Signal Processing and Machine Learning Automated Evaluation of Phrenic Nerve Affectation by Cardiac Stimulation

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Abstract

Cryo-ablation is a common procedure used in hospitals to eliminate certain arrhythmia, such as Atrial Fibrillation. Although this procedure is sufficiently proven, it sometimes involves treatments in areas close to the phrenic nerve with the subsequent risk of later damage to the aforementioned nerve. To avoid this, clinical practice incorporates manual safety protocols during ablation. In this work, we propose the development of an automated classifier that facilitates the clinical evaluation of possible conduction disorders produced in the phrenic nerve. To achieve this goal, polygraph signals extracted during the ablation process of ten patients were used. Signal processing, including pre-processing, noise filtering, and delineation, was applied to every available situation and signal. To unmask the residue of cellular muscle potential during the phrenic nerve stimulation process, the results when the sensor was placed on the phrenic nerve (activation capture) and when the sensor was displaced from the phrenic nerve (no capture) were compared. A linear classifier was applied to both situations to characterize muscle activity resulting from nerve activation. The results confirmed that it is possible to automatically classify the level of muscle activity from the phrenic nerve with 100% accuracy in this data set. The method proposed in this work constitutes an automated protocol to evaluate the eventual deterioration of the phrenic nerve conduction due to ablation in the vicinity, improving the existing protocol for clinical convenience.

1. Introduction

Cryo-ablation is an advanced technique widely used in hospitals to treat various cardiac arrhythmias, with atrial fibrillation being one of the most common. This procedure involves the application of extremely cold temperatures to eliminate or interrupt the abnormal electrical signals that cause the arrhythmia. Although cryo-ablation has proven effective in treating these conditions, there is an inherent risk of damaging nearby structures during the process. One of the most prevalent instances of this potential occurrence is the affection of the phrenic nerve. To measure the activity of the phrenic nerve, it is required to apply a stimulus close to the muscle [1].

The phrenic nerve plays a crucial role in the respiratory system as it innervates the diaphragm, one of the main muscles involved in respiratory function. Due to its proximity to the areas where the cryo-ablation procedure is performed, there is a possibility of the phrenic nerve being affected during the procedure, potentially leading to diaphragmatic dysfunction and respiratory difficulties in patients. Currently, in clinical practice, manual safety protocols are applied during cardiac ablation to prevent phrenic nerve deterioration [2]. These protocols involve placing the hand on the patient's diaphragm and subjectively evaluating the phrenic nerve activity while simultaneously inducing an electrical stimulation [3]. However, this manual evaluation is subject to inter-individual variations and has a certain degree of subjectivity.

Previous research has determined that the phrenic nerve's muscle activity can be quantified during the second peak of the triggered stimulus [4]. The advancement of signal processing techniques and machine learning have proven to be of relevant interest when proposing automated methods of detection and classification. In this paper, we propose to develop an automated method to objectively evaluate the conduction of the phrenic nerve throughout the cryo-ablation procedure and thus prevent it from eventual deterioration.

2. Materials and Methods

This section summarizes the clinical and methodological description of the data sets used in this study. We also describe the preprocessing, conditioning, and characterization of the recorded signals for the subsequent analysis. Finally, in this study is summarized the classification and signal processing techniques applied.

2.1. Dataset

In this work, a total of ten cases registered during ablation processes in cases of atrial fibrillation carried out at the Virgen de la Arrixaca University Clinical Hospital in Murcia, have been selected. The recording of these signals was carried out as follows. Polygraph signals related to the electrocardiogram and specialized sensors strategically placed in areas near the phrenic nerve were recorded to identify the stimulations induced during the procedure. These sensors are commonly used during the standard cryo-ablation procedure for phrenic nerve monitoring, following the clinical protocols established for this purpose. The dataset incorporated in this study consists of 10 cases, with the following demographics: 3 women and 7 men, and ages between 55 and 72 years, with an average age of 66.5 years. This sample can be considered diverse in terms of gender and age, according to the pathology identified. These demographic characteristics reflect an older adult population in which the cryo-ablation procedure was performed to treat various heart conditions. Using this dataset provides a solid basis for performing analyses and assessments of phrenic nerve muscle activity during the procedure. In particular, signals were recorded during phrenic nerve stimulation in two different situations: with activation capture and without activation capture. In the activation capture situation, the sensor is placed in the muscle to identify phrenic nerve activity. For the non-capture situation, the sensor was placed in areas not related to the phrenic nerve, which allowed us to obtain electrocardiographic recordings of reference signals, that is, not affected by the phrenic nerve.

For each case incorporated in this study, multiple measurements were recorded, applying various filters (50 Hz and 250 Hz) and pulse intensities of phrenic nerve stimulation. Additionally, to ensure the analysis was robust, multiple repetitions of phrenic nerve stimulation (with and without capture) were recorded for all cases and patients, following the methodology used during the cryo-ablation procedure.

2.2. Preprocessing

The necessary processing for this work has been carried out in four phases: preprocessing, template construction, characterization of templates, and classification.

In the preprocessing stage, while analyzing the surface electrocardiogram signal, the main objective was to detect and separate the nerve stimulation from the rest of the PQRST complex. To achieve this, and due to the spiking nature of the stimulation, a high-frequency filtering stage was performed that allowed the stimulation to be located. Subsequently, a correlation window of the original signal was applied to identify spikes in the filtered signal [5].

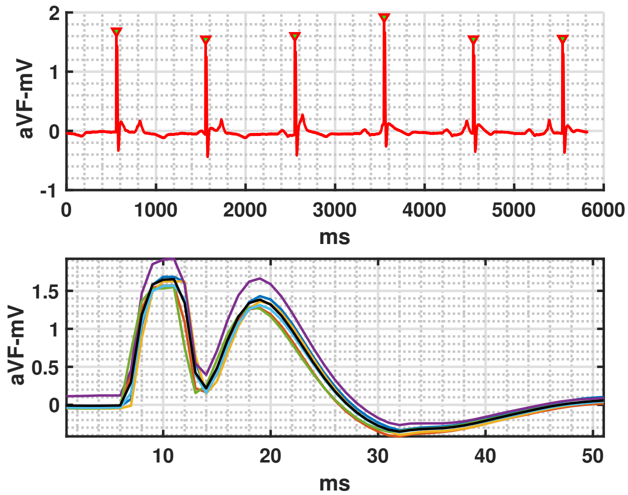


Figure 1. Peak detection and template creation.

2.3. Stimulation Template

Once the polygraph signals were pre-processed and filtered, We applied a delineation process [5]. In this step, the precise moments where the stimulation and consequent activation of the phrenic nerve occurred were identified according to the activation signals. After identifying these moments, the templates of the induced stimulation were obtained by consolidating the individual ones, obtained by signal windowing and applying an event detector developed. As a result, statistically denoised stimulation templates were obtained for the subsequent automated and precise analysis in each derivation and case.

2.4. Characterization

As a third phase, and after obtaining the stimulation templates for each of the leads and situations described above, all of them were mathematically characterized, both in amplitudes and duration and time-offsets, according to clinical criteria. The muscle activity was then compared throughout the multiple situations evaluated to detect the effective activation of the phrenic nerve using evaluating the differences between capture and non-capture.

2.5. Linear Classifier

Finally, it has been proposed the use of a linear classifier of vector support machines as a tool to categorize the different options. Linear classifiers are a type of machine learning algorithm that aims to establish linear decision boundaries for categorizing and distinguishing between different classes of data. A linear classifier divides the feature space into two regions corresponding to each class in a binary classification context where two classes are to be discriminated. The optimum hyperplane that separates the data points of distinct classes is fitted to achieve this separation. There are many benefits to using linear classifiers. They are computationally efficient and can scale well to large datasets. They can also be easily understood because linear functions define the decision boundaries. This interoperability can show how the input features and class labels relate to each other. The Support Vector Machine (SVM) algorithm is a powerful supervised learning method that is widely applied in a variety of classification applications. It is renowned for its robustness and efficacy. The SVM method provides the framework for the proposed linear classifier. The process of determining the ideal hyperplane involves identifying the support vectors, which are the data points closest to the decision boundary. These support vectors significantly impact the orientation and position of the hyperplane, permitting the linear classifier to develop higher accurate predictions. The selection and positioning of these support vectors are crucial as they help capture the essential characteristics and patterns necessary for effective classification.

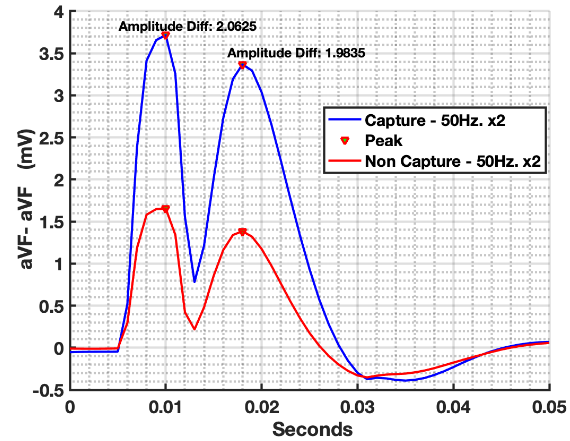
3. Experiments and Results

3.1. Stimulation template

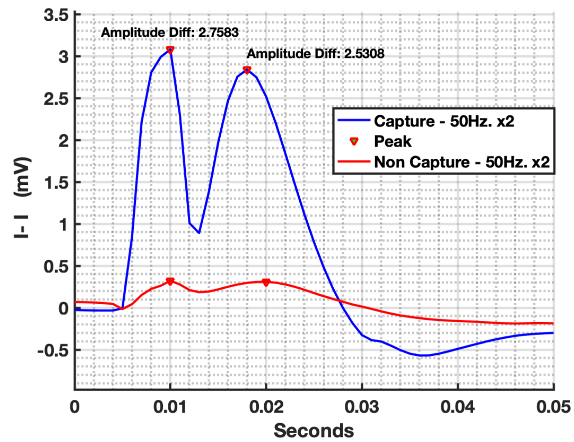
Following the early tests, which utilized the TETRA polygraph signal to effectively recreate the stimuli and the generated impulses, it was argued that the synchronism of the first peak and the linearity of the response to amplitude modification encouraged the notion that the first peak corresponded to the direct recording of the impulse itself rather than muscular activity, defining it as an artifact. On the other hand, the non-linearity of the response to the impulse in the second peak of the stimulus, coupled with its stable morphology in response to frequency changes, led us to consider that this peak corresponded to the muscular activity of the phrenic nerve, as several previous studies had already defined [1][4].

3.2. Template Characterization

To contrast the amplitudes of captured versus uncaptured muscle activity, numerous experiments and measurements were conducted in each scenario as the second peak difference amplitude we show in Table 1. We observed that the first and second peak amplitudes exhibited similar variations when capturing muscular activity. This confirmed that there is also a certain level of muscular activity of the phrenic nerve in the first peak of the measured stimulus. Additionally, by studying the pattern obtained in different cases for the non-captured nerve situation, we can observe that the second peak is not completely eliminated, confirming the presence of the first stimulus artifact in this maximum as well as we can observe in Figure 2 (a) and (b).



(a)



(b)

Figure 2. Comparison between capture and non-capture electrograms in lead aVF (a) and lead I (b).

After confirming these findings, we conducted the study for the entire stimulus, encompassing both peaks and performed temporal and amplitude measurements for both. Once the experimental strategy was established, an analysis of the 80 pre-existing subsamples was carried out to get the data ready for our linear classifier.

3.3. Linear Classifier

For this purpose, we used a linear classifier to analyze the features and patterns of the polygraph signals in each

Lead	Difference (Absolute)	Difference (Relative)
I	1,44 ± 2,20	26,85% ± 92,53%
II	2,11 ± 1,36	49,07% ± 26,85%
III	0,39 ± 0,57	4,28% ± 40,30%
aVR	1,90 ± 1,77	24,71% ± 95,56%
aVL	0,01 ± 1,67	-126,84% ± 160,46%
aVF	**1,37 ± 0,75**	**41,46% ± 19,65%**
V1	0,41 ± 0,57	22,00% ± 26,03%
V2	1,12 ± 1,11	38,81% ± 25,89%
V3	1,08 ± 1,02	35,55% ± 36,05%
V4	1,17 ± 1,01	44,02% ± 26,57%
V5	1,23 ± 0,98	49,20% ± 23,07%
V6	1,20 ± 0,78	48,27% ± 24,34%

Table 1. Differences in the second peak between capture and non-capture amplitudes.

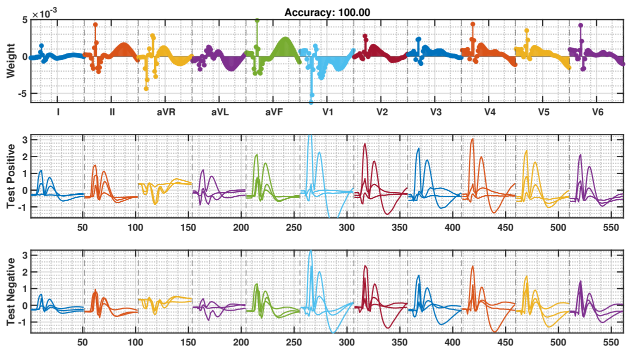


Figure 3. Lineal classifier weights for the experiment.

situation, determining the presence of specific muscle activity related to the phrenic nerve. By comparing the results of both situations, the phrenic nerve muscle activity during stimulation could be evaluated and quantified. In addition, as we can observe in Figure 3, the weights related to the linear classifier increase in the signal study areas, which confirms the accurate detection from the classifier.

Achieving a 100% accuracy in detecting phrenic nerve activity in this dataset validates the hypothesis of establishing an automated and unbiased protocol for the eventual measurement of phrenic nerve muscle activity and its potential deterioration due to the cryo-ablation procedure performed in proximity to it.

4. Conclusions

Furthermore, achieving a 100% accuracy in the automatic classification of phrenic nerve muscle activity allows for early and precise detection of potential conduction impairments in the nerve and accurate assessment of the associated risk. This, in turn, positions it as a potentially useful tool to enhance patient safety during this procedure. Therefore, we can conclude that this study has successfully demonstrated the feasibility and effectiveness of using an automated quantifier for the detection of phrenic nerve muscle activity during cryo-ablation and its evaluation of the resulting impairment.

Acknowledgements

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