FMM-HEAD: ENHANCING AUTOENCODER-BASED ECG ANOMALY DETECTION WITH PRIOR KNOWLEDGE

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ABSTRACT

Detecting anomalies in electrocardiogram data is crucial to identifying deviations from normal heartbeat patterns and providing timely intervention to at-risk patients. Various AutoEncoder models (AE) have been proposed to tackle the anomaly detection task with machine learning (ML). However, these models do not consider the specific patterns of ECG leads and are unexplainable black boxes. In contrast, we replace the decoding part of the AE with a reconstruction head (namely, FMM-Head) based on prior knowledge of the ECG shape. Our model consistently achieves higher anomaly detection capabilities than state-of-the-art models, up to 0.31 increase in area under the ROC curve (AUROC), with as little as half the original model size and explainable extracted features. The processing time of our model is four orders of magnitude lower than solving an optimization problem to obtain the same parameters, thus making it suitable for real-time ECG parameters extraction and anomaly detection.

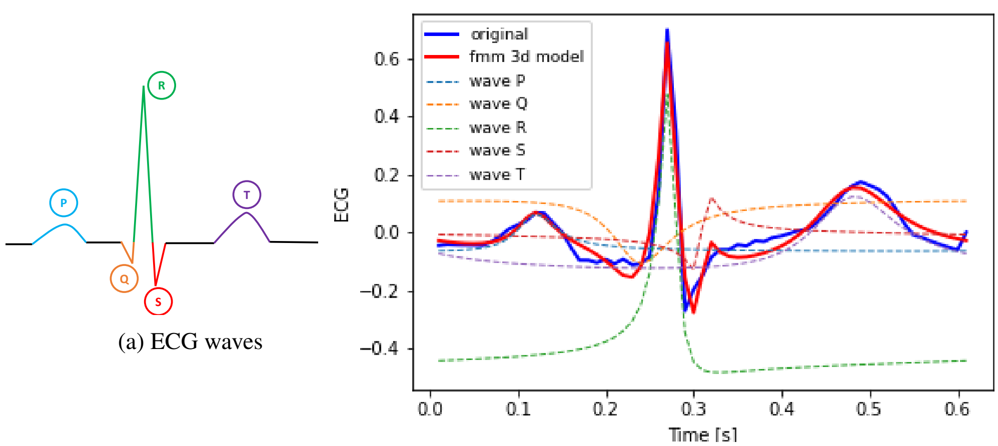
1 INTRODUCTION

Cardiovascular conditions are the main causes of death worldwide (Kaplan Berkaya et al., 2018). Tools such as electrocardiogram (ECG) measurements are utilized to monitor and identify these conditions. An ECG records the heart activity by detecting electrical signals. Electrodes positioned on different parts of the body measure the signal propagation through different planes (*i.e., leads*), thus allowing the analysis of multiple heart sections. Collecting ECG data is standard procedure for both hospitalized patients and outpatients since it allows detection of various cardiovascular conditions, such as myocardial infarction and arrhythmia. In recent years, the amount of available ECG data has increased considerably due to the availability of new data sources. Given the vast amount of available data, (*deep learning (DL)*) has been extensively employed to tackle multiple ECG-related tasks. In this paper, we propose to include ECG prior knowledge in neural networks to increase the detection of anomalies in ECG data and, at the same time, enhance explainability.

Three types of sources are driving the rapid increase in ECG data that needs to be processed. The first of these is smartwatches, such as Apple watches (Apple Inc., 2018) and Fitbit (Google, 2013) while wearable smart textiles (Nigusse et al., 2021) provide continuous and long-term ECG recording. The increasing adoption of smart, low-powered, ECG-capable devices produces a huge quantity of data, but moves the bottleneck from *monitoring* to **processing** the collected data. A second data source is the large shared databases of ECG signals. Institutions and governmental bodies are establishing digital spaces for health data to provide citizens access to their health records as well as supplying de-identified health data to companies for secondary use. Given access to these new data resources, it is expected that both foundational and clinical research will improve care processes by increasing precision in both measurement and downstream mapping onto patients. Thirdly, continuous ambulatory monitoring of high-risk patients produces a huge quantity of data, whose analysis can be difficult since it requires expert knowledge of cardiac conditions and their related effect on ECG measurements (Sampson, 2018a;b).

Anomaly detection through deep learning and (*ML*) models is a promising technique to improve care by spotting health records that deviate from the patterns of normal data *without* any knowledge of what the underlying conditions might be[1]. AutoEncoders (AEs) are a family of ML models that are trained to be able to reconstruct the original input signal. AEs are trained only on data which show no anomaly, so that during the testing and inference phases an anomaly alert will be raised if the input sample does not belong to the normal class. Since loss functions in AEs depend on the difference between the original and reconstructed data, one could infer the presence of an anomaly by looking at the reconstruction error (Hinton & Salakhutdinov, 2006). Specifically, an anomaly can be detected when the reconstruction loss is considerably higher than in the normal case. Multiple rule-based ECG anomaly detection methods have been proposed (Bortolan et al., 2021). Unlike ML models, these techniques rely on extracting well-known parameters that are indicators for specific heart conditions. However, these methods lack generalization capabilities since they rely on strong *a priori* knowledge of what these parameters are; therefore, these assumptions hinder their usability for anomaly detection of *unknown diseases*, *i.e.,* there is no *a priori* knowledge of them.

Although the most prominent strength of AEs is the lack of assumptions regarding the classes and shapes of different inputs, the inclusion of *a priori* information about the structure of input data may be beneficial for the learning procedure. While ECG signals demonstrate different patterns depending on the underlying heart condition, their shape is composed of five waves (shown in Figure 1a), which correspond to different instants of the heart's electrical signal, as measured via the electrodes. For different heart conditions, the shape of these waves change, but the number of waves and their general structure are steady. This *weak a priori* knowledge is valid for almost all ECG classes, but this knowledge is currently not exploited by state-of-the-art anomaly detectors.



(a) ECG waves

(b) FMM ECG Decomposition

Figure 1: (a) shows the ECG shape, while (b) shows the FMM decomposition of an ECG wave

Recently, Rueda et al. (2019) proposed *Frequency Modulated Möbius (FMM)* waves to provide explainable parameters for ECG data (Rueda et al., 2022). They proposed an optimization algorithm to iteratively compute the amplitude, position, direction, and frequency parameters for the five waves composing the ECG signal through a cycle of polarization and depolarization. However, this optimization takes tens of seconds to be solved for a single heartbeat, thus making it unsuitable for real-time monitoring of critical patients and processing of voluminous quantities of ECG data. Yang et al. (2022) have shown that a neural network (NN) can be used to approximate the FMM coefficients and correctly classify heartbeats, but did not apply it for anomaly detection.

Our contributions are threefold. Firstly, we develop FMM-Head, a first approach for incorporating *weak a priori* knowledge of the ECG leads' structure into an AE model. In particular, FMM-Head

[1]In contrast, ML *classification* requires labeled data from different health conditions (*i.e.,* classes) that are used to train the model.