Characterizing Atrial Fibrillation During and After Cardiac Surgery: An Exceptional Model Mining Approach on ECG Morphology Abnormalities*

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Atrial Fibrillation (AF) [6] is a cardiac arrhythmia occurring for 20%-50% of the patients that undergo cardiac surgery. Patients with AF experience an increased and irregular heart rhythm [1], which can lead to turbulent blood flow and in turn blood clots or even strokes. AF can be detected in the ECG signal recorded by the heartbeat monitor. Early prediction is useful to apply preventative medication to risk groups. Previous research applied several data mining techniques to extract features from electrocardiogram (ECG) signals [9], detect AF [2], and even predict AF [8]. The current applications have one thing in common: they are a black box. Instead, it would be valuable if medical workers knew how algorithms' decisions are made; this would increase their trust in the system and help in explaining the decision-making to patients.

Exceptional Model Mining (EMM) [5] is a Local Pattern Mining technique that aims to find interpretable and exceptional subgroups in the population. Interpretability is guaranteed since subgroups are selected based on their *descriptive attributes*. So, instead of looking at a random selection of ten patients, we look at all patients aged above 65 with chronic kidney disease. Exceptionality of within-subgroup behavior is gauged in terms of multiple *target attributes*, and formally expressed as a *quality measure*. With the use of an appropriate search algorithm and appropriate refinement and anti-redundancy strategies, we can characterize AF and support medical workers in their decisions regarding the need for preventative medication. The advantage of EMM over existing data mining techniques lies in its transparency. It is transparent in that it is known how the subgroups are formulated (subgroup description) and what each subgroup entails (target attributes). Compared to many data mining techniques, EMM discovers local patterns rather than global patterns; it helps to discover patterns that exist in subpopulations rather than in the overall population. Our application of the EMM framework is based on ECG morphology abnormalities. The sinus rhythm of a healthy patient has a PQRST-complex that starts with a P-wave, is followed by the QRS-complex, and is closed by the T-wave. This

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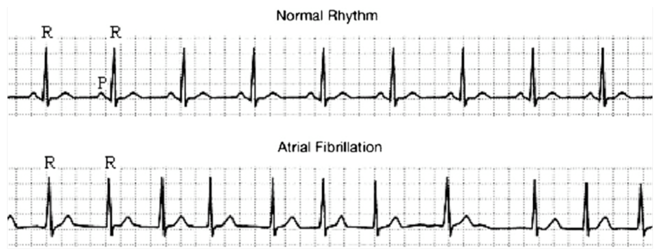

Fig. 1. A visual representation of an ECG signal for patients with a normal, healthy heart rhythm (top), and patients with AF (bottom) [10].

repetition of heartbeats is shown in Figure 1 for patients without and with AF. Patients with AF have absent P-waves and irregular intervals between successive R-peaks [7]. We use these morphology anomalies to identify and score the exceptional subgroups. And additionally use common medical characteristics from the Electronic Health Records (EHR) to define subgroups. An interesting aspect of our approach is that we evaluate discovered subgroups using data obtained with automated alarms from the monitors on AF and arterial blood pressure.

Our method combines the interest in the characterization of AF and the research field on EMM for time series. We do this on raw signals recording during heart operations. After preprocessing and cleaning the signals, we translate the ECG recordings into a database with the basic features of the PQRST-complex and the AF characteristics in the ECG in a transparent way using local maxima and the patients' average heartbeat before the surgery. In this EMM framework, beam search [3] goes over all characteristics in the EHR and uses refinement strategies to build onto existing descriptions. Occurring redundancy issues of the method are removed by keeping the most general description and removing duplicates if the scores of the descriptions are similar. We have tested several quality measures based on the morphology abnormalities.

We found descriptions that align with existing knowledge, and were able to identify unexpected subgroups with AF and subgroups with possible health risks caused by turbulent blood flow. Several new risk factors are present in the descriptions that we found. For instance, we discovered that subgroups of patients who use the laxative *macrogol* at home showed more heart rate variability than the population's average and all got AF after the surgery. And, we found that patients that got administered the painkiller *alfentanil* during the surgery had an increased number of missing P-waves which caused more AF registrations after the surgery. There is clinical relevancy to administering preventative medication to patients who match the descriptions. Looking at the mentioned instances, the doctors know if a patient uses macrogol at home or if they have administered alfentanil during the surgery, and can give these patients group medication to prevent AF and its consequences.

In future work, we will run the experiments on more patients and add DFD validation [4] to filter out false discoveries.

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