THE USE OF SHAPE FACTORS FOR HEART BEATS CLASSIFICATION IN HOLTER RECORDINGS

Piotr Augustyniak

Institute of Automatics, AGH-Technical University,
al. Mickiewicza 30, PL-30-059 Kraków, POLAND
e_mail: august@biocyb.ia.agh.edu.pl

Abstract

The heart-beat classification in Holter ECG processors can be succesfully done by comparing the shape coefficients of the around-QRS fragments instead of comparing the signals themselfs. The additional computation time is compensated during the classification procedure, since up to 10 coefficients are stored for each class and compared instead of 30 signal samples (for 3-channels, 128 Hz-sampled ECG, QRS duration about 100 ms). The most discriminative shape coefficients are choosen with regard to the particular heart-diseases probability supported by the MIT-BIH database. The newly proposed classification method has been verified and the reached misclassification error is of about 0.5%. The other advantage of our method is the insensibility to the amplitude changes nor to the small desynchronization between the compared QRS, thus the simplest and fastest fiducial point detectors can be used without the loss of

1. INTRODUCTION

An integral part of automated processors for Holter recordings is a beat classification procedure. This is very important, since the main advantage of Holter methods is the ability to find out unique isolated pathological beats among many correct ones. On the other hand, this should be done as fast as possible, as there are about 100 thousands beats in a typical 24 h record. Usually, the classification procedure is based on a tresholded correlation between the processed beat and the representative patterns for existing classes [1], [2], [3].

This paper introduces a new classification method based on shape factors [4], [5], [6], [7].

All detected heart beats are first processed to derive their shape factors, and than these factors (instead of signals themself) are compared [8]. Of course, the patterns (class centers) are also the corresponding shape factors. Since the simple verification of membership requires comparison of 3 variables only (3 different shape factors per beat per channel) instead of 10 (assuming the sampling rate of 100 Hz and QRS duration of 100 ms) we expected the new method to be up to 3 times faster than those used previously. The computation time for the shape factors is constant (not depend on class number) and relatively short if the class number exceeds 10.

2. MATERIALS AND METHODS

The aim of our investigation was to find the most specific shape factors for the frequently observed heart-beats types. As a medical reference we used the MIT-BIH standard database (directory: MITDB) containing 44 half-hour recordings [9]. Due to the poor signal quality, the records 104, 105, 208, 213, 223 and 228 were excluded. Among all annotated beat types the 9 most frequent (i. e. 99.3% of whole beat number) were choosen as shown in table 1.

Table 1. Heart beat types used to the classifiers adjustment and tests

MIT-BIH code	**abbreviation**	**MIT-BIH contribution *c* [%]**	**description**
1	NORMAL	64,5	normal beat
2	LBBB	7.98	left bundle branch block beat
3	RBBB	9.02	right bundle branch block beat
4	ABERR	0.05	aberrated atrial premature beat
5	PVC	4.26	premature ventricular contraction
6	FUSION	1.23	fusion of ventricular and normal beat
7	NPC	0.53	nodal (junctional) premature beat
8	APC	0.97	atrial premature contraction
12	PACE	9.45	paced beat

The learning set consisted of 10 randomly choosen examples for each considered beat type without regard to their contribution to the MIT-BIH database.

Initially we have proposed 10 different shape factors computed on the constant-length windowed signal. Since the applied QRS detector produces his positive response (fiducial point) in the initial sector of QRS, the window was assymetrical to the QRS fiducial point, that means the fiducial point is allways in 1/4 of window length. The window lengths were: 60, 80, 100, 120 and 140 ms. Having do this, the set of 50 shape factors was tested in order to discriminate the choosen 9 beat types. The best shape factor should meet both of the following criteria:

- maximize the average distance d between classes,
- minimize the average class size e.

All "geometry" values like "distance" or "size" are expressed in absolute logarithmic units regardless to their physical units. Initlialy we tried to separate all 9 classes by a single shape coefficient, but while the results were unsatisfactory we increasing the argument space (number of shape coefficients considered simultaneously) by 2, and then by 3. In order to express the

$$d_n = \frac{\delta_{1...n}}{\varepsilon_{1...n}} \qquad n = 2...9 \qquad (1)$$

discriminating capability by a single value, the quotient:

$$D = \sum_{i=2}^{9} c_i d_i \qquad (2)$$

is computed for a subset of 2, 3, 4 ... 9 most frequent classes, and the obtained values were cumulated with regard to the class contribution *c* in the MIT-BIH database (see tab. 1.).

and the maximum value of *D* is interpreted as the best class discrimination.

3. RESULTS

The detailed analysis of cumulated class distance to size quotients values led to following conclusions:

- Neither the 1-dimensional space, nor the 2-dimensional were not sufficient to separate all 9 classes perfectly,
- The classification should also include the local heart rate (HR) variability which is necessary to distinguish the normal (atrial as well as ventricular) and premature beats of similar shapes.

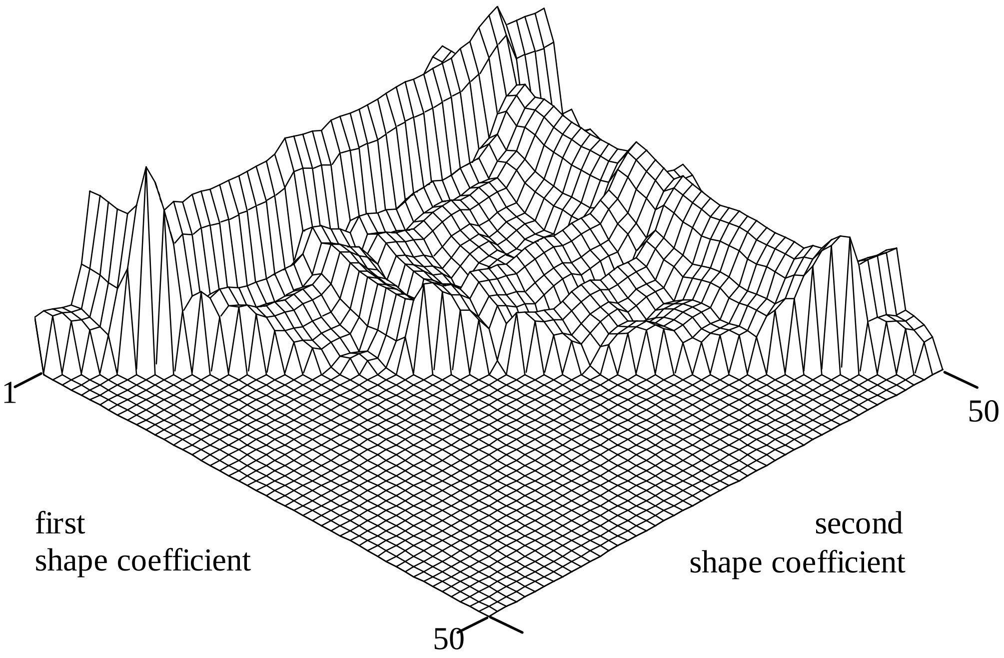

Fig. 1. An exemple plot of cumulated class distance to size quotients *D* values for all possible pair (2 dimensional space) of shape coefficient.

An example of 2-dimensional (2 shape coefficients) plot of all possible combination of them is shown on fig. 1.

For 3 dimensional space the best discriminating shape factors for the QRS classes were[1]:

$$h_1 = 10 \frac{\sum_{n=0}^{N} (|s(n)|)}{\sum_{n=1}^{N} (|s(n)-s(n-1)|)} \qquad (3)$$

---

[1] Please accept author's apology for the absence of detail matematical description of other shape coefficients, but due to the lack of space only the most important results can be presented.

$$h_5 = 1000 \frac{\max\limits_{n=2,\,N} (|s(n)+s(n-2)-2s(n-1)|)}{\left|\max\limits_{n=2,\,N} (s(n)) - \min\limits_{n=2,\,N} (s(n))\right|} \tag{4}$$

1 - process 1, window length of 60 ms,

$$h_{10} = \sum k : (s(k) - s(k-1)) \geq 0.4 \max_{n=1,\,N} (s(n) - s(n-1)) \tag{5}$$

23 - process 5, window length of 100 ms,

50 - process 10, window length of 140 ms.

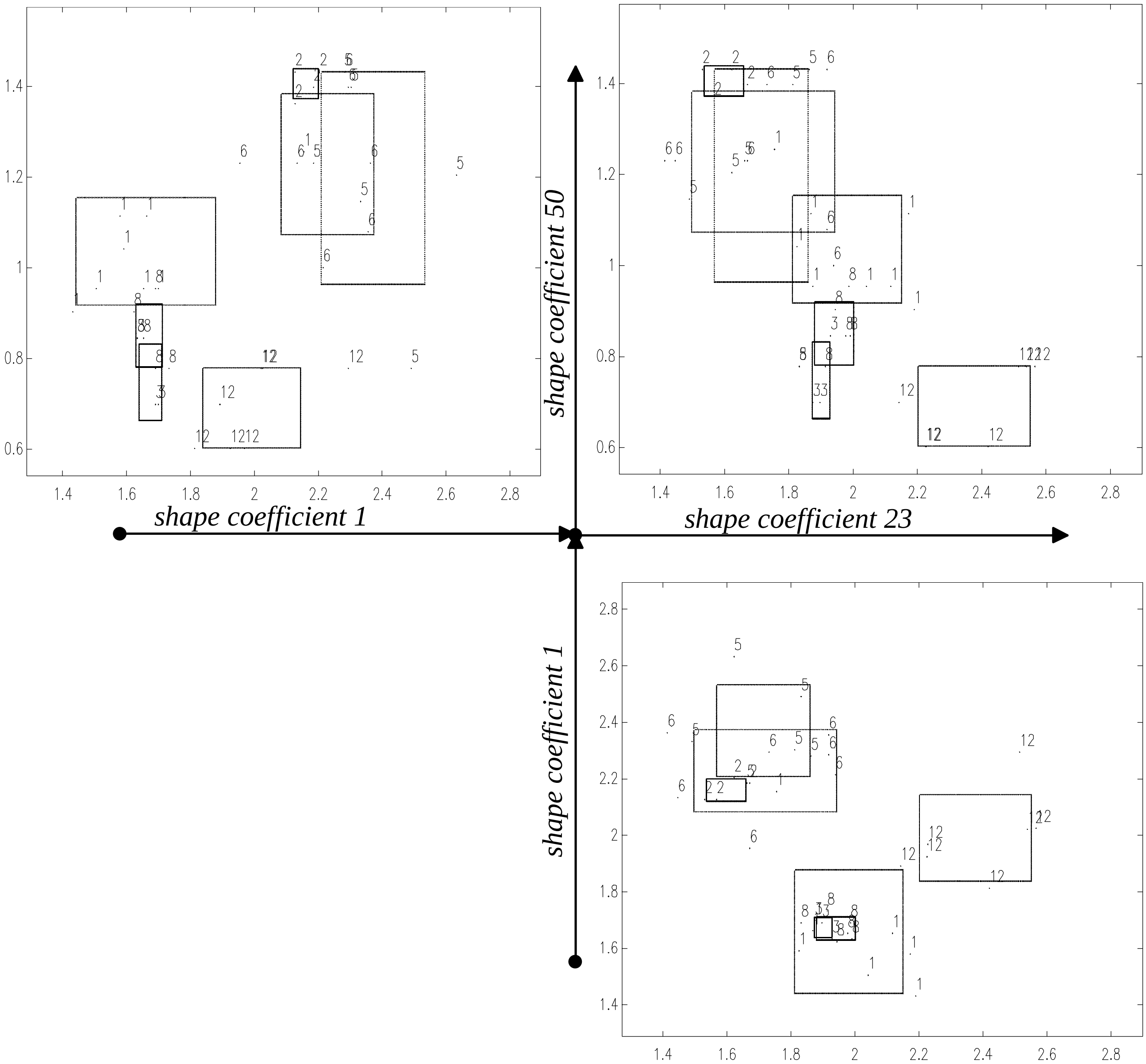

Fig. 2. The classification results obtained in the 3 dimensional decision space with use of shape coefficients 1, 23 and 50. All distances are expressed in logrithmic absolute values. Points with class numbers are particular class members positions, and rectangular boxes are class "territories"

The classification results obtained in the 3 dimensional decision space with use of shape coefficients 1, 23 and 50 is shown on figure 2. On the plot only the 9 most frequent MIT-BIH classes (i. e. 99.3% of total beats) are considered. For the exact class separation the additional use of HR (heart rate) is necessary. This is one value for all simultaneously processed channels and permits to distinguish the regular and irregular rhythms (i. e. class 5 and 6).

4. VERIFICATION

Having implemented the developped method in the real-time Holter processor, we used the whole database (directory: \MITDB) to test its performance.

The computation time[2] was shorter than for traditional classification method if the class number exeeds 8 (there are no record with smaller class number). The classification performance was satisfactory with the misclassification error (two different MIT-BIH types in one class) of about 0.5%. Table 2 summarizes results of the experiments.

Tab. 2. Results of the experiments witch use of whole MIT-BIH database

value	total	%
total number of QRS complexes:	48540	100
number of not classified QRS:	2525	5.202
number of erroneously classified QRS:	282	0.581
total number of created classes:	954	100
number of classes with misclassified beats:	68	7.128
average processing time for half-hour record (Pentium® 90MHz):	17.96s	

Additionally, the great advantage of the method is that it is not sensitive neither to signal amplitude changes, nor to the synchronisation error in time. Since the fiducial points are not required to be delimited very precisely, the use of simpler and faster detector is possible without deteriorating the general performance.

The main drawback of the proposed method is its large sensitivity to the signal quality. Particulary the high frequency noise and baseline wander should be removed before the classification is performed.

REFERENCES

[1]. Talmon J. L. Pattern recognition of the ECG. A structured analysis. PhD Thesis Free University of Amsterdam Utrecht 1983.

[2]. Willems J. L. Lesaffre E. Comparison of multigroup logistic and linear discriminant ECG and VCG classification J. Electrocardiol. 1987 vol. 20, N2, p. 83-92

[3]. Van Bemmel J.H. Recognition of electrocardiographic patterns. In: Handbook of statistics. P. R. Krishnaiah and L.N. Kanal Eds. Amsterdam North Holland 1982 vol. 2, p. 501-526.

[2] This value of computation time was reached with Borland C++ ver. 3.1 compiler without any code optimisation, and the machine code was not dedicated to Pentium processor. Further reduction of computation time is possible witch use of appriopriate programmer's tools.

[4]. Malinowska K. Ocena stopnia rozwinięcia kształtu przekrojów poprzecznych włókien. Przegląd włókienniczy, nr 4 1975,
[5]. Haralick R. M. A measure of circularity of digital figures. IEEE Trans. on Systems Man and Cybernetics. SMC-4, 1974.
[6]. Œluzek A. Zastosowanie metod momentowych do identyfikacji obiektów w cyfrowych systemach wizyjnych. Praca habilitacyjna, Instytut Automatyki Politechniki Warszawskiej, 1989.
[7]. Mikrut Z. Tadeusiewicz R. Automatyczna wizualna identyfikacja obiektów na zrobotyzowanych stanowiskach pracy. Zeszyty Naukowe AGH Elektrotechnika tom 9, zeszyt 3-4 1990.
[8]. Sornmo L. Borjesson P. Nygards M. Pahlm O. A method for evaluation of QRS shape features using a mathematical model for the ECG. IEEE Trans. on Biomedical Engineering vol. BME-28, N10, Oct. 1981, pp. 713-717
[9]. Moody G. Mark R MIT-BIH arrythmia database directory. Massachusetts Institute of Technology, Biomedical Engineering Center 1988.
[10]. Lin K. Chang W. QRS feature extraction using linear prediction. IEEE Trans. on Biomedical Engineering vol. 36 N 10, Oct. 1989, pp. 1050-1055.
[11]. Bortolan G. Degani R. Pedrycz W. A fuzzy pattern matching technique for diagnostic ECG classification. In Computers in Cardiology K.L. Ripley Ed. Long Beach Calif. IEEE Computer Society 1989. pp. 551-554.
[12]. Trahanias P. Skordalatis E. Bottom up approach to the ECG pattern-recognition problem. Medical & Biological Engineering & Computing 27, May 1989, pp 221-229