

# Context-Aware Approach for Cardiac Rehabilitation Monitoring

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**Abstract.** As technology advances, the usage and applications of context-aware systems continue to spread across different areas in patient monitoring and disease management. It provides a platform for healthcare professionals to assess the health status of patients in their care using multiple relevant parameters. Existing technologies for cardiac patient monitoring are generally based on the physiological information, mostly the heart rate or Electrocardiogram (ECG) Signals. Other important factors such as physical activities and time of the day are usually ignored. We propose a context-aware solution for cardiac rehabilitation monitoring using multiple vital signs from the physiological and activity data of the patient. This research considers the activity of the patient alongside the time of the activity to facilitate physicians decision-making process. We provide a personalised physical activity recognition processing by generating a personalised model for each user. A prototype is presented to illustrate our proposed approach.

**Keywords.** Cardiac Monitoring, Context-Aware, Cardiac Rehabilitation, Activity Recognition

## 1. Introduction

Cardiac diseases such as arrhythmia, stroke and coronary heart disease (CAD) could possibly be managed by monitoring of patients' bio-signals in real-time. The symptoms of these diseases are diverse, ranging from minor chest palpitations, chest pain, fainting (syncope) to sudden heart attack, depending on the type and severity of the heart disease [5]. According to British Heart Foundation statistics report, heart and circulatory diseases cause about 28% of all death in the UK, accounting nearly 170,000 deaths each year, an average of 460 people each day [4]. Public Health England also reported that it cost about 7.4 billion every year for healthcare relating to cardiovascular diseases [9].

Fortunately, the most recent advances in ECG monitoring and with the help of modern mobile phone technology, monitoring a patient at distance has become easier and more accessible. However, it is essential to note that in order to predict abnormalities, a specific vital sign such as heart rate, ECG signals may not provide sufficient knowledge to assist physicians in decision-making [20]. The combination of physiological param-

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eters and patient's activity details can go a long way in providing a platform that will enable physicians to make accurate and timely decisions; thereby, offer a better environment for cardiac rehabilitation monitoring. The rehabilitation process offers training and support that enable patients to recover and return to their normal activities [8]. It is the main aspect of secondary prevention of cardiovascular disease [16], which assists patient in the recovery process and provide a means for healthcare professionals to frequently assess the health status of patients using contextual information.

Context-aware approach can provide a platform to aggregate and correlate multiple vital parameters for effective cardiac rehabilitation monitoring. Generally, context-awareness is the ability of a system to use contextual information to provide services that are relevant to the stakeholders based on their preferences and needs [2]. In healthcare, a context-aware system could be regarded as a system that uses patient context details to provide useful information or services to clinicians, patient or relatives. These contexts could be location, time, identity or activity of the considered subject. It plays essential role in the healthcare delivery decision-making process, assisting physicians to effectively and timely monitor patients in their care.

Considering the increase in cardiac death and the financial burden it imposes on the government, individuals and different organisations [5], effective and efficient cardiac condition monitoring system is timely and need to be automated. This work aim to develop a context-aware solution for cardiac condition monitoring to facilitate the physician's decision making process. The proposed system is ongoing research targeting cardiac rehabilitation monitoring using context-aware approach. The work involves data collection from ECG and smartphone sensors, machine learning algorithm training for activity recognition, and personalized recommendation interface for effective monitoring. During the monitoring process, the subject will be required to carry a smartphone running android app for data collection and Holter monitor for ECG signals recording. The contextual information will be aggregated, analyzed and visualized for early abnormality detection, pattern discovery and personalized recommendations. The proposed system takes into consideration the activity of the patient and the corresponding time in decision-making process. We present a scenario below for more understanding of this work.

*Mike was recently discharged from the hospital after suffering from cardiac disease. In order to avoid cardiac readmission, his physician, Dr. Charles needs to keep in touch with him frequently. Mike lives far away from the hospital, therefore creating a barrier for constant visits to the hospital. To constantly monitor Mike's health status and offer personalised recommendations, Dr. Charles need a platform that will generate and correlate Mike's physiological signals and activity data from distance. The platform will enable Mike see his physician's recommendations and adjust accordingly without visiting the hospital.*

The rest of the work is organised as follow: In section 2, we presented related work by other researchers, discussing their strengths and limitations. Section 3 discussed context-aware system for cardiac rehabilitation monitoring. We talked about activity recognition process in section 4. Section 5 discussed the research methodology, while section 6 and section 7 presents experimental analysis and the system prototype respectively. Finally, section 8 shows the conclusion of the work and future research direction.

## 2. Related Work

There are several studies relating to cardiac condition monitoring. However, most of these studies focus on identifying irregularities in a specific vital sign. The authors in [3] introduced a prototype for continuous monitoring of cardiac activity using electrocardiography and heart rate. The system is made up of an intelligent sensor data acquisition system, a processing system based on Bluetooth technology and a communicator for transferring data to a medical server. The researchers in [17] presented android-based heart monitoring system that uses a heart rate monitor data to provide a detailed report about cardiac patient health status, transmit the data to an online database and generate an emergency alert when necessary. The evaluation of the system proved its effectiveness, however, using a single parameter of the considered patient might not provide enough knowledge to the clinician in order to make appropriate decisions [20].

Recently, some authors proposed context-aware system for cardiac patient monitoring, however, research in this area is still in infancy and needs significant improvement. Authors in [12] developed a system that record biosignal of the patients and request for context information when there is abnormality. The patient has to input information about his/her daily life activities. So this system is not fully automatic since it requires the user's intervention. The focus of [7] was in the older adult, they developed a cloud-based system that extracts health parameters from Fitbit device and ECG sensors. The context information of the patient is sent via social media to the patient's doctor, relative or friends when there is an abnormal change. The Fitbit device could only recognize steps of the subject and could not show specific activity performed such as walking, running and sitting. Fitbit device was also used in the work by [10] to collect the steps count of the monitored patient. An intelligent mobile system based on rule decision support system for cardiac patients was introduced by [18]. The system correlates data from the ECG sensor with physical activities such as walking, running and body posture. They used threshold rule to determine the activity of the patient and argued that testing the system with 15 healthy persons proved the effectiveness of the proposed approach. The researchers in [11] also used threshold approach to detect different activities (Lying, Standing, Walking, Jogging) for cardiac disease monitoring and achieved classification accuracy of 94%. Though the approach shows effective; however, using threshold rule to determine the activity of the user might not be the best option due to the wide range of physical activities. Another similar solution was presented by [14], they combined the ECG signals with physical activities for cardiac disease diagnosis. They applied machine learning techniques to recognize human activities. Machine learning provides computation methods and learning mechanism for developing a model to predict a situation based on the ground truth. They recruited seven healthy persons who wore ECG sensor on their chests and carried smartphones in their pockets to collect sensor data. Each subject was asked to perform three different activities (Running, Rest and Walking). The sensor data from the seven participants were aggregated, processed and used to train J48 decision tree algorithms in order to predict the activity of the users when new data without ground truth are fed into the model.

### 3. Context-aware Cardiac Condition Monitoring

The fundamental idea behind context awareness in healthcare is to develop a proactive and efficient system that can adapt to the changes in the patient's condition and environment [21]. This system makes use of multiple vital signs of the subject to provide useful and real-time information to the physicians. A context-aware system in healthcare could be regarded as a system that uses patient context details to provide useful information or services to clinicians, patient or relatives.

In this work, we consider the ECG signals from Holter monitor, activity data from smartphone and time of the day as essential contexts to provide effective and efficient system for cardiac rehabilitation monitoring. These contexts are selected based on interview with the stakeholders and the quest to present real-time, reliable and energy-efficient system. The system will collect and aggregate a vast amount of data from Holter monitor and smartphone, train algorithms to detect the activity and the corresponding time of the activity. This will enable the physician to monitor and assess the health status of the patient under their care and offer personalised recommendation.

The architecture of the proposed system is presented in figure 1. During the monitoring process, the subject will be required to carry a smartphone running the android app for activity data collection. Android is selected for this research due to the wide use of Android phones around the world. The android app will collect and aggregate a huge amount of data from the smartphone while the Holter monitor will collect and aggregate ECG signals from the user, this form the context acquisition unit. Then, at the modelling and storage stage, the acquired contexts will be presented in an efficient and structured format and stored in a database for retrieval; while at the context reasoning and visualisation stage, relevant features will be extracted from the data and fed into machine learning algorithms. Also at this stage, the outcome of the analysis will be presented as a decision support tool using mobile and web technologies. Finally, healthcare professionals will be able to offer personalised recommendations to the patient based on the contextual analysis. The recommendations could be in the form of text or auditory format advising patient regarding the state of his/her health.

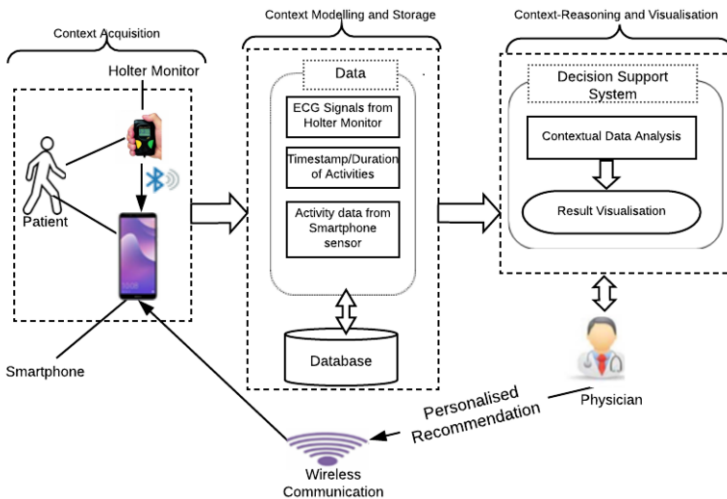
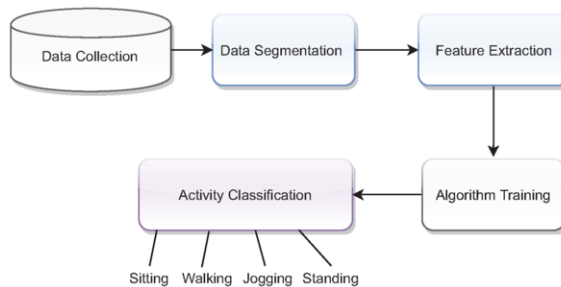


Figure 1. System Architecture

#### 4. Activity Recognition

Physical activity recognition is an essential part of cardiac rehabilitation monitoring [19]. Recognising human activities such as walking and running or human-related actions aims to observe and understand what type of activities or routines performed by the subject at time-interval [22]. The work in [19] pointed out that the primary focus of cardiac rehabilitation is on exercise and needs to be automated. There are several devices and apps available for activity recognition, however, these gadgets and apps are designed for the population and do not consider different patterns by which individuals carry out their physical activities. We present a personalised physical activity recognition system for cardiac rehabilitation monitoring. The system collects sensor data from the patient, trains the algorithms and uses it to recognition his/her activities. This approach will enable the algorithms to recognize the activities with high accuracy [13]. The system also considered the time of the activity in order to guide physician when making a decision for patient.

The built-in accelerometer sensor in modern Smartphones has made it possible to dynamically detect the activity of the user. To recognise user's activity, he/she need to carry the mobile phone while doing daily activities. As indicated in figure 2, the first phase of activity recognition is data collection using mobile app, the mobile app collects the x, y and z coordinates and in most cases along with the timestamps. Secondly, the sensor data are processed and partitioned into equal groups at time-interval representing the segmentation stage. In the third stage, time or frequency domain features are extracted from each group, and finally, the extracted features are used to train machine learning algorithm in order to classify new data without ground truth.



**Figure 2.** Activity Recognition Process

#### 5. Methodology

We adopted the User-Centred Intelligent Environments Development Process (U-CIEDP) for this research [1]. The stakeholders are at the heart of this methodology, hence making it crucial to involve the healthcare professionals at the early stage of this work. The initial stage is interview with cardiologist and a cardiac rehabilitation nurse to gather user requirements. The outcome of the interview reveals that physical activity recognition is an essential part of cardiac rehabilitation, this lead to the next stage, activity recognition.

As shown in figures 3, we implemented android app to collect accelerometer sensor data using smartphone. Members of the Research Group on Development of Intel-

lignant Environments of Middlesex University participated in the data collection. Each participant were asked to select the position of the phone and the activity to perform. To have uniform experimental analysis, each person has to select pocket as the position of the phone and carry out four different activities(sitting, standing, walking and jogging). Pocket were selected as the preferred position due to its convenient when doing daily activities. The sensor information were processed and used to train machine learning algorithms for activity recognition. The system detects activity of the subject and the corresponding time of the activity.

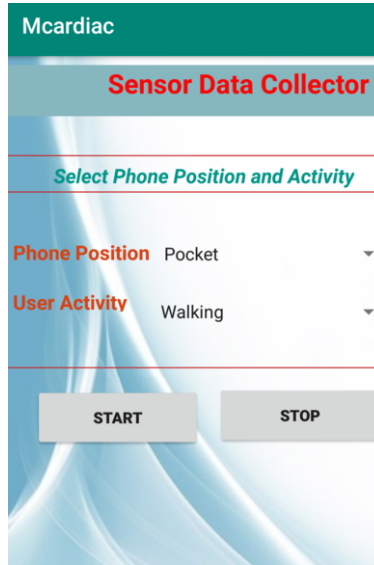


Figure 3. Sensor Data Collection App

## 6. Experimental Analysis

To carry out the experimental analysis, we collected samples of accelerometer data from five volunteers. The participants were asked to put the phone in the pocket and perform four activities; sitting, walking, jogging and standing. The mobile app collects the sensor data at frequency of 50Hz using the built-in function(Sensor\_Delay\_Game) provided by android. The frequency might vary depending on the processing capacity of the smartphone. The mobile app collects the x,y and z coordinates along with the timestamps. The magnitude of the three coordinates was computed to handle orientation problems of the smartphones making it four features; x,y,z, and magnitude. The magnitude (mg) of the total acceleration is computed by the square root of the sum of the squared acceleration of three axes in the Equation below.

$$mg = \sqrt{x^2 + y^2 + z^2}$$

The raw sensor data cannot be used to train machine learning algorithm directly, hence we applied sliding window technique to partition the sensor data into 4 seconds equal windows and extracted some time domain features from each segment. Assuming the

window length as  $w$ , for a given time series  $[x_1, x_2, x_3, \dots, x_n]$ , each window can be expressed as  $[xw_1, xw_2, xw_3, \dots, xw_n]$ , then features were extracted from each window and used to train machine learning algorithms. To provide a robust activity recognition approach, we personalised the activity recognition process by training and testing the algorithm using each participant’s dataset individually. Table 1 represents the extracted features for the analysis. Each feature represents an input vector used for the algorithm training. The extracted feature vectors were split into 70% for training and 30% for testing. We compared different machine learning algorithms using WEKA tool as presented in table 2. Each participants dataset were analysed and random forest performed better in teams of classification accuracy.

Random forest is an ensemble machine learning approach that works by averaging several predictions of independent base models [6]. It is developed by combining the prediction of different trees, each of which is trained individually. It can be used for both classification and regression tasks and is capable of handling noise data and can prevent data overfitting. Due to limited space, we present the confusion matrices for only Random Forest across the participants in tables 3,4,5,6,7 . The confusion matrices show the contribution of each activity in the classification accuracy of the algorithm. From the analysis, User2 and User4 had no misclassification while one or more misclassification are recorded in the rest of the users.

Furthermore, the dataset from User1 was used to train random forest algorithms in python environment. Personalised model generated and used to classify new datasets without ground truth. Figure 4a shows the graphical representation of the predicted activities from User1.

**Table 1.** Extracted features for algorithm training

Feature	Equation
Mean	$mean = \frac{1}{N} \sum_{i=1}^N x_i$
Variance	$var = \frac{1}{N} \sum_{i=1}^N (x_i - mean)^2$
Standard Deviation	$std = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - mean)^2}$
Minimum Value	$min = MIN(x_i)$
Maximum Value	$max = MAX(x_i)$
Median value	$median = \frac{N+1}{2}$
Standard Error of the Mean(sem)	$sem = \frac{std}{\sqrt{N}}$

## 7. System Prototype

Modern smartphones and wearable devices are contributing immensely to the healthcare delivery process by assisting doctors and healthcare professionals to monitor patients at

**Table 2.** Comparison of different machine learning algorithms

Algorithms	User1(%)	User2(%)	User3(%)	User4(%)	User5(%)	Average (%)
KNN(k=3)	95.24	96.67	95.65	100	90.24	95.55
Random Forest	97.62	100	95.65	100	92.68	97.19
Multilayer Perceptron	95.24	96.67	93.48	100	87.80	95.64
Naïve Bayes	97.62	100	89.13	100	87.80	94.91
Decision Tree(J48)	100	100	84.78	96.55	90.24	94.31

**Table 3.** User1

	Sit	Stand	Walk	Jog
Sit	14	0	0	0
Stand	0	9	0	1
Walk	0	0	10	0
Jog	0	0	0	8

**Table 4.** User2

	Sit	Stand	Walk	Jog
Sit	8	0	0	0
Stand	0	8	0	0
Walk	0	0	6	0
Jog	0	0	0	8

**Table 5.** User3

	Sit	Stand	Walk	Jog
Sit	10	0	0	0
Stand	0	9	1	0
Walk	0	0	11	1
Jog	0	0	0	14

**Table 6.** User4

	Sit	Stand	Walk	Jog
Sit	15	0	0	0
Stand	0	16	0	0
Walk	0	0	18	0
Jog	0	0	0	9

**Table 7.** User5

	Sit	Stand	Walk	Jog
Sit	2	0	0	0
Stand	0	8	0	0
Walk	1	1	4	0
Jog	0	0	0	24

distance. Sensors embedded in these devices could be used to collect and aggregate a large amount of data from patient's biosignals, and analysed to assist doctors in decision-making. The most regularly used tool for cardiac condition monitoring is the Holter monitor. Holter monitor is a portable and continuous monitoring device used to generate and record ECG signals [15]. Some of the modern Holter monitors allow users to wear the device while doing their normal activities and are capable of transmitting user's details to the physicians through mobile phones. The Holter monitor generates ECG signals, and the heart rate of the user can be computed from the signals. Smartphone is equipped with an accelerometer sensor that generates data regarding the movement of the user. The generated raw sensor data are processed and used to train machine learning algorithm for activity detection. The aggregation of the information from these gadgets could assist physicians in decision making. In figure 4, we provide a prototype showing the graphical representation of the activity information from smartphone and ECG signals from the Holter monitor.

The information from the Holter monitor represents the heartbeat at the time interval while the information from the smartphone shows the activity of the user at a time interval. The concept is to enable healthcare professionals to understand the activity of the patients when reading the ECG signals and the heart rate. If there are any irregularities in the signals, the physician can consider the activity of the subject as a guide in decision-making. For instance, if the heart rate is high, and the activity of the user is sitting. The physician might consider it as an abnormality, however, if the heart rate is high and the activity before or during that particular time is jogging, the physicians might argue that the increase in the heart rate might be due to the subject doing a rigorous activity which makes the heart to beat faster. This approach will enable the physician to offer right advice to the patient instead of prescribing unnecessary medications. Furthermore, as physical activity recognition is an essential part of cardiac rehabilitation, the system will enable healthcare professionals to assess the activity level of the patient under their care during rehabilitation monitoring.



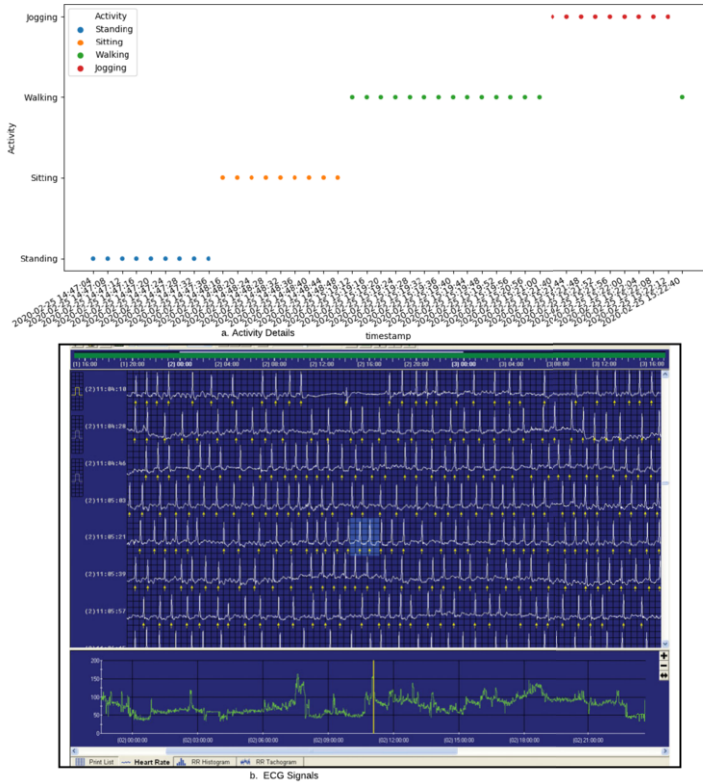


Figure 4. System Prototype Showing the (a) Activity Details and (b) ECG signals

## 8. Conclusion and Future Work

A prototype to illustrate a context-aware approach for cardiac rehabilitation monitoring is presented in this work. We considered the physiological information and activity details of the user in developing a context-aware system. The system could be used as a guide in the decision making process during rehabilitation. Due to the importance of activity recognition during the rehabilitation scheme, we automated the activity recognition process by training machine learning algorithm to automatically detect the activity of the user during the program. To present a robust activity recognition system, we personalised the process by using the individual dataset to train and test the algorithm.

In future, we will investigate more activities and experiment with more volunteers. Furthermore, as this is research in progress, we plan to implement a real-time activity recognition process and provide an interface for effective communication between the patient and the healthcare professional.

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