Automated Detection of Ventricular Heartbeats from Electrocardiogram (ECG) Acquired During Magnetic Resonance Imaging (MRI)

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Abstract

ECGs are highly distorted by the MRI environment, making automated ECG analysis highly difficult. This study aimed at implementing a machine-learning (ML) based heartbeat classifier, using hand-crafted features, for the automatic detection of ventricular heartbeats during MRI. A model was trained on the MIT-BIH Arrhythmia Database and assessed on an in-house database of ECG acquired inside a 1.5T MRI (ECG-MRI).Features were extracted for each heartbeat from single-lead ECG signals including QRS morphological features based on Hermite functions, and RR interval-based features. A support vector machine was trained to classify normal (N) and ventricular ectopic beats (V'). The classifier achieved F1 scores of 0.85 on the V' class on the validation fold on the MIT-BIH database, while it only achieved F1 scores of 0.15 on the ECG-MRI database. The proposed heartbeat classifier was developed on the MIT-BIH arrhythmia database using temporal features and QRS morphological features based on the assumption they would be less distorted by the MRI environment. However, even if performance on MIT-BIH were acceptable (although slightly lower than state-of-the-art approaches), results were poor on the ECG-MRI database. The results highlight the need for further developments by suppressing MRI-related artifacts, and by re-training on MRI specific datasets.

1. Introduction

Electrocardiogram (ECG) is a well-known clinical tool for assessing the electrical activity of the heart [1], while Magnetic Resonance Imaging (MRI) is a relatively recent imaging modality assessing morphological and functional depiction of the heart. ECG signals are acquired during MRI examinations for two main reasons: (i) Synchronizing MRI image acquisition with the heart activity (movement) in order to reduce motion artefacts, (ii) monitoring patients during MRI acquisition[2].

Inside an MRI scanner, a patient is subjected to three electromagnetic fields generating artefacts: (i) RF pulses, and (ii) varying magnetic fields (denoted gradients), during MRI acquisition can induce a voltage on the ECG; (iii) A strong static magnetic field, which in the presence of moving charged particles, like blood in the aorta also generates a voltage. This results in a distorted ECG signal inside the MRI scanner, which can impair the diagnosis usage of the recordings. [3]

This study aims to assess the generalizability of classical ML techniques for the classification of heartbeats on ECG signals acquired during MRI. We propose the use of Hermite-based [4, 5] features for the classification of QRS morphology which we assume to be less distorted by the MRI environment.

2. Methods

2.1. Datasets

Beat Type	DS1	DS2	MRI	OF	IF	IS
N	45862	44251	24007	5271	5571	13165
S	944	1837	48	13	19	16
V'	4202	3608	1344	302	224	818

Table 1. Database beat distributions for DS1, DS2 and MRI database including the full MRI database, in field (IF), out of field (OF), and during sequence (IS).

2.1.1. MIT-BIH Arrhythmia database

A classifier was trained on Physionet MIT-BIH Arrhythmia database [6]. Following the split proposed by [7], DS1 was used for training, and DS2 used a test set for comparison with other approaches.

2.1.2. ECG in MRI Database

A private database [8, 9] of ECG signals acquired inside a 1.5T MRI scanner was built. The ECG signals had 3 leads forming a cross on the patient's torso to mimic $-Vy$

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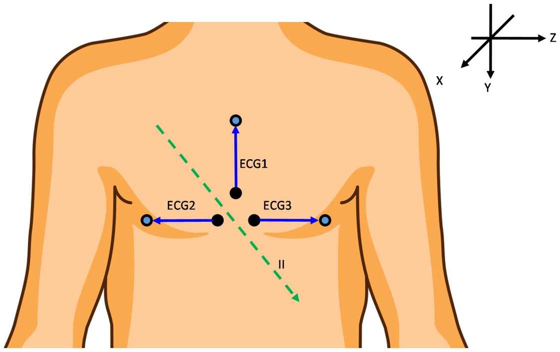

Figure 1. Electrode placement and ECG leads (blue arrows) from the MRI database [8]. The dashed lines corresponds to lead II, which was used on the MIT databases.

and Vz from the VCG. The total database contained 29 subjects. Among them, 9 subjects had ECG signals with pathological V' and/or S beats. 16 ECG recordings on average (q1=14, q3=19) were acquired for each subject. 3 were obtained outside the MRI out of field (OF), 3 inside the MRI bore without sequence in field (IF), while the others were acquired during sequence (IS). In total 492 ECG recordings were annotated manually beat by beat. Since the amount of S beats on the MRI database was too small (fewer than 50 S heartbeats) to draw conclusions, the study was restricted to the N and V' beat types.

2.2. Data Preparation

A single ECG lead was analyzed: The first ECG channel for MIT-BIH recordings, and lead ECG1 for the MRI database. The ECG signal was first band-pass filtered between 0.5 and 50Hz, and resampled to 360Hz (when necessary). The ECG recording was rescaled to have its minimum to zero and maximum to one. The QRS positions from the ECG annotation files were used for the extraction of a window around the QRS complex. The window was centered around each R peak with a window size of 333ms. Within this window, the QRS complex was detrended and centered to have a zero-mean.

2.3. Feature Extraction

Two classes of features were extracted for each heart: (i) morphological features (ii) temporal features. Morphological features using Hermite function decomposition up to degree 7 [5] were computed. The preceding (backward) and following (forward) RR interval were also included. Heart rate variability (HRV) features were computed using the last 60 and 180 heartbeats preceding the one considered. These features included the coefficient of sample entropy (CoSEn) [10] and log of the mean RR interval(rr_mean).

In parallel, the classification scheme proposed by Llamedo et. al. [11] was used as a baseline. Eight features were extracted following the preprocessing suggested in [7, 11]. Four features were based on the autocorrelation of the 4^{th} scale of quadratic spline wavelet transform on the two available leads on MIT database. The other four features were based on the RR interval time-series including: log of forward and backward differences, average RR interval over the last minute and 20 minutes before the considered heartbeat. Outliers were removed via elliptic envelope and a linear discriminant analysis classifier was trained on DS1. For the recordings from the MRI database, leads ECG1 and ECG3 were used.

		Llamedo		Hermite	
Truth	N	43590	661	43645	606
	V'	940	2668	467	3141
Prediction		N	V'	N	V'

Table 2. Confusion matrices on DS2 for the Llamedo baseline and Hermite based classifier.

		All		OF		IF		IS	
Truth	N	10858	13149	3953	1318	4031	1540	2912	10253
	V'	131	1213	17	285	15	209	74	744
Prediction		N	V'	N	V'	N	V'	N	V'

Table 3. Confusion matrices on MRI database for the Hermite based classifier.

2.4. Classifier Optimization

A support vector classifier (SVC) with radial basis function (RBF) kernel was trained. Its regularization parameter C was grid searched to maximize the five-fold cross-validation weighted precision score on DS1. The fitted SVM classifier was then calibrated via Platt's method [12] on DS1.

A sequential forward feature selection (SFFS) was used on DS1 to find which of the proposed features were the most important for the heartbeat classification task.

3. Results

The grid-search lead to set $C = 78.5$. Table 2 depicts the confusion matrices of the Hermite features-base (proposed) technique and Llamedo's approach [11] on DS2 for the detection of V' beats. Figure 3 shows the evolution of the precision cross validation scores obtained during the feature selection process woth increasing feature subsets. The first 8 selected features are the forward and backward RR intervals, rr_mean features, and higher order Hermite

Beat Type	DS2	MRI	OF	IF	IS
Llamedo features					
N	0.98	0.00	0.00	0.00	0.00
V’	0.77	0.10	0.10	0.07	0.11
Hermite features					
N	0.99	0.62	0.86	0.84	0.36
V’	**0.85**	**0.15**	**0.30**	**0.21**	**0.13**

Table 4. F1 scores for DS2 and MRI database for Llamedo baseline and Hermite based classifiers.

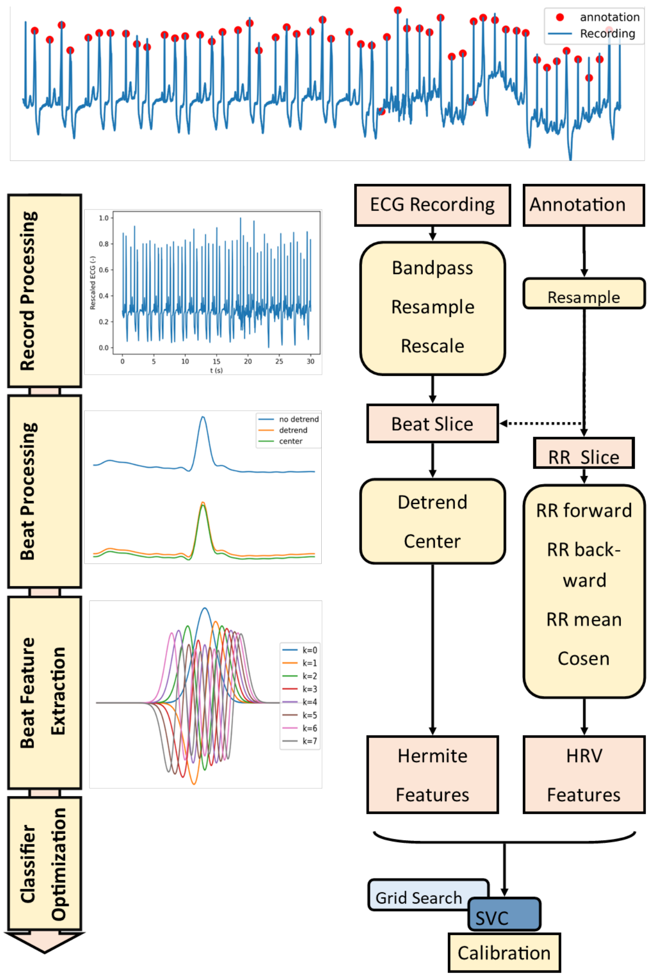

Figure 2. Record preprocessing pipeline.

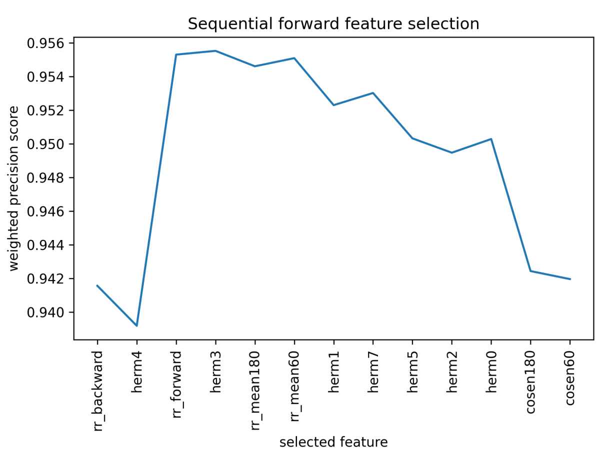

Figure 3. Feature selection on MIT database DS1.

decomposition coefficients. More sophisticated HRV features, such as CoSEn, were among the last ones selected.

Table 3 shows the confusion matrices of the Hermite-based classifier on the MRI database. The Llamedo baseline classifier only predicted V’ beats on this database. Table 3 shows the F1 scores for both classifiers on both databases. Overall the F1 score drops from 0.85 for the V’ class to 0.15 when going from the MIT-BIH DS2 to the MRI database. A first drop of the F1 score from 0.85 to 0.30 can be noticed in the detection of V’ beats between DS2 and the MRI database OF.

A second drop from 0.30 to 0.21 is observed in the F1 score between OF and IF. A significant increase of V’ false positives can be noticed when comparing IF and IS results, as seen on Table 3. These additional false positives lead to a drop of F1 score from 0.21 to 0.13 when comparing in bore recordings with recordings when MRI sequences are played (additional RF and gradient artifacts).

4. Discussion

A heartbeat classifier based on morphological and temporal features was implemented to detect ventricular beats from ECG signals obtained in a MRI environment. The proposed technique is based on morphological features assumed to be less distorted in MRI, and the classifier was trained on a standard ECG database (MIT-BIH arrhythmia database) and tested on a in-house ECG in MRI database.

The fact that rr_forward and rr_backward are among the first selected is consistent with the Llamedo’s model [11].

Overall the drop of F1 score between DS2 and the MRI database from 0.85 to 0.15 may show that directly plugging a heartbeat classifier from standard ECGs to ECGs obtained in MRI is not applicable in clinical practice. Without the difficulties related to MRI scanners, the drop of F1 between DS2 and OF already suggests difficulties to transfer the classifier fitted on DS1 to the ECG setup from MRI database. For both the Hermite features and Llamedo’s classifier, features were mainly based on lead II from the MIT-BIH database, while the ECG 1 from the MRI database was considered as a first approximation of lead II for the obtained classifier. This is even worse for the classifier from [11] as the wavelet-based features used the two channels of the ECG in MIT database, and the second lead on MIT database is most often a precordial lead (V1, V2, V5). This second lead was approximated by lead ECG3 in the proposed test, which may explain why the baseline classifier already always predicts V' beats even outside MRI. Hence, finding a lead-independent representation of the heartbeats, through the choice of the computed features, or by introducing a preprocessing such as a PCA to project the heartbeats on the main heart electrical axis could help to deal with this issue.

The drop of 0.09 in F1 score between the OF and IF condition on the MRI database might be mainly explained by the ditortion of the ECG signal by the MHD effect. This suggests the Hermite-based features are still affected by the MHD effect although the analysis window was focusing on the QRS complex.

The drop of F1 score between IF and IS conditions was expected as MRI pulse sequences introduce significant gradient noise. This result highlights the need to reduce this type of interference. Some techniques based on Kalman or particle filtering have already been applied for removing this type of noise [8] and have been successful in improving performance on QRS detection tasks in MRI [9]. A next step would be to apply these denoising methods as a preprocessing before the heartbeat classification.

This assessment showed the need to introduce specific signal preprocessing to remove MRI related noise to improve the heartbeat classifier performance inside MRI scanners, while also probaly the need to retrain the classifier on ECG IN MRI data. However given the paucity of databases with annotated pathological heartbeats in MRI [2, 8], assessing transfer learning approaches from conventional ECG to ECG in MRI would be an interesting avenue of research for future works.

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