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INTELLIGENT SYSTEM BASED ON GENETIC PROGRAMMING FOR ATRIAL FIBRILLATION CLASSIFICATION

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□ *This article focuses 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 the types of atrial fibrillations. First of all, we will study the ECG, and the treatment of the ECG in order to work with it with this specific pathology. In order to achieve this we will study different ways of elimination, in the best possible way, of any activity that is not caused by the auriculars. We will study and imitate the ECG treatment methodologies and the characteristics extracted from the electrocardiograms that were used by the researchers who obtained the best results in the Physionet Challenge, where the classification of ECG recordings according to the type of atrial fibrillation (AF) that they showed, was realized. We will extract a great amount of characteristics, partly those used by these researchers and additional characteristics that we consider to be important for the distinction previously mentioned. A new method based on evolutionary algorithms will be used to realize a selection of the most relevant characteristics and to obtain a classifier that will be capable of distinguishing the different types of this pathology.*

Atrial fibrillation (AF) is the sustained arrhythmia that is most frequently found in clinical practice, present in 0.4% of the total population. Its frequency increases with age and with the presence of structural cardiopathology (Chou and Chen 2008; Khasnis and Thakur 2008). Atrial fibrillation is especially prevalent in the elderly, affecting 2–5% of the population older than 60 years and 10% of people older than 80 years. It is an important cause of ictus, which can be found in about 15% of the patients that suffer from this phenomenon and in 2–8% of the patients

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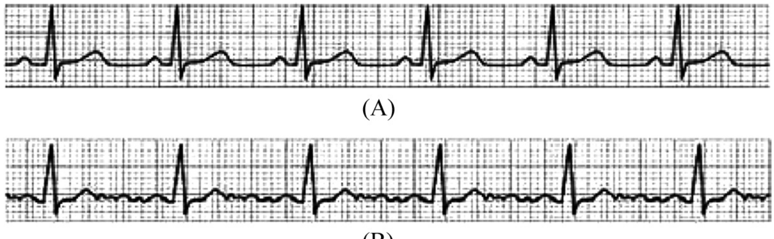
with transitory ischemic attacks. The occurrence of ischemic cerebral infarctations in patients with AF nonrheumatic oscillates between 2–5% a year. The recurrences vary in different studies between 2–15% in the first year and approximately 5% in the next year. The most important indication of recurrences is presented by patients with AF and rheumatic heart disease, but the occurrence has been decreasing during the last couple of years. Therefore the most frequent source of cardioembolism nowadays is nonrheumatic AF. Atrial fibrillation can be classified as initial or chronic. The risks of sustained AF include stroke and myocardial infarction, caused by the formation of blood clots within stagnant blood volumes in the atrial (Logan and Healey 2004). Atrial fibrillation is the result of an irregular and repetitive atrial depolarization. As a result of this, the auricle does not contract in a coordinated way, producing so-called "F-waves" or fibrillation waves, which would correspond to the multiple atrial depolarizations (contractions), with disappearing P-waves and disorganized waves appearing in its place. This can be seen in Figure 1.

The chronic forms of AF can be divided in three groups:

- Paroxysmal: The episodes generally end spontaneously and usually last less than 48 hours.
- Permanent: Where the conversion of sinusal rhythm is impossible or where there are quick relapses.
- Persistent: The AF persists but can be reverted to sinusal rhythm.

The decision to restore the sinusal rhythm or to control the ventricular frequency is of critical importance. In the case of a first episode of AF, restoring the sinusal rhythm should always be tried, but in the case of persistent chronic AF it should be attempted to define who benefits from the use of cardioversion and who should be treated with a control of the ventricular frequency and tromboembolic profilaxis (Reddy 2008).

In order to develop a better understanding of AF, in recent years intense investigation has been carried out (Chou and Chen 2008; Khasnis



(A)

(B)

FIGURE 1 ECG of a healthy patient (A), and one of a patient with atrial fibrillation, with multiple fibrillate waves in the wave P (B).

and Thakur 2008; Chiarugi et al. 2007). Time domain methods can be used to characterize the signal in the surface ECG. Analysis can be done through direct analysis of the original signal or through methods used to obtain and analyze atrial activity with statistical tools or sequential analysis methods. For example, Scherr et al. (2007) present a method based on complex fractionated atrial electrograms (CFAEs) as ablative targets for the treatment of AF. However, the process of CFAE identification is highly dependent on the operator's judgment. With the use of custom software, CFAE complexes were identified in more than 80% of the left atrial endocardial locations (Chiarugi et al. 2007). In the methodology presented by Cantini et al. (2004) the average of RR (index of ventricular activity) was related with the dominant atrial Frequency (DAF) (index of atrial activity). A linear classifier was evaluated separating the RR/DAF plane into the nonterminating AF (N-type), and AF that terminates immediately, within 1 second after the end of the record (T-type). The best score was 90% on testing the methodology. This article also proposed a new methodology for the second event of the challenge from PhysioNet and Computers in Cardiology: spontaneous termination of AF (Cantini et al. 2004). For this second event, AF terminating in 1 minute (S-type) versus AF terminating immediately (T-type), Cantini et al. (2004) used a method based on the correlation of the QRST-complex in order to preprocess the ECG, and after that, significative parameters were extracted in the DAFs during the penultimate and last 2 seconds of the ECG recording. The best score using this methodology was 80% on learning sets and 90% on testing sets.

Guler and Ubeyli (2005) proposed ensemble neural networks to guide model selection for classification of ECG beats. The ECG signals were decomposed into time-frequency representations using discrete wavelet transform and statistical features were calculated to depict their distribution. In order to obtain good classification results four sets of neural networks were trained. Networks in each group were trained by the Levenberg–Marquardt backpropagation algorithm with different targets. Three types of cardiac disease were classified: congestive heart failure beat, ventricular tachyarrhythmia beat, AF beat, obtained from the Physiobank database were classified with the accuracy of 96% by the ensemble system. In Christov, Bortolan, and Daskalov (2001) a method for automatic detection of atrial flutter and fibrillation by sequential analysis of the atrial activity in a single ECG lead is presented. A previous method for automatic detection of atrial flutter/fibrillation was based on the assessment of atrial activity in TP segments. The proposed methodology is based on the assessment of atrial activity in TP segments, connected with "P wave absence" and "ventricular arrhythmia detection," forming a combined algorithm with three consecutive logic steps. The sequential analysis correctly detects "fine" fibrillation where atrial activity is hardly visible. In Stridh and Sornmo (2002) a new methodology is presented for the classification of AF based on a time-frequency distribution of the QRST-cancelled signal. Information concerning temporal variations in fibrillation frequency and waveform shape is extracted and analyzed. Chiarugi et al. (2007) recently presented a noninvasive ECG tool for predicting AF, where the atrial and ventricular activities were separated using beat classification and class averaged beat subtraction, followed by the evaluation of seven parameters representing atrial or ventricular activity. As selected features for the classification of the ECG dominant atrial frequency (DAF, index of atrial activity) and average HRmean (HR, index of ventricular activity) was selected as optimal for classification. A linear classifier was designed for classification type-N and type-T cardiac disease, obtaining a performance of 90%. The same classifier led to correct classification in 89% of the 46 cases for N/S-type discrimination.

The goal of this article is to present a new technique to detect various types of terminating and nonterminating AF using an intelligent classifier based on soft-computing paradigm (nonlinear classifier), using a powerful tool such as genetic programming, capable of using in conjunction with several features employed by different publications appearing in the bibliography.

PROCESSING OF THE ECG'S

The data at our disposal consists of 60 second recordings captured at a rate of 128 bits per second. However, these captured signals are not clean. On the one hand, they possess noise within the captured signal caused by the recording material or by other physical activities, such as, for example, breathing, and on the other hand the activity of other parts of the heart, such as, for example, the ventricles (since, obviously, for the auricular fibrillation only the activity of the auricles is of interest). All these noises will cloud the captured signal and will have to be eliminated in order to be able to work with them, using several mechanisms that will be explained later on, obtaining characteristics that are more solid. Since the biggest part of the useful energy of the ECG is found below 40 Hz, a filtrate between [0.5–40 Hz] has been obtained, to eliminate the noise that is not cardiac activity. In order to be able to correctly analyze the activity of the auricles, which is where the auricular filtration can be identified clearly, the signal will have to be cleared of all activity that is of no interest. To be able to eliminate the reflection of the ventricular activity in the QT-section of the signal, we cannot just apply a mere filtrate of a frequency range as in the case of noise caused by equipment, since the QRS-complex covers the entire range of highly energetic frequencies. To obtain a clean signal of the auricular activity in the ECG, two different approaches will be contemplated:

1. Cancelling the activity of the QRST complex, subtracting a morphologic average of its activity from the signal, and applying it to every heartbeat.
2. Detecting the TQ section between every beat (which are clean zones of the ventricular activity) and analyzing only what is produced in these zones.

There is a great variety of algorithms to carry out the extraction of the auricle activity from the electrocardiogram (Thakor, Webster, and Tompkins 1984), such as, for example, Thakor's method (structure of recurrent adaptive filter), the method of adaptive filtering of the entire band, methods based on neural nets, methods of space-time cancellation (Stridh and Sornmo 2001), methods based on the application of wavelet (Guler and Ubeyli 2005), or based on the use of the PCA-concept (Petrutiu et al. 2006). A fundamental step that these approaches have in common is the detection of the QRS-complex, that is to say, of every heartbeat. Since there is not an especially outstanding method for the detection of QRS in the ECG recordings, the application of a simple technique based on the derivative of the signal will be enough. In summary the method is as follows: the sum of the absolute values of the derivatives of both channels is obtained, the sections with the largest incline (R-wave) are identified, and the QRS-complex demarcated. As a result of this entire algorithm, we will have detected the places in the electrocardiogram where there are QRS-complexes, with which we will have the starting point for the application of the different techniques of QRST-cancellation. In this article, two different methods have been analyzed:

1. QRST methods of space-time cancellation (Stridh and Sornmo 2001), which consists of the realization of the space-time alignment of an average form of the heartbeat before eliminating that from every specific heartbeat of the ECG, with which the resulting residues would correspond with the signal of the "auricular fibrillation." This method is orientated on a continuous input signal, as would be the case with an input signal in real-time, in which the average heartbeat adapts to the variations that the heartbeats in the ECG undergo through time. However, in the specific case that is of concern to us, there is a recording of limited time (60 sec), for which a progressive adaptation of the heartbeat does not seem recommendable. Furthermore, on having the complete register and without the necessity of processing it little by little, which would be the case in an analyzing system in real-time, we can use all the available heartbeats to adjust the average heartbeat as much as possible. Because of this, the technique previously mentioned

will not be used to realize the QRST-cancellation in the development of this project, although without doubt it is useful as an orientation.

2. QRST-cancellation through morphologic clustering (Cantini et al. 2004; Chiarugi et al. 2007). With this technique as well, the subtraction of every heartbeat from a template of the average heartbeat takes place, but in this case the template used is specific to every heartbeat, and it can be very different from the template used for the prior heartbeat. This is caused by the fact that this average heartbeat is no longer actualized little by little, with every new heartbeat analyzed in comparison to the previous one, as could be done with the continuous entry of the ECG signal, but rather that a clustering is realized, in groups of different forms (morphology) of the heartbeats of the recording.

DETECTION OF THE SEGMENTS OF AURICULAR ACTIVITY

Another focus that can be used to obtain the auricular activity that is different from the subtraction of the ventricular activity proposed in the two previous approaches, is the proposal by Lemay, Ihara, Vesin, and Kappenberger (2004), which consists of the use of the segments of the recording outside the QT-intervals. Although the proposal seems straightforward, the difficulty lies in the fact that detecting this interval QT is not a trivial task, but actually an open field of research. It is not in vain that it was the proposal for the competition of PhysioNet for the year 2006. Detecting the start of the Q-wave is not overly complicated because the QRS-complex is easy to find and because of the great variety of algorithms to detect it. Nevertheless, detecting the T-wave and its end forms a complicated task, since in AF-recordings even by simply looking at it, it is hard to demarcate the end of the T-wave, which means that designing an algorithm that does that automatically in a great variety of circumstances will continue to be complicated.

FEATURE EXTRACTIONS

The present idea in this work is to use the biggest quantity possible of features that have been used satisfactorily by other authors. It is probable that the individual who uses a characteristic does not contribute to a correct classification; however, using diverse characteristic in a no-lineal classifier, the interactions among different features can improve the classification results considerably. The features analyzed were selected by the article who obtained the best results in the completion, and therefore the way they processed the ECG and the characteristics they used should, in theory, be representative of the recordings. In total 55 different characteristics were used, from the following articles: Cantini et al. (2004), Lemay et al. (2004), Hayn et al. (2004), Raine and Langley (2004), Mora and Castells (2004), Scherr et al. (2007), Petrutiu et al. (2006), and Chiarugi et al. (2007).

A NEW INTELLIGENT CLASSIFIER BASED ON GENETIC PROGRAMMING

In the different articles we have presented in the previous sections, the authors did not use any algorithmic method in order to try to classify the electrocardiograms. The authors applied simple methods to try to establish the possible classification based on the classification capacity of one single characteristic or pairs of characteristics (through a graphic representation). Nevertheless, the fact that one single characteristic might not be perfect individually to classify a group of patterns in the different categories, does not mean that combined with another or others, it does not obtain some high percentages in the classification. Due to the great quantity of characteristics obtained from the ECG, a method to classify the patterns was needed, alongside a way of selecting the subgroup of characteristics optimal for classifying, since the great quantity of existing characteristics would introduce noise as soon as the search for the optimal classifier of the patterns of characteristics begins. In this article, a new intelligent algorithm based on genetic programming (GP) for simultaneously selecting the best features is proposed for the problem of classification spontaneous termination of AF. In this algorithm GP is used to search for a good classifier at the same time as the search for an optimal subgroup of characteristics. The algorithm consists of a population of classifiers, and each one of those is associated with a fitness value that indicates how well it classifies. Each classifier is made up of the following:

- A binary vector of characteristics, which indicates with 1's the characteristics it uses.
- A multitree with as many trees as classes as has the collection of data of the problem. Every tree i distinguishes between the class i (giving a positive output) and the rest of the classes (negative output). Furthermore, it is connected to values p_j (frequency of failures) and w_j (frequency of successes). The trees are made up of function nodes $[+, -, *, /$, trigonometric functions (sine, cosine, etc.), statistic functions (minimums, maximums, average)], and terminal nodes {constant number and features}. Their translation to a mathematical formula is immediate.

The initial population is created by randomly making up trees, and using the characteristics from a randomly chosen subgroup as possible characteristics, giving more probability to small subgroups. The algorithm consists of a loop in which in each repetition a new population is formed from the previous through the genetic operators. The classifiers that scores the highest on fitness will have more possibilities to participate, with which the population will tend to improve its quality with the successive generations. The proposed algorithm has the following building blocks: genetic operators and fitness function.

Genetic Operators

Genetic operators are applied to each individual within the population, with an application probability p_c for the crossover operators, and p_m for the mutation operators. Due to the problems of establishing these probabilities *a priori*, the algorithm presented here implements a dynamic adaptation mechanism of p_c and p_m (Srinivas and Patnaik 1994) which chooses the values that are appropriate at all times, based on the state of convergence of the population. Once the probabilities have been chosen, the genetic operators described below are applied. The evolutionary operators described in this section have been specifically designed for the problem of optimizing the parameters of the genetic programming system. These new operators not only apply random changes to the individuals they affect in order to maintain the diversity in the population and to provide mechanisms to escape from local minima (Gonzalez et al. 2002; Castillo-Valdivieso et al. 2002), but they also try to avoid the application of changes that could worsen the fitness of the solutions. In intelligent systems it is very important to determine which are the main operators (Rojas et al. 1999, 2000), being for our system the following:

- Reproduction operator: a classifier chosen proportionally to the fitness passes on, intact, to the next generation.
- Mutation operator: a classifier is selected randomly and nodes of a tree are changed, giving more probability to the worst trees.
- Crossover operator: homogeneous cross (classifiers with the same characteristics) and heterogeneous cross (classifiers with a similar subgroup). It realizes the exchange of subtrees and trees between the classifiers. Figure 2 shows the behavior of this operator.

At the end, the algorithm produces the best classifier (the highest score on fitness) that has been found during the execution of the algorithm. In order to try to improve the percentages of classification obtained with the algorithm, the ability to use Elitism was added and also an important previous step to the assessment of characteristics. It was thought to be useful to value the characteristics first, and use this assessment when a

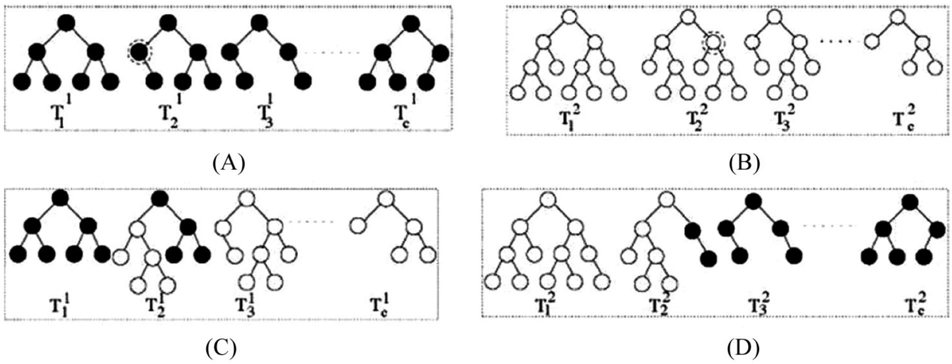


FIGURE 2 An example of a crossover operation in the proposed multitree classifier. (A) and (B) are initially the classifiers. As it can be seen they exchange the low subtree at the selected nodes, besides the complete trees which represent the bigger classes of the trees that exchange their subtrees. In (C) and (D) the results of the crossover operator is presented.

subgroup would be assigned to the classifier. This is performed in the following steps:

- A probability is given to each characteristic of being assigned to the initial subgroup of the classifier proportional to its assessment.
- G-flip was used to assess the characteristics (Gilad-Bachrach, Navot, and Tishby 2004). G-flip is a greedy search algorithm for maximizing an evaluation function that takes into account the number of features selected. The algorithm repeatedly iterates over the feature set and updates the set of chosen features. In each iteration it decides to remove or add the current feature to the selected set by evaluating the margin term of the evaluation function with and without this feature. This algorithm is similar to the zero-temperature Monte-Carlo (Metropolis) method. It converges to a local maximum of the evaluation function, as each step increases its value and the number of possible feature sets is finite.

  In order to obtain the best features for the classifier in the initial population, an evaluation function that assigns a score to the different features according to margin, is used. A margin is a geometric measure for analyzing the robustness and evaluating the confidence of a classifier with respect to its decision. The margin as a function of the selected set of features is defined as

$$M_P^w = \frac{1}{2}\left(\|x - nearmiss(x)\|_w - \|x - nearhit(x)\|_w\right) \tag{1}$$

  where P is a set of point and x be an instance. The vector of weight w measures the relative importance of each feature in the input space.

It is important to note that $M_P^{\lambda w}(x) = |\lambda| M_P^w(x)$ for any crisp value λ, and therefore it is natural to establish the normalization constrainmax $w_i^2 = 1$. To define the evaluation function of a specific value of the weight vector w, the margin of the complete sample points is used. The margin of each instance x is obtained with respect to the complete sample excluding x. Therefore, the evaluation function to be optimized for a specific weight vector w, given a training set S, is defined as

$$\Psi(w) = \sum_{x \in S} M_{S \backslash x}^w(x) \tag{2}$$

- The proposed methodology devalues bad characteristics in groups with a large quantity of characteristics, thus accelerating their convergence to good groups of characteristics and good classification results.

Fitness Function

The fitness function combines the double objective of achieving a good classification and a small subgroup of characteristics:

$$Fitness = f \cdot \left(1 + \alpha e^{-\frac{\beta}{n}}\right) + \lambda\Phi. \tag{3}$$

In this equation, f is the sum of the cases of success in the classification of the trees, β is the cardinality of the feature subset used, n is the total number of features, and α is a parameter which determines the relative importance that we want to assign for correct classification and the size of the feature subset. The exponential factor decreases exponentially with an increase in cardinality of the feature subset used and so is the fitness function. Thus, if two classifiers make a correct decision on the same number of training points, then the one using fewer features is assigned a higher fitness. We decrease the penalty for using larger feature subsets with generations to improve the classification accuracy. So initially we use fewer features, but as learning progresses we give more importance to better classification performance. In order to perform this behavior, the parameter *alpha* is defined as follows:

$$\alpha = C\left(1 - \frac{gen}{TotalGen}\right) \tag{4}$$

where C is a constant, and *TotalGen* is the number of generations of the genetic algorithm, and *gen* is the current generation. The function Φ in (3) is a regularization function that measures the smoothness of the intelligent multitree system in order to improve generalization capability for the classifier design. The parameter λ is a constant value that multiplies the effect of the regularization function in order to obtain the final fitness function. The regularization method was presented originally by Tikhonov (1963) and Wei, Zhang, Ng, and Wei (2007) for solving ill-posed problems. If the Euclidean norm of the solution vector as Φ is selected, a zero-order Tikhonov regularization is used. The main idea of regularization is to stabilize and measure the smoothness of the obtained classifier by means of some auxiliary nonnegative functional that gives prior information about the classifier. By analyzing the behavior of the intelligent classifier during the training phase, it is possible to observe that the nonlinear function to be modelled by the GP can be abruptly modified and the output for a certain point in the input space can be immediately adapted. This behavior cannot be effectively detected and removed for the training phase of the parameter of the intelligent classifier by only considering a point at $\vec{x}_i$ $(i = 1, \ldots, n)$. Therefore, this is the reason to use the following regularization function (Yun, Kyung, Sang, and Young 2001):

$$\Phi = \frac{1}{n+1}\left\{\sum_{i=1}^{n} T_{Out}\left(\vec{x}_i\right)\right\}\left(\left|T'_{Out}\left(\vec{x}_1\right)\right| + \left|T'_{Out}\left(\vec{x}_n\right)\right| + T'_N\right) \tag{5}$$

where T'_N is the curve length of the first derivative of the output function of the multitree intelligent classifier, defined as $T'_{Out}\left(\vec{x}\right) = \frac{\mathrm{d}T_{Out}}{\mathrm{d}\vec{x}}$, and evaluated between x_1 and x_n. As can be easily observed, the computational time required for obtaining the function Φ in (5) is longer than for obtaining the Tikhonov regularization; however, this function is very effective obtaining smooth behavior on the classifier.

EXPERIMENTATION AND RESULTS OF CLASSIFICATION WITH THE AF DATA

In the first place, the realization of the events of Challenge 2004 of Physionet (2004) was carried out with the characteristics obtained from each author that obtain positive results, to test the validity of the implementation of their methodology, and to compare these results with the results obtained by the proposed methodology (see Table 1).

There are two different events:

Event A: Differentiate between Group N (nonterminating AF, defined as AF that was not observed to have terminated for the duration of the long-term recording, at least an hour following the segment) and Group T (AF that terminates immediately, within 1 second after the end of the record).

Event B: Differentiate between Group S (AF that terminates 1 minute after the end of the record) and Group T.

TABLE 1 Comparison of the Proposed Methodology with the Winners of Challenge 2004

	Classification success (in %)	
	Event A	Event B
Petrutiu et al. (2006)	97	100
Hayn et al. (2004)	93	80
Cantini et al. (2004)	90	90
Lemay et al. (2004)	90	60
Proposed methodology	100	95

Test set A contains 30 records, of which about one-half are from group N, and of which the remainder are from group T. Test set B contains 20 records, 10 from each of groups S and T.

Apart from events A and B, other classifications have been realized (see Table 2):

Event C: the separation of permanent AF (recording of type N) from paroxysmal AF (recording of type S and type T). This turns out to be interesting from a clinical point of view, since the risk of reoccurrence in case of treating the permanent AF is very high, and it can be of interest not to revert to sinoauricular rhythm but instead to treat the fibrillation frequency.

Event G: the separation of three recording types simultaneously.

In the experiments that were carried out, all the extracted characteristics were used. In events A and C, results of 100% for learning set and 100% and 97% for test set were obtained respectively, comparable to those of the authors, which shows that there is a quite clear separation between them. In event B, a 95% result was achieved with the proposed algorithm, but other author's winners of this challenge obtain poor results, which gives reason to think that there is not a good separation at least with these characteristics or it is very important to select the

TABLE 2 Results of the Proposed Methodology for the Four Events

	# Characteristic		Learning set		Test set	
	Number	Mean	Best (%)	Mean (%)	Best (%)	Mean (%)
Event A	6	6.2	100	95	100	92
Event B	8	8.4	98	91	96	87
Event C	5	5.2	100	98.5	97	93
Event G	6	6.7	94	87	89	86

TABLE 3 Results of a Neural Network Classifier for the Four Events, Using Three Feature Selection Algorithms and Using all the Characteristics

	Infogain					Relief					G-flip					All characteristics				
	Best		Mean			Best		Mean			Best		Mean			Best		Mean		
Event	Lrn	Tst	Lrn	Tst	#C	Lrn	Tst	Lrn	Tst	#C	Lrn	Tst	Lrn	Tst	#C	Lrn	Tst	Lrn	Tst	#C
A	95	93.3	96.7	91.1	7	100	83.3	98.3	80	6	100	83.3	98.3	83.3	6	70	63.3	58.3	63.3	55
B	50	70	76.7	66.7	9	95	65	81.7	63.3	8	80	70	68.3	70	7	60	80	53.3	73.3	55
C	96.7	92	84.4	88	8	73.3	72	73.3	70	5	96.7	86	95.6	86	8	63.3	70	65.6	68.7	55
G	90	64	73.3	62.7	11	76.7	56	56.7	54	8	86.7	64	77.8	64	9	33.3	50	51.1	48	55

#C = number of characteristics used.

appropriated characteristics. In event G, the results are worse, achieving 94% for learning set and 89% for test set.

In addition we have wanted to carry out the same events with another technique to compare the results of classification, particularly with neural networks. Because in the case of learning with neural networks or neurofuzzy systems, using all the characteristics could lead to unsatisfactory results (Rojas et al. 1999, 2000), the most promising characteristics have been selected for each event using different techniques, like for example InfoGain, Relief and G-Flip (Gilad-Bachrach et al. 2004) (see Table 3). As can be seen quite similar results have been obtained in the "easy" events, being inferior in the "difficult ones," which were obtained with the previous classification algorithm. In respect to the comparison of the classification results between the classification algorithm proposed and the neural networks, it can be seen that using all the characteristics in the neural networks, worse results in all events are achieved. This is caused by the fact that a great number of characteristics create confusion in the system, and therefore it is preferable as can be seen to use a selection of algorithm characteristics to choose a good group of characteristics. With the classification algorithm proposed in this article, it can be observed that although using all the characteristics, equally good results are achieved compared to the best results obtained with the neural networks, converging the algorithm towards the use of good subgroups of characteristics.

CONCLUSIONS

In this article, a new online feature selection algorithm using genetic programming technique has been proposed as a classifier for classification spontaneous termination of AF. In a combined way, our genetic programming methodology automatically selects the required features while design the multitree classifier.

A different genetic operator has been designed for the multitree classifier, and a for a better performance of the classifier, the initialization process generates a solution using smaller feature subsets which has been previously selected with a greedy search algorithm (G-Flips) for maximizing the evaluation function. Therefore, the best features have higher probability to be selected in the multitree classifier initially constructed for the genetic programming algorithm. The effectiveness of the proposed scheme is demonstrated in a real problem—the classification of spontaneous termination of AF. At this point, it is important to note that the use of different characteristics gives different classification result as can be observed by the authors working in this challenge. The selection of different features extracted from an electro-cardiogram has a strong influence on the problem to be solved and in the behavior of the classifier. Therefore, it is important to develop a general tool capable of facing different cardiac illnesses, which can select the most appropriate features in order to obtain an automatic classifier. As can be observed, the proposed methodology has very good results compared to the winner of the challenge from PhysioNet and Computers in Cardiology 2004, even if this methodology has been developed in a general way to resolve different classification problems.

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