Framework for ECG analysis*

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. We aim to identify, on streaming data, life-threatening hearth electric patterns to reduce the number of false alarms, using low CPU and memory maintaining robustness. 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 real monitors to reduce alarm fatigue indeed. We expect to identify the obstacles of detecting life-threatening ECG changes within memory, space, and CPU constraints and to reduce ECG monitor's false alarms using the proposed methodology, and assess the feasibility of implementing the algorithm in the real world and other settings than ICU monitors.

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. 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%[12].

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[24]. In 1982 it was recognized 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[24].

In April of 2013, The Joint Commission[5].

In February of 2015, the CinC/Physionet Challenge 2015 was about "Reducing False Arrhythmia Alarms in the ICU[20]. There are many arrhythmias but those which should be most accurate are those that requires immediate attention, specifically those called life-threatening. The life-threatening CinC/Physionet Challenge 2015 addressed are shown on Table 1.

~~The present paper demonstrates a set of methods to improve the accuracy in real-time analysis using 12 seconds of one ECG channel. Our contributions are:~~

- blabla
- blabla
- blabla

*This work has been done under the scope of - and funded by - the PhD Program in Health Data Science of the Faculty of Medicine of the University of Porto, Portugal - heads.med.up.pt

Table 1: Definition of the 5 alarm types used in CinC/Physionet Challenge 2015 challenge.

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

Table 2: Challenge Results on Streaming

Score	**Authors**
81.39	Filip Plesinger, Petr Klimes, Josef Halamek, Pavel Jurak
79.44	Vignesh Kalidas
79.41	Krasteva et al.??? did I miss that?
79.02	Paula Couto, Ruben Ramalho, Rui Rodrigues
76.11	Sibylle Fallet, Sasan Yazdani, Jean-Marc Vesin
75.55	Christoph Hoog Antink, Steffen Leonhardt

Objectives and the research question

This research aims to identify, on streaming data, abnormal hearth electric patterns, specifically those which are life-threatening, to be a reliable signal for Intensive Care Units to respond quickly to those situations. It also may be able to continuously analyze new data and correct itself shutting off false alarms.

As it is known, this goal is not a new problem, so the main questions to solve are: (1) Can we reduce the number of false alarms in the ICU setting? (2) Can we accomplish this objective using a minimalist approach (low CPU, low memory) while maintaining robustness? (3) Can this approach be used in other health domains other than ICU or ECG?

Related Works

The CinC/Physionet Challenge 2015 produced several papers aiming to reduce false alarms on their dataset. On Table 1 it is listed the five life-threatening alarms present in their dataset.

They used as score the following formula, which penalizes five times the false negatives (since we do not want to miss any real event):

$$Score = \frac{TP + TN}{TP + TN + FP + 5 * FN}$$

The five-best scores in this challenge are presented on Table 2[11, 13, 16, 18, 22].

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.

The planned approach and methods for solving the problem

State of the art

A literature review of the last ten years is being conducted to assess state of the art for ECG automatic processing collecting the following points if available : (1) The memory and space used to perform the primary goal of the algorithm (sound an alarm, for ex.). (2) The type of algorithms used to identify ECG anomalies. (3) The type of algorithms used to identify specific diagnoses (like a flutter, hyperkalemia, and others). (4) Their performance (accuracy, ROC, etc.)

A broad search will be conducted on Pubmed, Scopus, Google Scholar, device manuals, and other specific sources.

Keywords:

- ECG AND monitoring AND ICU
- ECG AND[time series]
- ECG AND automatic AND interpretation

Articles published after "The PhysioNet/Computing in Cardiology Challenge 2015: Reducing False Arrhythmia Alarms in the ICU" will also be analyzed.

Research plan and methods

This research is being conducted using the Research Compendium principles[3]:

1. Stick with the convention of your peers;
2. Keep data, methods, and output separated;
3. Specify your computational environment as clearly as you can.

Data management is following the FAIR principle (findable, accessible, interoperable, reusable)[25].

Currently, the dataset used is stored on a public repository[2].

Type of study

This thesis will be a diagnostic study as the algorithm must classify the change in pattern as positive or negative for life-threatening.

The data

Initially we will use the CinC/Physionet Challenge 2015 dataset that is publicly available on Physionet. This dataset is a good start for exploring the main goal of reduce false alarms. This dataset was manually selected for this challenge and the events were labeled by experts, so it is not RAW data. All signals have been resampled (using anti-alias filters) to 12 bit, 250 Hz and have had FIR bandpass [0.05 to 40Hz] and mains notch filters applied to remove noise. Pacemaker and other artifacts may be present on the ECG[10]. Furthermore, this dataset contains at least two ECG derivations and one or more variables like arterial blood pressure, photoplethysmograph readings, and respiration movements.

These variables may or may not be helpful for increasing the sensitivity or specificity of the algorithm. It is planned to use the minimum set of variables as it is known in multi-dimensional analysis that using just two (or some small subset) of all the dimensions can be much more accurate than either using all dimensions or a single dimension[15].

It is desirable that real data extracted from Portuguese ICU could be used in further stage to assess the validity of the model in real settings and robustness (using RAW data instead of filtered data). The variables available on Physionet's dataset are commonly available on Portuguese ICU's.

Workflow

All steps of the process will be managed using the R package `targets`[19] from data extraction to the final report, as shown in Fig. 1.

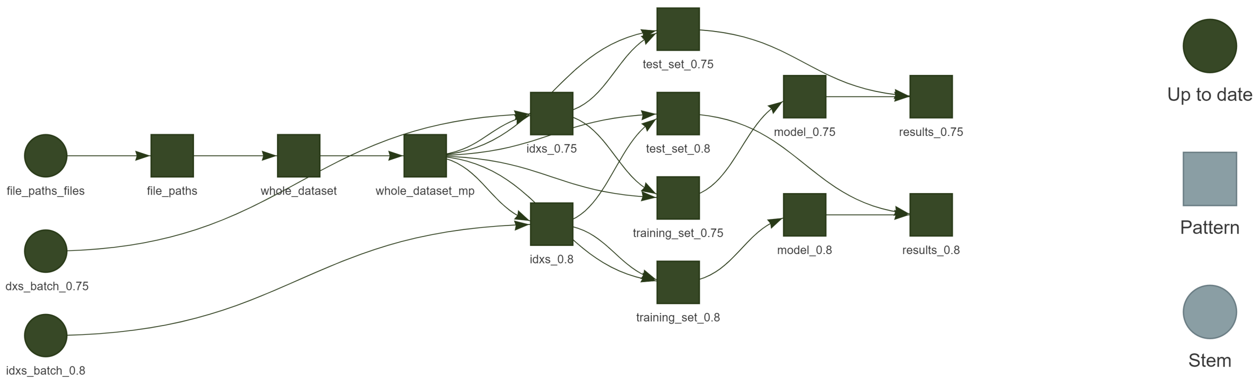

Figure 1: Reprodutible research workflow using ‘targets‘.

The report will then be available on the main webpage[2], allowing inspection of previous versions managed by the R package `workflowr`[8], as we can see in Fig. 2.

Summary | Checks ✔ | Past versions

These are the previous versions of the repository in which changes were made to the R Markdown (`analysis/index.Rmd`) and HTML (`docs/index.html`) files. If you've configured a remote Git repository (see `?wflow_git_remote`), click on the hyperlinks in the table below to view the files as they were in that past version.

File	Version	Author	Date	Message
Rmd	b869025	Francisco Bischoff	2021-03-24	targets and workflowr
html	52e7f0b	GitHub Actions	2021-03-24	Build site.
Rmd	c87e8e1	Francisco Bischoff	2021-03-24	targets and workflowr
Rmd	7c3cc31	Francisco Bischoff	2021-03-23	Targets
html	7c3cc31	Francisco Bischoff	2021-03-23	Targets
html	01a7ace	Francisco Bischoff	2020-07-23	Refactor
html	5f450d2	Francisco Bischoff	2020-05-05	gh-pages placeholder

Figure 2: Reprodutible reports using ‘workflowr.‘

Statistical analysis

The Statistical analysis will be performed using R language v4.0.4 or greater and it will be computed the ROC curve for the algorithm.

The experiment will be conducted using the Matrix Profile concept[15].

In addition, we will combine the fading factors[14, 23] strategy to minimize the memory and space consumption lowering the processor power needed, allowing this algorithm to be used in almost any device.

Research Team

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

Expected results and outcomes

We expect the following results: (1) Identify the obstacles of identifying life-threatening ECG changes within memory, space, and CPU constraints. (2) Be able to reduce ECG monitor's false alarms using the proposed methodology. (3) Assess the feasibility of implementing the algorithm in the real world and other settings than ICU monitors.

And outcomes: (1) To achieve a better score of false alarm reduction than the best on Physionet's 2015 challenge. (2) To push forward the state-of-the-art technology on false alarms reduction, maybe even being domain agnostic. (3) To draw more attention to fading factors as a reliable, fast, and cheap approximation of the true value. (4) To draw more attention to the matrix profile concept as an efficient, agnostic, and almost parameter-free way to analyze time series. (5) To draw more attention of the Patient Monitorization industry on solving the false alarm problem.

Some other facts elsewhere

[ ] >16 seconds of data before the alarm seems to not be better than <16s [7]

References

1. Franzbischoff/false.alarm: PhD programme in health data science, https://github.com/franzbischoff/false.alarm, last accessed 2021/04/08.

2. Franzbischoff/false.alarm: Reproducible reports, https://franzbischoff.github.io/false.alarm, last accessed 2021/04/08.

3. Research compendium, https://research-compendium.science, last accessed 2021/04/08.

4. The joint commission, https://www.jointcommission.org, last accessed 2021/04/08.

5. The joint commission - national patient safety goals, https://www.jointcommission.org/standards/national-patient-safety-goals/hospital-national-patient-safety-goals/, last accessed 2021/04/08.

6. The PhysioNet computing in cardiology challenge 2015 - dataset, https://zenodo.org/record/4634014, last accessed 2021/04/08.

7. Alinejad, G.M. et al.: 2019 27th iranian conference on electrical engineering (ICEE). Presented at the April (2019). https://doi.org/10.1109/iraniancee.2019.8786614.

8. Blischak, J.D. et al.: Creating and sharing reproducible research code the workflowr way [version 1; peer review: 3 approved]. F1000Research. 8, 1749, (2019). https://doi.org/10.12688/f1000research.20843.1.

9. Chambrin, M.C.: Alarms in the intensive care unit: How can the number of false alarms be reduced? Critical care (London, England). 5, 4, 184–8 (2001). https://doi.org/10.1186/cc1021.

10. Clifford, G.D. et al.: The PhysioNet/computing in cardiology challenge 2015: Reducing false arrhythmia alarms in the ICU. In: Computing in cardiology. (2015). https://doi.org/10.1109/cic.2015.7408639.

11. Couto, P. et al.: 2015 computing in cardiology conference (CinC). Presented at the September (2015). https://doi.org/10.1109/cic.2015.7411019.

12. Donchin, Y., Seagull, F.J.: The hostile environment of the intensive care unit. Current Opinion in Critical Care. 8, 4, 316–320 (2002). https://doi.org/10.1097/00075198-200208000-00008.

13. Fallet, S. et al.: 2015 computing in cardiology conference (CinC). Presented at the September (2015). https://doi.org/10.1109/cic.2015.7408640.

14. Gama, J. et al.: On evaluating stream learning algorithms. Machine Learning. 90, 3, 317–346 (2013). https://doi.org/10.1007/s10994-012-5320-9.

15. Gharghabi, S. et al.: Domain agnostic online semantic segmentation for multi-dimensional time series. Data Mining and Knowledge Discovery. 33, 1, 96–130 (2018). https://doi.org/10.1007/s10618-018-0589-3.

16. Hoog Antink, C., Leonhardt, S.: 2015 computing in cardiology conference (CinC). Presented at the September (2015). https://doi.org/10.1109/cic.2015.7408642.

17. Joint Commission: Sentinel event alert - Medical device alarm safety in hospitals. 50, 1–3 (2013). https://www.ncbi.nlm.nih.gov/pubmed/23767076.

18. Kalidas, V., Tamil, L.S.: 2015 computing in cardiology conference (CinC). Presented at the September (2015). https://doi.org/10.1109/cic.2015.7411015.

19. Landau, W. et al.: Ropensci/targets, dynamic function-oriented 'make'-like declarative workflows. Zenodo (2021). https://doi.org/10.5281/ZENODO.4062936.

20. Lawless, S.T.: Crying wolf: False alarms in a pediatric intensive care unit. Critical care medicine. 22, 6, 981–5 (1994). https://www.ncbi.nlm.nih.gov/pubmed/8205831.

21. Parthasarathy, S., Tobin, M.J.: Sleep in the intensive care unit. Intensive Care Medicine. 30, 2, 197–206 (2004). https://doi.org/10.1007/s00134-003-2030-6.

22. Plesinger, F. et al.: 2015 computing in cardiology conference (CinC). Presented at the September (2015). https://doi.org/10.1109/cic.2015.7408641.

23. Rodrigues, P.P. et al.: Memoryless Fading Windows in Ubiquitous Settings. In: Proceedings of the first ubiquitous data mining workshop. pp. 23–27 (2010).

24. Sendelbach, S., Funk, M.: Alarm Fatigue. AACN Advanced Critical Care. 24, 4, 378–386 (2013). https://doi.org/10.4037/nci.0b013e3182a903f9.

25. Wilkinson, M.D. et al.: The FAIR Guiding Principles for scientific data management and stewardship. Scientific Data. 3, 1, (2016). https://doi.org/10.1038/sdata.2016.18.

26. Yeh, C.-C.M. et al.: 2016 IEEE 16th international conference on data mining (ICDM). Presented at the December (2016). https://doi.org/10.1109/icdm.2016.0179.