Is it possible to distinguish different types of ECG-holter beats based solely on features obtained from windowed QRS complex?

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Abstract— **The main focus of this paper is to investigate the possibility to distinguish among different classes of beats, as provided by ANSI/AAMI EC57:1998 standard, from the ECG holter recordings. We compare the performance of an ensemble classifier based on three classifiers on distinguishing ECG beats from holter recordings characterized by two distinct sets of features.**

The first feature set is one relying upon the "classical" time interval measurements of QRS complex and T-wave. The second one tries to describe the beat using means as simple as possible resulting in a description of the QRS complex in terms of "easy-to-compute" statistical moments; hermite coefficients and Karhunen Loeve coefficients.

The results of the ensemble classifier consisting of three different classifiers – namely a k-NN classifier, a Back propagation Neural Network and a Support Vector classifier- are as general as possible by using global training/testing approach that uses one half of the recordings from the MIT-BIH database for training and the other half for testing. Results of the classifier are computed using sensitivity (Se) and specificity (Sp) for both feature sets. The best results achieved during the experiments were those using the "classical" feature set and the ensemble classifier. The specificity for detection of normal beats was 74.26% and sensitivities were 68.19%, 45.73%, 35.19%, 48.70% for ventricular, bundle branch blocks, supraventricular, and fusion beats respectively. The results achieved on the "easy-to-compute" approach are comparable to those from "classical" approach when dealing with the detection of ventricular beats with specificity 74.73% and sensitivity 59.97% – but they have performed much worse when trying to detect the other classes such as supraventricular, fusion or bundle branch block beats.

Keywords— **ECG holter, classification, Ventricular beats, ensemble classifier, feature set comparison**

I. Introduction

Many different methods have been proposed to solve the crucial problem of long-term holter recordings evaluation which can be transformed into the problem of discrimination between normal 'N' and variety of other beats mainly premature ventricular 'V' beats; bundle branch block beats (BBB) and supraventricular beats (S).

Lot of research effort has been put to examine and classify data using methods that are usually based on beat-shape description parameters [1], shape descriptive parameters transformed with the Karhunen–Loeve method [2], and Hermite polynomials [3]. Other works use time-frequency features [4] and features obtained from heartbeat interval measurements [5, 6] to identify cardiac arrhythmia.

In any case, for the comparison of different approaches the setup of the experiments, where the type of the training and the selection of testing sets are defined, is of major importance. There are two main setups to be considered: training based on a *local* learning set [7] and on a *global* learning set [8].

The main reason for using local classifier is the fact that beats within one patient tend to look alike – but tend to differ widely between patients – therefore using local classifier usually leads to better overall result in a personalized medicine approach using the patient as its own control. Further remarks on both approaches are presented in Chapter IV.

In this paper we attempt, using as guideline our experiments dealing solely with distinguishing between normal and ventricular beats [9], to provide a thorough investigation of different pattern analysis techniques using an ensemble classifier on two different global feature sets. The MIT-BIH database [10] is used for our experiments. Finally the results are then compared using sensitivity and specificity.

The rest of the paper is organized as follows: Section II presents the feature extraction process. Section III briefly describes the classification methods involved. In Section IV the selection of the training and testing sets is given and the results are presented in Section V. Section VI concludes the paper giving some directions for future.

II. Feature sets

A. Preprocessing

For the purposes of the processing methods used in this paper all records were re-sampled to 500Hz from the

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original 360Hz. No filtering was performed on any of the signals.

For the detection of R-peaks a method proposed firstly by Christov [11] was applied. Based on the R-peak findings two different ways of processing are then followed. For the "easy to compute" feature set the maximum of the major R-peak is found and a window of 128 samples with R peak centered on position 64 is selected for further computation. For the "classical" feature set each beat enters a measurement procedure where based on tresholding of specifically filtered parts of the signal the important points of the signal are found. The important points measured are QRS-complex onset, offset, T-wave offset and amplitudes of the Q, R, S and T waves.

If the measurement procedure failed the beat was discarded from further processing. Therefore we have skipped 5 beats from each signal (the first three and last two of the recording) and additionally 4927 beats were skipped in total from records 108, 203 and 219.

B. Feature extraction

The "classical" feature set followed the standard extraction of features based on time intervals, amplitudes and its ratios based on the important points measured from the signal. Features computed are presented in Table 1.The "easy to compute" feature set consists of features that are computed solely on the 128 samples around the R-peak. Those features consist of 4 normalized statistical moments (mean, standard deviation, skewness and kurtosis) and a selected number of Karhunen-Loeve[12] and Hermite coefficients. These second set features are also presented in Table 1.

Since one of the main purposes of holter measurement is to recognize arrhythmic beats in both feature set the RR-interval change based prematurity indicator computed as relative prolongation of the current RR interval in comparison to the median of 10 preceding beats without prematurity larger than 0.15.

Table 1 Enumeration of the features in "classical" and "easy to compute" feature sets

"Classical" features	"Easy to compute" features
Beat prematurity	Mean
QRS interval	Standard deviation
Q, R, S amplitudes	Skewness
T-positive amplitude	Kurtosis
T-negative amplitude	First nine Karhunen-Loeve coefficients
QT interval	Nine Hermite coefficients
R/Q, R/S, R/T	Beat prematurity
Areas under wave - Q,R,S,T	All features were computed on 128-sample beat excerpt centered on the R peak

C. Comparison of feature sets

The motivation for having two sets of features is to check whether an “easy to compute” set can perform comparably to the “classical” but more computational demanding set. The "classical" feature set is a slight simplification of the feature set obtainable from the clinically used holter devices.

The "easy to compute" feature set is based only on the ability to find correctly the maxima of the major R-peak. Then all the features are computed based on the “truncated” signal itself without the need of any other measurements. Therefore this feature set stands as a model for classifying the data obtained by telemedicine application devices. In our case it also means we have no information from the depolarization phase of the beat cycle – since the behavior of the T-wave varies wildly in terms of shape and length it is in our view not possible to use without other measurements such as end of T-wave.

III. CLASSIFICATION METHODS

For the classification purposes we have chosen three different classifiers – a k-nn classifier, an artificial neural network, and an SVM. In the following paragraph a short description and more importantly the settings of the methods used will be given. WEKA [13] was used for executing all the classification experiments.

A. k-NN classifier

The *k*-nearest neighbor classifier [14] is used as an example of a simple classifier, yet in cases of biomedical data often a very effective one. In our case the NN classifier called NNge in WEKA was used with the number of attempts to generalize set to 10, and the number of folders for mutual information set to 5.

B. Back propagation NN

Back Propagation Neural Network is a well-known supervised learning technique used for training artificial neural networks with one or more hidden layers [15].

During the recall phase, the sample is presented to the network and values are propagated from inputs to outputs of the ANN. The difference between desired and actual outputs is calculated formulating the overall network’s error. This error is propagated backwards from output neurons toward inputs. For each neuron its contribution to the output error is calculated and the weights of its connections are adjusted accordingly.

The back-propagation network used in this study (selected after thorough testing of different configurations) had 7 neurons in the first hidden layer and 4 neurons in the second. For training of the ANN, the standard BP algorithm is implemented in WEKA with momentum and decreasing learning rate.

C. SVM

Support Vector Machines (SVMs) are learning systems that are trained using an algorithm based on optimization theory [16]. The SVM solution finds a hyperplane in the feature space that keeps the empirical error small while maximizing the margin between the hyperplane and the instances closest to it. Every new pattern x is classified to either one of the two categories through:

$$f(\mathbf{x}) = sign\left(\sum_{i=1}^{n} y_i a_i K\left(\mathbf{x}, \mathbf{x}_i\right) + b\right)$$

where b is a threshold parameter. For this study SVMs with RBF kernels were employed [16].

D. Ensemble classifier

As a final means of classification an ensemble classifier was used, based on the classification outcomes of the above described classifiers, employing a majority voting scheme.

IV. DATA AND TRAINING OF THE CLASSIFIERS

For evaluation of our approach we have used the commonly used MIT-BIH database [9].There are two ways of training the classifiers with the database.

The first one is to use local training – using vertical division of the database. That means that, usually, the beginnings of each of the recordings from the database are used for training and the rest of each of the recordings is used as a testing set. Although this type of training brings usually results close to absolute sensitivity and specificity and is often encountered in the literature e.g. [1, 7] it is very controversial from the point of view that any practical application would require additional annotation of at least a short part of each patient's recordings.

Table 2 Beat types and its mapping on the MIT database

Beat Label – AAMI inspired	Beat Label in MIT db
N – normal	N, e, j
BBB – bundle branch block	L, R
S – supraventricular ectopic beat	S, a, A, J
V – ventricular ectopic beat	V, E
F – fusion	F
Q – other	Q

The second approach is to use the so called global training. In this case the database is divided horizontally and only those recordings that are not used for training are used for testing. This approach is less commonly used e.g. [8] and it yields about twenty percent worse results both in sensitivity and specificity. Nevertheless results obtained, using this approach, are more general and also reproducible on other data sets.

After considering the above mentioned advantages and disadvantages the results reported in the next section are based on the global classification approach using half of the records from the database for training and the other half for testing purposes.

The beat types classified are shown in Table 2 together with its mapping to annotations of the MIT database – for further information refer to [9].

Besides a total of 5337 beats skipped due to preprocessing reasons as described in Section II A also all the recordings with paced beats (records number 102, 104, 107, 217) were excluded from the data set.

V. RESULTS

Results for each classifier separately and the ensemble classifier are shown in the Table 3. Table 3 shows the Specificity for detection the N beats and separate sensitivities for all other not-normal beats. Since in the data set there are very few questionable beats the algorithm were not able to train for them. BBBs are often classified as N; the same is true for supraventricular beats.

VI. CONCLUSIONS

Based on our results it seems that for "easy to compute" features it is possible to compete with the "classical" ones only when dealing with distinguishing N and V beats.

Table 3 The overall results for the "classical" feature set (CLA_S) and the "easy to compute" feature set (ETC_S) for each classifier k-th Nearest Neighbor (k-NN), Back Propagation Neural Network (BPNN), Support Vector Machine (SVM) and ensemble classifier based on the previous three. The results shown for AAMI inspired classes Normal (N); Ventricular (V); Bundle branch blocks (BBB); Supraventricular (S); Fusion (F) and Other (Q) beats.

	N-Sp[%]	**V- Se[%]**	**BBB-Se[%]**	**S-Se[%]**	**F- Se[%]**	**Q-Se[%]**
ETC_S_kNN	61,34	51,94	23,23	20,10	39,02	0
ETC_S _BPNN	75,35	56,66	25,78	25,16	29,61	0
ETC_S _SVM	73,80	59,09	29,12	32,10	41,38	0
ETC_S _Ensamble	**74,73**	**59,97**	**30,20**	**28,13**	**42,73**	**0**
CLA_S_kNN	62,13	58,13	43,76	35,10	31,20	0
CLA_S _BPNN	81,92	53,44	44,13	33,18	39,23	0
CLA_S _SVM	75,46	65,94	52,15	40,17	45,18	0
CLA_S _Ensamble	**74,26**	**68,19**	**45,73**	**35,19**	**48,70**	**0**

For all the rest of classes the "easy to compute" features results are worse than the results of classifiers based on classical features. In comparison to papers using similar methodologies [1] our results are in general comparable. For further experiments the area of the T-wave will have to be included into consideration for "easy to compute" based features to improve the results. Also to separate classification based on prematurity of the beat prior to further classification might be useful.

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References

1. P. de Chazal, O. O'Dwyer, and R.B. Reilly, "Automatic Classification of Heartbeats Using ECG Morp. Heartbeat Interval Features", IEEE Trans. on Biom. Eng., vol. 51, No. 7, pp 1196-1206, 2004
2. D. Cuesta-Frau, J.C. Perez-Cortes, and G. Andreu-Garcıa, "Clustering of electrocardiograph signals in computer-aided Holter analysis," Computer methods and programs in Biomedicine, vol. 72, pp. 179-196, 2003
3. Moody G, Mark R. QRS morphology representation and noise estimation using the Karhunen-Loeve transform. Comput Cardiol 1989;16:269–72
4. M. Lagerholm, C. Peterson, G. Braccini, L. Edenbrandt, and L. Sornmo, "Clustering ECG complexes using hermite functions and Self-organizing maps," IEEE Trans. Biomed. Eng., vol. 47, pp. 838–848, 2000
5. I. Christov, G. G. Herrero, V. Krasteva, I. Jekova, Atanas Gotchev, K. Egiazarian, Comparative study of morphological and time-frequency ECG descriptors for heartbeat classification", Medical Engineering & Physics 28 (2006) 876-887
6. M.G. Tsipouras, C. Voglis, I.E. Lagaris and D.I. Fotiadis, Cardiag Arrhytmia Classification Using Support Vector Machines The 3rd European Medical and Biological Engineering Conference, 2005
7. G. Bortolan, I. Jekova, I. Christov, "Comparison of Four Methods for Premature Ventricular Contraction and Normal Beat Clustering", Computers in Cardiology 2005; vol. 32, pp.921-924
8. Y. H. Hu, S. Palreddy, and W. J. Tompkins, "A patient-adaptable ECG beat classifier using a mixture of experts approach," IEEE Trans. Biomed. Eng., vol. 44, pp. 891–900, Sept. 1997.
9. V. Chudáček, L. Lhotská, C. Stylios, G. Georgoulas and M. Staviař., "Comparison of Methods for Premature Ventricular Beat Detection In: Int. Special Topics." ITAB Conference, Piscataway: IEEE, 2006
10. A.L. Goldberger, L. Amaral, L. Glass, J.M. Hausdorf, P.C. Ivanov, R.G, Mark, J.E. Mietus, G.B. Moody, C.K. Peng and H.E. Stanley,. "PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals," Circulation vol. 101, no. 23, pp.e215-e220
11. Ivaylo I Christov: Real time electrocardiogram QRS detection using combined adaptive threshold; Biomed. Eng. OnLine, 2004.
12. Loève, M. M. Probability Theory. N.J.: Van Nostrand. 1995.
13. I. Witten, and F. Eibe, Data Mining: Practical machine learning tools and techniques, 2nd Edition, San Francisco, 2005
14. Aha, D. 1992. Tolerating noisy, irrelevant, and novel attributes in instancebased learning algorithms. International Journal of Man-Machine Studies 36(2):267–287.
15. D. E Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," Nature, vol. 323, pp. 533-536. 1986
16. K. R. Muller, S, Mika, G. Ratsch, K. Tsuda, and B. Scholkopf, "An Introduction to Kernel-Based Learning Algorithms," IEEE Trans. Neural Networks, vol. 2, no. 2 pp 181-201, 2001.

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