INFORMATICA, 2005, Vol. 16, No. 4, 587–602

T Wave Alternans Features for Automated Detection

Tomas KULVIČIUS, Minija TAMOŠIŪNAITĖ
Department of Applied Informatics, Vytautas Magnus University
Vileikos 8, 44404 Kaunas, Lithuania
e-mail: m.tamosiunaite@if.vdu.lt

Rimas VAIŠNYS
Department of Electrical Engineering, Yale University
Becton Center, P.O. Box 208284, New Haven, CT 06520-8284, USA
e-mail: rimas.vaisnys@yale.edu

Received: May 2005

Abstract. T wave features suitable for automatic T wave alternans detection in low signal-to-noise ratio electrocardiograms are explored using a correlation-to-template-based algorithm for detecting T waves of variable duration. Amplitude and area features of T waves are found to be notably less sensitive to template selection than are duration features. T wave alternans features and measures which can be determined more stably provide better classification accuracy of patients with and without coronary artery lesions.

Key words: T wave alternans, TWA detection, T wave detection, correlation method, spectral analysis, automated analysis.

1. Introduction

The T wave that is the focus of this study is one of the five main waveforms in an electrocardiogram (ECG) and corresponds to the repolarization phase of the heartbeat (Pastore *et al.*, 1999; Armoundas *et al.*, 2002). In some pathological conditions the morphology of the T wave may change from beat to beat, the simplest and most easily recognizable change being an amplitude change of the wave. When the alteration of amplitude is regular and repeats every second heart beat one has T wave amplitude alternans, a phenomenon recognized over ninety years ago (Lewis, 1910) and illustrated in Fig. 1. As will be observed, the alternation is relatively easy to recognize visually. The more general T wave alternans (TWA) is defined as a regular and repeating change in any characteristic of the T wave, not only the amplitude, and such changes may be much less obvious. To consider novel features and the presence of noise in real signals requires computer aided detection, characterization, and analysis of TWA. If such generalized TWA can be reliably detected and characterized they may provide a useful diagnostic or prognostic tool for the cardiologist.

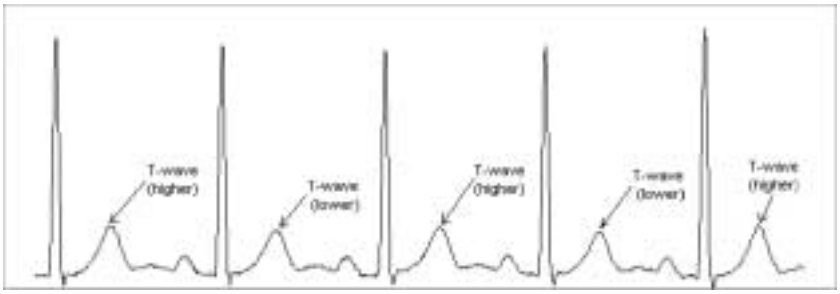


Fig. 1. A fragment of an ECG with observable T wave alternans.

Advances in technology have made long duration high resolution ECG's practicable but routine automatic analysis is possible only for some features (e.g., R-R interval analysis, Colombo *et al.*, 1989). T waves are often low in amplitude and can have varied shapes so that their detection is more difficult to automate. Yet for clinical use such automation is a practical necessity. Hence in this paper we explore and test a template based correlation method for T wave detection with minimal intervention by an experienced cardiologist. Once the T wave sequence is available we use it to explore the use of features other than T wave amplitude for the characterization of TWA. Finally, we examine the extent to which the TWA defined by various features can be used to classify patients whose cardiac medical status has been verified by an independent method. The questions to which we wish to contribute are: Which feature of a T wave provides useful concordance between manual and automatic alternans analysis? To what extent can alternans analysis be automated? Which alternans feature and measure choices provide useful classification of patient ECG's?

The plan of the paper is as follows: The next section reviews information related to alternans, with one subsection devoted to primarily medical issues, and a second one to signal analysis matters. This is followed by a description of our data base and the methods used in signal processing, with operational details being given in appropriate appendices. We then present a comparison between manual and automated T wave detection results. The section after that describes classification experiments with a mixed patient population. The last section summarizes the results for both detection and classification.

2. Review of T Wave Alternans

2.1. *Medical Aspects*

As mentioned above, macroscopic T wave alternans has been observed since the early days of electrocardiology in the beginning of the 20th century. The advent of tools to observe the alternans phenomenon at the microvolt level, not readily seen with the naked eye and thought to be a much more frequent phenomenon, has lead to a great increase in the number of publications about TWA (see (Cambridge Heart,

2002) for a recent review) at the microphenomenon level and also to the introduction of the first commercially distributed TWA diagnostic system (CH2000 described at `http://www.cambridgeheart.com`).

TWA has been investigated as a marker for life-threatening heart rhythm disturbances (Armoundas *et al.*, 1998; Gold *et al.*, 2000) and also has been found to be relatively frequent in cardiomyopathies (Adachi *et al.*, 1999; Konno *et al.*, 2001; Kitamura *et al.*, 2002). The signifance of TWA was also investigated in patients with ischemic heart disease and heart failure (Tanno *et al.*, 2000; Pedretti *et al.*, 2000; Klingenheben *et al.*, 2000), and as an indicator of long-term survivability after myocardial infarction (Tapainen *et al.*, 2001).

The presence and clinical significance of TWA depends upon the conditions under which it occurs. It has been found that the extent of TWA increases with an increase in heart rate (Kavesh, 1998; Tanno *et al.*, 2000). Further it has been demonstrated that at high heart rates TWA is also present in normal individuals (Walker *et al.*, 2003; Cheung *et al.*, 2001). In usual practice TWA is evaluated during an exercise test and is classified as "positive" if alternans is observed at heart rates not higher than 110 beats per minute (or is present at rest) using the CH2000 system (Bloomfield *et al.*, 2002). Under such circumstances microvolt TWA analysis may be an alternative to invasive electrophysiological testing (Smith *et al.*, 1988; Armoundas *et al.*, 1998; Bloomfield *et al.*, 2002).

2.2. *Signal Processing Aspects*

The traditional feature of the T waveform used in TWA analysis is presence of amplitude fluctuations in time aligned T waves. The corresponding points in the T waves of an ECG are used to construct a signal sequence, Fourier analysis is used to obtain a power spectrum for the sequence, the steps are repeated for each point of the T wave, and the resulting power spectra are averaged. Note, however, that the notion of a "power spectrum" should be considered with caution here, as frequency is defined on the basis of heart beats, and the heartbeats do not follow exactly spaced in time. Because the study involves empirical correlation of invasive and non-invasive methods, what is important is that the procedures be well defined and realizable, with the theoretical justification being a secondary matter. The presence of alternans is indicated by the presence of a peak at a frequency of 0.5 cycles per beat in the averaged power spectrum (Armoundas *et al.*, 2002). The analysis is summarized by two measures: the alternans magnitude (V_{alt}) and the alternans ratio (k). V_{alt} represents the magnitude of the voltage fluctuation between successive heartbeats, and the alternans ratio is the ratio of alternans power to background noise power. The alternans test is considered positive if V_{alt} is at least 1.9 μV and $k \geqslant 3.0$ (Armoundas *et al.*, 2002). The method makes sense for steady state alternans; intermittent alternans would give rise to lower frequency spectral components which would significantly bias the evaluation.

An alternative approach to detecting TWA is the correlation method (Burratini *et al.*, 1998) where a dimensionless alternans correlation-based index (ACI) is computed for each of the consecutive T waves by comparing each T wave to the median wave in

the sequence. An $ACI > 1$ corresponds to a T wave larger than the median, whereas $ACI < 1$ corresponds to a T wave smaller than the median. Thus, in the presence of TWA the ACI will alternate between values greater than and less than one. Since the value of ACI is calculated for each T wave, the correlation method allows one to determine the duration of the TWA episode in terms of the number of alternating beats, and to estimate the TWA amplitude. Alternating wave patterns in as few as seven consecutive beats are considered informative. Complex demodulation method seeks alternans with varying amplitude and phase, considered to be inscribed onto a regular every other beat alternating pattern (Nearing *et al.*, 1991; Martinez *et al.*, 2000).

Still other choices may be made both in the T wave feature to be used in constructing an alternans sequence and in the way the resulting sequence is analyzed. Among the former, in addition to the amplitude alternans already discussed, one may mention the use of explicit T wave characteristics such as length or duration (Acar, 1999), of a T wave lability index (measured as the difference between two consecutive T waves (Nemec *et al.*, 2003)) and the introduction of multiplicative factors (characterizing a T waves series in comparison with a prototypical wave (Tamosiunaite *et al.*, 2002)). With regard to sequence analysis, increasing attention is being devoted to the detection of a non-sustained (nonstationary) or even aperiodic alternation in T waves (Nemec *et al.*, 2003; Burratini *et al.*, 1998). Finally, among methods which attempt to combine feature choice and sequence analysis in one step one may mention the use of the Karhunen–Loeve decomposition (Laguna *et al.*, 1999).

Because it is not exactly clear how TWA arises, the choice of which features of the T waveform to use and what analyses are most useful must be made on empirical grounds using patient populations. Here one is faced with three important issues: one must distinguish between noise and significant signal, one must cope with statistical fluctuations encountered with small populations, and one must find a reliable independent diagnosis for the problem being studied.

3. Data and Methods

3.1. *ECG Database*

The database consisted of 400 ECG's collected in the KMU Institute of Cardiology and included 238 patients with coronary artery lesions (CL class) and 162 patients without the condition (HL class). Division into these classes was performed according to coronarography results, obtained after injecting contrast material into the heart coronary arteries and performing X-ray studies. The ECG recordings were obtained at rest, sampled at 2 kHz, with a resolution of 12 bits. The lead V3 was chosen for TWA examination, because the noise level in this lead tends to be low and T waves are clearly represented.

To explore how the method of detecting T waves influences alternans analysis ten CL and ten HL ECG's were selected from the database. The following criteria were used in this selection: no premature beats, no significant baseline drifts, ST segment is always

on the baseline, and both the beginning and the end of T waves are clearly visible to an experienced cardiologist. Further sets of 65 HL and 90 CL ECG's were found in the database for our classification experiments under less restrictive conditions, with recordings in the database being discarded if one of the following held: 1) high noise level (high frequency noise, or considerable baseline wander); 2) very low T wave amplitude; 3) spacing between consecutive T waves is too variable.

The ECG signals were preprocessed to eliminate baseline wander. Wavelet based filtering (`http://www.mathworks.com/access/helpdesk/help/toolbox/wavelet/wavelet.html`) with 4th order Coiflets was used, and signal reconstruction was made up to the 11th level (tuned for the 2 kHz sampled ECG signal). T waves were detected with a correlation-based algorithm without preliminary low pass filtering (no high frequency noise elimination).

3.2. *Outline of the Experiment*

We first summarize the information processing steps:

a) Each ECG is converted into a sequence of T waves using manual or automated detection of T waves. The procedures are specified in Subsection 3.3. 128 consecutive waves are analyzed as conventionally used in spectral methods (Armoundas *et al.*, 2002).

b) The desired T wave feature is evaluated for each T wave in a series by calculating the appropriate functional value, so that a sequence of 128 feature values is obtained. In this study T wave amplitude, duration, and area features were used. The features are described in more detail in Subsection 3.4.

c) The power spectrum of the selected feature sequence is obtained, estimated via the discrete Fourier transform of a Hanning-windowed sample autocorrelation function (following (Burattini, 1998)). The examples of a spectrum when TWA is present is provided in Fig. 2(a), and when TWA is absent are provided in Fig. 2(b). The power spectrum in this case represents oscillations on a heart beat scale, which is not exactly regular in time, as mentioned earlier in Subsection 2.2. TWA is defined as change in the amplitude, duration or form of the T wave occurring in every other heartbeat basis, so TWA appears in the spectrum as a peak at the highest frequency, further denoted by F_{65}, where the index 65 represents the place of the highest frequency component in the spectrum computed from a sequence of 128 points.

d) Three T wave alternans measures (m_1, m_2, m_3) are calculated from the power spectrum function. The measures differ in the degree of averaging used and hence in the degree to which they are affected by noise. Averaging is desirable to reduce the influence of noise but does decrease the resolution that might be obtained.

The measures are defined as follows:

$$m_1 = \frac{\sum_{j=63}^{65} F(j)}{\sum_{j=60}^{62} F(j)}, \quad m_2 = \frac{\sum_{j=63}^{65} F(j)}{\sum_{j=1}^{65} F(j)}, \quad m_3 = \frac{F(65)}{F(64)},$$

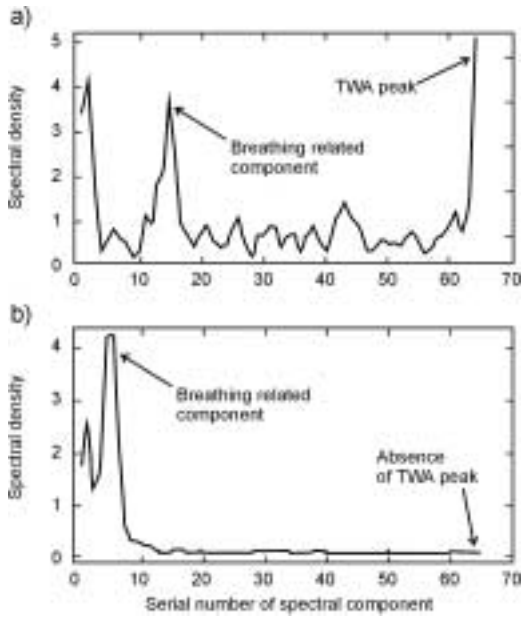


Fig. 2. A power spectrum example where TWA is present (a) and TWA is absent (b).

where $F(j)$ – the power spectrum function of the T wave feature (e.g., amplitude), $j = 1 \ldots 65$.

The measures define ratios of the highest frequency components of the spectrum function to the indicated lower frequency components. The measure m_1 shows the ratio of the energy in the last components representing the highest frequencies to the energy of the preceding three components, which are supposed to represent noise energy. Note that a wider spectral interval for alternans components is used here than in the traditional spectral method, allowing for some deviation from strict alternation in the amplitude. The measure m_2 expresses the ratio of the last three highest frequency components to the overall spectrum energy, while m_3 includes no averaging, and simply relates the energy of the component representing the exact alternans pattern, to the preceding frequency component used as a measure of noise.

3.3. *T Wave Detection*

To explore alternative strategies for T wave detection we chose twenty test ECG's, as described in the previous section. Manual detection was used to provide a known reference for the exploration, so these ECG's were first annotated completely by an experienced cardiologist. In the procedure of manual detection a cardiologist reads each ECG and marks the beginning and end of every T wave. An interactive computer program aids this task.

Automated detection was carried out using a template T wave matching algorithm, based on beginning and end point correlations. The template waves were selected man-

ually with the aid of an interactive computer program in each ECG, and then the other T waves were detected by comparing each T wave of every ECG to one (or several) template T waves; the automatic detection algorithm is described in Appendix A. To minimize cardiologist involvement and computational effort one would like to use the minimum number of templates possible, but T waves can be quite variable not only in amplitude but also in shape, so one set of calculations was done with one template, another set with five templates. In the latter case the five templates were selected by dividing the ECG signal into five intervals and choosing a T wave at random within each interval to serve as a template; each of these templates was used to analyze the complete ECG and the results were averaged.

The possibility that different patient classes may have systematically different T wave forms was examined by using manually detected T wave features in three stages: the CL class of ECG's, the HL ECG class, and finally the pooled ECG's. No statistically significant difference was observed in these results so further calculations were with the pooled sample.

Note that the overall processing uses sequences which were generated by one of three T wave detection procedures: manual, automatic with one template, automatic with five templates (recall Appendix A), so that the calculations to follow are done thrice for each study ECG.

3.4. *Feature Evaluation*

The features chosen for exploration were the following: amplitude of T wave maximum, four types of T wave duration features, and two types of T wave area features. The choices were made by balancing algorithmic considerations for reliable automation of the TWA analysis against expectations of noise sensitivity. In addition to being the traditional choice, the amplitude feature was expected to be not very sensitive to errors in the detection of the beginning and end point of the T wave, and was expected to be sensitive

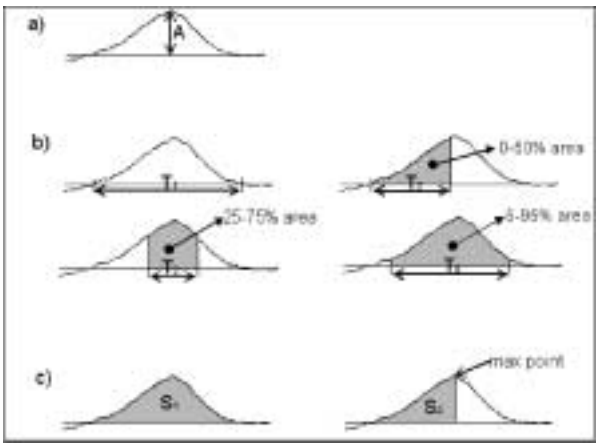


Fig. 3. T wave features: amplitude feature(a), duration features (b) and area features (c).

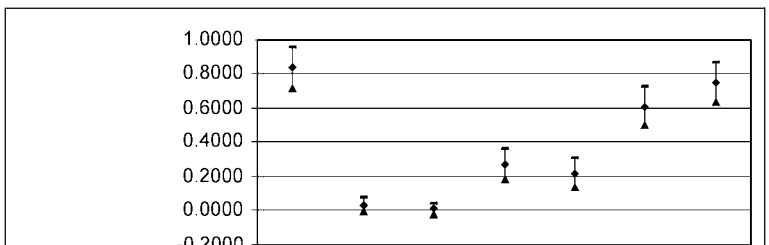
only to high frequency (myoelectric) noise on the wave. The area features were presumably the least noise-sensitive ones, both in respect to the inaccuracies in wave extraction and to the myoelectric noise due to averaging inherent in area evaluation. The duration features were expected to have the greatest variability. The nature of the different features is illustrated graphically in Fig. 3, with the algorithmic definition given in Appendix B.

4. Results

4.1. *Feature Suitability for Automation*

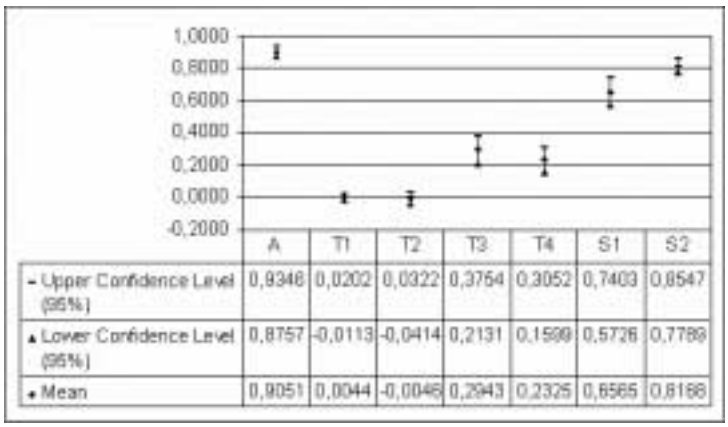
To evaluate the extent to which a given feature is suitable for automatic T wave detection we compute feature specific correlation coefficient between the automatically detected feature sequences, e.g., amplitudes of T waves $A^{aut}(1)$, $A^{aut}(2)$, ..., $A^{aut}(128)$, and the ones calculated using manual T wave detection: $A^{man}(1)$, $A^{man}(2)$, ..., $A^{man}(128)$. Fig. 4 presents correlation coefficients for features A, T1, T2, T3, T4, S1, S2, averaged over the 20 analyzed ECG's when the detection is done with one template wave form. Fig. 5 summarizes the results when automatic detection involves five templates. Five correlation coefficients (one for each template) in this case were averaged for each feature of each ECG. In addition to the mean result we also present the 95% confidence intervals based on the sample of 20 analyzed ECG's. The meaning of the feature symbols was shown in Fig. 3.

Another way to assess the influence of the template wave form in T wave detection is to check for consistency among the five templates used in the automatic T wave detection algorithm by computing the correlations among the different template results. Here we average correlation coefficients obtained for all template pairs. The summary calculations are shown in Fig. 6.



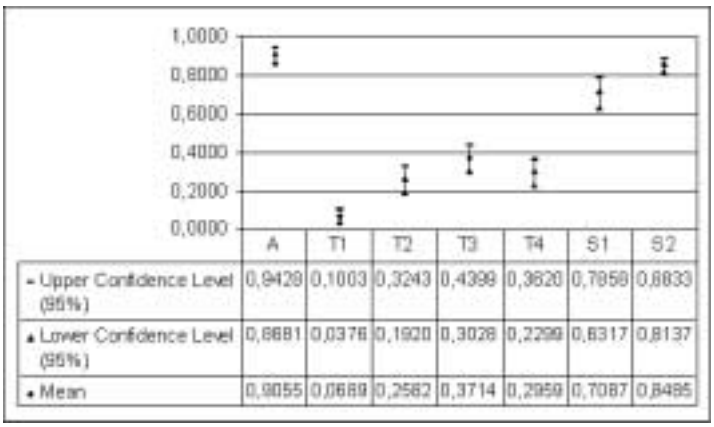
	A	T1	T2	T3	T4	S1	S2
- Upper Confidence Level (95%)	0.9557	0.0770	0.0389	0.3642	0.3057	0.7200	0.8664
▲ Lower Confidence Level (95%)	0.7197	-0.0061	-0.0197	0.1796	0.1361	0.5051	0.6384
◆ Mean	0.8377	0.0355	0.0096	0.2719	0.2209	0.6126	0.7524

Fig. 4. Correlations between T wave features detected automatically (one template) and manually.



	A	T1	T2	T3	T4	S1	S2
- Upper Confidence Level (95%)	0,9348	0,0202	0,0322	0,3754	0,3052	0,7403	0,8547
▲ Lower Confidence Level (95%)	0,8757	-0,0113	-0,0414	0,2131	0,1599	0,5726	0,7789
● Mean	0,9051	0,0044	-0,0046	0,2943	0,2325	0,6565	0,8168

Fig. 5. Correlations between T wave features detected automatically (five templates) and manually.



	A	T1	T2	T3	T4	S1	S2
- Upper Confidence Level (95%)	0,9428	0,1003	0,3243	0,4399	0,3820	0,7958	0,8833
▲ Lower Confidence Level (95%)	0,8881	0,0376	0,1920	0,3028	0,2299	0,6317	0,8137
● Mean	0,9055	0,0689	0,2582	0,3714	0,2959	0,7087	0,8485

Fig. 6. Mutual correlations between T wave features obtained using different templates (five templates automatic detection).

The agreement between manual and automatic detection methods is improved by using several templates, and is best for the T wave maximum amplitude, the traditional feature, with area features being almost as good, and time interval features performing poorly. Increasing the number of templates would narrow the confidence intervals but is unlikely to change the correlations themselves.

4.2. *Classification Experiments According to* $\boldsymbol{T}$ *Wave Alternans Measures*

Classification of patients whose medical condition is known provides an additional way to evaluate the utility of different T wave features. Classification of ECG recordings obtained from patients with documented coronary artery stenosis (CL – 90 cases) vs. ECGs obtained from patients without such lesions (HL – 65 cases) was performed, hypothesizing that the two classes would show different amounts of T wave alternans (Laguna *et*

Table 1

Classification errors of patients with and without stenosis, using different alternans features with different measures

Feature	Measure	e_{CL}	e_{HL}	e_T
A	m_1	0.56	0.34	0.45
	m_2	0.45	0.18	0.31
	m_3	0.62	0.45	0.53
T_1	m_1	0.62	0.36	0.49
	m_2	0.53	0.36	0.44
	m_3	0.50	0.55	0.52
T_2	m_1	0.45	0.57	0.51
	m_2	0.56	0.40	0.48
	m_3	0.22	0.73	0.47
T_3	m_1	0.56	0.33	0.44
	m_2	0.46	0.23	0.34
	m_3	0.52	0.54	0.53
T_4	m_1	0.52	0.27	0.39
	m_2	0.45	0.19	0.32
	m_3	0.62	0.46	0.54
S_1	m_1	0.57	0.25	0.41
	m_2	0.44	0.13	0.28
	m_3	0.56	0.49	0.52
S_2	m_1	0.52	0.52	0.52
	m_2	0.34	0.15	0.24
	m_3	0.45	0.59	0.52

al., 1999). Fisher's linear discriminant function (Raudys, 2001) was used for classification, and classification accuracy was evaluated on a test set. Data was divided randomly one thousand times into learning (2/3 of data) and test (1/3 of data) sets in order to avoid accommodation to some specific division of a data set, and the resulting classification errors were averaged.

The resulting classification errors according to T wave alternans measures m_1, m_2, m_3 for each of the features are presented in Table 4.1. Here e_{CL} denotes errors in the class with coronary artery stenosis, e_{HL} – errors in the class without coronary artery lesions, and e_T – the total classification error.

Patients with stenosis are classified best by using the duration feature T_2 and measure m_3, while patients without stenosis are classified best by area feature S_1 and measure m_2. Total classification error e_T is the smallest for feature S_2 and measure m_2. The cardiologist's problem is what to do with a patient whose stenosis status is not known at presentation. To give an answer to that question the results are further condensed in Fig. 7.

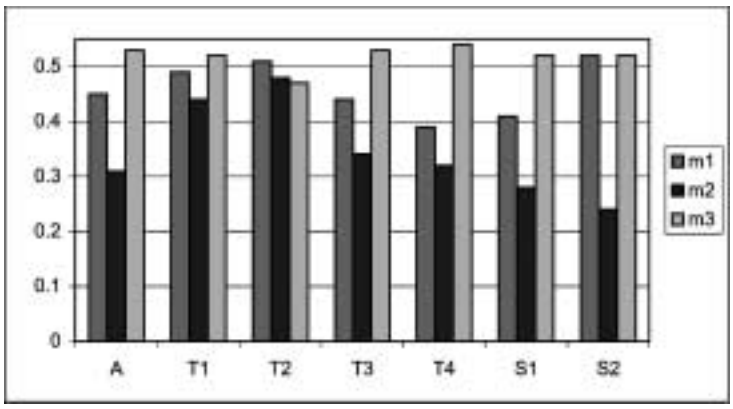


Fig. 7. Classification errors e_T using different alternans features with different measures.

Here the overall classification errors e_T grouped by features and measures are presented. It might be noticed that the measure m_2 systematically gives smaller classification errors than the other measures, while the results obtained using measure m_3 are dispersed around 50% and show no potential to separate the two classes. In that situation the results obtained with area feature S_1, or S_2 and measure m_2 are more relevant, and the ones obtained with duration feature T_2 and measure m_3 might be hypothesized as having given good classification results for the class with coronary artery stenosis just by chance in the relatively small sample analyzed here. For the feature S_2 and measure m_2 the average error achieved is 0.24, with individual contributions of $e_{CL} = 0.34$ and $e_{HL} = 0.15$. The next best diagnostic is provided by area feature S_1 and measure m_2, with an error of 0.28, while the more traditional amplitude feature A with measure m_2 gives a slightly worse error of 0.31. The duration feature T_4 with measure m_2 does equally well. Other temporal features provide substantially worse classification of these patients. Usually features and measures which involve an appropriate amount of averaging provide better results in classification than do such measures as m_3 which involve no averaging at all, as might be expected from noise sensitivity considerations.

5. Conclusions

In this paper we presented experiments with a novel procedure for automatic T wave characterization and T wave alternans analysis and applied the approach to the problem of classifying patients whose status with respect to the presence or absence of cardiac artery stenosis had been verified by coronarograhy, an independent albeit invasive diagnostic technique. It was seen that once an experienced cardiologist has annotated a small number of T waves, say five or fewer, the patient's ECG can be processed automatically with acceptable results. In addition we explored several different T wave features which might be used for TWA characterization. Overall it was found that there are several features which can be used in an automatic TWA analysis with performance close to that

achieved by an experienced cardiologist. These same features perform well when used in a clinical lesion classification setting. Features and measures which effectively integrate the information given by an ECG seem to give the best results so that development of automated analysis methods that use long ECG's, with minimal involvement of a cardiologist, may be a promising approach for cardiac diagnosis. It may be worthwhile to seek new features as well.

Appendix A. T Wave Detection Algorithm

Algorithm uses the following initial quantities:

1. *Discrete ECG signal* $Y(t)$, $t = 1, 2, \ldots, N$, where N – number of samples in the ECG.
2. A *template* T *wave* defined by the beginning point t_{b_templ} and the end point t_{e_templ} of the selected T wave (t_{b_templ}, t_{e_templ} – manually defined).
3. A *template time interval* a_{templ} *between two adjacent* T *waves* defined as a distance between the template and the adjacent T wave maximum points: $a_{templ} = t_{m\_templ} - t_{m\_adj}$, where t_{m_templ} – maximum point of the template wave and t_{m_adj} – maximum point of the adjacent T wave (t_{m_templ}, t_{m_adj} – manually defined).
4. A *template time interval* a_{1_templ} *between the beginning point and the maximum point* of the template wave: $a_{1\_templ} = t_{m\_templ} - t_{b\_templ}$, and *template time interval* a_{2_templ} *between the maximum point and the end point*: $a_{2\_templ} = t_{e\_templ} - t_{m\_templ}$.
5. *Template beginning and end signals* $F_{b\_templ}(x)$ and $F_{e\_templ}(x)$: $F_{b\_templ}(x) = Y(t)$, $t = t_{b\_templ} - 50..t_{b\_templ} + 50$, $x = 1 \ldots 101$; $F_{e\_templ}(x) = Y(t)$, $t = t_{e\_templ} - 50..t_{e\_templ} + 50$, $x = 1 \ldots 101$, the constants being adapted to the 2 kHz sampled ECG signal.
6. The *initial point* $t = t_0^1$ of T waves series analysis (detection process is started at the approximate maximum point of a T wave in the beginning of a signal, t_0^1 – manually defined).

Manual definitions were done by a cardiologist using an interactive computer program.

Algorithm for detection of the ith T wave in a sequence operates as follows:

1. The time interval $[t_1, t_2]$ around the initial point t_0^i, approximately defining the position of the ith T wave, is constructed, where $t_1 = t_0^i - 0.4a_{1\_templ}$, and $t_2 = t_0^i + 0.4a_{2\_templ}$. Then the maximum point t_m^i of this interval (i.e., the maximum of the ith T wave) is computed, $t_m^i = \max\{Y(t)\}$, $t = t_1 \ldots t_2$.
2. The *initial beginning* t_b^i *and end* t_e^i *points* for the ith wave are computed as follows: $t_b^i = t_m^i - a_{1\_templ}$, and $t_e^i = t_m^i + a_{2\_templ}$.
3. Correlation-based refinement of the *initial beginning and end points* t_b^i, t_e^i is carried out and this *refined beginning point* $t_{b\_ref}^i$ is obtained. At first $t_{b\_ref}^i = t_b^i$ is defined. Then time interval $[t_{b\_1}, t_{b\_2}]$ is constructed, where $t_{b\_1} = t_b^i - 75$, and

$t_{b\_2} = t_b^i + 75$. From the beginning point of this interval the algorithm shifts trough all the points computing the correlation coefficient r between signals $F_{b\_templ}(x)$, $x = 1 \dots 101$, and $Y(t)$, $t = i_0 \dots i_0 + 100$ (in the beginning $i_0 = t_{b\_1}$), which is compared with the given correlation coefficient $r_u = 0,98$. If $r = r_u$, the point $t = t + 50$ is fixed as the final beginning point of the T wave. Else i_0 is increased, $i_0 = i_0 + 2$, and correlation coefficient r is computed again.

4. If r_u is not achieved in the given interval $[t_{b\_1}, t_{b\_2}]$, then r_u is decreased $r_u = r_u - 0.02$, and the algorithm returns to the beginning of the interval. The action is performed until $r >= r_u$ is achieved.
5. In a similar way as the *refined beginning point* in step (3), the *refined end point* $t^i_{e\_ref}$ of the T wave is computed. In that case the correlation coefficient between signals $F_{e\_templ}(x)$, $x = 1 \dots 101$, and $Y(t)$, $t = i_0 \dots i_0 + 100$ is calculated.
6. Correlation coefficient r_u for the end template match is decreased in the same way as in step (4) for the beginning template match if the required precision is not achieved in step (5), and this step is repeated until $r >= r_u$ is achieved for the end template match.
7. Further with $t_0^{i+1} = t_0^i + a_{templ}$ the algorithm returns to the 1st step to process the next wave. The process is repeated until the required number of T waves is achieved, i.e., $i = 128$.

Appendix B. Features of T wave

The amplitude feature was evaluated by calculating the functional value for each T wave:

$$A(i) = Y(t_m^i) - \frac{Y(t_b^i) + Y(t_e^i)}{2},$$

where $Y(t)$ – ECG signal, t_m^i – the maximum point of ith T wave, t_b^i – the beginning point of ith T wave, t_e^i – the end point of ith T wave, $i = 1 \dots 128$ (see Fig. 3(a)).

For duration feature determination four different functional values need to be computed. One of them depends only on wave boundaries: $T_1(i) = t_e^i - t_b^i$.

The other three additionally included area information:

$T_2(i) = t^i_{S_{0.5}} - t_b^i$ – measures the time interval to accumulate from 0 to 50% of the T wave area, where $t^i_{S_{0.5}}$ is defined by the equation

$$\sum_{t=t_b^i}^{t^i_{S_{0.5}}} Y(t) = 0.5 \cdot S_1(i).$$

$T_3(i) = t^i_{S_{0.75}} - t^i_{S_{0.25}}$ – measures the time interval to accumulate from 25 to 75% of the area, where $t^i_{S_{0.75}}$ and $t^i_{S_{0.25}}$ are defined by the following equations:

$$\sum_{t=t_b^i}^{t^i_{S_{0.25}}} Y(t) = 0.25 \cdot S_1(i), \quad \sum_{t=t_b^i}^{t^i_{S_{0.75}}} Y(t) = 0.75 \cdot S_1(i).$$

Finally, the time interval to accumulate from 5 to 95% of the area (see Fig. 3(b)) $T_4(i) = t^i_{S_{0.95}} - t^i_{S_{0.05}}$, where $t^i_{S_{0.95}}$ and $t^i_{S_{0.05}}$ are defined by the following equations:

$$\sum_{t=t^i_b}^{t^i_{S_{0.05}}} Y(t) = 0.05 \cdot S_1(i), \quad \sum_{t=t^i_b}^{t^i_{S_{0.95}}} Y(t) = 0.95 \cdot S_1(i).$$

Two functional values directly reflecting the T wave area were calculated:

$$S_1(i) = \sum_{t=t^i_b}^{t^i_{pb}} Y(t), \quad S_2(i) = \sum_{t=t^i_b}^{t^i_m} Y(t),$$

where $S_1(i)$ – T wave area from the beginning point to the end point, $S_2(i)$ – area from the beginning point to the maximum point (see Fig. 3(c)).

Acknowledgements

Authors thank Prof. Juozas Blužas and his research group from the Institute of Cardiology, Kaunas, for the data sets and helpful discussion, and especially thank Dr. Gražina Urbonavičienė who carried out the manual ECG labeling used in this study.

References

Acar, B. (1999). New approaches to T-wave analysis from Surface ECG. *Cardiac Electrophysiology Review*, **3**, 319–323.

Adachi, K., Y. Ohnishi, T. Shima *et al*. (1999). Determinant of microvolt level T wave alternans in patients with dilated cardiomyopathy. *Journal of the American College of Cardiology*, **34**(2), 374–380.

Armoundas, A.A., G.F. Tomaselli and H.D. Esperer (2002). Pathophysiological basis and clinical application of T wave alternans. *Journal of the American College of Cardiology*, **40**(2), 207–217.

Armoundas, A.A., D.S. Rosenbaum, J.N. Ruskin, H. Garan and R.J. Cohen (1998). Prognostic significance of electrical alternans versus signal averaged electrocardiography in predicting the outcome of electrophysiological testing and arrhythmia-free survival. *Heart*, **80**, 251–256.

Bloomfield, D.M., S. Hohnloser and R. Cohen (2002). Interpretation and classification of microvolt T wave alternans. *Journal of Cardiovascular Electrophysiology*, **13**(5), 502–512.

Burattini, L. (1998). *Electrocardiographic T-wave Alternans Detection and Significance*. Doctoral Thesis, University of Rochester, Rochester, NY.

Burattini, L., W. Zareba, E. Rashba, J.P. Couderc, J.A. Konecki and A.J. Moss (1998). ECG features of microvolt T wave alternans in coronary artery disease and long QT syndrome patients. *Journal of Electrocardiology*, **31**, 114–120.

Cambridge Heart (August 2002). *Review of Key Clinical Literature on Microvolt T-Wave Alternans*. `http://www.cambridgeheart.com`

Cheung, M.H., A.M. David, R.J. Cohen and J.L. Wilkinson (2001). T wave alternans threshold in normal children. *Journal of Cardiovascular Electrophysiology*, **12**, 424–427.

Colombo, R., G. Mazzuero, F. Soffiantino, M. Ardizzoia and G. Minuco (1989). A comprehensive PC solution to heart rate variability. In *Computers in Cardiology*. IEEE Computer Society Press, Los Amitos. pp. 475–478.

Gold, M.R., D.M. Bloomfield, K.P. Anderson, N.E. El-Sherif, D.J. Wilber, W.J. Groh, N.A. Estes, E.S. Kaufman, M.L. Greenberg and D.S. Rosenbaum (2000). A comparison of T wave alternans, signal averaged electrocardiography and programmed ventricular stimulation for arrhythmia risk stratification. *Journal of the American College of Cardiology*, **36**(7), 2254–2256.

Kavesh, N.G., S.R. Shorofsky, S.E. Sarang and M.R. Gold (1998). Effect of heart rate on T wave alternans. *Journal of Cardiovascular Electrophysiology*, **9**, 703–708.

Kitamura, H., Y. Ohnishi, K. Okajima, A. Ishida, E. Galeano, K. Adachi and M. Yokoyama (2002). Onset heart rate of microvolt-level T wave alternans provides clinical and prognostic value in nonischemic dilated cardiomyopathy. *Journal of the American College of Cardiology*, **39**(2), 295–300.

Klingenheben, T., M. Zabel, R.B. D'Agostino, R.J. Cohen and S.H. Hohnloser (2000). Predictive value of T wave alternans for arryhthmic events in patients with congestive heart failure. *The Lancet*, **356**, 651–652.

Konno, Y., J. Watanabe, Y. Koseki *et al.* (2003). Microvolt T wave alternans in human cardiac hypertrophy: electrical instability in Abnormal Myocardial Arrangement. *Journal of Cardiovascular Electrophysiology*, **12**(7), 759–763.

Laguna, P., G.B. Moody, J. Garcia, A.L. Goldberger and R.G. Mark (1999). Analysis of the ST-T complex of electrocardiograms using the Karhunen–Loeve transform: adaptive monitoring and alternation detection. *Medical & Biological Engineering & Computing*, **37**(2), 175–189.

Lewis, T. (1910). Notes upon alternation of the heart. *Quart J. Med.*, **4**, 141–145.

Martinez, J.P., S. Olmos and P. Laguna (2000). T wave alternans detection: a simulation study and analysis of the European ST-T database. *Computers in Cardiology*, **27**, 155–158.

Nearing, B.D., A.H. Huang and R.L. Verrier. Dynamic tracking of cardiac vulnerability by complex demodulation of the T wave. *Science*, **252**, 437–440.

Nemec, J., J.B. Hejlik and W.K. Shen (2003). Catecholamine-induced T wave lability in congenital long QT syndrome: a novel phenomenon associated with syncope and cardiac arrest. *Mayo Clin. Proc.*, **78**, 40–50.

Pastore, J.M., S.D. Girouard, K.R. Laurita, F.G. Akar and D.S. Rosenbaum (1999). Mechanisms linking T wave alternans to the genesis of cardiac fibrillation. *Circulation*, **99**(10), 1385–1394.

Pedretti, R.F.E., S. Sarzi Braga, A. Picozzi and A. Laporta (2000). Prognostic value of T wave alternans in patients with congestive heart failure. *Journal of the American College of Cardiology*, **P93**/10335, 64.

Raudys, S. (2001). *Statistical and Neural Classifiers*. Springer.

Smith, J.M., E.A. Clancy, C.R. Valeri *et al.* (1988). Electrical alternans in cardiac electrical instability. *Circulation*, **77**, 110–121.

Tamosiunaite, M., R. Vaisnys, T. Kulvicius, G. Urbonaviciene, S. Kaminskiene and I. Bluzaite (2002). Search for T wave alternans by multiplicative factor method. In J. Jan, J. Kozumplik and I. Provaznik (Eds.), *Analysis of Biomedical Signals and Images*: *Proceedings of the 16th international EURASIP Conference BIOSIGNAL 2002*, *16th International Conference Biosignal 2002*, *June 26–28*, Brno, Czech Republic. pp. 103–105.

Tanno, K., Y. Kobayashi, T. Adachi, S. Ryu, T. Asano, C. Obara, T. Baba and T. Katagiri (2000). Onset heart rate and microvolt T wave alternans during atrial pacing. *The American Juornal of Cardiology*, **86**, 877–880.

Tapainen, J.M., A.M. Still, K.E. Airaksinen and H.V. Huikuri (2001). Prognostic significance of risk stratifies of mortality, including T wave alternans, after acute myocardial infarction: results of a prospective follow-up studies. *Journal of Cardiovascular Electrophysiology*, **12**(6), 645–652.

Walker, M.L., and D.S. Rosenbaum (2003). Repolarization alternans: implications for the mechanism and prevention of sudden cardiac death. *Cardiovascular Research*, **57**, 599–614.

T. Kulvičius received his MS degree in informatics from Vytautas Magnus University. Currently he is a PhD student at Vytautas Magnus University. His research interests include medical signal analysis.

M. Tamošiūnaitė received her engineer diploma from Kaunas University of Technology, and PhD in the field of informatics from Vytautas Magnus University. Currently she is working as an associate professor at Vytautas Magnus University. Her research interests include biological system modeling, biosignal analysis.

R. Vaišnys received his PhD from the University of California, Berkeley. Currently he is a professor at Yale University. He analyzes biological systems.

T dantelio požymių tinkamumo automatiniam alternacijos įvertinimui tyrimas

Tomas KULVIČIUS, Minija TAMOŠIŪNAITĖ, Rimas VAIŠNYS

Tiriama, kokie T dantelio požymiai tinka automatiniam T dantelio alternacijos elektrokardiogramoje įvertinimui, kai signalas yra nedaug stipresnis už triukšmą. Kintamo ilgio T dantelių išskyrimui naudojamas koreliacija su šablonu pagrįstas algoritmas. Randama, kad amplitudės ir ploto požymiai yra žymiai mažiau jautrūs šablono parinkimui, negu ilgio požymiai. Tie T dantelio požymiai ir alternacijos matai, kuriuos įmanoma patikimiau įvertinti, teikia geresnį klasifikavimo tikslumą, atskiriant pacientų su koronarinių arterijų pažeidimais ir be pažeidimų elektrokardiogramas.