The Classification of PVCs Using Filter Bank Features, Induction of Decision Trees and a Fuzzy-Rule-Based System

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Abstract—*The classification of heart beats is important for automated arrhythmia monitoring devices. This study describes two different classifiers for the identification of premature ventricular contractions (PVCs) in surface ECGs. A decision tree algorithm based on inductive learning from a training set and a fuzzy-rule-based classifier are explained in detail. Traditional features for the classification task are extracted by analyzing the heart rate and morphology of the heart beats from a single lead. In addition, a novel set of features based on the use of a filter bank is presented. Filter banks allow for time-frequency dependent signal processing with low computational effort. The performance of the classifiers is evaluated on the MIT-BIH Database following the AAMI recommendations. The decision tree algorithm had a gross sensitivity of 85.29% and a positive predictivity of 85.23%, while the gross sensitivity of the fuzzy-rule-based system was 81.34% and the positive predictivity 80.64%.*

Keywords—*Beat classification, ECG analysis, Fuzzy logic, Filter bank, Time-frequency analysis*

1 Introduction

THE correct classification of heart beats is fundamental to ECG monitoring systems such as in intensive care, automated analysis of long-term recordings, arrhythmia monitors, and cardiac defibrillators. Counting the occurrence of ectopic beats is of particular interest to support the detection of ventricular tachycardia and to evaluate the regularity of the depolarization of the ventricles. For example, the risk of sudden death for patients with a structural heart disease is higher with an increased occurrence of premature ventricular contractions (PVCs) (HAMDAN and SCHEINMAN, 1995).

Variability in morphology and heart rate from patient to patient and even for the same patient, noise present in the signal, or other arrhythmias make correct classification of PVCs a challenging task, and reported results leave room for improvement. Different classification approaches based on features such as heart rate, shape and correlation with templates are proposed in the literature for classification of surface electrocardiograms (ECGs) (WANG, 1983; RAPPAPORT *et al.*, 1982; DASSEN *et al.*, 1995; CHOW *et al.*, 1992; HU *et al.*, 1994; SILIPO *et al.*, 1995; JENKINS and CASWELL, 1996).

An evaluation of the performance of algorithms reviewed in the literature is difficult because the authors use different databases or their own data sets and different learning strategies for their algorithms. The *Association for the Advancement of Medical Instrumentation* (*AAMI*) recommends standards for the development of classifiers based on a training set and beat-by-beat testing of the performance of arrhythmia monitoring algorithms to avoid such confusion (AAMI, 1998). Moody and Mark (1982) report a gross PVC sensitivity of 95.31% and a positive predictivity of 90.65% for an algorithm which uses seven features from both channels in the *MIT-BIH Arrhythmia Database* (MIT-BIH, 1988).

The purpose of this study is to introduce a new set of features based on a filter bank concept and to compare two methods for beat classification. Afonso et al. (1996; 1997; 1999) introduced the use of a filter bank to address different issues of monitoring systems, such as signal enhancement and beat detection. This approach offers the possibility of processing the original signal in subbands representing different frequency ranges in the signal.

The two classifiers, a decision tree and a fuzzy-rule-based system, differ widely in their implementation and representation of knowledge. The induction of a decision tree (QUINLAN, 1986) is a self-learning algorithm, which analyzes a classified training set to develop a successful strategy. On the other hand, the fuzzy logic approach is a rule-based system, which takes advantage of knowledge implemented by a human expert. Fuzzy logic allows the use of linguistic variables to formulate rules, which are intuitively plausible. It also avoids fixed thresholds or distance measures and therefore accounts for noise and uncertainties in measured data. The principles of neural networks and fuzzy logic can be combined for classification of ECGs (HAM and HAN, 1996).

2 Data Selection and Feature Extraction

2.1 Data selection

The ECG records from long-term Holter recorders analyzed in this study are from the *MIT-BIH Database*, which contains 48 records. The upper channel, a modified limb lead II (MLII) in 47 records, was chosen, because normal QRS complexes usually have a large R wave in this lead.

The *AAMI* standard recommends the exclusion of records with paced beats (4 records) from the performance evaluation of beat-by-beat testing of arrhythmia monitoring algorithms. Premature ventricular contractions and ventricular escape beats are grouped in the class *P* of positive instances. An annotated normal beat, left and right bundle branch block beat, atrial premature and aberrated atrial premature beat, nodal (junctional) premature beat, supraventricular premature beat, or an atrial or nodal (junctional) escape beat are referred to as a ‘non-PVC’ or negative instance, belonging to the class *N*.

2.2 Preprocessing of the data

The annotations in the database for the locations of R waves are used as ideal beat detectors. For our study an algorithm searched for the local maximum or minimum peak near the beat label to establish fiducial points instead of using the annotated locations which are based on an integrative centroid measurement.

Characteristic variables in the ECGs such as the current heart rate or the magnitude of the R wave for the same beat type may vary significantly from patient to patient or even for the same patient. A normalization process must be used to provide the classifier with comparable features. The choice of the normalization process is crucial because it has a great impact on the results of the classifier (RAPPAPORT *et al.*, 1982). We chose to establish a reference buffer for each variable by averaging the measurement for the first eight beats of each record and continuously updating this buffer with incoming ‘normal’ beats. A feature of a beat is considered to represent a ‘normal’ value whenever an incoming measurement lies within $\pm 15\%$ of the mean of the buffer or $\pm 15\%$ of the last measurement added to the buffer. The complete buffer for a feature is overwritten if the measurements of eight consecutive beats lie within $\pm 15\%$ of their mean.

2.3 Heart rate features

Three features related to the heart rate are extracted from the ECG recordings using the corrected peak locations: 1) the normalized R-R interval *norm-*RR_0 between the preceding and the current R wave, 2) the ratio RR_1*-to-*RR_0 obtained by dividing the R-R interval RR_1 between the current and the following R wave by the previous R-R interval RR_0, and 3) the *irregularity* of the heart rate, which is defined as the standard deviation over the mean (RIPLEY *et al.*, 1989).

2.4 Morphological features

Four morphological features were chosen to represent information about the shape of the QRS complexes: 1) normalized amplitude, 2) peak-direction, and 3) width of the largest local minimum or maximum nearest the annotation (derived by a 15% threshold between baseline and peak), and 4) the normalized peak-to-peak distance within the QRS complex.

2.5 Features extracted from a filter bank

Filter banks allow for the separation of a signal $x(n)$ into M different subbands, each representing the signal content in a certain frequency range (SOMAN *et al.*, 1993). The implemented filters were developed by the lapped orthogonal transform (LOT) (MALVAR, 1992). The filter bank contains M = 32 filters with equal bandwidths and each of a length $L = 2 \cdot M = 64$. Due to the frequency range of the digitized signal from 0 to 180 Hz, the bandwidth of every subband is 180 Hz / 32 = 5.625 Hz. The sampling frequency of each downsampled subband is 360 Hz/M = 11.25 Hz.

The analysis filter of the first subband (subband 0) is a low-pass filter with a cutoff frequency at 5.625 Hz. The next 30 subband filters are bandpass filters, and the filter of the last subband

(subband 31) is a high-pass filter with a cutoff frequency at 174.375 Hz (see Figure 1). The even subbands have symmetric analysis and synthesis filters, and the uneven subbands have antisymmetric filters. All filters have linear phase to allow independent analysis in the subbands with the same delay for fiducial points. The filters are orthogonal to ensure that the energy of the signal is preserved in each subband. All filters have a finite impulse response, and the attenuation of the highest sidelobes is greater than -20 dB (AFONSO *et al.*, 1996).

The idea behind the use of different subbands is to recognize the PVCs by their energy distribution over the frequency range. Intuitively, the wider shape of the PVCs compared to normal beats with sharper peaks, leads to the assumption that the low-frequency energy is greater than the high-frequency energy. Thakor et al. (THAKOR *et al.*, 1984) present a power spectral analysis of ECG waveforms, in which the relative power spectrum of the QRS complex has a high amplitude between 5-25 Hz. Clayton et al. (CLAYTON *et al.*, 1995) evaluated the frequency spectrum of ventricular tachycardia and ventricular fibrillation with a Fast Fourier Transform (FFT) using consecutive one second epochs. They conclude that differences in the frequency spectrum, such as the mean dominant frequency and the width and proportional size of the peak in the spectrum, allow differentiation of different ventricular arrhythmias.

The time interval between two samples in the downsampled subbands is only 88.89 ms. This leaves a representation of a normal QRS complex (80 ms) by two samples, which is insufficient for a detailed analysis of the shape of the waveform. Therefore, all seven features using the filter bank are extracted from upsampled subbands. Let the energy $e_k(n)$ of a subband k be represented by the squared amplitude $o_k(n)$ in the subband (see Figure 1):

$$e_k(n) = o_k^2(n) \, .$$

The mean value of the amplitude during the previous second was subtracted from the amplitude in subband 0 to account for the dc component. We implemented a moving window integrator (MWI), which adds up the squared amplitudes over a rectangular window with a length of 122 ms. The maximum energy E_k in a subband is then represented by the peak in the output of the MWI within ± 35 samples of the annotated beat location. The maximum energy $E_{x,x+1}$ in adjacent subbands was determined by the same procedure after summing up the two outputs $o_k(n)$ and $o_{k+1}(n)$. The feature set consists of 5 ratios of maximum energies in different adjacent subbands and 2 different widths of the MWI for the energy of the lowest subbands $E_{0,1}$. Two parameters *MWI-15* and *MWI-30* represent the time that the actual energy is above 15% or 30% of the maximum energy. The energy ratios are calculated with respect to the energy $E_{0,1}$, which represents the sum of the energy of the signal in subbands 0 and 1 corresponding to a frequency range from 0 to 12.25 Hz. The five ratios are $E_{2,3}/E_{0,1}$, $E_{4,5}/E_{0,1}$, $E_{6,7}/E_{0,1}$, $E_{8,9}/E_{0,1}$, and a weighted ratio $E_{0,1}/E_{07}$ of most of these energies combined:

$$\frac{E_{0,1}}{E_{07}} = \frac{E_{0,1}}{E_{0,1} + 2E_{2,3} + 10E_{4,5} + 100E_{6,7}}$$

where E_{07} is the weighted sum of the energies in all subbands from 0 through 7. The weighting factors were found empirically to compensate for differences in signal amplitudes in the subbands. The denominator includes $E_{0,1}$ to bound the ratio to values between 0 and 1.

3 Classification Methods

3.1 Classification with induction of decision trees

Induction means to extract knowledge about the behavior of features in a set of given examples which are related to different classes and to apply this knowledge to unseen instances. A decision tree provides a kind of representation of acquired knowledge. Decision trees are fairly robust, capable of dealing with noisy data, and result in a simple classifier with easily interpreted decision rules (QUINLAN, 1986).

A decision tree is characterized by nodes and leaves as shown in Figure 2. A node represents a test being performed on a feature and contains branches for the possible outcomes. The branches lead to another node or a leaf, which determines the affiliation to a class. The classification process starts in the node at the roof of the tree, performs tests in successive nodes and takes the appropriate branches until categorization to a class in a leaf. The number of branches that separate the root from the most distant leaf determines the level of the decision tree. We used the decision tree algorithm *MC4* from the *MLC++* library (KOHAVI *et al.*, 1995).

The stages in creating the final decision tree include the construction of an initial tree and a subsequent pruning of the branches to simplify decision rules which overfit the data. The criteria to derive the initial decision tree are based on an analysis adopted from information theory. The decision tree is generated by placing the feature with the highest *gain ratio* at the root of the tree. Each subset or branch induces a new decision tree evaluated by the same criterion. The general principle of inductive learning, often called Ockham's razor, is that "The most likely hypothesis is the simplest one that is consistent with all observations." Thus, the search for the perfect decision tree is determined either when all examples in the training set are correctly classified, when more branches do not increase the accuracy of the algorithm on the training set, or when the complexity of the tree exceeds certain thresholds.

Two independent procedures help to prevent a loss of generalization: finding criteria to stop the growing process of the tree and pruning of the derived tree. The algorithm can be adjusted by limiting the number of levels in the tree and determining a minimum amount of instances *min instances*, that must trickle down at least two branches of a node. This amount is derived for each node over a weighting factor *split weight*, which represents the percentage of instances divided by the number of classes. If the number of instances present in a node is either very high or very low, the calculated *min instances* may not be adequate. To avoid this problem, *min instances* is bounded on both sides. The subsequent automatic pruning of the decision tree involves the removal of branches, which do not contribute significantly to the performance, for the sake of less complex results.

3.2 Classification with a fuzzy logic system

Zadeh (1965) introduced the theory of fuzzy sets, where the membership of objects to classes is a matter of degree. This is an extension of the conventional crisp set theory, where partial memberships are not possible. A Fuzzy Logic System (FLS) maps crisp inputs, such as a feature vector, nonlinearly into crisp outputs. Fuzzy logic allows for implementation of rules by an expert using linguistic variables. The advantages of a FLS are that it is robust and cost-effective in the implementation of existing knowledge. Figure 3 shows its four components: fuzzification, rules, inference engine, and defuzzification (MENDEL, 1995).

The process of fuzzification is a form of quantization, where crisp numbers are mapped into fuzzy sets. The degree of membership of an input feature to fuzzy set is evaluated by the membership functions of the fuzzy sets. Fuzzy sets are defined within the range of the feature (universe of discourse) and associate a degree of similarity between the value of the feature and the fuzzy subset.

Rules in a FLS have the form of IF-THEN statements:

IF *antecedent* THEN *consequent* ,

where the antecedent represents a fuzzy set or relations between fuzzy sets and the consequent assigns a fuzzy set to the ouput. Rules are embedded using linguistic variables and map fuzzy sets into fuzzy sets. As they are all evaluated in parallel, the order of rules is unimportant.

The inference engine determines the degree of activation of each rule based on the values of the antecedents. It also combines the usually equally weighted rules which may have coincidental or contradictory consequents. The results derived in this stage are fuzzy ouput sets, which are not the desired outputs of the system.

The defuzzifier transforms the fuzzy sets into crisp numbers, because the desired output of a fuzzy system is a scalar. Popular defuzzification methods are the centroid of area method, mean of maximum method, and largest and smallest of maximum method.

The classifier was implemented using the *Fuzzy Logic Toolbox for use with MATLAB* (GULLEY and JANG, 1995). All membership functions associated with the features were implemented as generalized bell curve functions because of their smoothness and adaptability in width and steepness:

$$f(x) = \frac{1}{1 + \left| \frac{x-c}{a} \right|^{2b}} .$$

Table 1 summarizes the fuzzy input sets and their parameters. A total of nine features was chosen to reduce the complexity of the system. Only two filter bank features (*MWI-15* and $E_{0,1}/E_{07}$) were selected because their characteristics were similar to *MWI-30* and the other energy ratios and, therefore, they would have been redundant. The parameters of the membership functions were initially derived with a fuzzy c-mean clustering algorithm (BEZDEK, 1981). We then improved the performance by fine-tuning the membership functions with scatter plots from the training set (WIEBEN *et al.*, 1997).

A total of 15 rules (e.g. IF *norm-*RR_0 is premature and RR_1*-to*RR_0 is long THEN *beat type* is PVC) was implemented based on expert knowledge and cluster plots. The fuzzy output *beat type* is defined on a universe of discourse from 0 to 1. Two triangular waveforms, namely *non-PVC* and *PVC*, with a width of 0.5 are centered at 0.25 (*non-PVC*) and 0.75 (*PVC*). The intersection of fuzzy sets is implemented as the minimum operator and the union as the maximum operator. The contribution of all rules is accounted for by the sum of each rule's output set. The defuzzification reduces the degree of membership to the sets *non-PVC* and *PVC* to a single number with the center of area method. If that number is larger than or equal to 0.5, the incoming beat will be defined as a PVC, otherwise it will be classified as a non-PVC.

3.3 Training and testing of the classifiers

The *AAMI* standard recommends methods for the training and testing practice as well as the presentation of performance results. The test should report the performance of the algorithm to new data and, therefore, the training and test set must be strictly separated from each other. Different methods, such as cross validation, are used to evaluate classification performance in the field of pattern recognition. However, following the *AAMI* recommended standards the first five minutes of each record are used for training purposes while the last 25 minutes are used for testing in the *MIT-BIH Database*. Only the training set should be used to extract information on rhythm analysis, morphology of beats, cluster plots, tuning the algorithm, etc.

Only 24 of the records include PVCs in the first five minutes. These records were considered as the training set for the decision tree algorithm with 1080 PVCs and 8089 non-PVCs. Features could not be derived for the first eight beats in the training sets and the last beat in the training and test sets. The standard analysis software in the *MIT-BIH Database* includes these considerations and was used to report the test results. The test set includes 5,900 PVCs and 77,394 non-PVCs.

4 Results

The number of nodes in the generated decision trees was varied to evaluate the relationship between the complexity of the tree and the positive predictivity and sensitivity of the classification process. Therefore, the *split weight* was varied between 0 and 5 to influence the growth of the decision tree while *min instances* was bounded between 2 and 25 instances and the pruning factor was fixed. Table 2 shows that a split weight of 0.2 achieved the most balanced classification for the test set in terms of gross PVC sensitivity (85.29%) and positive predictivity (85.23%) for all beats (average sensitivity = 80.47%; average positive predictivity = 58.00%). The achieved sensitivity with the Fuzzy Logic classifier is 81.34% and the positive predictivity is 80.64% for all beats (average sensitivity = 74.58%; average positive predictivity = 66.54%). Experiments using the fuzzy c-mean clustering algorithm for adjusting the membership functions to the training set resulted in a worse performance.

5 Discussion

The use of a filter bank allows for a computationally effective implementation of a time-frequency analysis. The ratio of the energy in higher subbands to lower subbands was found to be significantly lower for most PVCs compared to non-PVCs. This ratio and the width of a moving window integrator of the energy around the peak are additional criteria for the separation of PVCs from non-PVCs. Such features from a time-frequency analysis support the classification process, but they cannot be extracted from the downsampled subbands. These features could potentially be helpful for other analysis tasks in ECG monitoring; including the differentiation of more heart beat types or rhythms such as ventricular fibrillation. In another study (AFONSO *et al.*, 1997), a similar approach showed promising results for distinguishing paced and non-paced beats.

The decision tree algorithm used features related to the heart rate and morphology in the highest levels of the tree. They appear to be the most efficient features in the differentiation between PVCs and non-PVCs. The algorithm produced robust classification schemes, which differed little for changes in the pruning and *split weight* parameters.

The decision tree classifier performed better than the fuzzy-rule-based classifier when averaged over all beats. In addition, fine-tuning of the fuzzy logic system by changing membership functions or adding rules turned out to be difficult due to the nonlinear behavior of the classifier. However, the fuzzy-rule-based classifier is robust and only uses 9 features and 15 rules with a maximum of two fuzzy sets in each of the antecedents. The fuzzy logic system also has a more balanced performance averaged over the 44 records (74.58% sensitivity and 66.54% positive predictivity) than the reported decision tree classifier (80.47% sensitivity and 58% positive predictivity).

Records with atrial fibrillation and atrial premature beats, where the heart rate and R-R intervals are irregular, increase the number of false and true negative classifications for both classifiers. This is due to the fact that the classifiers emphasize the heart rate features, which are good discriminators in the majority of the records. The results for the decision tree algorithm improved significantly when trained and tested on a selected subset of the 44 records as done by others (RAPPAPORT *et al.*, 1982; SILIPO *et al.*, 1995; HAM and HAN, 1996). However, the purpose of the study was to evaluate the performance of the algorithms on a large number of different records to identify the strengths of the classifiers as well as their limitations.

The most important factors in a classification process are the choice of features and their normalization. More features and a feedback loop from the classifier to the process of normalization of the features may result in more accurate classifications. Incorporation of the information from additional leads of the ECG could also potentially increase the performance significantly. A better lead could be analyzed in case of possible electrode problems (e.g. dead segments in the signal) or near isoelectric amplitudes in one lead. Moody and Mark (1982) report a 42% reduction in number of false negative classifications when analyzing features from two ECG leads simultaneously instead of just one lead. The task for a multilead analysis is to resolve discrepancies in case of contradictory results from the leads, e.g. when waveforms of PVCs appear similar to non-PVCs in one lead while differences are acccentuated in a second lead.

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Table 1 Linguistic description of the fuzzy input sets and the parameters a, b, and c of their generalized bell curve membership functions.

Feature	Fuzzy input set	Bell function parameters		
		a	*b*	*c*
norm-RR_0	premature	0.29	5	0.5
	on_time	0.115	1.5	1
	delayed	0.8	8	2
RR_1-to-RR_0	short	0.7	5	0
	regular	0.2	2	1
	long	2.5	15	4
irregularity	small	9	2	0
	large	55	7	75
norm-amp	small	0.7	10	1
	average	0.2	2	1
	enlarged	0.2	2.5	1.5
	highly_enlarged	2.3	10	4
peakdirection	identical	0.25	2.5	0
	opposite	0.25	2.5	1
peakwidth	normal	0.06	5	0
	wide	0.9	50	1
norm-peak-to-peak	small	0.6	5	0
	average	0.25	2.5	1
	enlarged	2.1	25	3.5
MWI-15	normal	0.22	6	0
	wide	0.14	10	0.44
$E_{0,1}/E_{07}$	low	0.3	7	0
	high	0.51	10	1

*Table 2 Results of the decision tree algorithm for varying split weights. The number of nodes, leaves, and features chosen by the algorithm are included. Sensitivity (*Se*) and positive predictivity (*+P*) for the training and test set are reported as gross statistics.*

				Training set		Test set	
Split weight	Nodes (#)	Leaves (#)	Features (#)	*Se* (%)	+*P* (%)	*Se* (%)	+*P* (%)
0	131	66	14	98.97	97.87	86.08	80.32
0.1	125	63	14	98.97	97.87	86.17	79.67
0.2	119	60	14	98.96	97.04	85.29	85.23
0.3	121	61	13	98.77	97.04	82.76	84.35
0.4	121	61	14	98.68	96.76	85.80	83.84
0.5	105	53	13	98.48	96.02	85.31	84.33
0.6	105	53	14	98.29	95.65	83.51	86.00
0.7	117	49	13	98.02	96.30	84.03	84.96
0.8	85	43	13	97.15	94.81	82.19	85.57
0.9	79	40	14	96.93	93.70	80.85	84.53
1.0	47	24	10	94.11	93.24	81.54	82.98
1.1	29	15	10	92.78	92.78	83.15	82.41
5.0	29	15	10	92.78	92.78	83.15	82.41

LIST OF FIGURE CAPTIONS

Fig. 1 *Upsampled and interpolated outputs from the filter bank for record 116. The original signal (top row) is split in 32 different subbands, where* o_0 *(second row) represents a low-pass filtered portion of the original signal. The mean of the preceding 360 samples is subtracted from* o_0 *to compensate for the offset in the original signal. Rows three and four show the ouputs* o_3 *and* o_5 *of the filter bank.*

Fig 2 *The decision tree created by MC4 for a split weight of 1.1. The tree has 29 nodes, 15 leaves, 7 levels and uses 10 features. The classification process starts at the root of the tree. An incoming beat travels down the branches of the tree depending on the result of the test on a feature. The procedure ends when the beat arrives at a leaf 'P' (PVC) or 'N' (non-PVC).*

Fig 3 *Block diagram for a Fuzzy Logic System for classification. Incoming data are preprocessed and features are extracted before the fuzzification. The inference engine combines the fuzzy sets and the implemented rules to a fuzzy output set. As a final result, the defuzzifier transforms fuzzy output sets into crisp data (classes).*

Fig. 1 *Upsampled and interpolated outputs from the filter bank for record 116. The original signal (top row) is split in 32 different subbands, where* o_0 *(second row) represents a low-pass filtered portion of the original signal. The mean of the preceding 360 samples is subtracted from* o_0 *to compensate for the offset in the original signal. Rows three and four show the ouputs* o_3 *and* o_5 *of the filter bank.*

Fig 2 *The decision tree for a split weight of 1.1. The tree has 29 nodes, 15 leaves, 7 levels and uses 10 of the available 16 features. The classification process starts at the root of the tree. An incoming beat travels down the branches of the tree depending on the result of the test on a feature. The procedure ends when the beat arrives at a leaf 'P' (PVC) or 'N' (non-PVC).*

Fig 3 *Block diagram for a Fuzzy Logic System for classification. Incoming data are preprocessed and features are extracted before the fuzzification. The inference engine combines the fuzzy sets and the implemented rules to a fuzzy output set. As a final result, the defuzzifier transforms fuzzy output sets into crisp data (classes).*