A faster approach to ECG analysis in emergency situations

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Abstract— **Every day, a substantial number of people need to be treated in emergencies and these situations imply a short timeline. Especially concerning heart abnormalities, the time factor is very important. Therefore, we propose a full-stack system for faster and cheaper ECG taking aimed at paramedics, to enhance Emergency Medical Service (EMS) response time. To stick with the golden hour rule, and reduce the cost of the current devices, the system is capable of enabling the detection and annotation of anomalies during ECG acquisition. Our system combines Machine Learning and traditional Signal Processing techniques to analyze ECG tracks to use it in a glove-like wearable. Finally, a graphical interface offers a dynamic view of the whole procedure.**

I. Introduction

Heart Diseases and, in particular, Cardiovascular Diseases (CVDs) are the number 1 cause of death globally [1]. Among the most common disorders are heart attacks and strokes, which occur when blood is blocked from flowing into the heart or the brain. The concept of "golden hour", first coined by R Adams Cowley [2], applies to such diseases. It refers to the critical time which occurs after an injury or traumatic event has happened in which the likelihood of preventing death through proper care is the highest. Great effort is put into improving intensive and immediate care to lower fatalities. The approach taken in recent years is to have a pre-evaluation of the ST-Elevation Myocardial Infarction (STEMI) [3] patients on-site using electrocardiogram (ECG) monitoring systems, to direct the ambulance to a Hospital where a primary percutaneous coronary intervention [4] (PCI) is available. Interpretation of the ECG requires an understanding of the fundamental structure of the heart and its electrical signals. Analysis of the ECG can give precious information for monitoring and detecting abnormal situations, namely rhythm disturbances or arrhythmia, heart block, electrolytes disturbances and intoxication, ischemia and infarction, or structural problems. The main objective is to obtain useful information about the activity of the heart.

ECG signal in emergencies is usually taken using 10 electrodes, providing a view of the heart from 12 different angles [5]. Studies like the one made by Gordon E. Dower [6] have shown that it is possible to obtain the same 12 views of the heart using a reduced number of electrodes with the EASI placement of the electrodes (E, A, and I from the Frank lead system plus S positioned over the upper end of the sternum) [5] [7]. The reduction of the number of leads results in a faster placement of the gel-coated electrodes for the paramedics. Therefore, one of the most relevant challenges in computer science and medicine is how to properly combine the field-specific knowledge to offer a better, more secure, and faster solution. This concept led to the development of several [8] [9] new devices aimed at detecting ECG making use of a reduced number of electrodes, with vast experimentation on the positioning of the sensors, and to the application of computationally intensive methods for signal analysis in the biomedical field. Many of these methods fall under the wide spectrum of Machine Learning, in which statistical methods are used to progressively improve the ability of a computer program to recognize patterns in data [10]. This approach is often used in classification tasks, where data has to be categorized and recognized.

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The main contributions of this work can be summarized as follows:

- Development of a model combining Machine Learning and traditional Signal Processing for ECG annotation and analysis.
- Exploration of the reduction of electrodes in emergencies.
- Design of a dynamic interface as a support for medical personnel.

The rest of the paper is organized as follows: Section II explores the state of the art and the latest research regarding innovative methods of obtaining the ECG signal and analyzing it; Section III describes the development process and the design choices; Section IV presents the most notable results. Finally, Section V explores options for future developments.

II. Related Work

Electrical signal acquisitions from the heart were first recorded in 1872 [11]. The state of the art has thus seen a lot of changes over time, regarding both the physical and the analytical part. Initially, the ECG was taken using only three leads [12]. Later on, thanks to the introduction of the precordial and the augmented unipolar limb leads [13] medics were able to obtain the 12-lead ECG which in 1954 was recognized by the American Heart Association as the standard [14]. Looking at Italy, in hospital environments, Cardioline and Nihon Kohden are the go-to for the professional acquisition of 12-leads ECG signal. In pre-hospital environments, especially in emergencies, the choice is limited mainly to the PhysioControl LIFEPAK 12/15 and

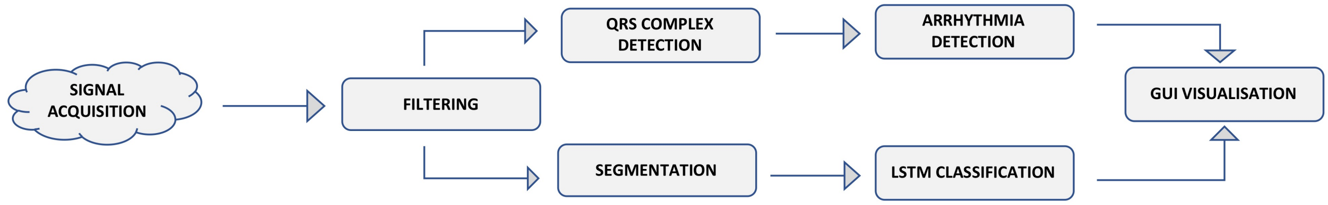

Fig. 1. High level schema of the end-to-end ECG acquisition system and analysis, divided into a signal processing branch and a Machine Learning one

the Mortara ELI10. New developments have taken place in the hardware area, mainly regarding portability. Small devices, such as the AliveCor KardiaMobile [8], allow for self-taking of ECG signal, but they are limited in the number of views obtained. For this reason, they provide just basic diagnoses, such as Atrial Fibrillation [15]. Another solution is the PhysioGlove by Commwell [9], a reusable 12-lead ECG acquisition system implemented in a glove that is designed to be worn by the patient.

Given the different possibilities of acquisition systems, big steps have been made also in ECG signal analysis, among which is the employment of Machine Learning (ML). Most approaches are based on classical ML models such as K-Nearest-Neighbors and Decision Forests [16]. Artificial Neural Network (ANN) based solutions have started to emerge. ANNs often perform better and require fewer data preprocessing compared to traditional solutions. For example, Convolutional Neural Networks have been used in ECG analysis to unify feature extraction and data analysis into a single model [17].

III. Methodology and Implementation

This Section presents a description of the proposed end-to-end solution, namely two parallel processing workflows and a Graphical User Interface (GUI) to display the obtained results, as shown in Fig. 1. To provide a proof of concept solution we researched an innovative sensor placement over a wearable ECG acquisition system. The results we obtained are exposed in Section IV.B. The remainder of the Section provides an in-depth description of each of the stages of the proposed solution.

A. Dataset selection

The first step to develop our system was to select a dataset eligible for analysis. The data had to have enough samples, annotations, and all 12 derivations. Many and diverse samples are needed for a machine learning model to generalize on new data, and annotations are needed for training a neural network for a classification task. Working with all 12 derivations would allow us to achieve the best performance possible, as well as experimenting by training the model on a subset of the derivations. Our final decision fell onto the St. Petersburg dataset. It is composed of 75 12-leads 30 minute long segments extracted from 32 holter records. The original records were collected from patients undergoing tests for coronary diseases. The annotations in the dataset were produced by an automatic algorithm and then manually corrected, according to the PhysioBank beat annotation definitions. The annotations appearing in the St. Petersburg dataset are normal beat, left bundle branch block beat, right bundle branch block beat, atrial premature beat, supraventricular premature or ectopic beat, premature ventricular contraction and R-on-T premature ventricular contraction.

B. Data preparation

As shown in Fig. 1 a step of data preparation was necessary ahead of the data analysis. The proposed pipeline is composed of a filtering stage and a segmentation stage.

1) Data Filtering: The reference unfiltered dataset has two main problems: baseline shift, caused by involuntary movements of the patient, and high-frequency noise, which accompanies every electrical measurement. These issues were solved using a bandpass filter, which removed both the low-frequency baseline shift and the high-frequency noise, retaining only the meaningful part of the data.

2) Data Segmentation: The raw data, being 30-minutes acquisitions, was not fit for training our machine learning model. To have more usable data, we extracted many 2 second long annotated samples. Each sample was labeled according to the anomalies it contained, including the case of normal ECG. This step allowed us to compose the data into different datasets and preform class balancing.

C. Machine Learning

We used a particular neural network architecture called Long Short-Term Memory (LSTM) [18]. Such architecture is particularly well suited for processing sequences of data [19], and ECG signals in particular [20] [21]. We aimed to identify the category of disturbance present in short segments of signal. One method to achieve this is to construct a multi-classification network which, however, requires the classes to be mutually exclusive. Since more anomalies can show up in the same segment, we decided to develop a solution based on training a binary classifier for each class, an approach that trades efficiency with the accuracy of the diagnosis. This way every neural network is trained to distinguish between the presence or absence of a particular anomaly. We elaborated an algorithm to create a different dataset for each anomaly in the ECGs. Every dataset was composed of *"ill"* samples, each made of the segments containing a specific anomaly, and *"sane"* samples, each made of segments which did not contain any trace of the specific anomaly, but that could contain all other anomalies together with normal beats. This allows the single binary classifier to recognize the presence of a generic anomaly as well as the specific type of anomaly. We then proceeded with class balancing. If classes are not balanced the model just learns to recognize every sample as the most common class. This problem falls in the category known as overfitting; we solved it by undersampling the most common class in every dataset. The different availability of anomalies in the St. Petersburg dataset reflected in the size of the dataset for each anomaly. The biggest dataset was the one related to Premature Ventricular Contraction with 12800 samples, followed by the Atrial Premature Beat dataset with 3600 samples. Every dataset was split into training, validation, and testing using a 70-15-15 ratio. The architecture of the neural network we developed makes use of the LSTM architecture to analyze and extract information from the sequences of readings that make up the ECG segments. The output of the LSTM layers is passed to a dense network, which reduces its dimensions to two and makes possible the classification through a softmax function. The structure of the network is made up of three consecutive LSTM layers with 32 hidden neurons, followed by two fully connected layers of size 16 and 2. While the LSTM layers are fed the entire sequence, only the last activation is passed to the fully connected layers. Every neural network was trained on its dedicated training set using the ADAM policy for 10 epochs with a batch size of 128 and using the accuracy as minimization criteria. At inference time the ECG segment is analyzed by all neural networks. We created our RNNs using various MATLAB libraries (Parallel, Signal Processing, Deep Learning) and then trained them on a GTX 1050 Ti NVIDIA GPU to enable hardware acceleration within MATLAB.

D. Signal Analysis

As can be seen in Fig. 1, signal processing is the approach we chose to detect QRS Complexes and to detect Tachycardia and Bradycardia anomalies. We used QRS complex detection to calculate the BPM trend. The algorithm we developed to calculate the BPM takes a filtered ECG signal, finds and marks the R peaks of the signal, and transforms it into an R or not-R binary signal. Starting from the binary signal, the algorithm counts the number of R peaks in the interval that it is analyzing (n_p) and calculates the distance between the first and the last peak (d_p). The algorithm calculates the BPM trend using the following formula: $BPM = 60 \cdot \frac{f_s \cdot n_p}{d_p}$ where f_s is the sampling rate. Using the output of this algorithm we were able to detect Tachycardia and Bradycardia by developing an algorithm that considers both the age of the patient and the trend of the BPM value. Our algorithm detects Tachycardia and Bradycardia following the guidelines from the U.S. National Library of Medicine.

E. GUI

The final part of our system is the GUI, which was designed to be easy to use and to display the results obtained using our solution to doctors and other users. To develop it we used MATLAB tools for a clean and simple interface. The idea behind our GUI was to have a main page where the user could see a general ECG and BPM trend of the whole measurement and have a clear vision of anomalies found in the track. A secondary page was used to display only the samples found to contain anomalies. An operating example of the most significant components of our interface is visible in Fig. 2, where you can see one of four panels that graphically shows the progress of the ECG where anomalies were found, an index of distortion of the original signal, the maximum BPM value recorded during the track and 10 buttons that take on different colors depending on the frequency of detection of the specific anomaly within the track.

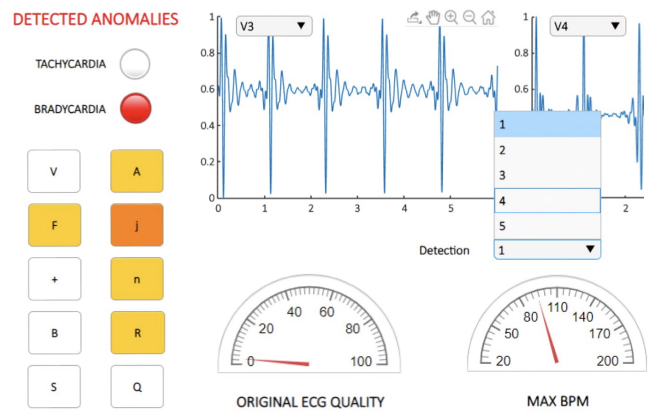

Fig. 2. Main components of the GUI

TABLE I
TABLE OF ACCURACY RESULTS

Anomaly	Accuracy
Premature Ventricular Contraction	98%
Atrial Premature Beat	81%
Fusion of Ventricular and Normal Beat	73%

IV. EXPERIMENTAL RESULTS

In this section, we present the obtained results dividing them into hardware and software.

A. Software

Our signal analysis software uses two simultaneous approaches: Machine Learning and Signal Processing. Regarding the performance of the neural network, we obtained varying results. We managed to improve them through filtering the data, improving the segmentation algorithm, and experimenting with different neural network structures. The final results come from the evaluation of the performance of the predictive models on the respective test datasets. We believe that the performance of the machine learning model is strictly related to the availability of data regarding the specific anomalies, as all of the metrics we used showed the same descending trend as the number of available samples decreased. We observed clear signs of over-fitting in the machines trained to recognize anomalies that were not present in large quantities ($<$1000 samples) in the data-set.

Table 1 shows the accuracy results of the 3 most common anomalies in the dataset, detected with a machine learning approach. The levels of sensitivity and specificity reached above 95% for the most common anomalies, progressively lowering as the availability of data decreased. We observed 99,8% accuracy in detecting tachycardia and bradycardia, in line with the traditional state of the art signal analysis methods. Those two approaches are then combined in a simple-to-use interface (GUI visualization).

B. Hardware

Various solutions for the implementation of a possible wearable were explored. A first attempt revolved around capacitive sensors. However, they tend to be noisy and unreliable especially in emergency situations [22], so we opted for wet (gelled) Ag/AgCl electrodes with the adhesive approach, making them more workable on fast and dynamic environments. To lower the placement time of those sensors we focused on the EASI solution, which provides easier to find positions for the electrodes and reduces their number by half, leaving the chest available for the medical personnel. The acquired signal is filtered by an Arduino MKR1010, that was able to apply in real-time a notch and HPF filter, while detecting QRS complexes, demonstrating that the whole idea of a portable device is feasible. The signal from the Arduino is then transmitted to a cloud computing platform where it is processed by the LSTM networks.

V. Conclusions

With this work, we have given first proof that a fast and dynamic approach in ECG taking is possible. The proposed solution will increase the comfort and ease of use for paramedics. Given the fewer sensors required, it will be a cheaper alternative to commercially available products as it can analyze an ECG trace taken in a short time detecting a significant number of anomalies. Ideally, our future developments will focus on developing a glove which fully supports EASI placement that, in combination with our analysis system, will form a complete product and then obtaining a bigger and richer dataset to work with. Finally, creating a custom loss function for the neural network to give more weight to false negatives and less on false positives.

VI. Acknowledgements

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