ADAPTIVE CHANNELS WEIGHTING FOR THE QRS DETECTION IN LONG-TERM ELECTROCARDIOGRAMS

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Abstract: The adaptive adjustment of the channels' contribution in the QRS wave detection is described in this paper. The automatic choice of the 'best channel' is particularly justified in tong-term recordings exposed to the variability of recording conditions of environmental and physiological origin. Two adaptation schemes and two different signal quality estimators are proposed and tested in course of the numerical experiment. The feedback-based scheme uses the Signal-to-Noise Ratio computed on the baseline and QRS segment, so it needs the detection to be performed beforehand. The feedforward-based scheme uses a custom developed signal quality estimator without any anticipating processing. The results show the growth of the detection reliability, even in variable recording condition, for both adaptation schemes. The statistical outcome indicates slightly higher performance of the feedforward scheme.

Introduction

The topic of the QRS detection in the electrocardiogram is already widely exploited. The detection of the ventricles' contraction representation is a fundamental and mandatory subroutine for any automated ECG processing [1] [2]. However, if a long-term multichannel recording is considered, the assumed stability of recording conditions is no longer sufficient and the initial channel weighting may need to be continuously updated for the optimal detection. The problem of adaptive channels weighting during the ECG acquisition in an unsteady environment is concerned in this paper.

The detection of QRS wave may be performed in many possible ways, among of which three main methods can be distinguished:

- The extraction of mathematically derived features of the signal followed by the binary decision procedure.
- The pattern matching procedure using a multi-entry dictionary usually yielding the morphology recognition along with the QRS detection.
- The time or transform-domain features extraction and processing with use of fuzzy logic or artificial neural networks.

No matter how the detection procedure works, in case of multilead recordings the simultaneous channels may be processed:

- Separately – the logical output information for each channel is independent and thus all ambiguities are resolved at the logical level,
- Jointly – the contribution of each channel is weighted at the level of features extraction, so the intra-channels synergy (or coherence) is the final decision base.

The main advantage of the long-term recordings is the ability of ECG measurements in the natural life conditions of the subject. The variability of these conditions implies the random occurrence of side signals and their interference with the electrical representation of cardiac activity. In consequence, improved immunity of the recording system is required for these applications. But even if all artifact of technical origin might be avoided with use of high performance equipment, the biological sources of side signals still remain active. These sources are:

- Skin activity, that covers a large amount of phenomena involved in transforming the electric information from the ion conductance-based environment to the electronic circuit.
- Muscles activity, that represents the continuous vital processes of any cells not belonging to the cardiac muscle and conductive system. For the very similar origin, these activities are represented in the electric signal by components of the same amplitude and frequency ranges as the cardiac information.

The biologically conditioned unstability of the recording conditions and the lack of guidelines motivated us to design and develop an appropriate algorithm for continuous and adaptive optimization of the channel's contribution by the software. Without loosing the generality of the viewpoint, in the further part of the paper we focus on the QRS detector based on the mathematically derived features of the ECG signal. These features are usually represented by the discrete time domain "detection function" those values are a kind of probability of the QRS wave's occurrence. In case of multilead recording, these features are usually derived in a subset of simultaneous channels (*1 ... n*) and contribute to the global decision with the channel-dependent constant ratio *wn* (figure 1). This ratio is initially assigned to each channel and works fine as long as the assumption of the stability is fulfilled. For the long-term signals, however, the initial contribution of each channel should be continuously updated to follow the changes in recording conditions.

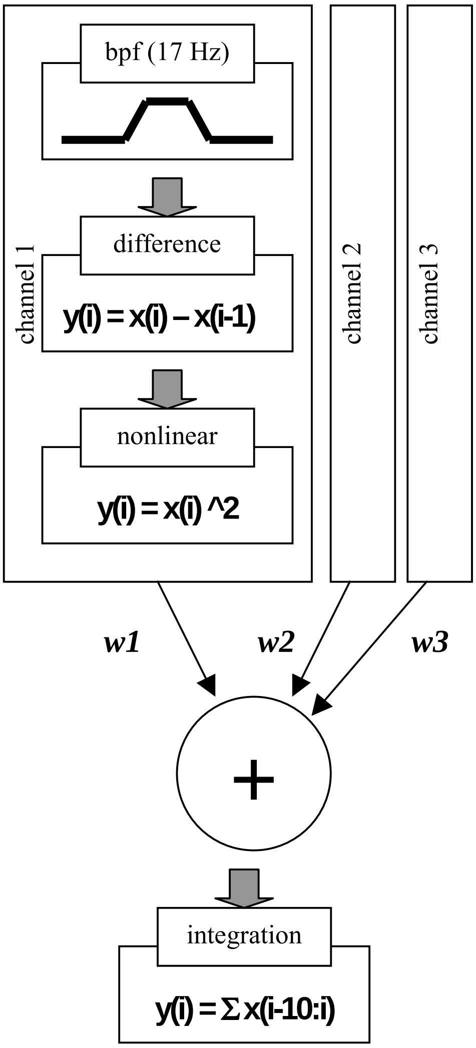

Figure 1. The example processing scheme for a multichannel detection function

The adaptive adjustment of the channel contribution may be considered as a typical automation process and needs two interdependent issues to be considered:

- The control scheme.
- Definition and measurement of driving features.

There are two possible schemes of the control: feedforward and feedback (figure 2). The feedforward scheme uses the pre-extracted signal features in each channel to modify the contribution weights. Main drawback here is the lack of information on the signal contents and thus additional processing of high complexity is needed. The feedback scheme relies on previously detected QRS wave and on the assumption of short-term stability of recording conditions. The processing is less complex, using the definition of the ECG "signal" and "noise" that assumes the detection of QRS wave completed beforehand. Like the classical digital IIR filters, unfortunately, the feedback scheme yields the oscillatory response if overwhelmed.

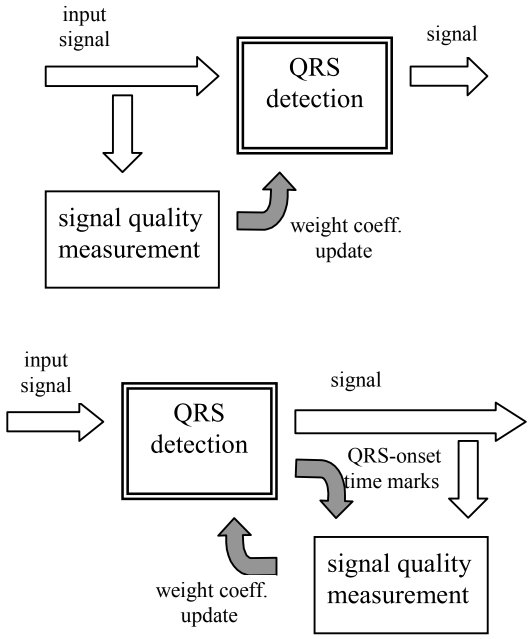

Figure 2. The feedforward and feedback scheme of the adaptive channels wieghting for QRS detection

The signal features driving the adaptive adjustment of the channel contribution have to be extracted directly from the signal and, in case of feedforward control scheme, the possible low computational complexity is an important criterion. In this case, for the lack of time indices, the whole signal has to be scanned for the desired features. On the contrary, once the QRS wave is detected, it becomes the most important time indice and the signal is processed only for the QRS and the baseline segments (on average approximately 30% of the signal length). The feedback scheme supports the use of wide range of signal quality estimators: from the simple RMS noise measure [3] to the advanced modeling of background activity [4].

Materials and methods

Two different algorithms were designed, developed and tested for performance. The first one uses the feedforward scheme and the custom-developed coefficient PMR of the Signal-to-Noise Ratio (SNR) type, described hereafter. The second algorithm bases on the feedback scheme and the CSE-recommended RMS noise measure. More advanced measures of signal quality, although interesting, were not considered for their computation complexity and the overgrowth of the resulting data sets.

The Peak-to-Median Ratio (PMR) is the result of the statistic processing of the time-windowed signal (fig. 3).

```
function z=pmr(s, t)
% s - input ecg signal (one channel)
% t - current sample
prr=256; % sampling frequency 128 Hz
win=16; % 117 ms
winc=ceil(prr/win); % windows count
wins=zeros(winc, 1); % average buffer
for i=1:winc
  wins(i)=sum(abs(s(t+(i-1)*win+1:t+i*win)));
end;
wins=wins-min(wins);
z=max(wins)/median(wins);
```

Figure 3. Listing of the procedure of the Peak-to-Median Ratio computation

For the constant pre-roll time of 2 s before the currently processed sample, the signal is segmented by adjacent positions of the rectangular window. The length of the window equals to 117 ms (16 samples), what is a compromise between the baseline length and the QRS wave's length. For each segment the sum of absolute value of the signal samples is calculated and compared to other sums in all the pre-roll time. The minimum value is representative for the baseline and subtracted from the others, the peak value P represents the signal amplitude in the QRS-wave while the median value M represents the signal amplitude for other ECG components. The Peak-to-Median Ratio is thus the measure of how the QRS-wave is distinct from the signal and from the detector's point of view is the representation of the local signal quality.

Each channel is then assigned a percentage (weight) of contribution in the detection function proportional to the computed signal quality.

$$w_i = \frac{PMR(i)}{\sum_{k=1}^{N} PMR(k)} \cdot 100\% \qquad (1)$$

The alternative measure of signal quality is the Root-Mean-Square (RMS) estimator of the noise level recommended by the CSE (Common Standard for Quantitative Electrocardiography) [3].

$$RMS = \sqrt{\frac{\sum_{i=1}^{10} \left(s(i) - s(i-1)\right)^2}{10} + 0.5} \qquad (2)$$

This coefficient gives an accurate measure of the noise contribution in the ECG. It bases on the physiological assumption of the electrical inactivity of the heart during the conduction of stimulus in the Atrio-Ventricular Node, represented in the ECG by the PR distance. This assumption is fairly fulfilled thanks to the low velocity of conduction in AVN tissues and to the central position of the node close to the electrical center of the heart. In consequence, the baseline level is widely recognized reference point in the electrocardiogram. The RMS gives an accurate measure of the noise and, compared to the QRS amplitude yields the correct estimation of Signal-to-Noise Ratio. The computation complexity is not very important here, since the processing concerns only two short signal segments per heartbeat. The calculation of the RMS, however, must be anticipated by the detection of the QRS-wave and (at least) by the determining of the QRS-onset point. Another drawback of the RMS consists in the definition of the noise contribution is as frequent as the heartbeats are. If the noise estimation is needed more frequently or at the uniform rate, the involvement of linear or spline-based interpolation is necessary. In our algorithm the local stability of the recording condition is assumed and the SNR-based weighting coefficients (3) computed for the last detected QRS-wave is used to modulate the channels contribution in the next detection.

$$w_i = \frac{SNR(i)}{\sum_{k=1}^{N} SNR(k)} \cdot 100\% \qquad (3)$$

The performance of both proposed algorithms was measured with use of 360 s three-channel Holter recording (128 sps, 10 bits - figure 4). The noise strips originate from the MIT-BIH Arrhythmia Database (the NSTDB folder, files Bw.dat, Em.dat and Ma.dat) [5]. Before the use in the experiment, the noise patterns were resampled to 128 Hz, cut in length to 360 s and combined to yield a three-channel uncorrelated noise (figure 5). To simulate the variability of recording conditions, all noise channels were independently modulated with a positive valued sinus envelope containing 3 periods in the first channel and respectively 4 and 5 periods in the remaining channels (figure 6). After the normalization of energy at five different levels varying from –30 dB to –6 dB, the noise patterns were added to the ECG reference signal. The global energy of the added noise was a parameter for six successive testing steps. This simulates the unstability of the recording environment in long-term acquisition of the ECG [6].

The numerical experiment was designed and carried out in Matlab environment, except for the QRS detecting procedure natively coded in C++. This procedure is the modified working version with added the "detection function" output and weighting coefficients input. Six trials were performed for each noise level (one additional for the signal without the added noise). Two previously described channel adjustment schemes were tested and compared to the fixed adjustment based on the amplitude ratio in the initial section. The local signal quality estimators and the resulting weighting coefficients were recorded along with the signal. Moreover, the final performance of the detector (the percentage of false detection events) was recorded and processed statistically. The experiment was expected to support the choice between the feedback- and feedforward-based algorithm and to give an insight on how far the increase of noise level in a particular channel may be compensated by the optimization of the channels contribution.

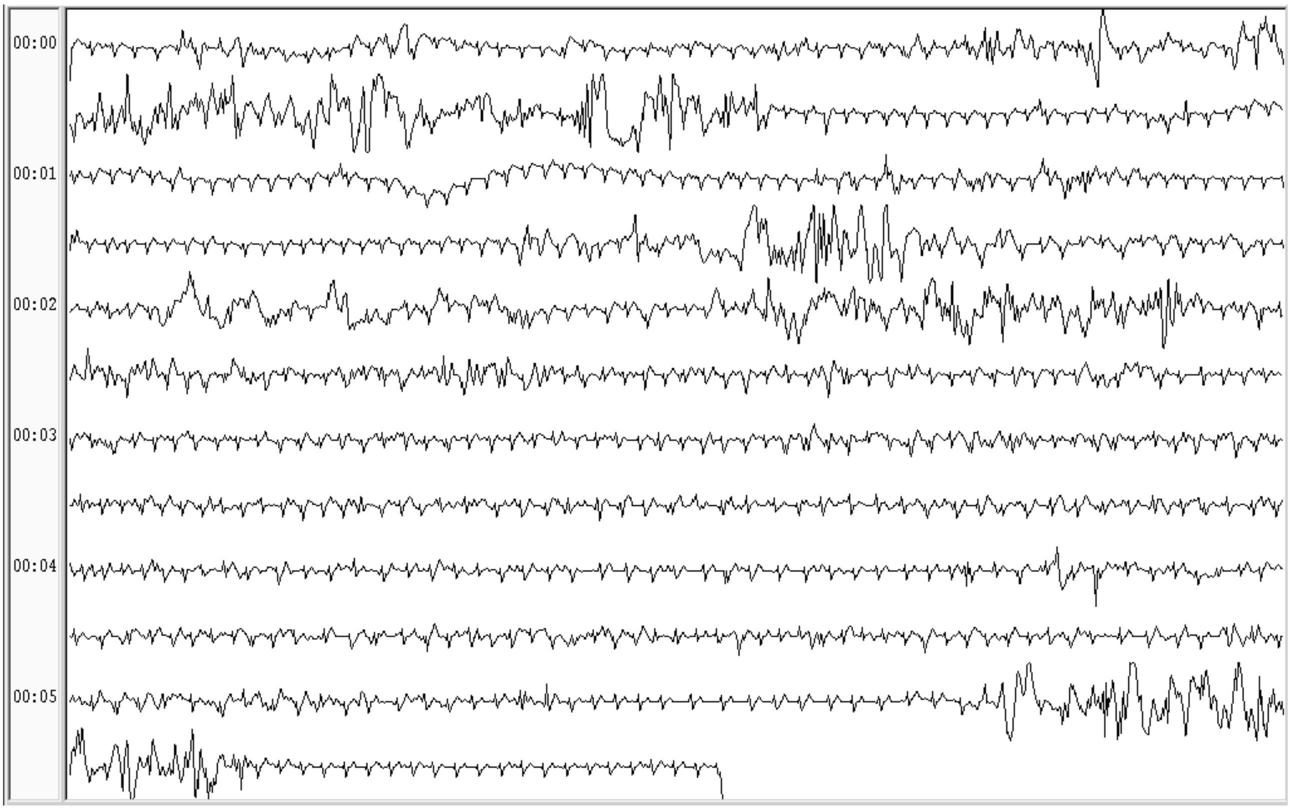

Figure 4. The full disclosure of 3-channel Holter recording (128 sps, 10 bits, channel 1) used for the numerical tests

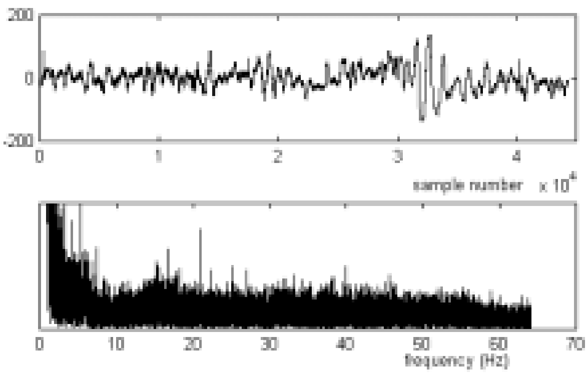

Figure 5. Noise properties in time domain and in frequency domain (channel 1)

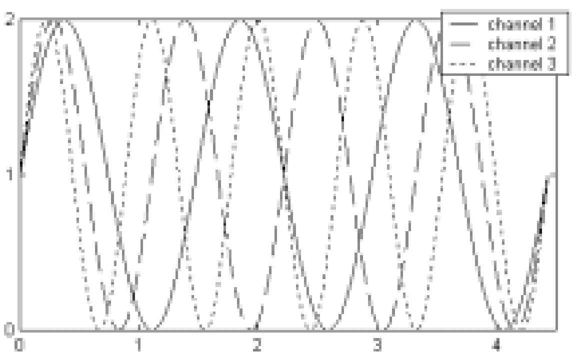

Figure 6. Noise modulation in three channels

Results

The results obtained for the performance test of the modified QRS-wave detector are statistically processed and displayed in the Table 1. The detailed results, however, being the number of errors in the consecutive 16 s strips are also very interesting, because of representing the detector's behavior in the 'easy' and the 'difficult' parts of the signal (fig. 4). These results cannot be completely displayed for the lack of space, and thus table 2 presents only the outcome for the noise level –12 dB. Additional plot in the figure 7 is devoted to the presentation of the data from the table 1. It facilitates the interpretation of the 'best adjustment scheme'. Figure 8 displays a short signal strip with large variability of the recording conditions. The weighting coefficient values displayed along with the three-channel signal gives an insight how the channel contribution is modified due to the interference or poor signal quality. Figure 9 displays the difference in variability of channel contribution between the PMR-based feedforward and the SNR-based feedback control schemes. These plots were not initially expected for presentation, but the study on detailed results and in particular the pursuit for the false negative detections are well supported by observed differences in variability.

Table 1. The performance of the modified QRS detector

noise level	**fixed**		**feedforward**		**feedback**	
	fn	fp	fn	fp	fn	fp
off	23	54	16	32	16	44
-30	45	44	14	35	26	41
-24	19	50	12	29	14	31
-18	46	49	16	37	17	46
-12	37	38	10	44	23	35
-6	53	45	31	55	41	52
total	657					

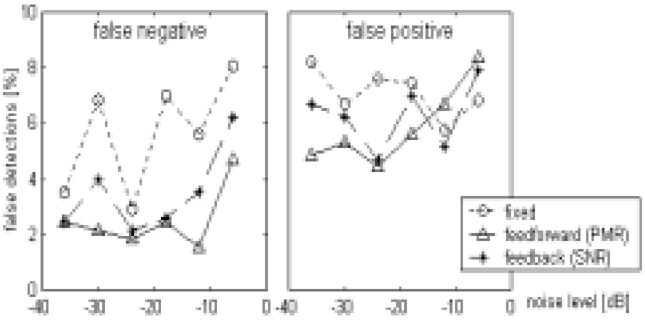

Figure 7. False detection percentage for the fixed channel contribution based QRS detector and the new algorithms.

Table 2. Detailed results for the noise level –12 dB

strip nbr	**fixed**		**feedforward**		**feedback**	
	fn	fp	fn	fp	fn	fp
1		1		1	1	
2		7		3		2
3	23	7	1	6	7	10
4		1		1		
5		1		1		2
6		1		2		
7	1	7	2	7	3	5
8				1		1
9	2	7	2	9	4	4
10		2		5		2
11		1		1		
12						
13						
14						
15						
16						
17		1		1		1
18						
19						
20						
21	11	2	5	6	8	8
22						
total	37	38	10	44	23	35
QRS	648		677		651	

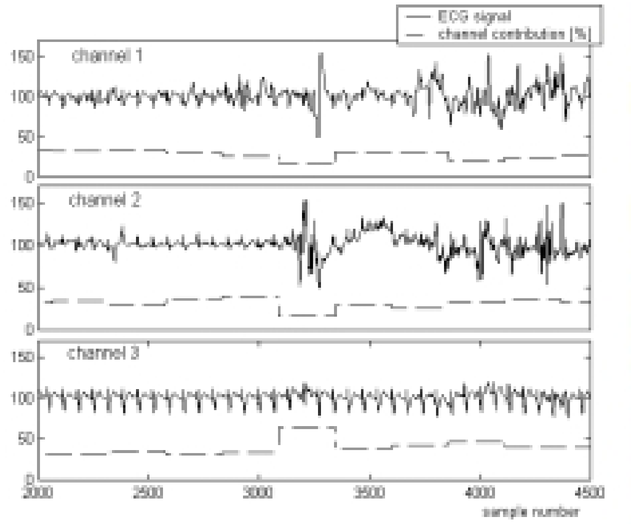

Figure 8. Example of the signal strip with large variability of the recording conditions.

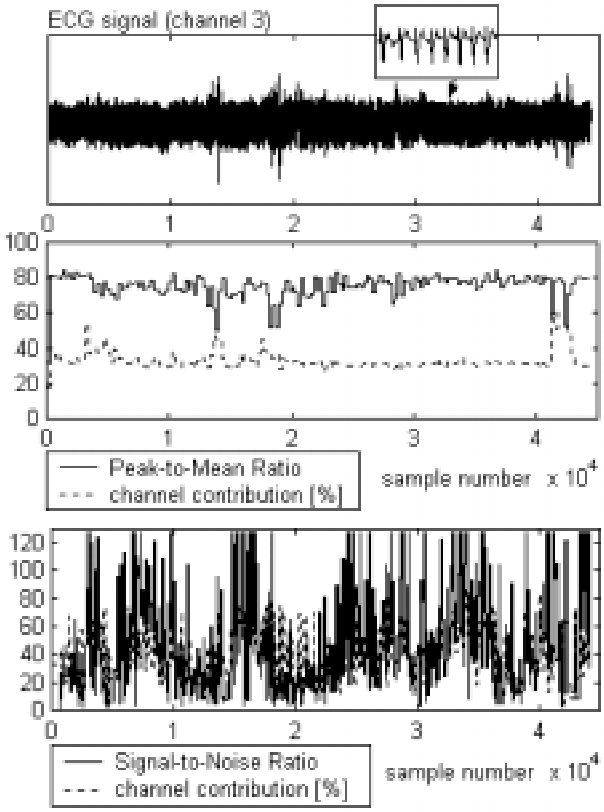

Figure 9. The study of the quality estimator and channel 3 contribution variability. Upper plot – the ECG signal; middle plot – the result for PMR-based feedforward scheme (standard deviations: **0.066** and **0.058** respectively); lower plot – the result for SNR-based feedback scheme (standard deviations: **0.364** and **0.179** respectively);

Discussion

The results of the numerical tests prove the initial assumptions that the adaptive adjustment of channel contribution ameliorates the detector's performance. Except the case of very high noise level (-6 dB), the performance of detector fed with an adaptively weighted three-channel recording was better than the performance of the fixed-contribution detector.

The choice of the control scheme, however, is not so evident. The feedforward PMR-based control scheme yields lowest occurrence of false negative detections, but in the same time exhibits the important growth of the false positive beats for the noisy recordings. The feedback SNR-based control is less sensitive to the signal quality, the number of false detection is relatively higher than for the feedforward detector, but only slightly depends on the added noise. The feedback-based detector controls the signal quality at the irregularly distributed time points and thus the variability of the output is much higher than for the feedforward-based detector. In particular, the false positive detections cause the computation of SNR at the sections that are assumed to be the baseline, but in reality are not. For this reason, many sudden changes in channels' contribution, not justified by real variations of the signal quality, may lead to the false negative or another false positive detector's response. That suggests, even for the feedback-based control scheme, the use of constant-rate parameter for estimation the local signal quality. This parameter should be immune to the eventual false detections.

Another issue is the correct choice of the signal quality estimator. The numerical experiment did not answer (but it was not expected to) whether the proposed Peak-to-Mean Ratio (fig. 3) is an accurate representation of the noise. Additional study would probably determine the optimal parameter, but assessing the operation of the adjustment scheme did not indicate a necessity for a better estimator. For this application, the PMR has two important advantages: low computation cost and processing of an unannotated signal.

The detailed results on the number of errors in the consecutive 16 s strips, summarized for the single case of noise level –12 dB, represent the detector's behavior in presence of noise variability. The rowwise study of these tables for all noise levels spots the detector's output on the 'easy' and the 'difficult' parts of the signal. These study yields several remarks:

- poor signal quality always causes false detections, they can be reduced, but not completely avoided with use of an adaptive adjustment of channels contribution (tab. 2 strip 3);
- if all three channels exhibit high noise level, the adjustment algorithm may cause supplementary false detection (tab. 2 strip 9);
- the spike in channel 1 (fig.4, at 00:04:45) always yields the false positive detection (tab. 2 strip 17) – the event is shorter than the adaptation time.

The use of the adaptive adjustment of channels' contribution improves the detector's performance. The algorithm for the adaptive control of channel's contribution weighting coefficients was designed and implemented in the C-coded commercial software. Currently, the self-adjustable detector is tested against the library of 300 all-day Holter recordings and the preliminary results are very close to those presented hereby.

Acknowledgement

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