Intelligent systems to autonomously classify several arrhythmia using information from ECG.

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Abstract— **This paper is focused on the development of intelligent classifiers in the area of biomedicine, focusing on the problem of diagnosing cardiac diseases based on the electrocardiogram (ECG), or more precisely, on the differentiation of several arrhythmia using a large data set, by an autonomous intelligent system which can be used as an expert system to support human experts in the diagnosis and, moreover, to autonomously display an alarm to the user in case of a dangerous situation. We will study and imitate the ECG treatment methodologies and the features extracted from the electrocardiograms used by the researchers, which obtained the best results in the PhysioNet Challenge. We will extract a great amount of features, partly those used by these researchers and some additional others we considered to be important for the distinction previously mentioned. A new method based on different paradigms of intelligent computation (such as extreme learning machine, support vector machine and feature selection) will be used to select the most relevant characteristics and to obtain a classifier capable of autonomously distinguishing the different types arrhythmia from the ECG signal. Finally, the behavior and performance of the classifier have been tested using data from several cardiac pathologies, obtaining good classification results.**

Keywords—SVM; classification; ECG analysis; heart disease; assisted diagnosis

I. INTRODUCTION

Nowadays heart disease is one of the most usual causes of death in developed countries and, besides, a common cause of disability. There exist many different forms of cardiac pathologies; moreover, available data from year 2012 indicates that nearly half of the deaths in Spain along year 2010 were caused by four different heart diseases: cancer, ischemic heart disease, cardiovascular disease and mellitus diabetes, confirming these diseases constitute an important wealth problem affecting all developed countries. These cardiovascular diseases are caused by different heart and vascular disorders, among which are coronary cardiopathies (heart attacks), brain-vascular diseases (apoplexy), increasing of arterial pressure, peripheral vascular pathologies, rheumatic cardiopathies, congenital cardiopathies and heart failure.

There are many different factors related to the emergence of heart arrhythmia, which may even affect heart function, generating another kind of heart diseases or even death. Depending on the kind of arrhythmia, the level of heart impairment will vary, so the consequences will be different for a tachycardia (unusually accelerated heart rate) or for an atrial fibrillation; in this latter case heart rate may even reach 220 beats per minute, and the affected patient may suffer from thrombosis, embolism or even death, if proper assistance is not provided or some complications with arterial pressure occur.

Electrocardiogram is an important source of information to identify these conditions, therefore, becomes necessary to seek for an advanced system of diagnosis based on these signals. Atrial fibrillation is one of the most common causes of external consultation and demand of emergency units, usually related to elder people. Once the patient have suffered from arrhythmia, he must receive proper medical attention and be kept under medical surveillance.

Obtaining an automatic diagnosis model based on ECGs could in fact make real impact in the quality and speed of medical services. This fact makes the search of new and more precise classification mechanisms a key factor to objectively assist clinical decisions. Although there are many different systems and devices to provide reliable service in the study of heart dysfunctions, their cost and performance may still be doubted.

Through feature extraction in biomedical signals aimed to pathology detection, it is possible to obtain measures which may be relevant in the diagnosis process. Moreover, signal processing allows us to use other characterization mechanisms as estimation of coefficients and mathematical indexes, which may not have direct clinical sense but indeed are very helpful when creating patterns for independent classes. For these issues we have relied heavily in the solutions proposed in the PhysioNet Web (Computing in Cardiology Challenges) performed by different participants.

In this paper we collected samples of electrocardiograms of MIT-related database with ten types of pathologies and a rate corresponding to normal (healthy patient), which are processed and used for extraction. Next, several techniques have been applied to feature selection based on genetic algorithms, principal component analysis and mutual information (MILCA, mRMR, NMIFS). These techniques allow us to achieve greater efficiency in the classification methods used, namely support vector machines and decision trees, to perform a comparative analysis between them. The main purpose of this paper is to provide an automatic diagnosis tool for different diseases using

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intelligent systems, which could be used as support for medical human experts.

In this work we also analyze different strategies based in the combination and selection of features, in such a way we can obtain the most optimized and precise data sets from each of them. In this last step we study two different supervised classification methods, and we will use them on the set of features resulting from the dimension reduction strategies. All this work is headed to improve the characterization of recognition patterns and to diminish the computational complexity of the training stage in a heart diseases' diagnosis system.

II. USED DATABASE AND METHODOLOGY.

To evaluate the processing algorithms we used the MIT database as, besides all the previously mentioned advantages, it provides a library of functions (WFDB) which allows to work with ECGs' signals (format conversion, part selection, frequency conversion, etc.). All these signals and functions are accessible through the PhysioNet[1] society, where all the available resources are publicly offered via three related components:

PhysioNet: it is an online forum conceived to share, bring together and exchange all kinds of biomedical signals and open-source analysis software, making easier to cooperate, study, evaluate and test new proposed algorithms.

PhysioToolkit: it presents a processing and analysis software compilation for physiological signals and for detection of significant physiological events. It must be considered that hidden information extraction from biomedical signals is one of the topics that most unify several lines of investigation. Moreover, it can be really helpful in the early diagnosis of several diseases.

PhysioBank: formed by a growing digital registry of physiological signals, it is freely offered through the web to the international scientific community investigating on these topics. PhysioBank includes a great variety of databases with biomedical signals trying to embrace a wide range of real cases from both healthy and ill patients.

Nowadays, PhysioBank comprises around 26 different ECG databases; the ones used in this work are the following:

- **MIT-BIH Arrhythmia Database (mifdb):** it is a collection of 48 fragments of 30 minutes obtained from two channels, including annotations. The sampling frequency is 360 Hz, with 11 bits of resolution and a 10 mV range.
- **MIT-BIH Malignant Ventricular Arrhythmia Database (mfdb):** it comprises 22 registries of 30 minutes. Annotations are related to changes in the rate. The signals come from two channels sampled at a 250 Hz rate.
- **MIT-BIH Atrial Fibrillation Database (atr):** completed in 2004, it contains 30 learning recordings and two groups of 20 and 30 registries, respectively, coming from two input channels and 1 minute duration. It is sampled at 128 Hz.
- **Sudden Cardiac Death Holter Database (sddb):** a collection of 23 registries sampled at 250 Hz. Many of the recordings belonging to the *MIT-BIH Malingnant Ventricular Arrhythmia Database* are extracts from the registries in this database.
- **BIDMC Congestive Heart Failure Database (chfdb):** 15 registries of 20 hours each. It uses 2 channels at 250 Hz.

The selection of databases was made according to the number of available registries and their duration, also considering the need of proper annotations as we do not have the knowledge to properly interpret the ECGs. We used a total of 28 registries of 24 seconds for each of the selected pathologies, from which 22 of them will be used for training and 6 for test. As we will see afterwards, we will use the test registries in a supervised classification with Support Vector Machines (SVM) and decision trees.

The used signals in this work are the following:

- Sinusoidal normal rhythm.
- Auricular flutter.
- Supra ventricular tachycardia.
- Nodal rhythm.
- First grade AV blockage.
- Pacemaker.
- Heart failure.
- Ventricular bigeminy.
- Atrial fibrillation.
- Ventricular tachycardia.
- Ventricular fibrillation.

Dimension reduction in the features' space is mostly due to the quality and precision requirements when representing functional status, thus making necessary methods of feature selection and extraction as a fundamental step in the classification process. The figure 1 represents a scheme of the process, divided in 5 blocks.

Signal acquisition will be performed using the ECGs registries provided by the MIT database and the software ECGPUWAVE available at the Physionet website.

The pre-processing consists in a set of operations on the magnitude of retrieved signals, and provides a numerical value to work within the following steps.

[1] www.physionet.org

From the resulting signals in step 2, we extract a whole set of data which determines the features defining the signal.

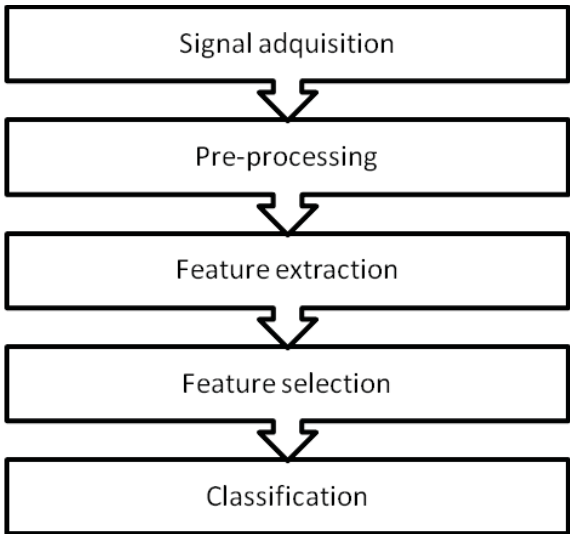

Figure 1 – General scheme of the samples-based classification system.

The feature selection permits to eliminate the redundancy within data, and optimize it in a set of values containing the most representative data (dimension reduction) for the next task.

Last step is classification, attending to the set of features obtained in the previously, in a way such each vector is properly related with its corresponding class.

III. FEATURES EXTRACTION.

Feature extraction is defined as the processing stage in which relevant information contained in an ECG is obtained and represented in a fixed set of coefficients. This way, the signal can be represented in a space which metric minimizes the distance between patterns of the same class, and maximizes the one of different classes. Following this step, we are able to perform an efficient selection of features, reducing the dimension of the initial set feeding the classifier and maintaining a proper discriminating level to recognize patterns of different pathologies.

The features extraction technique used in this work consists in diagnostic measures [18]. This technique is used mainly in arrhythmias detection because it simplifies the process of finding variations in the intervals comprising the ECG signal. However, this technique does not consider the non-stationary nature of ECG signals and so, it is highly sensitive in its estimation. In order to avoid this issue the wavelet transform (WT), with allows simultaneous time and frequency event location, will also be used, as it is adequate for non-stationary signals. The WT decompose the signal in its spectral components so each of them will have a resolution according to its own scale.

The number of extracted features was 142, 76 of them belonging to the first derivation and 76 from the second; so in the end, we defined 76 features, named as C1-C76, extracted from the first and the second derivation. Such features belong both to the time and frequency domains; in some references it is shown that spectral domain is more suitable for short term techniques, where as long term techniques fit the best with time domain. In spite of using short term segments (24 seconds) both domains will be used for feature extraction in this work.

The choice of 24 seconds segment was made according to some references [20] and to the fact that 24 is actually a multiple of 8 seconds, which was the segment time duration which offered the best results after performing several tests. Another benefit arising from this choice is that, using the re-sampled files at 250 Hz, we obtain 1024 points to perform the frequency features extraction techniques, which is exactly the same number of points of the Fourier Transform (FT) of the signal, thus increasing the correctness of the analysis. So, most of the features will be extracted from an 8-seconds segment, or averaging three subsequent segments to make sure we are not facing an isolated episode of the pathology.

Finally, we considered two different possibilities relating the features extraction: applying the algorithms to the whole signal or just individual heart beats. We chose the first option as, otherwise, the analysis will be very dependent on the initial segmentation stage, thus needing a robust divisor (which was unavailable) when facing abnormal or noisy situations. Only for wavelet-based features samples were taken from individual heart beats.

IV. ADVANCED CLASSIFIER USING SVM.

In this work we use the support vector machine theory (SVM) as a classification methodology, initially proposed by Vladimir Vapnik [73]. Formally, it is constituted by a static network based in kernels which performs a linear classification over vectors mapped into a higher dimension space, i.e., it separates the vectors by an optimal hiperplane in the transformed space, becoming an efficient classification technique to handle big amounts of data.

A. Advantages of using SVM.

SVM training procedure is a convex quadratic programming (QP) problem, and thus it has the following characteristics:

- It provides powerful tools and algorithms to find a solution in a quick and efficient manner.
- It is able to find a unique and optimal solution as this method is not halted by local minima.
- It reduces the classification error during training phase.
- Unlike other methods, it is not affected by over-training.
- It maintains the independence between the problem definition structure and its solution.

- It permits to work with non linear data using kernels.
- It performs reasonably well with low training data.
- Training phase is reasonably simple.

B. Disadvantages of using SVM.

- It needs a proper choice for the kernel.
- It is limited by the complexity arising when using huge amounts of training data.
- It deliberately utilizes a random number of base functions, considering that the number of support vectors increases linearly with the size of the training set; in addition, it can be proven that the number of support vectors is an upper bound of the classifier's risk.
- Prediction from the classifier does not have a probabilistic meaning.

V. RESULTS

After selecting the features as exposed in previous sections, we used all different sets of data as inputs to the classifiers: SVM and decision trees. Table 1 shows the results obtained when applying classification over the general classes, i.e., considering 11 types of independent signals:

Selection methods	DT (precision)	SVM (precision)
Original matrix (142 features)	69.7%	86.4% (57/66)
MILCA (31 features)	62.1%	80.3% (53/66)
GA (84 features)	69.7%	84.8% (56/66)
mRMR (15 features)	60.6%	78.8% (52/66)
NMIFS (15 features)	71.2%	81.8% (54/66)

Table 1 - General mode classification performances.

A. SVM classifier.

Table 2 shows the resulting values of the confusion matrices, sensibility, specificity, preciseness and performance of classification achieved by SVM in general mode, for each of the features selection methods previously mentioned.

From table 2 it emerges that the data with better behavior, considering the resulting parameters, are those corresponding to ventricular tachycardia, ventricular fibrillation, supra-ventricular tachycardia and nodal rhythm.

B. Selection method: genetic algorithms.

In this scenario we obtained almost the same results as in the previous section (shown in table 3), where no selection algorithm was applied. Nevertheless, genetic algorithms have outperformed SVM as we have decreased the number of features from 142 to 84 maintaining the general results.

C. Selection method: MILCA.

Using MILCA method, in general, leads to the same classification results obtained previously, except in the case of ventricular tachycardia, which has experienced a significant decrease in sensibility. Nonetheless, it has to be considered that the number of features has been reduced to 31. Results are shown in table 4.

D. Selection method: mRMR.

This rMRM method provides, in general, good sensibility, specificity and performance values, all the more considering only 15 features have been used, in contrast with the 142 features of the initial scenario. Results are gathered in table 5.

E. Selection method: NMIFS.

This method is in general better than the previous one, except in the case of auricular fibrillation, which sensibility is too low. All results are shown in table 6.

	TP	TN	FP	FN	Sensibility	Specificity	Preciseness	Performance
atf	3	54	2	3	50.0%	96.4%	91.9%	86.4%
bg	6	51	2	0	100%	96.2%	96.6%	
nsr	4	53	0	2	66.6%	100%	96.6%	
chf	6	51	3	0	100%	94.4%	95.0%	
vt	6	51	0	0	100%	100%	100%	
vf	6	51	0	0	100%	100%	100%	
afl	5	52	1	1	83.3%	98.1%	96.6%	
svta	6	51	0	0	100%	100%	100%	
nod	6	51	0	0	100%	100%	100%	
bl	4	53	0	2	66.7%	100%	96.6%	
p	5	52	1	1	83.3%	98.1%	96.6%	

Table 2-Sensibility, specificity, preciseness and performance achieved by SVM.

	TP	TN	FP	FN	Sensibility	Specificity	Preciseness	Performance
atf	4	52	2	2	66.7%	96.3%	93.3%	84.8%
bg	6	50	3	0	100%	94.3%	94.9%	
nsr	3	53	0	3	50.0%	100%	94.9%	
chf	6	50	4	0	100%	92.6%	93.3%	
vt	6	50	0	0	100%	100%	100%	
vf	6	50	0	0	100%	100%	100%	
afl	5	51	0	1	83.3%	100%	98.2%	
svta	6	50	0	0	100%	100%	100%	
nod	6	50	0	0	100%	100%	100%	
bl	3	53	0	3	50.0%	100%	94.9%	
p	5	51	1	1	83.3%	98.0%	96.5%	

Table 3 – Sensibility, Specificit, preciseness and performance for GA and SVM.

	TP	TN	FP	FN	Sensibility	Specificity	Preciseness	Performance
atf	4	49	0	2	66.6%	100%	96.3%	80.3%
bg	6	47	1	0	100%	97.9%	98.1%	
nsr	5	48	0	1	83.3%	100%	98.1%	
chf	6	47	1	0	100%	97.9%	98.1%	
vt	1	52	1	5	16.6%	98.1%	89.8%	
vf	5	48	4	1	83.3%	92.3%	91.3%	
afl	5	48	2	1	83.3%	96.0%	94.6%	
svta	6	47	0	0	100%	100%	100%	
nod	6	47	0	0	100%	100%	100%	
bl	4	49	1	2	66.6%	98.0%	94.6%	
p	5	48	3	1	83.3%	94.1%	92.9%	

Table 4 – Sensibility, specificity, preciseness and performance for MILCA and SVM.

	TP	TN	FP	FN	Sensibility	Specificity	Preciseness	Performance

atf	2	50	2	4	33.33%	96.15%	89.66%	78.79%
bg	5	47	3	1	83.33%	94.00%	92.86%	
nsr	4	48	2	2	66.67%	96.00%	92.86%	
chf	4	48	0	2	66.67%	100.00%	96.30%	
vt	6	46	1	0	100.00%	97.87%	98.11%	
vf	5	47	0	1	83.33%	100.00%	98.11%	
afl	4	48	2	2	66.67%	96.00%	92.86%	
svta	6	46	0	0	100.00%	100.00%	100.00%	
nod	6	46	0	0	100.00%	100.00%	100.00%	
bI	4	48	1	2	66.67%	97.96%	94.55%	
p	6	46	3	0	100.00%	93.88%	94.55%	

Table 5 – Sensibility. specificity and preciseness for mRMR and SVM.

	TP	**TN**	**FP**	**FN**	**Sensibility**	**Specificity**	**Preciseness**	**Performance**
atf	1	53	1	5	16.6%	98.1%	90.0%	81.8%
bg	5	49	2	1	83.3%	96.1%	94.7%	
nsr	4	50	0	2	66.6%	100%	96.4%	
chf	6	48	2	0	100%	96.0%	96.4%	
vt	5	49	1	1	83.3%	98.0%	96.4%	
vf	5	49	1	1	83.3%	98.0%	96.4%	
afl	5	49	2	1	83.3%	96.0%	94.7%	
svta	6	48	2	0	100%	96.0%	96.4%	
nod	6	48	0	0	100%	100.0%	100%	
bI	5	49	1	1	83.3%	98.0%	96.4%	
p	6	48	0	0	100%	100%	100%	

Table 6 – Sensibility. specificity. preciseness and performance for NMIFS and SVM.

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