	57	43197	1886	2005	2770	1842	1850	1797
9	0	255	58	43357	1880	1964	2775	1843	1850	1797
10	0	255	59	43517	1901	1987	2787	1843	1850	1797
11	0	255	60	43677	1879	1982	2784	1845	1849	1797
12	0	255	61	43837	1890	1997	2773	1847	1850	1797
13	0	255	62	43997	1880	1989	2776	1848	1848	1796
14	0	255	63	44157	1888	1992	2777	1848	1849	1795

Fig. 1. A portion of the raw data exported to a comma separated value file

## 2 Related Work

The proliferation of pervasive and ubiquitous computing has accelerated the emergence of a new era of primary healthcare that has the potential to change the way healthcare is delivered and health is assessed. The American Medical Association (AMA) recently passed a resolution stating that insurers should reimburse for email consultations. In the resolution, there is also an encouragement for the reimbursement of other forms of virtual care including remote monitoring services. Recent advancement has helped to monitor the activities of daily

living of seniors living alone using a combination of low-cost sensors, advanced mesh networking technologies and profile-based anomaly detection engines [12]. Individuals can also be monitored for illness and early symptoms with the help of real time monitoring, analysis and extrapolation of physiological data such as blood pressure, blood glucose levels, motion data, body weight etc. [8].

Wireless sensor networks will continue to play an important role in next generation smart healthcare. The Fitbit [7], a fitness monitoring equipment based on inertial sensors tracks a user's daily activities and the calories that the user has burned. This same motion data can also be used to monitor patients' progress in rehabilitation programs and to design new regimen. The data collected from body-worn accelerometers, gyroscopes, magnetometers, and pedometers can be assessed for the detection and treatment of gait anomalies, Parkinson's disease, stroke, total knee replacement, fall detection and prevention, etc., even when the subject is located in the home environment. Thus our goal is to provide therapists the technology that will help them to get high-fidelity real time context of the patients without manual intervention. Such technological advances will help people with functional disabilities to live in their home environment and manage their diseases from day to day in the best possible ways.

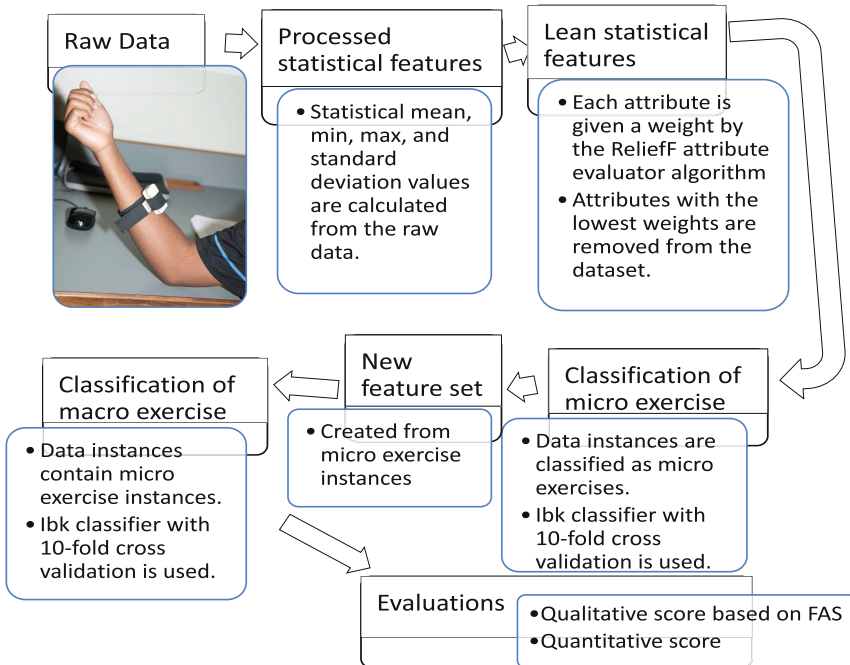
Existing advanced physiotherapy rehabilitation systems mostly use optical motion systems with high speed cameras for kinematic data collection. These systems are expensive, require a large space, and cannot be used outside a laboratory environment [13]. Other relatively standard systems using magnetic and sonic technologies are difficult to be applied without the patient being in rehabilitation clinic. These and other available industry products such as KinTools RT [9], OrthoTrak [10], and Phoenix Technologies Inc [11] do not possess the diversity of sensing systems necessary to monitor a patient's entire physiotherapy conditions, e.g., they lack an EMG sensor based system to measure muscle stiffness. A wearable sensor system with low cost that is easy to deploy and has a robust supporting software infrastructure will be an effective solution in this immersive physiotherapy domain [14]. Such systems can provide additional features to support tele-physiotherapy services and replace the intensive manpower needed for existing in-place physiotherapy approaches. A pervasive computing based physiotherapy approach will also extend the capabilities of monitoring to more varied settings, thereby making it simpler for therapists to examine new exercise regimen and interventions that might improve the patients' overall conditions.

Most of the above system target a specific healthcare problem instead of being adaptive to general purpose physiotherapy. The existing systems are often complex, closed-loop, expensive and proprietary. But recent advancement of pervasive computing and communications encourage us to go beyond the existing systems and visualize an open platform that can support a variety of healthcare services with a little modification on top of the single general-purpose underlying platform for situated health monitoring and maintenance. In relation to physiotherapy, this open platform will enable patients to avail themselves of physiotherapy treatment independent of their location and available clinical resources.

In the more general sense, this enables better awareness of general health and possible interventions that take advantage of a person's everyday environment. Motivated by these challenges and shortcomings we perform preliminary studies to attest the promise of remotely monitoring patient recovery using wireless physiotherapy devices.

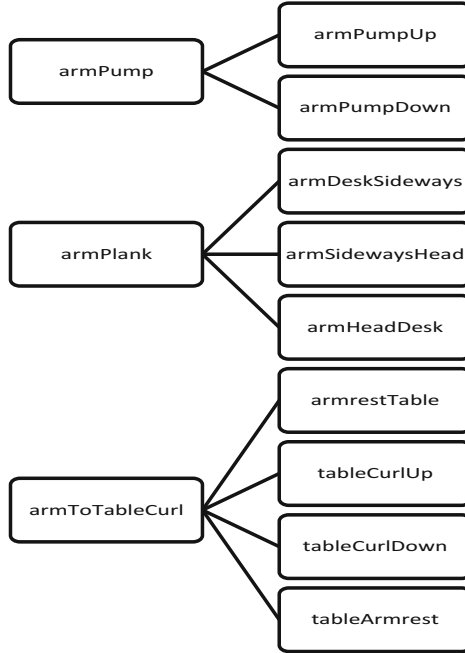
### 3 Methodologies

In order to record exercise data, we used a SHIMMER (Sensing Health with Intelligence, Modularity, Mobility, and Experimental Reusability) wireless sensor [4]. The datasets have been collected from three subjects in a controlled environment using this SHIMMER sensor. Each of the subjects have been asked to perform 10 sets of the three exercises. We then combined the data for each set together to generate the training datasets. Figure 2 shows a flowchart of our data being collected and then segmented into micro and macro exercises in order to determine a qualitative and quantitative result [6]. We collected data that fell into two categories, micro exercise data and macro exercise data. More accurately, we collected macro exercise data and then segmented the exercise into sub exercises known as micro exercises. We then collected data for each individual micro exercise for classification. In total, we collected data about three



**Fig. 2.** An overview of the qualitative and quantitative evaluation procedure of micro and macro exercises

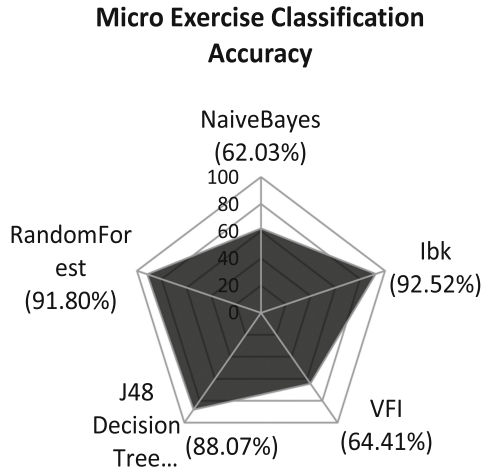
macro exercises and their eleven micro exercises that the macro exercises were segmented into. The three macro exercises we collected were named *armPump*, *armPlank*, and *armToTableCurl*. Each macro exercise was segmented into two, three, or four micro exercises.



**Fig. 3.** Macro to micro exercise mapping

Figure 3 shows our macro exercises and which micro exercises they were segmented into. When classifying macro exercises, we chose to include the set of all eleven micro exercises, even though not all eleven micro exercises were used in a single macro exercise. In order to classify the macro exercises, we first needed to process the micro exercises that the macro exercises were segmented into. From the raw sensor data, we calculated the statistical mean, min, max, and standard deviation of the acceleration and orientation data with a window size of five. With our statistical data, we tested five algorithms implemented in WEKA [5], a program that contains a collection of machine learning algorithms for use in solving data mining problems, to determine which algorithm would provide us with the maximum accuracy in correctly classifying micro exercises. The Fig. 4 shows our results - the micro classification accuracies of each of the five algorithms.

Using WEKA's Ibk classifier gave us the highest percentage of correctly classified micro instances, so we decided to use that. In addition to that, we also used WEKA's implementation of the ReliefF attribute selection algorithm to



**Fig. 4.** Comparisons of micro exercise classification accuracies using various classification algorithms

determine which attributes were least important in classifying. Through experimentation, we determined that removing the five least important attributes, determined by the ReliefF algorithm, before classifying our data with the lbk algorithm resulted in the highest correct classification accuracy.

The same steps used to classify segmented micro exercises were also used to classify the macro exercises. As with the process for the micro exercises, the raw acceleration and orientation data is extracted from the initial comma separated value file and then a window size of five is used to calculate statistical mean, min, max, and standard deviation values of the data. The same five least important attributes that were removed from the micro exercise instances are again removed from the macro exercise instances. However, instead of simply attempting to classify a macro exercise at this stage, we again use the lbk classifier, but this time we also use the micro exercise classification file as a training set to classify each macro exercise instance. This classifies instances of a macro exercise as one of the micro exercise instances in our training set. From there, we further process the segmented macro exercise by taking a count of the micro exercises classified within a window size of five. While this additional step reduces the macro exercise classification accuracy by around one percent, it has the added benefit of being able to use a vastly reduced sample size, thereby requiring less processing power to compute.

Figures 5 and 6 show the confusion matrices of the two methods of processing macro exercises. Our method is to classify a macro stretch according to the micro exercise count within a window size of five, rather than just the processed statistical data.

```

=== Confusion Matrix ===
      a   b   c  <-- classified as
4082   0  25 |   a = armPlank
   0 2392   0 |   b = armPump
   24   5 4112 |   c = armToTableCurl

```

**Fig. 5.** Confusion matrix of macro exercise classification using statistical instances

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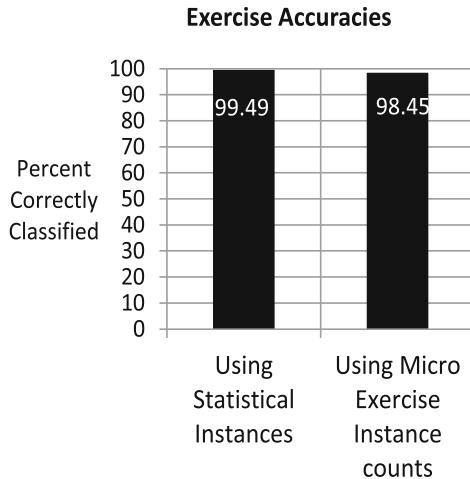
=== Confusion Matrix ===
      a   b   c  <-- classified as
 810   0  11 |   a = armPlank
   2 475   1 |   b = armPump
  17   2 809 |   c = armToTableCurl

```

**Fig. 6.** Confusion matrix of macro exercise classification using micro instance counts

## 4 Evaluation Results

We found that classifying our macro exercises using just the statistical data yielded a higher percentage classification than our method of classifying macro exercises using the counts of micro exercise instances. Figure 7 details the accuracy comparison between the two methods aforementioned. The difference in accuracies of the two methods is close to one percent, which at 99.49% and 98.45% respectively is still fairly reasonable accuracies.



**Fig. 7.** Comparison in accuracies of the two methods, statistical and micro instance counts

In addition to being able to classify over 98% of our macro exercises correctly, we have also developed prototype software that enables us to count the number of *armToTableCurl* macro stretches that a user has performed.

## 5 Discussion and Conclusion

Our decision to classify macro exercises based on the number of micro exercise instances rather than just the statistical mean, min, max, and standard deviation values of the raw data was based on the hope that our method would provide higher exercise classification accuracy over the other method. However, our classification method was not quite as accurate as simply classifying based on statistical values. Our method, however, does provide a couple of obvious benefits over the other method. The first being that the size of the data required to classify is much less. In our case, since we chose to count the micro exercise instances in a window size of five, our data set was five times smaller than the other method. The second benefit is that because the dataset is smaller, the time required to classify macro exercises is greatly reduced. Since our goal was to create a mobile app, having a faster classification time is a benefit when dealing with a smaller, mobile processor.

Future work for this project would include providing a more exhaustive qualitative feedback score based on the Functional Ability Scale (FAS) [3], as well as an improved method of determining the quantitative feedback. In addition to these, we would also need to refine our algorithm to be more lightweight in order for our application to be viable for use in a mobile phone as well as collect data from a more diverse set of micro and macro exercises.

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