Detecting life-threatening patterns in Point-of-care ECG using efficient memory and processor power*

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Abstract. Currently, Point-of-Care (POC) ECG monitoring works either as plot devices or alarms for abnormal cardiac rhythms using predefined normal trigger ranges and some rhythm analysis, which raises the problem of false alarms. In comparison, complex 12-derivation ECG machines are not suitable to use as simple monitors and are used with strict techniques for formal diagnostics. Thinking outside the ICU setting, where high-end devices are available for patient monitoring, we aim to identify, on streaming data, life-threatening hearth electric patterns using low CPU and memory, enabling ward monitors, home devices and even wearable devices to be able to identify such events.

Keywords: anomaly detection · ECG · matrix profile · time series · point-of-care

1 Introduction

Currently, Point-of-Care (POC) ECG monitoring works either as plot devices or alarms for abnormal cardiac rhythms using predefined normal trigger ranges. Modern devices also incorporate algorithms to analyze arrhythmias improving their specificity. On the other hand, full 12-derivation ECG machines are complex, are not suited to use as simple monitors, and are used with strict techniques for formal diagnostics of hearth electric conduction pathologies. The automatic diagnostics are derived from a complete analysis of the 12-dimension data after it is fully and well collected.

In February of 2015, the CinC/Physionet Challenge 2015 was about "Reducing False Arrhythmia Alarms in the ICU" [3]. The introduction article stated that it had been reported that up to 86% resulting of the alarms are false, and

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this can lead to decreased staff attention and an increase in patients' delirium [2, 7, 9].

This subject draws attention to the importance of correctly identify abnormal hearth electric patterns. Meanwhile, this opens the opportunity of thinking outside the ICU setting, where we still monitoring patients (and ourselves) using devices with low processing power, as for example ward monitors, home devices and wearable devices.

2 Objectives and research question

While this research was inspired on the CinC/Physionet Challenge 2015, its purpose is not to beat the state of the art on that challenge, but to identify, on streaming data, abnormal hearth electric patterns, specifically those which are life-threatening, using low CPU and low memory requirements.

The main questions is: can we accomplish this objective using a minimalist approach (low CPU, low memory) while maintaining robustness?

3 Related Works

Their algorithm did a pretty good job on the Physionet test set. However, independently of their approach to this problem, none of the authors reported benchmarks, memory usage, robustness test, or context invariance that could assure its implementation on real monitors to reduce alarm fatigue indeed.

There are other arrhythmias that this challenge did not assess, like atrial standstill (hyperkalemia), third-degree atrioventricular block, and others that may be life-threatening in some settings. Pulseless electrical activity is a frequent condition in cardiac arrest but cannot be identified without blood pressure information. This information is usually present in ICU settings but not in other locations.

4 The planned approach and methods for solving the problem

4.1 The data

The dataset used is the CinC/Physionet Challenge 2015 public dataset [3], composed of 750 patients with at least five minutes records. The *events* we seek to identify are the life-threatening arrhythmias as defined by Physionet in Table 1.

4.2 Matrix Profile

This work will use the state-of-the-art [4, 5] time series analysis technique called Matrix Profile (MP) that once computed, allows us to derive frameworks to all

Table 1. Definition of the five alarm types used in CinC/Physionet Challenge 2015.

Alarm	**Definition**
Asystole	No QRS for at least 4 seconds
Extreme Bradycardia	Heart rate lower than 40 bpm for 5 consecutive beats
Extreme Tachycardia	Heart rate higher than 140 bpm for 17 consecutive beats
Ventricular Tachycardia	5 or more ventricular beats with heart rate higher than 100 bpm
Ventricular Flutter/Fibrillation	Fibrillatory, flutter, or oscillatory waveform for at least 4 seconds

sorts of tasks, as motif discovery, anomaly detection, regime change detection and others [11].

The streaming data, coming from one patient, is processed to create its MP in real-time. Then, the FLOSS algorithm [6] is computed for detecting a regime change. When a new regime is detected, a sample of this new regime is analysed by a model and a decision is made. If the new regime is life-threatening, the alarm will be fired.

4.3 Detecting regime changes

The regime change detection will be using the FLOSS algorithm [6] which is an on-line algorithm built on top of the computed MP. The algorithm is based on the assumption that between two regimes, the most similar shape (its nearest neighbor, 1-NN) is located on "the same side". The details of the algorithm are described in the original paper [6]. In short, the algorithm keeps track of the number of 1-NN references (called *Arc Counts*) that crosses a point in time. As shown on the original article, figures 2 and 3 [6], a drop in the Arc Counts indicates a regime change.

4.4 Classification of the new regime

The next step towards the objective of this work is to verify if the new regime detected by the previous step is indeed a life-threatening pattern that we should trigger the alarm.

The method of choice is classification. The simplest algorithm could be a `TRUE`/`FALSE` binary classification. Nevertheless, the five life-threatening patterns have well defined characteristics that may seem more plausible to classify the new regime using some kind of ensamble of binary classifiers or a "six-class" classifier (being the sixth class the `FALSE` class).

Since the model doesn't know which life-threatening pattern will be present in the regime (or if it will be a `FALSE` case), the model will need to check for all five `TRUE` cases and if none of these cases are identified, it will classify the regime as `FALSE`.

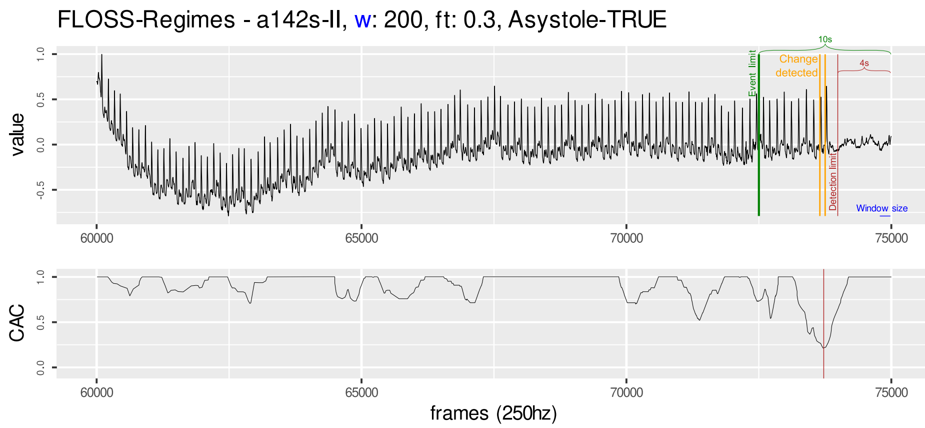

Fig. 1. Regime change detection example. The graph on top shows the ECG streaming; the green line marks the ten seconds before the original alarm was fired; the red line marks the minimum amount of time for asystole criteria; the blue horizontal line represents the size of the sliding window. The graph on the bottom shows the Corrected Arc Counts as seen by the algorithm; the red line marks the detection point.

In order to avoid exceeding processor capacity, an initial set of shapelets [10] can be sufficient to build the `TRUE`/`FALSE` classifier. And to build such set of shapelets, leveraging on the MP, we will use the Contrast Profile [8].

The Contrast Profile (CP) looks for patterns that are at the same time very *similar* to its neighbors in class A while is very *different* from the nearest neighbor from class B. In other words, this means that such pattern represents well class A and may be taken as a "signature" of that class.

For a more complete understanding of the process, in the original article, the figure 6 shows a practical example [8].

In this work, an example of candidates for ventricular tachycardia is presented on Fig. 2.

4.5 Feasibility trial

A side-project called "false.alarm.io" has been derived from this work (an unfortunate mix of "false.alarm" and "PlatformIO" [1], the IDE chosen to interface the panoply of embedded systems we can experiment with). The current results of this side-project are very enlightening and show that the final algorithm can indeed be used in small hardware. Further data will be available in the future.

5 Research Team

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- Co-supervisor: Professor Eamonn Keogh (UCR, Riverside)

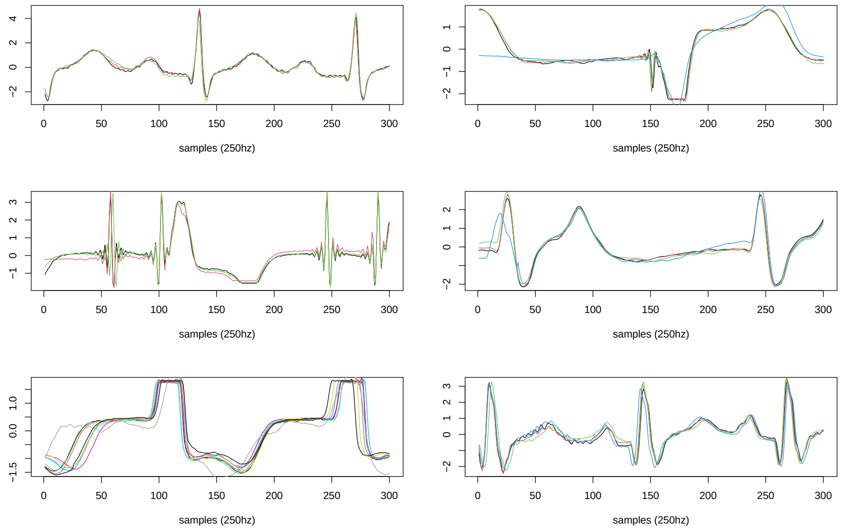

Fig. 2. Shapelet candidates for Ventricular Tachycardia.

6 Expected results and outcomes

At the end, this thesis will provide a framework for identify life-threatening conditions using biological streaming data on devices with low CPU and low memory specifications. We expect to achieve a high quality model on identifying these pathological conditions, maintaining its robustness in presence of noise and artifacts seen on real-world applications.

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