Development of a System for Detection and Monitoring of Heart Diseases based on ECG and Activity Recognition

Pinar Bisgin, M.Sc.

HealthCare, Fraunhofer Institute for Software and System Engineering, Dortmund, Germany
Email: pinar.bisgin@isst.fraunhofer.de

***Abstract*—Patients with suspected chronic heart failure or symptomatic arrhythmias receive long-term Electrocardiogram ECG. The ECG device records the electrical activity of the heart in a variety of activities in everyday life. The patient must record a protocol during the measurement to demonstrate the various activities of daily life and at different times of the day. The protocol to be made is usually inaccurate because the patient has not usually logged every single activity. Through the fusion of activity detection and ECG, this information is passed on to the physician to aid in the assessment of the diagnosis. Furthermore, the method can be used for therapeutic purposes to consider cardiac activity in specific activities. Human daily activity recognition has gained much attention since it has a wide range of applications. In the preliminary work was a Body Sensor Network (BSN) developed consisting of accelerometer, gyroscope, and barometer. For that purpose 20 subjects are participated. This collected sensor data was evaluated using Machine-Learning algorithms. Finally, the averaged classification results could be obtained: achieving F1 score of (89.22 ± 3.18) % with the SVM algorithm. In upcoming work, the proposed activity classification module will be combined with a mobile ECG sensor. This combination can be provided with a possible and correct protocol, but also relieve the patient. In further steps, the data can be identified using the combined sensor data which have pathological patterns. For this purpose, classification algorithms will be used.**

***Keywords*–Human-activity recognition; activity recognition; wearable sensors; mobile healthcare system; ECG; fusion.**

I. Introduction

Patients with chronic heart failure or symptomatic arrhythmias, a long-term Electrocardiogram (ECG) is usually performed. Long-term ECG is an important tool for diagnosing cardiovascular diseases and assessing the involvement of the cardiovascular system in primary extracardiac disorders. The long-term ECG and the accompanying activity measurement can be used to monitor the state of health. The vital parameters of the patient can be recorded at a defined load. The resting pulse, pulse during exercise and the respiratory rate can be recorded - especially in the larger efforts, such as climbing stairs. The recording of activities with a longer period of time is very important. With the pacemaker already the activity can be measured. Thus, the health condition of the patient can be observed and deteriorations can be detected. Furthermore, it is suitable for controlling antiarrhythmic pharmacotherapies [1], i.e. Congestive Heart Failure (CHF). To diagnose these arrhythmias, patients are medically monitored in their everyday life. The monitoring can take several hours to several days. The measurement takes place at the home of the patients. The ECG device records the electrical activity of the heart in a variety of activities in everyday life. The patient must protocol the various activities they are performing during the measurement using a long-term ECG [2], because the doctor wants to evaluate the heart activity of the patient. The patient protocols his activities so that the doctor can look at each recorded heart activity, what the patient was doing, and whether the heart activity is in the normal range. After the data has been recorded, it is evaluated by a physician. However, the protocol to be made is usually inaccurate because the patient usually has not logged every single activity. If irregularities are identified by the doctor, it cannot be understood exactly what the patient was doing at a given time. This combination can be provided with a possible and correct protocol, but also relieve the patient. Furthermore, pathological patterns can be identified from the data by using classification algorithms.

The paper addresses past work, and aims to unveil future work as part of a PhD. The paper is organized as follows: Section 2 describes the preliminary work for activity recognition. Finally, section 3 describes some thoughts of the dissertation.

II. Preliminary Work

A. Body Sensor Network

In order to achieve therapeutic success, an attempt is made to recognize the activity by means of a BSN. A BSN includes a number of implanted, portable (near-the-body) or near-remote sensors and low power actuators. The purpose of BSNs is not only to monitor the patient's illness, but also to make predictions about the course of the disease. For long-term patient monitoring, daily activities must be detected with high accuracy. The focus is on activities in daily life such as rest, walking, jogging, and climbing stairs.

Figure 1. Wearable sensor platform fixed at a test subject's upper body.

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The BSN is based on an Arduino Micro, which contains a ATmega32U4 microcontroller. The data is provided via I2C by the 10DOF sensor module GY86, which comprises the barometric pressure sensor MS5611, as well as the MPU6050 3D accelerometer and 3D gyroscope. A MicroSD breakout board+ was used for data storage. The entire platform is fixed at the test subject's upper body by use of a chest band (see Figure 1) [3]. The study was conducted with 20 healthy volunteers ($45/55$ % male/female) with age (24 ± 4) years (range 21–38 years). The study protocol was divided into two parts, which provided the training and test data and had an approximate duration of 20 min and 30 min, respectively. Both protocol stages comprised several phases of the activities standing, walking, jogging, upstairs and downstairs.

B. Activity Classification

Activity classification can aid in the evaluation of the medical data. The classification task is usually used to provide medical sensor systems with context information such as the ECG. For this purpose, positioned a sensor platform on the back of the subjects. Subsequently, a study was carried out with the sensor platform. The platform recorded sensor data stored on an integrated SD card. For evaluating the sensor platform with efficacy the conducted study was divided into two parts. In the two parts, the algorithm's training and evaluation data were collected on the classes walking, standing, running, ascending stairs and descending stairs. The goal was to evaluate daily activities with the algorithm.

This sensor data were evaluated using Machine-Learning algorithms like k-Nearest-Neighbors (KNN), Support Vector Machines (SVM), Neural Networks, Random Forest and AdaBoost. The process caused the calculation of various features and several feature selection techniques used to reduce dimensionality. It helped to improve the classification quality. Finally, parameter optimization was carried out for each classifier. The hyperparameter was optimized with respect to the F1 score [4]

$$\mathrm{F1} = \frac{2 \cdot \mathrm{P} \cdot \mathrm{S}}{\mathrm{P} + \mathrm{S}}, \tag{1}$$

which combines the two common measures of classification accuracy, sensitivity *S* and precision *P*

$$\mathrm{S} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \qquad \mathrm{P} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}, \tag{2}$$

where TP, FP, and FN denote true positives, false positives, false negatives, respectively. As a result, an optimal combination was obtained of parameters for the respective classifiers. After completion of optimization, the second part of the study was evaluated using a grid search. Then, averaging of the optimized parameters over all the subjects was done.

TABLE I. SVM CLASSIFICATION RESULTS.

Activity	*Sensitivity [%]*	*Precision[%]*	*F1-Score [%]*
idle	97.69 ± 1.76	99.02 ± 1.71	98.33 ± 1.04
walk	85.80 ± 7.11	94.88 ± 3.74	89.88 ± 3.79
run	95.11 ± 6.29	99.79 ± 0.94	(7.28 ± 3.60)
up	91.51 ± 11.81	76.85 ± 11.55	82.35 ± 7.55
down	85.91 ± 8.81	73.69 ± 13.38	78.26 ± 8.57
total	91.21 ± 3.39	88.85 ± 2.51	89.22 ± 3.18

With these values, finally, the averaged classification results could be obtained: F1-score of the SVM $(89.22 \pm 3.18)\%$, which achieved the best results. While KNN, Random Forest and AdaBoost had promising results, too, Neural Networks did not work on the data. The results of the classification using SVM of the activities *idle*, *walk*, *run*, *up* and *down* are summarized in TABLE I.

III. Upcoming Work

With the accelerometer, gyroscope and the barometer, it is possible to recognize the activities standing, walking, jogging, upstairs and downstairs. There were no motion artifacts detected by positioning the BSN on the back. The portable device activity classification module is developed on a continuous basis because of the following requirements: classification accuracy, energy consumption and computation time.

In my dissertation, I would like to expand the activity recognition by adapting the sensor system to real-time measurement. The research question is: the combination of heart data and activity helps to better differentiate physiological states. Furthermore, the proposed scheme has great potential in real-time applications due to its inability to dimensionality reduction, simple classifier structure, and good recognition performance.

In addition to the activity, a continuous ECG measurement should take place in order to detect direct changes. This component should also be integrated into the sensor network. With the combination of the ECG and activity detection, on the one hand, the physician can receive the assignment of heart activities during daily activities. On the other hand, an evaluation can be made by the algorithm, so that a home monitoring system can detect pathological patterns from the data without going to a doctor. For this reason, I have to involve clinical partners to consider patients with CHF. The CHF is a chronic progressive disease that affects the pumping capacity of the heart muscle. The heart is unable, despite sufficient blood supply, to promote sufficient cardiac output. Cardiac output refers to the volume that the heart spills into the circulation per minute [5]. Patients and clinical partners will be involved during these projects from the University Hospital Aachen and Bonn, Germany.

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