FILTER BANK-BASED ECG BEAT CLASSIFICATION

Valtino X. Afonso, Oliver Wieben, Willis J. Tompkins, Truong Q. Nguyen, Shen Luo

Department of Electrical and Computer Engineering, University of Wisconsin-Madison
1415 Engineering Drive, Madison, WI. 53706, USA

Abstract: A multirate digital signal processing algorithm to classify heart beats in the electrocardiogram (ECG) is presented. The algorithm incorporates a Filter Bank (FB) which decomposes the ECG into subbands with uniform frequency bandwidths. The FB-based algorithm enables independent time and frequency analysis to be performed on the ECG. Various features are computed from the subbands to distinguish between between paced and non-paced beats. These features are computed in a very computationally efficient manner. A machine learning method is used to design a decision tree to be used in the classification process. The classification algorithms were tested on records from the MIT/BIH database. The paced beat classification algorithm has a sensitivity of 87.64 % and a positive predictivity of 90.97 %. The FB-based structure is useful for performing multiple ECG processing tasks using one set of preprocessing filters.

I. INTRODUCTION

A. *Objective:* Figure 1 represents the overall goal of using one set of preprocessing filters to successfully perform a variety of ECG processing tasks. The choice of a filter bank based system inherently leads to a multirate strategy for processing the ECG. This implies that processing tasks can be performed at a lower rate than the input sampling rate. This paper focuses on studying the use of filter bank systems for classifying various arrhythmic ECG beats.

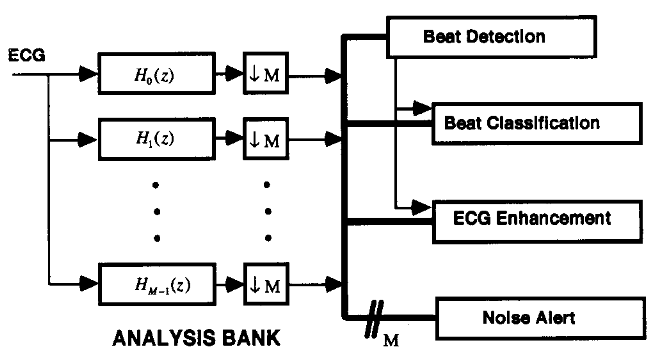

Figure 1: One set of preprocessing filters decompose the ECG into subbands with uniform bandwidths. Time and frequency dependent processing can be performed on the subbands to accomplish multiple tasks at the reduced subband rate.

B. *Literature review:* Various algorithms have been designed to classify between abnormal and normal beats [1, 2, 3, 4]. [1] presents a method of computing features from a wavelet based transform. This transform is similar to a filter bank approach in that the input signal is decomposed into multiple frequency subbands. Features such as the energy in certain subbands are computed to distinguish between normal, PVC, and ischemic beats. [2] presents a frequency domain method to compute features which distinguish between various life threatening arrhythmias. The features include the frequency with the predominant energy in the frequency domain. [3] presents a method using fuzzy adaptive resonance theory mapping to classify cardiac arrhythmias. The QRS segment is preprocessed by bandpass filtering, scaling, and filtering with a Hamming window. Two linear predictive coding coefficients of the filtered QRS are then used to classify the beats. [4] presents a method that uses hidden Markov models for each class of beats to be classified. Statistical modeling is then used to classify an incoming ECG into one of the classes.

A system that performs beat classification can be partitioned into two subsystems. The first subsystem preprocesses the ECG to compute discriminatory features from the ECG. The second subsystem incorporates a technique to categorize the features into one of several classes. The preprocessing subsystem, or filters, used in the algorithms reported in the literature are not useful for other ECG processing tasks such as beat detection, and ECG enhancement. These preprocessing filters also operate at the input rate of the ECG.

C. *Filter Bank processing:* [5, 6, 7] present extensive works on the design and use of filter banks. A FB contains M analysis filters which decompose the bandwidth of the input signal into subband signals with uniform frequency bandwidths. Since the subbands have a bandwidth which is lower than that of the input signal it can be downsampled. Depending on a specified application of interest, different processing functions can be performed on the subbands. The input signal can also be exactly reconstructed at the output by processing the subbands with the synthesis filters. Figure 2 shows a block diagram of a FB based processing system and ideal magnitude responses of each filter.

The subband signals provide information from various frequency ranges, and thus it is possible to quantify the input signal in a time and frequency dependent manner. Because the subbands are downsampled, processing can occur at a lower rate than the input sampling rate. Figure 1 shows that the downsampled subbands are input to processing blocks which perform beat detection, beat classification, ECG enhancement, and noise alert functions. [8] describes the algorithm for beat detection and [9, 10] describe the ECG enhancement algorithm. Thus with one set of preprocessing filters there is a potential to perform multiple ECG processing tasks.

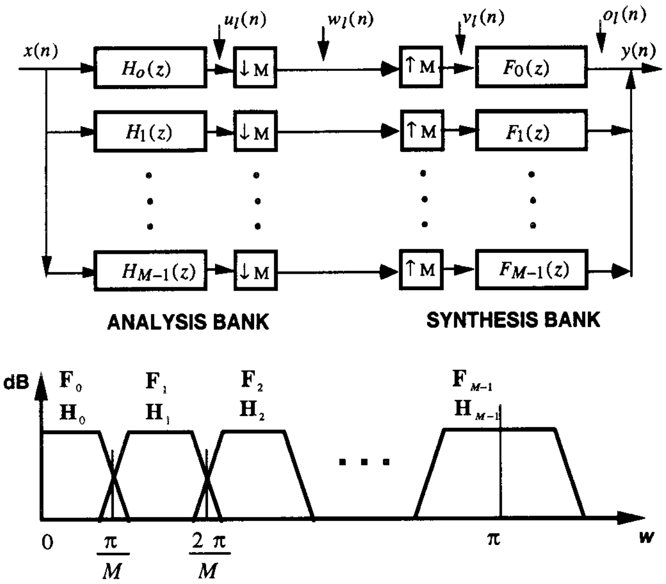

Figure 2: A filter bank contains a set of analysis filters which decompose the input signal into subbands with uniform bandwidths. The filters can be designed to reconstruct the subbands to result in a perfect reconstruction of the input signal. Ideal magnitude responses of the filters are shown.

II. METHODS

A. *Data:* The MIT/BIH [11] was used to train and test the classification algorithms. Channel 1 of the database was used in this study. Records 102, 104, 107, and 217 include paced beats. The original analog recordings from which the MIT/BIH database was digitized, did not represent the pacemaker artifacts with remarkable signal fidelity for pulse amplitude or duration to be used in paced beat detection. However, the database records have sufficient fidelity for use in evaluating pacemaker artifact detectors.

When designing classification algorithms it is important to maintain separate testing and training data sets in order to measure the true performance of the algorithm. In the studies performed in this work, the first 5 min of a record were used for training the algorithms and the remaining 25 min of the record were used for testing. This is in accordance with the recommendations set forth in [12].

B. *Filter Bank processing:* The filter bank used in this study has 32 analysis and synthesis filters designed using a method in [13]. The analysis filters along with the downsampling operators filter the ECG to produce the downsampled signal $W_l(z)$, see Figure 2. For beat classification it is necessary to compute features which will help discriminate between various arrhythmias.

The synthesis and upsampling filters can operate on the subband signals $W_l(z)$ to perfectly reconstruct the input of the FB. In order to compute features from specific frequency ranges, a subset of the subbands can be reconstructed. For example to compute features associated with the [0, 11.25] Hz frequency range only the first two subbands, $O_l(z)$ $l = 0,1$ should be reconstructed. This process is performed to compute features for frequency ranges of interest around the R wave of the QRS complex.

Features which are computed from only one subband signal $O_l(z)$ include n_i for $i = 0,1,2,\ldots,5$. The features n_i are computed from subbands $O_i(z)$ for $i = 0,1,2,\ldots,5$ respectively. The subband signals $O_l(z)$ are computed around the R wave for a specified window length. The feature is obtained by computing the average of the square of the signal in the window centered on the R wave. For the first subband [0, 5.625] Hz the average of the subband signal in the window is removed before computing the square of the signal.

Features which are computed from two subband signals $O_l(z)$ include n_i for $i = 6,8,9,10,11$. Feature n_6 includes $\{O_0(z), O_1(z)\}$, n_8 includes $\{O_2(z), O_3(z)\}$, n_9 includes $\{O_3(z), O_4(z)\}$, n_{10} includes $\{O_4(z), O_5(z)\}$, and n_{11} includes $\{O_5(z), O_6(z)\}$. The subband signals $O_l(z)$ are computed and partially reconstructed around the R wave for a specified window length. The feature is obtained by computing the average of the square of the partially reconstructed signal in this window. As explained above for the first subband signal the average in the window is removed before reconstructing with other subbands.

Features which are computed from three subband signals $O_l(z)$ include n_i for $i = 12,13,14$. Feature n_{12} includes $\{O_5(z), O_6(z), O_7(z)\}$, n_{13} includes $\{O_6(z), O_7(z), O_8(z)\}$, and n_{14} includes $\{O_7(z), O_8(z), O_9(z)\}$. The subband signals $O_l(z)$ are computed and partially reconstructed around the R wave for a specified window length. The feature is obtained by computing the average of the square of the partially reconstructed signal in this window.

C. *Frequency measures:* Based on preliminary studies of various features the following filter bank-based features are used for paced versus non-paced beat classification.

$$P\_1 = \frac{(n_{10} + n_{12} + n_{13}) \times k_1}{(n_0 + n_1 + n_2 + (n_3 + n_4) \times k_2)}$$

$$P\_2 = \frac{(n_{13} + n_{14}) \times k_3}{(n_{10} \times k_4 + (n_{13} + n_{14}) \times k_3)}$$

$$P\_3 = \frac{(n_{13} + n_{14}) \times k_5}{(n_9 \times k_6 + n_{11} \times k_7 + (n_{13} + n_{14}) \times k_5)}$$

where k_1 = 1e3, k_2 = 1e2, k_3 = 1e3, k_4 = 0.3, k_5 = 1e1, k_6 = 0.5, and k_7 = 0.9. The weighting factors k_i were chosen empirically based on preliminary analysis of the training set of the MIT/BIH database. These features are designed to indicate any increase in the higher frequency content of a beat as would normally be expected in the morphology of many paced beats.

D. *Decision Tree algorithms:* In this study a decision tree classification algorithm [14] is used for evaluating features computed from the filter bank. One of the important reasons for this choice of classification algorithm is that the "if-then" rules which encapsulate the information learned from training data sets can be implemented efficiently. The decision tree takes as input the features of a beat which is to be classified, and based on each of the nodes in the tree determines which class the beat belongs to. The computational efficiency of the decision tree is apparent immediately since at each node a simple "if-then" statement is processed on a specific feature of a beat.

The induction of a decision tree from a training data set is a very simple and robust algorithm. The decision tree used in this study is developed by a machine learning algorithm called MC4 [15, 16]. It is a supervised method of learning in that a training set is required to feed the learning algorithm. The training set consists of examples of features from known beat types. The decision tree induction algorithm MC4 is available from [15].

III. RESULTS & DISCUSSION

A. *Results:* The classification algorithm was trained using the first 5 minutes of an equal number of records with {102, 104, 107, 217}, and without {106, 109, 203, 233} paced beats. The performance of the classification algorithm on the testing set (remaining 25 min) of these records is given in Table I. There were 8848 TNs, 516 FPs, 733 FNs, and 5199 TPs. The algorithm had a sensitivity of 87.64 %, a specificity of 94.49 %, a false positive rate of 5.51 %, and a positive predictivity of 90.97 %. Record 107 accounted for 588 of the 733 FNs, record 102 had 3 FNs, and record 104 had no FNs.

TABLE I
FILTER-BANK BASED PACED VERSUS NONPACED BEAT CLASSIFICATION

Tape No.	TN	FP	FN	TP
106	1595	100	0	0
109	2007	91	0	0
203	2219	257	0	0
233	2510	50	0	0
102	2	2	3	1781
104	97	2	0	1182
107	57	0	588	1138
217	361	14	142	1098
	8848	516	733	5199
	Se %	Sp %	FPR %	Pp %
	87.64	94.49	5.51	90.97

B. *Discussion:* The number of channels directly relates to the bandwidth of the subband signals and hence to the correlation of features with a specific frequency range of interest. For example the features designed to distinguish between paced and non-paced beats were inherently limited to the 5.6 Hz frequency bandwidth of the subband signals. Increasing the number of channels in the filter bank system would result in narrower bandwidth signals, but would also possibly result in analysis filters with more coefficients, and hence a larger delay through the system. There are techniques to filter each downsampled subband signal using another filter bank system and thus obtain a tree structured filter bank system. This method would be useful in obtaining features which correlate to narrower frequency ranges and which may be potentially more discriminatory in beat classification.

The features computed in this study are illustrative of filter bank-based features which can be used for paced beat classification. This study does report very promising classification rates for paced beats. Most of the false negative classifications occur in one of the only four records which have paced beats in the MIT/BIH database. The filter bank-based strategy is useful in computing features from different subbands, especially higher frequency ranges, to distinguish paced beats from nonpaced beats.

[8] presents a beat detection algorithm which is incorporated within a FB framework. [9] and [10] present an algorithm to reduce the level of noise in the stress ECG. This paper presents a method for computing features from the subbands in the FB to distinguish between paced and non-paced beats. A noise alert algorithm which indicates the fidelity of noise and also characterizes the nature of noise that may be present in the ECG is also potentially possible by analyzing the subbands in the FB system. The FB-based strategy enables the design of ECG processing systems to be performed efficiently using one set of preprocessing filters.

C. *Future work:* Further improvements to the beat classification system may be achieved by designing and testing more features of frequency components in the ECG.

IV. CONCLUSION

A new method is presented in which discriminatory features are computed from the subbands in a filter bank system. A decision tree algorithm is used to perform the classification process since it is computationally efficient to implement. Discriminatory features are presented which distinguish between paced and nonpaced beats.

The classification rates for paced versus non-paced beats is very promising. Algorithms which distinguish between these classes of beats have not been reported in the literature before. The FB framework offers a method to compute features which correlate with energy in higher or lower frequency bands. Thus paced beats which normally have a sharp morphology can be distinguished from nonpaced beats.

As demonstrated in our previous work [8, 9, 10] and this paper, the FB-based algorithm provides a unified framework for ECG signal processing tasks such as beat detection, signal enhancement, and noise alert functions.

V. ACKNOWLEDGMENTS

Part of this work was supported by a grant from Burdick Inc., Milton, Wisconsin, USA.

VI. REFERENCES

[1] L. Senhadji, G. Carrault, J. J. Bellanger, and G. Passariello, "Comparing wavelet transforms for recognizing cardiac patterns," IEEE Eng. in Med. and Biol. Mag., vol. 14, no. 2, pp. 167–173, 1995.

[2] S. Barro, R. Ruiz, D. Cabello, and J. Mira, "Algorithmic sequential decision-making in the frequency domain for life threatening ventricular arrhythmias and imitative artefacts: a diagnostic system," J. Biomed. Eng., vol. 11, 320–328, 1989.

[3] F. M. Ham and S. Han, "Classification of cardiac arrhythmias using fuzzy ARTMAP," IEEE Trans. Biomed. Eng., vol. BME-43, pp. 425–430, 1996.

[4] D. A. Coast, R. M. Stern, G. G. Cano, and S. A. Briller, "An approach to cardiac arrhythmia analysis using hidden Markov models," IEEE Trans. Biomed. Eng., vol. BME-37, pp. 826–836, 1990.

[5] P. P. Vaidyanathan, Multirate systems and filter banks. Englewood Cliffs, NJ. Prentice-Hall, 1993.

[6] G. Strang and T. Q. Nguyen, Wavelets and Filter Banks. Wellesley, MA, Wellesley-Cambridge Press, 1996.

[7] A. K. Soman, P. P Vaidyanathan, and T. Q. Nguyen, "Linear phase paraunitary filter banks: Theory, factorizations and designs," IEEE Trans. on Signal Processing, vol. 41, no. 12., pp. 3480–3495, 1993.

[8] V. X. Afonso, W. J. Tompkins, T. Q. Nguyen, and S. Luo, "Filter bank-based ECG beat detection," Proc. Annu. Int. conf. IEEE Eng. Med. Biol. Soc., Nov. 1996.

[9] V. X. Afonso, W. J. Tompkins, T. Q. Nguyen, K. Michler, and S. Luo., "Comparing stress ECG enhancement algorithms: With an introduction to a filter bank based approach," IEEE Eng. in Med. and Biol. Mag., vol. 15, no. 3, pp. 37–44, 1996.

[10] V. X. Afonso, W. J. Tompkins, T. Q. Nguyen, S. Trautmann, and S. Luo, "Filter bank-based processing of the stress ECG," Proc. Annu. Int. conf. IEEE Eng. Med. Biol. Soc., Sep. 1995.

[11] MIT/BIH Database Distribution, Massachusetts Inst. Technol., 77 Massachusetts Avenue, Room 20A–113, Cambridge, MA 02139.

[12] AAMI, Association for the advancement of medical instrumentation, "Recommended practice for testing and reporting performance results of ventricular arrhythmia detection algorithms," 1986.

[13] H. S. Malvar, Signal processing with lapped transforms, Artech House, Norwood, MA, 1992.

[14] J. R. Quinlan, "Induction of decision trees," in Machine Learning, vol. 1, pp. 81–106, 1986.

[15] R. Kohavi, D. Sommerfield, and J. Dougherty, "Data mining using MLC++: A machine learning library in C++, in Tools with Artificial Intelligence, IEEE Computer Society Press, 1996.

[16] J. R. Quinlan, C4.5: Programs for Machine Learning, Morgan Kaufmann Publishers, Inc., Los Altos, California, 1993.