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

Francisco Bischoff[1,2][0000−0002−5301−8672]
Pedro Pereira Rodrigues[1,2][0000−0001−7867−6682]

[1] Department of Community Medicine, Information and Health Decision Sciences (MEDCIDS), Faculty of Medicine, University of Porto, Porto, Portugal
[2] Center for Health Technology and Services Research (CINTESIS), Faculty of Medicine, University of Porto, Porto, Portugal

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. The study design is comparable to a diagnostic study, where high accuracy is essential. Physionet's 2015 challenge yielded very good algorithms for reducing false alarms. However, none of the authors reported benchmarks, memory usage, robustness test, or context invariance that could assure its implementation on small devices. We expect to identify the obstacles of detecting life-threatening ECG changes within memory, space, and CPU constraints and using the proposed methods, assess the feasibility of implementing the algorithm in the real world and other settings than ICU monitors.

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

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the author's name. Submissions should also include a short abstract, keywords, introduction to the topic being addressed in the project and relevant research questions, a brief state of the art in the field, and the methodology to be pursued.

1 Introduction (introduction topic being addressed in the project)

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. Both systems do not handle disconnected leads and patient's motions, being strictly necessary to have a good and stable signal to allow proper diagnosis. These interferences with the data collection frequently originate false alarms increasing both patient and staff's stress; depending on how it is measured, the rate of false alarms (overall) in ICU is estimated at 65 to 95% [10].

Alarm fatigue is a well-known problem that consists of a sensory overload of nurses and clinicians, resulting in desensitization to alarms and missed alarms (the "crying wolf" situation). Patient deaths have been attributed to alarm fatigue [18]. In 1982, the increase in alarms with "no end in sight"; studies have demonstrated that most alarm signals have no clinical relevance and lead to clinical personnel's delayed response. Ultimately patient deaths were reported related to inappropriate responses to alarms [18].

In April of 2013, The Joint Commission [3] issued the Sentinel Event Alert [13], establishing alarm system safety as a top hospital priority in the National Patient Safety Goal. Nowadays (2021), the subject is still on their list, in fourth place of importance [4].

In February of 2015, the CinC/Physionet Challenge 2015 was about "Reducing False Arrhythmia Alarms in the ICU [8]. The introduction article stated that it had been reported that up to 86% resulting of the alarms are false, and this can lead to decreased staff attention and an increase in patients' delirium [7, 14, 16].

This subject draws attention to the importance of correctly identify abnormal hearth electric patterns in order to avoid the overload of clinical staff. 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 the research question (relevant research questions)

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 in order to be able to generalize the use of such information on lower-end devices, outside the ICU, as ward devices, home devices, and wearable devices.

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

3 Related Works (a brief state of the art in the field)

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 (the methodology to be pursued.)

4.1 Research plan and methods

Matrix Profile Matrix Profile (MP) [19], is a state-of-the-art [9, 11] time series analysis technique that once computed, allows us to derive frameworks to all sorts of tasks, as motif discovery, anomaly detection, regime change detection and others [19].

For brevity, let's just understand that the MP and the companion Profile Index (PI) are two vectors that hold one floating point value and one integer value, respectively, regarding the original time series: (1) the similarity distance between that point on time (let's call these points "indexes") and its first nearest-neighbor (1-NN), (2) The index where this this 1-NN is located. The original paper has more detailed information [19]. It is computed using a rolling window but instead of creating a whole distance matrix, only the minimum values and the index of these minimum are stored (in the MP and PI respectively).

The MP implementation in R is being used on this thesis.

The data The dataset used is the CinC/Physionet Challenge 2015 public dataset [8], modified to include only the actual data and the header files in order to be read by the pipeline and is hosted by Zenodo [2] under the same license as Physionet.

The dataset is 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.

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

The fifth minute is precisely where the alarm has been triggered on the original recording set. To meet the ANSI/AAMI EC13 Cardiac Monitor Standards [6], the onset of the event is within 10 seconds of the alarm (i.e., between 4:50 and 5:00 of the record). That doesn't mean that there are no other arrhythmias before.

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

Detecting regime changes The regime change approach will be using the *Arc Counts* concept, used on the FLUSS (Fast Low-cost Unipotent Semantic Segmentation) algorithm, as explained by Gharghabi, *et al.*,[12].

The FLUSS (and FLOSS, the on-line version) algorithm is built on top of the Matrix Profile (MP)[19]. Recalling that the MP and the companion Profile Index (PI) are two vectors holding information about the 1-NN. One can imagine several "arcs" starting from one "index" to another. This algorithm is based on the assumption that between two regimes, the most similar shape (its nearest neighbor) is located on "the same side", so the number of "arcs" decreases when there is a change on the regime, and increases again. As shown on the original article, figures 2 and 3 [12], this drop on the *Arc Counts* is a signal that a change on the shape of the signal has happened.

The choice of the FLOSS algorithm (on-line version of FLUSS) is founded on the following arguments:

- **Domain Agnosticism:** the algorithm makes no assumptions about the data as opposed to most available algorithms to date.
- **Streaming:** the algorithm can provide real-time information.
- **Real-World Data Suitability:** the objective is not to *explain* all the data. Therefore, areas marked as "don't know" areas are acceptable.
- **FLOSS is not:** a change point detection algorithm [5]. The interest here is changes in the shapes of a sequence of measurements.

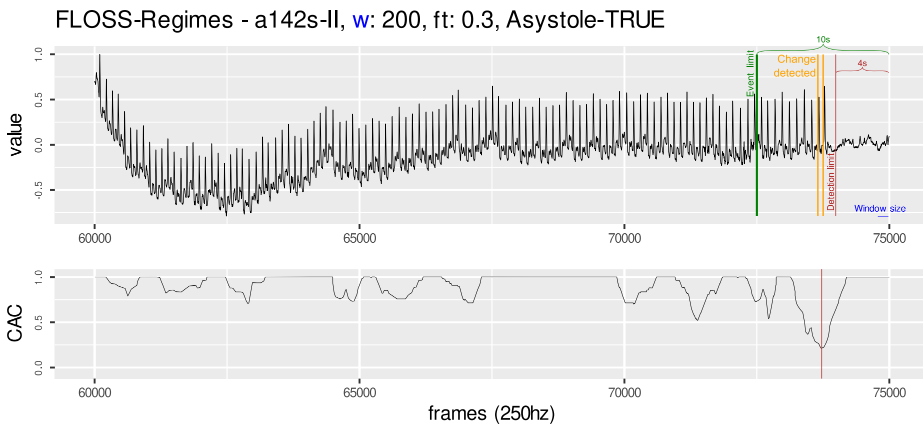

Fig. 1. Regime change detection example. The graph on top shows the ECG streaming; the blue line marks the ten seconds before the original alarm was fired; the red line marks the time constraint of 1250; the dark red line marks the limit for taking a decision in this case of Asystole the blue horizontal line represents the size of the sliding window. The graph on the middle shows the Arc counts as seen by the algorithm (with the corrected distribution); the red line marks the current minimum value and its index; the blue horizontal line shows the minimum value seen until then. The graph on the bottom shows the computed Arc counts (raw) and the red line is the theoretical distribution used for correction.

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`.

In order to avoid exceeding processor capacity, an initial set of shapelets [17] 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 [15].

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 [15].

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

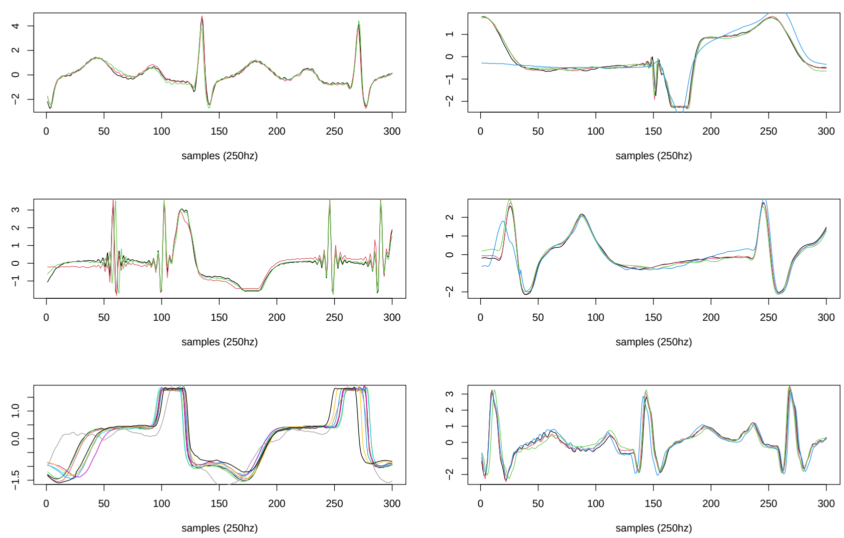

Fig. 2. Shapelet candidates for Ventricular Tachycardia.

4.2 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.

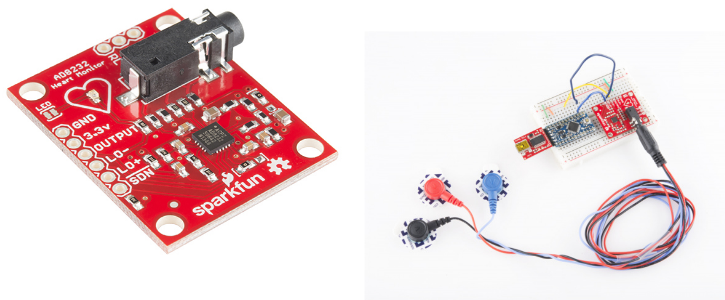

Fig. 3. Single Lead Heart Rate Monitor

A brief mentioning, linking back to the objectives of this work, an initial trial was done using an ESP32 MCU (Fig. 4) in order to be sure if such small device can handle the task.

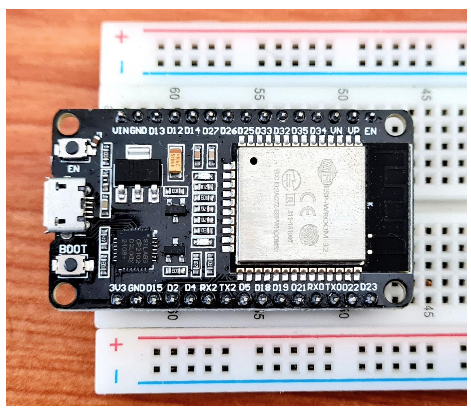

Fig. 4. ESP32 MCU

Research Team

- Thesis Author: Francisco Bischoff
- Supervisor: Professor Pedro Pereira Rodrigues
- Co-supervisor: Professor Eamonn Keogh (UCR, Riverside)

4.3 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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