Efficacy of Spectral Signatures for The Automatic Classification of Abnormal Ventricular Potentials in Substrate-Guided Mapping Procedures

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Abstract

Several peculiar spectral signatures of post-ischaemic ventricular tachycardia (VT) electrograms (EGMs) have been recently published in the scientific literature. However, despite they were claimed as potentially useful for the automatic identification of arrhythmogenic targets for the VT treatment by trans-catheter ablation, their exploitation in machine learning (ML) applications has been not assessed yet.

The aim of this work is to investigate the impact of the information retrieved from these frequency-domain signatures in modelling supervised ML tools for the identification of physiological and abnormal ventricular potentials (AVPs). As such, 1504 bipolar intracardiac EGMs from nine electroanatomic mapping procedures of post-ischaemic VT patients were retrospectively labelled as AVPs or physiological by an expert electrophysiologist. In order to assess the efficacy of the proposed spectral features for AVPs recognition, two different classifiers were adopted in a 10-time 10-fold cross-validation scheme. In both classifiers, the adoption of spectral signatures led to recognition accuracy values above 81%, suggesting that the use of the frequency-domain characteristics of these signals can be successfully considered for the computer-aided recognition of AVPs in substrate-guided mapping procedures.

1. Introduction

Nowadays, trans-catheter ablation guided by electroanatomic mapping has been revealed as an effective treatment for post-ischaemic ventricular tachycardias (VTs) [1], [2]. During these clinical procedures, the identification of VT arrhythmogenic sites for their subsequent ablation relies on different signal characteristics and mapping tools, necessarily requiring high expertise of the clinical operators. Specifically, during substrate-guided mapping, bipolar electrograms (EGMs) recorded from damaged myocardial areas are carefully inspected by electrophysiologists, in order to identify those late and fractionated pathological deflections associated with arrhythmogenic areas. These pathological potentials, generally named abnormal ventricular potentials (AVPs), have been often associated with high-frequency components in the scientific literature [3]–[7], and more recently, their spectral contents have been deeply investigated [8], highlighting the presence of peculiar spectral signatures for AVPs. However, there is no evidence that such spectral signatures may be effective for the automatic recognition of AVPs and physiological EGMs, despite the usefulness of artificial intelligence tools for the recognition of arrhythmogenic zones in patients suffering from post-ischaemic VT has been already investigated [9], [10].

In this study, we aim at investigating the impact of these frequency-domain signatures [8] of post-ischaemic EGMs in modelling effective supervised machine learning tools for the classification of physiological EGMs and AVPs.

2. Materials and methods

2.1. Dataset

This retrospective study on anonymised data was approved by the Independent Ethical Committee of the ATS (Azienda Tutela Salute, Sardegna). All the participants provided their signed informed consent.

We considered bipolar EGMs collected from nine patients with post-ischaemic VT during electroanatomic

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mapping procedures in sinus rhythm by the CARTO®3 mapping system (Biosense Webster, Inc., Diamond Bar, California). The recorded EGMs were sampled at 1 kHz and band-pass filtered between 16 and 500 Hz. All EGM segments around the reference annotation were labelled by an experienced electrophysiologist as physiological beats or AVPs, following [8], [10], thanks to an ad-hoc MATLAB graphical user interface. In order to provide the classifiers with a balanced dataset exhibiting an equal number of AVPs and physiological potentials, we included in this study only 1504 EGMs (i.e., 752 signals for each class).

Some examples of AVPs and their spatial localisation on the voltage map are provided in Figure 1.

2.2. Extraction of spectral features

In recent investigations [8], some spectral signatures have been identified as relevant for the characterization of post-ischaemic physiological bipolar EGMs and AVPs, at least from a statistical point of view.

The extraction of these features has been based on the computation of the power spectral density (PSD), as shown in Figure 2. Specifically, in [8], the PSD-based relative power analysis, which was introduced to get rid of the EGM voltage amplitude influence, was found to be particularly significant to distinguish among the different types of AVPs and post-ischaemic ventricular potentials. The frequency band of the signal was divided into non-overlapping 20-Hz sub-band partitions up to 320 Hz. Then, the relative power content in each sub-band was computed as the ratio between the absolute power contained in that sub-band and the power related to the whole PSD curve up to 320 Hz. We excluded from this analysis the 20-40 Hz sub-band, as it didn't present any statistical relevance in the distinction between the two

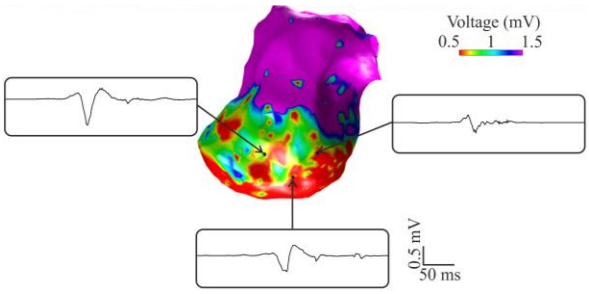

Figure 1. Examples of AVPs and their spatial location onto the voltage map. Specifically, from left to right, an AVP exhibiting deflections during and after the surface QRS (left), after its end (middle), and falling within the surface QRS (right) are represented and included in the adopted dataset.

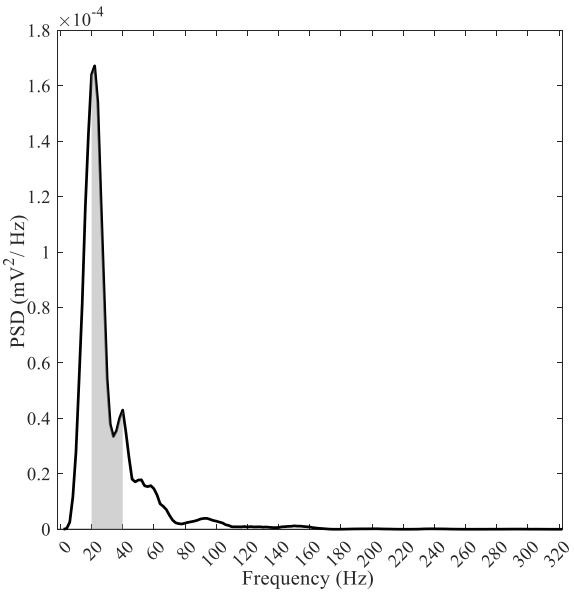

Figure 2. An example of PSD for an AVP. Here, the relative power has been estimated from the area under the PSD in each 20-Hz sub-band, except for the 20-40 Hz sub-band (highlighted as grey area).

classes (physiological and AVP EGMs) [8].

According to [8], some further spectral features were introduced, in order to describe some intrinsic aspects of the PSD morphology. Accordingly, on the PSD of each EGM, we computed the mean frequency (MNF), the peak frequency (PKF), the mean spectral power (MNP), and the power spectrum ratio (PSR). Specifically, MNF was introduced to indicate around which frequency most of the power spectral contents were localized, the PKF identified the frequency in correspondence with the maximum power content in the PSD, whereas the MNP and the PSR reflected the average power spectral contents below 320 Hz and around the PKF, respectively.

Overall, 19 features were extracted from each EGM. All these features were used to train a support vector machine (SVM) and a K-Nearest Neighbours (KNN) classifier, as explained in detail in the following section.

2.3. Classification tools

In this work, the proposed features have been used to train and test two feature-based supervised classification models for the recognition of AVPs and physiological potentials. In particular, we investigated the efficacy of the proposed frequency-based signatures by exploiting an SVM classifier with 2nd-order polynomial kernel function and box constraint equal to 1, and a KNN model based on Euclidean distance computation with inverse distance weighting and the number of nearest neighbors set at 10.

Remarkably, default parameters were chosen in order to avoid presenting overfitted results.

2.4. Performance evaluation

In order to assess the trained models, a 10-time 10-fold cross-validation with stratified partitions was adopted. Remarkably, at each time, both classifiers were trained on the same folds, and their recognition capabilities were assessed on the same test data.

For a quantitative evaluation of their performance, the following metrics were computed and compared: the accuracy (ACC), the True Positive Rate (TPR), the True Negative Rate (TNR), the False Positive Rate (FPR), the F1-score and the Positive Predictive Value (PPV), as

$$ACC = (TP + TN)/(P + N) \quad (1)$$

$$TPR = TP/P \quad (2)$$

$$TNR = TN/N \quad (3)$$

$$FPR = FP/N \quad (4)$$

$$F1 - score = 2(PPV \cdot TPR)/(PPV + TPR) \quad (5)$$

with

$$PPV = TP/(TP + FP) \quad (6)$$

where P and N represent the total number of AVPs and physiological EGMs, respectively, TP and TN the number of AVPs and physiological potentials correctly recognized, and FP identifies the total number of physiological potentials classified as AVPs.

For each dataset partition, the EGM samples were randomly divided into 90% for training and 10% for testing. The process was repeated ten times and, at each time, the cumulative metrics over the 10 folds has been computed. Then, for a more robust assessment, the mean and the standard deviation of the metrics over the 10 times have been compared.

3. Results

Table 1 summarizes the mean and standard deviation for all metrics evaluated for both classifiers, whereas in Figure 3, the cumulative confusion matrices of the tested classifiers are reported.

As can be seen, the strategy of modeling classifiers for the automatic recognition of AVPs using only information from the frequency domain led to classification models with accuracy above 81%. Interestingly, the KNN

Table 1. Performance indexes for the proposed SVM and KNN classifiers.

	Classifier	
	SVM	KNN
Accuracy [%]	81.2 ± 1.1	85.0 ± 0.9
TPR [%]	82.4 ± 1.6	85.3 ± 1.5
TNR [%]	79.9 ± 1.1	84.7 ± 1.5
FPR [%]	20.1 ± 1.1	15.3 ± 1.5
F1-score	0.82 ± 0.01	0.85 ± 0.01

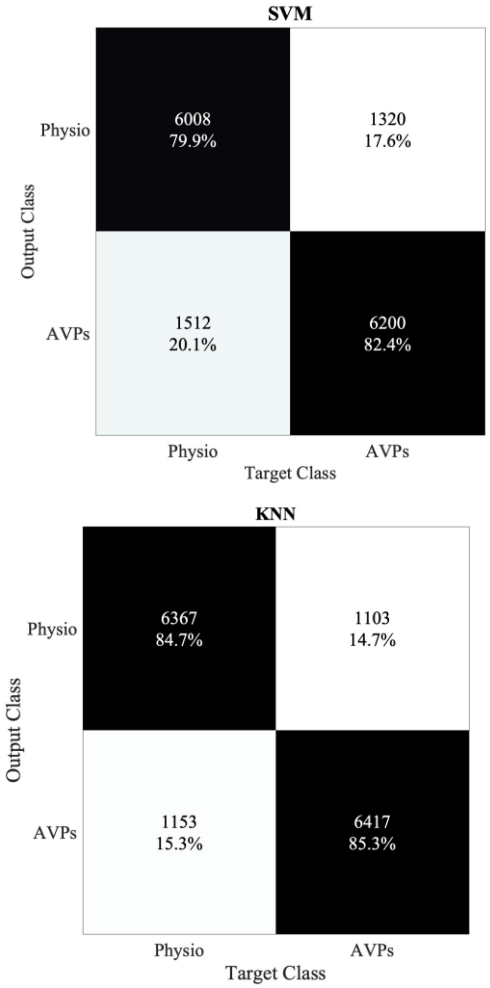

Figure 3. Cumulative confusion matrices for the two classifiers. In each matrix, the TPR (black box on the bottom-right corner) and the TNR (black box on the top-left corner) are reported along with their respective false negative rate (white box on the top-right corner) and FPR (light box on the bottom-left corner).

outperforms the SVM in all evaluated metrics. In particular, the accuracy obtained with the KNN reaches 85.0%, which is +3.8% higher with respect to the SVM. Moreover, also the values of TPR and TNR are markedly different between the two classifiers: the KNN reports similar values (about 85%), while the SVM showed TPR=82.4% and TNR=79.9%. However, even if the SVM showed higher false positive alarms (i.e., 20.1% vs. 15.3%), it is not strictly a downside limiting its application, since it reflects a more conservative behavior that draws the attention of clinicians to physiological potentials that are recognized as AVPs. Remarkably, SVMs have been already successfully adopted for the real-time classification of biopotentials on low-power digital architectures [11], thus allowing to envision an effective embedding into a real electroanatomic mapping system. Finally, both classifiers exhibited quite similar F1-score.

4. Conclusions

In this work, the adoption of the statistically significant spectral signatures proposed in [8] has been investigated for the development of an effective supervised machine-learning tool able to distinguish between AVPs and physiological potentials. Our results highlighted that the proposed frequency-domain features may lead to very high AVPs recognition performance, which may attain 85% in accuracy and TPR when a KNN classifier is chosen. These findings are promising, despite an accurate validation on a larger dataset with multiple annotators needs to be pursued before clinical exploitability.

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