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BISPECTRAL FILTERING OF ECG SIGNALS

Viunytskyi O.H.
Ph.D., as. prof.
ORCID: 0000-0002-1806-6193
Totsky O.V.
d.t.s., prof.
National Aerospace University "Kharkiv Aviation Institute",
Kharkiv, Vadim Manka, 17, 61070

Abstract. *Due to the influence of a large number of interference contributions contained in the recorded ECG signal, advanced techniques and algorithms are commonly used to extract the useful signal in noise background environment. However, existing filtering techniques have a large number of problems when using them for ECG signal processing. One of the main requirements is to develop such technique that would allow for the gradual measured data to carry out the accumulation and averaging procedures to suppress effectively the interferences. In addition, this technique should also be invariant to the typical random ECG signal time shifts that sufficiently destroy coherent signal accumulation. It should also be able extracting important information about the phase coupling arising due to the nonlinear processes in cardiovascular activity. One of such signal processing technique having noted features is bispectrum-based data processing technique. A novel technique of adaptive nonlinear filtering based on bispectral signal processing is proposed in the present paper. Suggested technique provides an average improvement by 1 dBW of the filtering performance in the range of signal-to-noise ratio (SNR) variations from –20 to 0 dBW. However, at a higher SNR, the proposed technique provides a worse result due to the contribution of distortions to the initial signal. Note, that suggested bispectrum-based filter is more effective to be used to remove additive gaussian noise components from the ECG signal at a low SNR. The advantage of the proposed technique is invariance to non-stationary changes in the waveform of the ECG signal which makes the proposed method adaptive and robust to any changes.*

Key words: *ECG signal, bispectrum, bispectrum-based signal processing, nonlinear filtering.*

Introduction.

Due to the presence of a large number of interference contributions in the ECG signal, various advanced techniques and algorithms are used to extract the useful signal in noise environment. Such common techniques as independent component analysis technique [1], filtering technique [2], their combinations [3] to achieve the best result [4], wavelet transform [5], techniques of decomposition of signals into empirical modes [6], correlation techniques [7], as well as non-adaptive methods [8] are widespread today. In turn, they can be divided into single-channel methods [9] and multi-channel methods [10,11]. Standard Kalman filters (KF) were built to process stationary processes. However, since medical signals are more related to non-stationary processes and they have a nonlinear nature, modifications of KF such as the extended

Kalman filter (EKF) are more often used to implement extracting an ECG signal from a mixture of a useful signal and noise. Its peculiarity is the following. The result is the separation of ECG components while other components and interference components of the ECG signal are considered as noise [12]. This approach allows for the evaluation of the noise of the original signal value with new signal values. Therefore, this method is actively used in long-term monitoring as it allows adapting to each specific case [13] for the removal of nonlinear interference.

There is also another modification of this technique called extended Kalman smoothing (EKS). It is based on the EKF using inverse smoothing [14,15]. The ECG signal is processed by determining the average value of the ECG component heart rate which is then approximated using a Gaussian kernel. The signal is then amplified using a gain factor which is used to correlate the observed signals and taking into account the dynamics of the system. However, these filters are not adaptive to non-stationary changes in the ECG signal in which the shape of the QRS complexes may change during signal recording due to the influence of other interference contributions. Some QRS complexes may be removed after using this type of filter. However, it will lead to further errors in ECG signal processing.

There are also independent component analysis techniques. Their concept is based on the fact that the source is statically independent while the ECG signal is a mixture of signals at the output [16]. To estimate each individual component of the ECG signal, a separation matrix is used. It allows by multiplication to obtain separate estimates for each separate source of the ECG signal. It should be noted that the separation matrix cannot be calculated exactly. Therefore, when using blind source separation approach the approximate estimates of the original source signals are obtained. These techniques belong to the class of second-order estimates which are called Independent Component Analysis (ICA) [17-18]. There is also another class of these methods called as periodic component analysis or periodic component analysis (πCA) [19-20]. The main problem when using ICA methods is that after obtaining estimates of individual sources of the ECG signal, it is impossible to reliably determine the order of the sources, as well as the scaling of the sources and their sign. However, a large number of modifications have been introduced that based on these algorithms. Wavelet transform techniques are also actively used. They are also implemented as methods of nonlinear filtering of ECG signals combining them with other nonlinear filtering methods [21], thereby replacing Kalman filters or using them in combination [21]. In [22], the effectiveness of using simlet wavelets for preprocessing of ECG signals has been demonstrated in order to reduce the level of noise in the initial signal. However, this method is not adaptive to nonlinear changes in the signal and to implement such adaptability. It is necessary to use modified threshold values, adaptive thresholds or hard thresholds which will allow when using the proposed approach to remove noise components from the ECG signal as much as possible.

Taking into account these peculiarities and problems, the wavelet transform is also not suitable for solving the problem of filtering ECG signals due to the need for preliminary calculations. Accordingly, it is necessary to determine an analysis technique that would allow for the gradual accumulation and averaging of information to suppress the maximum amount of interference arising due to such accumulation. It should also be invariant to random signal shifts. It should also have information exclusively about the phase coupling properties contained in the nonlinear ECG signals. One of such ECG signal analysis technique is bispectrum-based signal processing.

Bispectrum is a complex-valued function of two frequency variables. Bispectrum is given by its bimagnitude and biphase functions. The estimate of the bispectral density (third-order spectral density or cumulative spectrum) allows us to correctly describe the statistical characteristics of the observed process and determine the presence of correlations between spectral components. The main difference between the bispectrum and the energy spectrum is the preservation of phase information and the possibility of its restoration. Expression for the bispectrum estimate can be written as discrete function of the following triple product form:

$$B_x(p,q) = \left|B_x(p,q)\right| exp\left[j\varphi(p,q)\right] = \langle X_m(p) X_m(q) X^*_m(p+q)\rangle_M , \tag{1}$$

where Bx(p, q) is a complex-valued function of two discrete frequency variables; $|B_x(p,q)|$ is the bimagnitude; φ(p,q) is the biphase; <…> denotes ensemble averaging;

p = –I+1,…,I–1 and q= –I+1,…,I–1 are the frequency indices; $X_m(\ldots)$ is the discrete Fourier transform computed for m-th realization of the process under study; m = 1, 2,…,M is the number of observed realization; symbol * denotes complex conjugation; $j = (-1)^{1/2}$

Note the useful features of bispectrum. First, bispectrum of gaussian noise tends to zero. Second, bispectrum is able to extract phase coupling contributions contained in nonlinear process. Third, bispectral signal statistical processing can provide coherent accumulation for the number of signal realizations that are randomly shifted during the averaging time interval.

Materials and Methods

An open-source electrophysiological toolbox (OSET) [23] has been developed for the generation and study of ECG signals. This toolbox includes tools such as ECG signal generators and noise generators based on real-life signal models. OSET is a collection of open-source code for generating, modeling, processing, and filtering biological signals released in June 2006. The toolbox is distributed under the Berkeley Software Distribution (BSD) license and can be used freely. Figure 1 shows an example of a generated ECG signal.

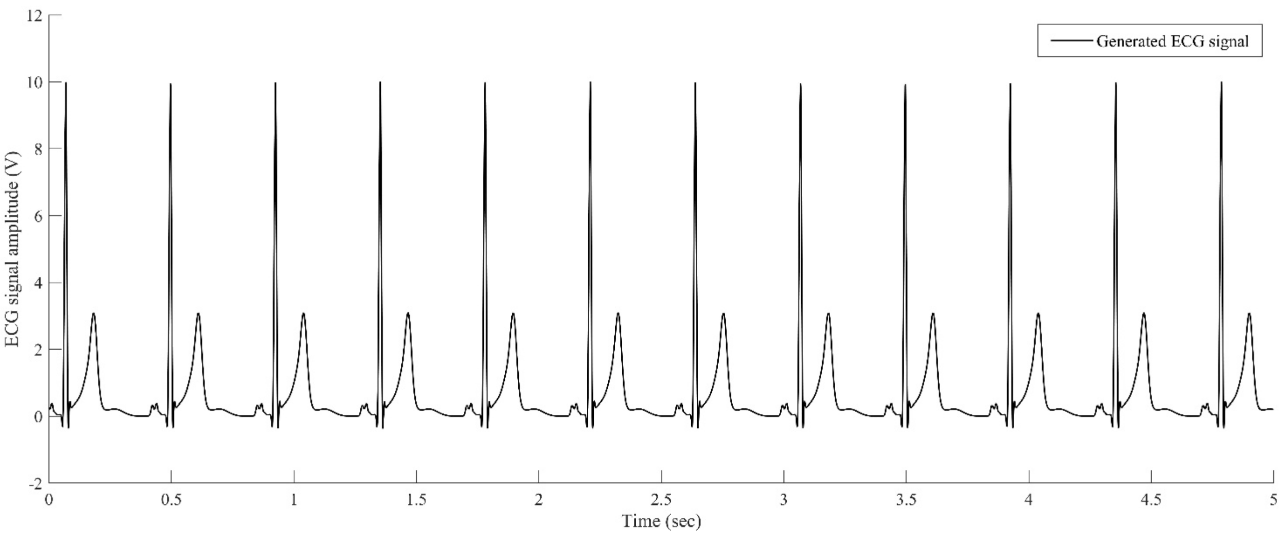

Figure 1 - Generated ECG signal

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The OSET system allows to create a number types of noises, namely white noise, colored noise, simulate noises caused by muscle contractions, electrode movement, and baseline drift. There is also the possibility of generating combined noise which consists of the previous ones. For example, it is possible to simulate the simultaneous superposition of interference caused by electrode movements, muscle contraction, and baseline drift. This combined interference can be used when testing the noise immunity of the developed methods or testing adaptive filters to suppress these classes of noise that arise when recording real data. Therefore, the system is flexible for studying the ECG signal processing techniques.

Figure 2 shows an example of generating an ECG signal with superimposed white noise with a signal-to-noise ratio of 30 dB, as well as a combination of noises caused by muscle contraction, electrode movement, and baseline drift, and also with a signal-to-noise ratio of 30 dB.

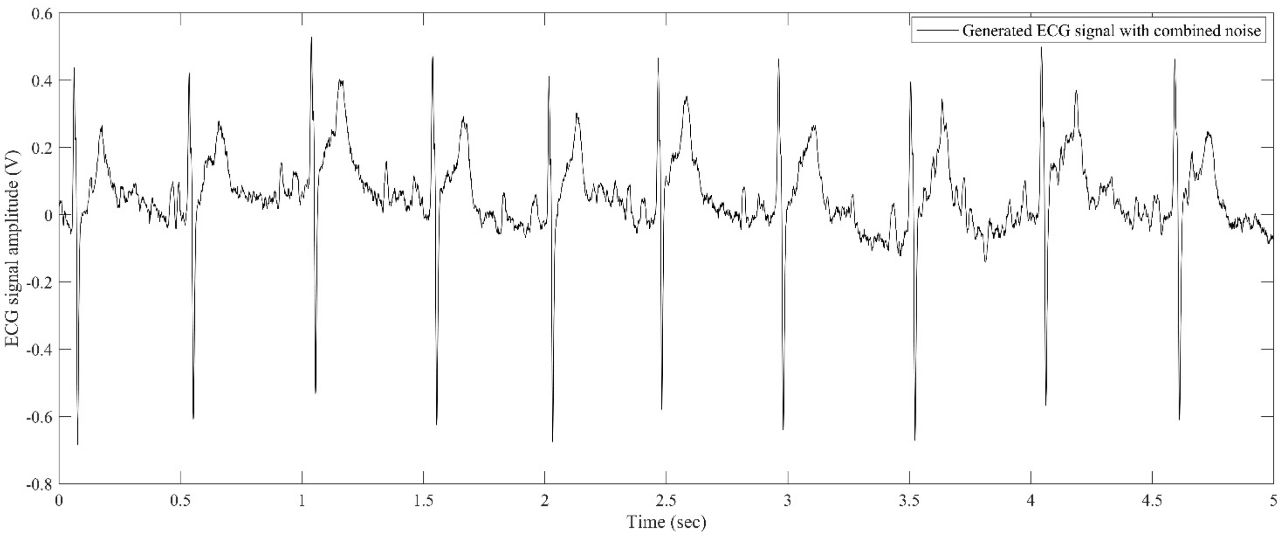

Figure 2 - Mixture of generated signal and combined noise

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Using this ECG signal generation system, it is possible to study the efficiency of filtering since the SNR is known, as well as the parameters of the signals themselves which will also allow investigating the degree of distortions introduced by filtering into the shape of the initial signals.

Bispectral estimation of the ECG signal is performed at the first stage of data processing. To do this, bispectral averaging is performed in the Fs/2 window of the signal with the same step, where Fs is the sampling frequency of the ECG signal. In this case, noise components are removed during such accumulation. Figure 3 demonstrates the averaged bimagnitude estimate (1) for the ECG signal in the form of a contour image. Figures 4 and 5 demonstrate real and imaginary parts of bispectrum estimate (1), respectively.

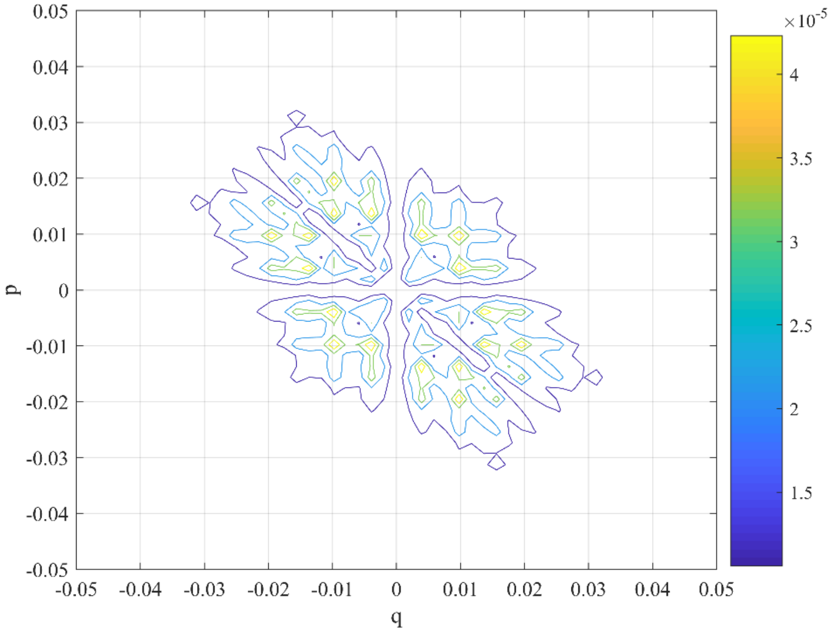

Figure 3 - Bimagnitude estimate computed for ECG signal

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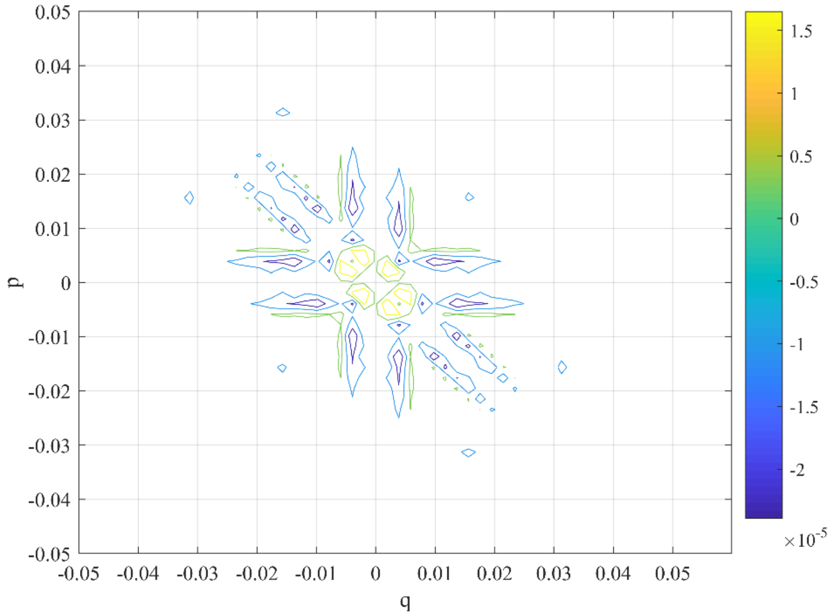

Figure 4 - Real part of bispectrum estimate computed for ECG signal

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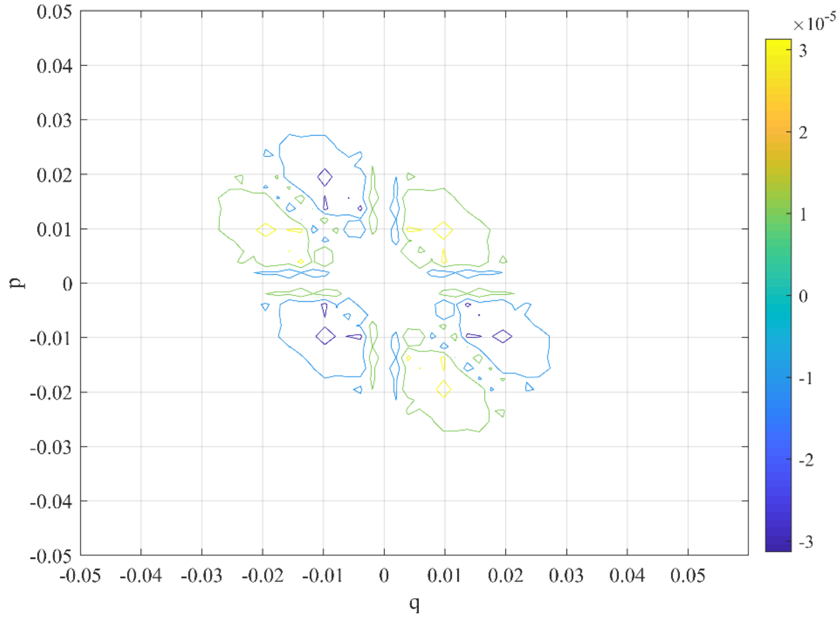

Figure 5 - Imaginary part of bispectrum estimate computed for ECG signal

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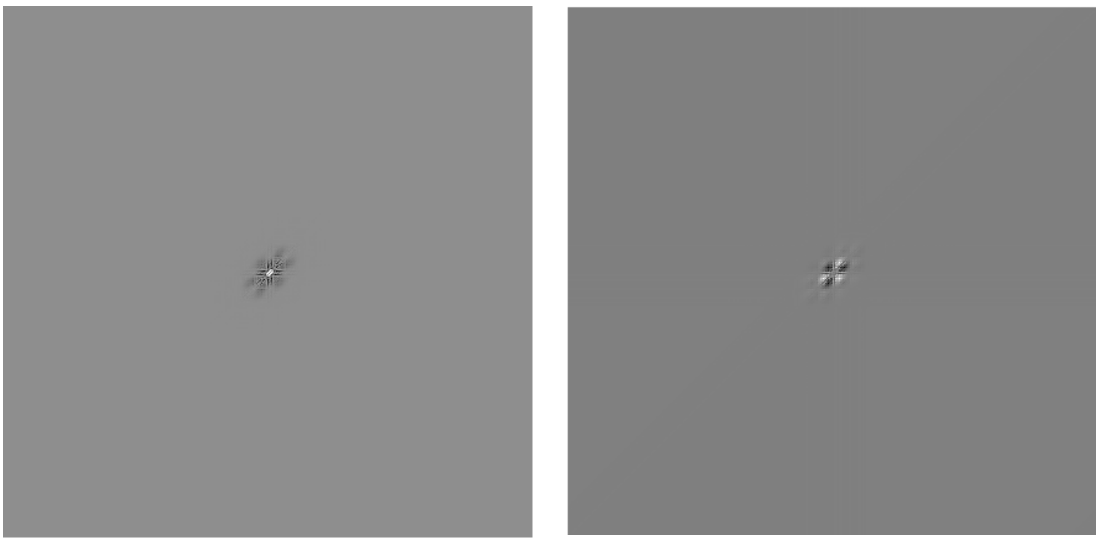
At the second data processing step, the filter mask is calculated. In order to calculate the mask for filtering, the real and imaginary parts of the bispectral estimate are used. To obtain a mask from the real or imaginary part, the matrix is converted into a gray scale image. Figure 6 demonstrates the example of the matrix conversion.



(a) **(b)**

Figure 6 - Example of transform into the gray scale image performed for real (a) and imaginary (b) part of bispectral estimate. The images are mirrored to their counterparts in Fig. 4 and 5, and for a larger expansion along the axes

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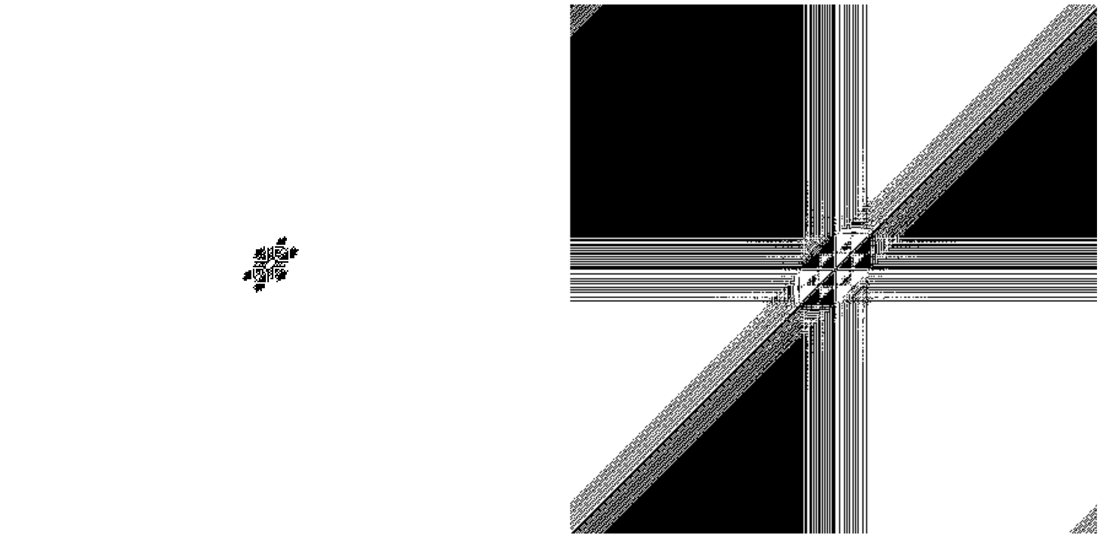
After computations, correspondent matrices are obtained in the image intensity withing the range from 0 to 1. In order to compute the mask for the filter, it is necessary to convert the image into binary format so that the final matrix contains intensity values of either 0 or 1. Accordingly, filtering will occur in intensity zones contained 1, and no filtering will occur in zones contained 0. A threshold of 0.5 is selected to calculate the binary image. Figure 7 shows the example of computing binary matrices for the real and imaginary parts of bispectrum estimate.



(a) (b)

Figure 7 - Example of transform to the binary images performed for real (a) and imaginary (b) part of ECG signal bispectrum estimate. The images are mirrored to their counterparts in Fig. 4 and 5, and for a larger expansion along the axes

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After computing these matrices, the signal is filtered. At the very beginning processing step, Fs/4 zero values are added to the left and right of the signal from the signal. This is necessary because the filtering must be performed from the very beginning of the signal to the very end. After that, a sliding window is determined corresponding to the size of the matrix of the bispectral estimate. It is equal to Fs/2. This window moves along the signal with a step of one sample, and the bispectrum estimate is calculated for the signal that falls into the window. After that, the bispectrum estimate obtained for the local fragment of the signal is divided into real and imaginary parts. Obtained real and imaginary local parts are multiplied by binary images as demonstrated in Fig. 7. After that, the obtained matrix is filtered by an averaging filter with a window size of 5 x 5 samples. Next, a new matrix of local bispectral estimate is formed from the filtered matrices. A signal is converted using the inverse transform performed from bispectral to the time space. Next, the obtained signal is averaged over the entire range, and one value is stored into the central element of the window in a new array that will be responsible for the filtered signal. Next, the window is shifted by one element and all processing steps are repeated until the processing of the entire signal is completed. At the very end of the data processing, zero values that were added at the very beginning are removed. Below a parametric method for signal recovery from bispectral transform [24] is represent.

Algorithm 1. Signal reconstruction from bispectrum (RecBisp)

```
Initialize Alfa[K×K], Beta[K×K] to zeros
Compute md2 ← round(K / 2)
For i = 1 to md2+1
  For q = 1 to i and (q + i – 1 ≤ md2+1)
    Beta[i,q] ← phase of Bisp[i,q]
    Alfa[i,q] ← magnitude of Bisp[i,q]
  End For
End For
Set Alfa[1,1] ← small value if zero
Compute d[1] ← cube root of Alfa[1,1]
Compute d[2] ← sqrt(Alfa[2,1] / d[1]) if d[1] ≠ 0
Initialize recf2[1] ← exp(–j·Beta[1,1])
If usenoise = 1, set recf2[1:2] ← exp(j·noisephase[1:2])
For p = 2 to md2+1
  For q = 1 to p while (p+q–1 ≤ md2+1)
    Update d[p], d[p+q–1] based on Alfa and noise
    Compute reincr ← exp(j·(arg(recf2[p]) + arg(recf2[q]) – Beta[p,q]))
    Update recf2[p+q–1], cour[p+q–1], sred_a[p+q–1]
  End For
End For
Mirror spectrum: d[K–p+1] ← d[p+1], re[K–p+1] ← –re[p+1]
Compute y_est ← real part of IFFT(d · exp(j·re))
Return y_est
```

The main filtering algorithm is represented below.

Algorithm 2. Bispectrum Filtering Procedure

1. Set default values for msk1, msk2, type_filter, and f_size if not provided
2. Pad the input signal with fs/4 samples at both ends using edge repetition
3. Define a list of window start indices (ii) using step size st
4. If the final window would exceed signal length, extend ii accordingly
5. Compute overlap index k and determine last_element for averaging
6. Initialize output signal container signal_result
7. For each index i in ii:
8. Extract a signal window of length s_w
9. Compute its bispectrum Bispecd
10. Separate real and imaginary parts of the bispectrum
11. Create 2D filter kernel H based on type_filter and f_size
12. Apply H to real and imaginary parts using masks msk1 and msk2
13. Combine filtered parts into complex bispectrum bisp_n
14. Reconstruct time-domain segment Sig_M from bisp_n via RecBisp
15. Align Sig_M with original window using circular shifts:
16. For each shift m:
17. Compute correlation between shifted Sig_M and original
18. End For
19. Find the best alignment based on maximum correlation
20. Apply the optimal shift to Sig_M
21. Merge Sig_M into signal_result based on the value of st:
22. If st == s_w → concatenate directly
23. If st == 1 → retain original edges and average mid-samples
24. If s_w/2 ≤ st < s_w → average overlapping regions with buffer
25. Else → raise error if step size is invalid
26. Update position index k
27. End For
28. Normalize signal_result by (max_si / max_re)
29. Remove fs/4 padding samples from both ends
30. Return result_filtering as the final filtered signal

To perform bispectral signal transform, you can use the original code at the link: https://github.com/synergetics/HOSA_Octave, function 'BISPECD.m'. The following parameters must be set: nfft = signal length in samples; wind = 0; nsamp = signal length in samples; overlap leave unchanged. Only with this use will the RecBisp algorithm be able to restore the original signal from the bispectral estimate. Or you can use the simplified version given below.

Algorithm 3. Bispectrum Computation

```
1.  If isfft is not provided, compute FFT of input signal y → ffty
2.  Initialize bispectrum matrix Bisp with zeros
3.  Set md2 ← round(K / 2)
4.  If ch == 1, initialize Bisp as a full K×K zero matrix
5.  If isfft exists:
6.      Set ibnet ← K, jbnet ← K, Bisp ← zeros(K,K)
7.  Else:
8.      Set ibnet ← md2 + 1, jbnet ← md2 + 1
9.  Set md2 ← K / 2  (reassigned, possibly for loop bounds)
10. For ib from 1 to ibnet:
11.     For jb from 1 to ib:
12.         If (ib + jb – 1) ≤ K:
13.             Compute triple product:
14.                 Bisp(ib,jb) ← ffty(ib) · ffty(jb) · conj(ffty(ib+jb–1))
15.             Enforce Hermitian symmetry:
16.                 Bisp(jb,ib) ← Bisp(ib,jb)
17.     End For
18. End For
19. Return Bisp
```

The difference of this function is that it does not calculate the symmetric sections of the bispectral estimate.

To estimate the effect of filtering on the parameters of the signal under study, we can consider SNR which is determined by the following expressions:

$$SNR = D_s / D \tag{2}$$

$$D_s = \frac{1}{n} \sum_{i=1}^{n} \left| xi - \mu s \right|^2 \tag{3}$$

$$\mu_s = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{4}$$

where D_s is the variance of initial variable signal upon absence of additive gaussian noise; D is the variance of the difference between filtered and initial signal; x_i is the signal before filtering; μ_s is the mean value of initial signal; n is the number of signal samples.

In order to represent the values (2) in dB, the following expression must be used

$$SNR_{dB} = 10 log10\left(SNR\right) \tag{5}$$

where SNR_{dB} is the SNR in dB; SNR is the value given in (2).

To study the effectiveness of filtering, one can examine the SNR values before and after filtering. However, this cannot be done using recorded real-life signals, because the data records do not contain information about these SNR values prior to the use of noise filtering procedures.

Results

Figure 8 shows the filtering result for an artificial signal generated by the OSET model with combined noise superimposed on the ECG signal with a SNR value equals to 20 dB.

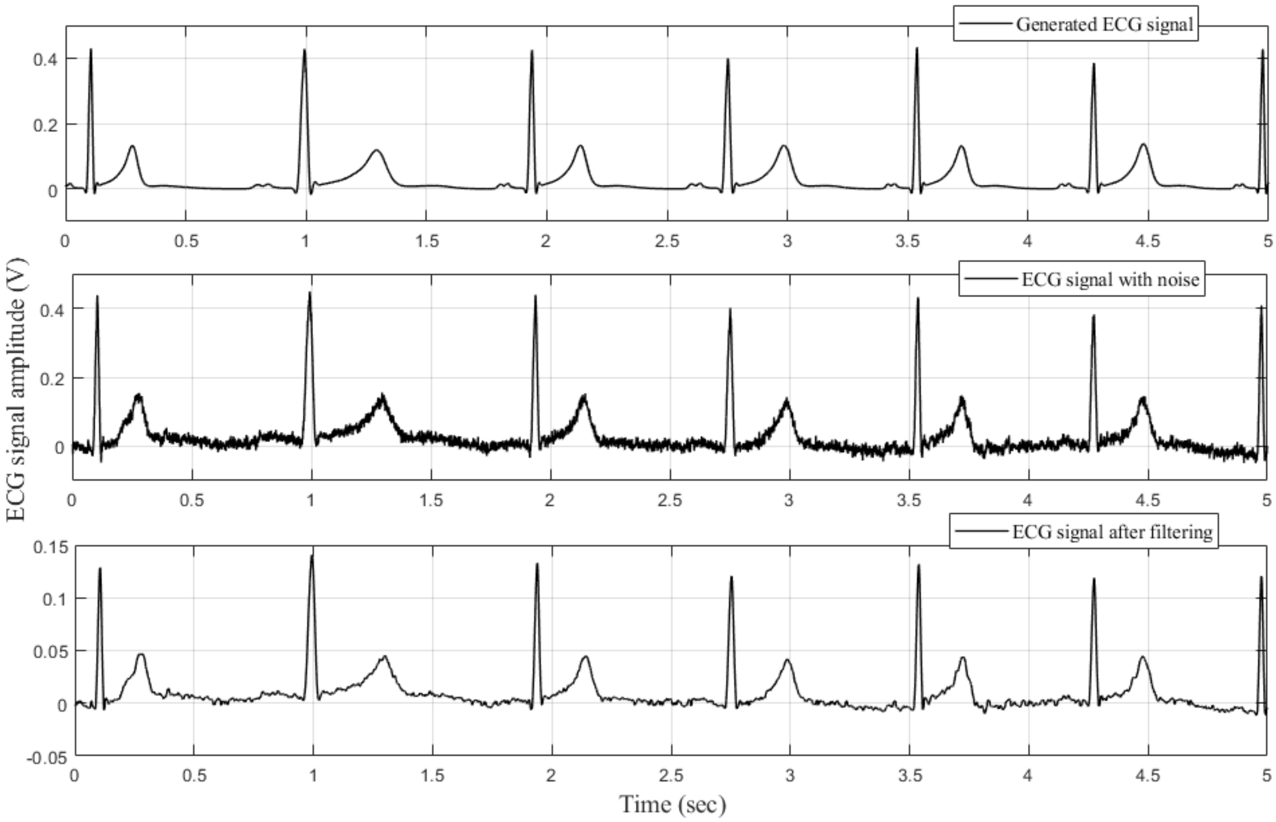

Figure 8 - Results obtained using bispectral filtering. The top curve is the generated ECG signal before filtering, and the bottom curve is after bispectral filtering

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Proposed filter, by calculating the filtering mask which is defined as a binary matrix of the bispectral estimate is adaptive to the waveform changes. Therefore, it can be used with any waveform type of initial signal. Figure 9 shows the filtering result for combined noise superimposed on the ECG signal with a SNR value equals to 5 dB.

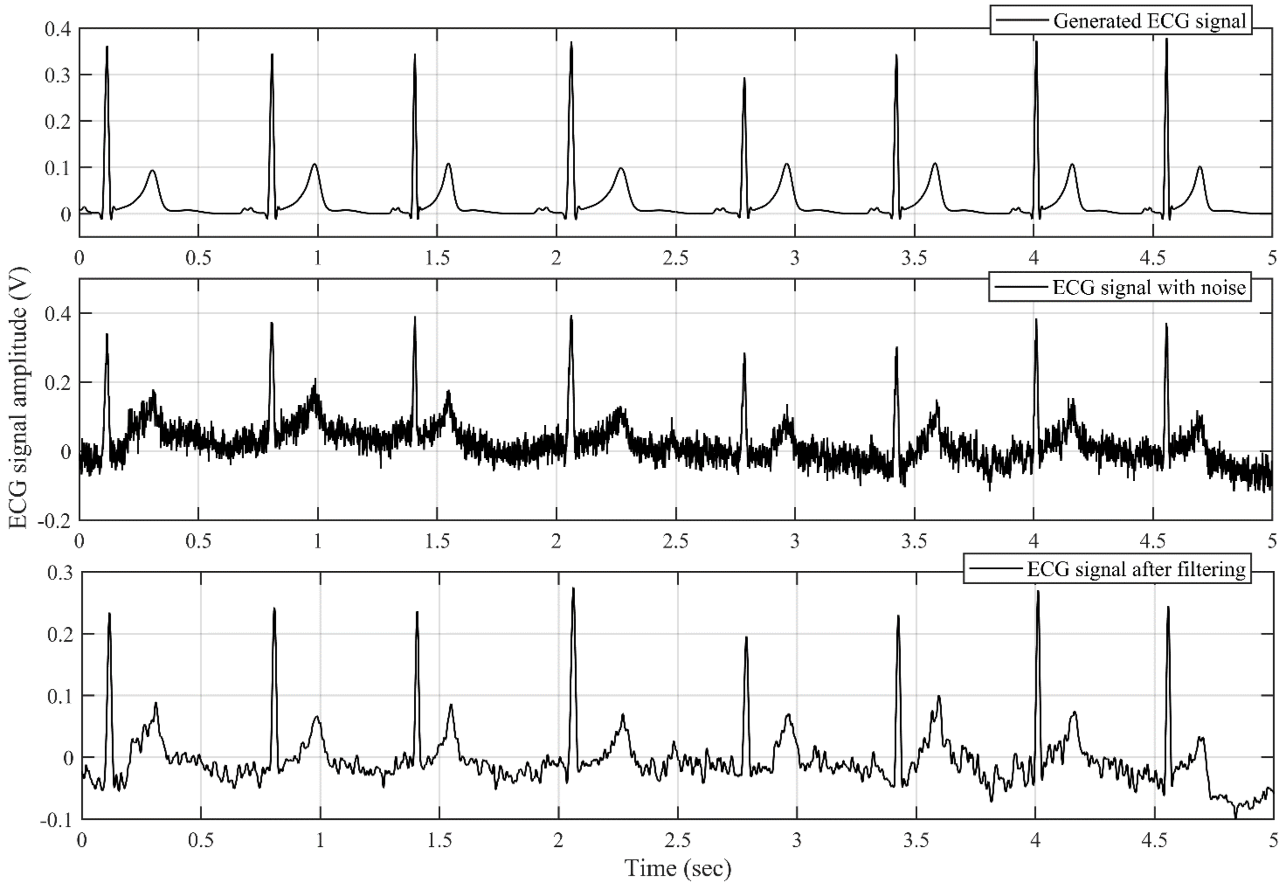

Figure 9 - Results obtained using bispectral filtering. The top curve is the generated ECG signal before filtering, and the bottom curve is after bispectral filtering

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The results of study of the filtering performance in comparison with common nonlinear filters are demonstrated below. It has been considered the following filters: averaging and median filters (AF and MF, respectively) with different window sizes (1x3, 1x7, 1x11, 1x23), as well as wavelet filters (Daubechies (db4), Symlets (sym4), Fejér-Korovkin (fk4), Coiflets (coif4)) with decomposition into 5 levels. Corresponding results are demonstrated in Table 1.

From the results of Table 1, it can be seen that the proposed bispectral filter provides an average of 1 dBW or 1.25 W better filtering result within the SNR range from –20 to 0 dBW. However, at a higher SNR value it provides a worse result due to the contribution of distortions to the initial signal.

Table 1 - Performance of the filtering provided by different types of filters

Filter	SNR before filtering, dBW														
	-20	**-15**	**-10**	**-5**	**0**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
	SNR after filtering, dBW														
AF 1x3	-15	-10	-5	0	4,8	9,7	15	20	**24**	**29**	**33**	32	37	36	37
AF 1x7	-11	-6	-1	3,1	8,1	13	18	19	18	20	22	19	23	21	23
AF 1x11	-10	-4	0,4	4,4	8,7	12	17	14	12	14	16	13	16	15	16
AF 1x23	-6	-2	1,7	3,9	5,5	7,1	10	7,3	5,7	6,6	7,8	5,9	8,3	7,5	7,9
MF 1x3	-16	-11	-7	-2	3,6	8,5	14	18	23	28	**33**	**36**	**41**	**43**	**45**
MF 1x7	-13	-8	-3	1,6	6,6	11	16	20	22	26	29	25	30	28	30
MF 1x11	-11	-6	-1	3,1	7,9	12	17	18	16	18	21	17	22	20	21
MF 1x23	-9	-3	0,2	3,1	5,4	7,7	12	8,0	5,8	6,8	8,7	6,2	9,3	8,2	8,8
db4	-6	-2	2,8	6,6	11	13	20	21	23	27	31	27	35	32	34
sym4	-6	-1	2,7	6,4	11	**15**	**21**	**22**	23	26	29	26	34	31	32
fk4	-6	-1	3,0	6,8	11	14	20	21	22	24	27	28	29	27	28
coif4	-6	-1	2,7	6,4	11	14	20	**22**	23	26	28	29	31	29	30
Bisp	**-5**	**0**	**3,3**	**7,2**	**12**	13	14	15	14	15	15	16	14	15	15

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Discussion

It should be noted that the developed algorithm can only work with periodic signals such as ECG, PPG, and others. That is, with signals in which some information is repeated over time as, for instance, for QRS-complex commonly contained in ECG signals. If the signal is not periodic, i.e., has significant changes over time, then the bispectral evaluation of the signal will give averaged information over all spectral components in the signal. That is why, the mask will be used incorrectly during filtering. Also, it is worth testing the developed algorithm on real signals to make sure of its resistance to nonlinear changes that occur in them.

The calculations necessary for obtaining bispectral estimate and reconstructed signal requires considerable computations. Proposed technique was developed so that all data processing procedures are performed using a sliding window. The window size is of 512 samples, and the bispectral estimate matrix itself is of 512x512 = 262144 complex values. Each sample is allocated 64 bits which gives 16 777 216 bits for the real part and 16 777 216 bits for the imaginary part. One matrix weighs about 2 MB. Since the memory stores one averaged bispectral estimate for the entire record and one local bispectrum for the current signal fragment. Hence, about 4-6 MB of RAM is needed to accumulate bispectral estimates.

As for real-time processing, proposed technique is not currently implemented yet. However, since proposed filtering is performed by window mode, this procedure can be implemented in the future. But it is worth noting that the filtering performance in this mode will change over time, since more separate bispectral estimates will be added to the averaged bispectral estimate over time for sufficiently suppression the noise level in the bispectral estimate. This will allow us to calculate the filter mask more accurately and obtain certain benefit.

It is necessary to study in more detail the direction and possibility of applying the developed algorithm to other applications and problems. The study of the influence of nonlinear changes in ECG signals such as arrhythmia or artifacts associated with pathologies will be studied additionally by us in the future. Given the obtained results, proposed filtering algorithm would be best applied to the important problems of extracting fetal ECG from the noninvasive abdominal signal performed after removing the interference contribution of maternal ECG. It may be necessary to use adaptive thresholds, but the algorithm for calculating the adaptive threshold is not yet clear, but we will also study this issue in the future.

Conclusions

The paper proposes an adaptive technique for nonlinear filtering of the ECG signals based on bispectral signal processing. In this study, we used a noise mixture (White Noise (WN); Colored Noise (CN); Real Muscle Artifacts (MA); Real Electrode Movements (EM) and Real Baseline Wander (BW)) with the same signal-to-noise ratio to investigate performance of interference immunity provided by proposed technique. Proposed technique provides an average improvement by 1 dBW ± 0.73 SD or 1.25 W ± 0.73 SD of the filtering result in the range of signal-to-noise ratio values from –20 to 0 dBW. However, at a higher SNR value, the proposed technique provides a worse result due to the contribution of distortions to the initial signal unlike existing common methods. Proposed bispectrum-based type of filter is recommended to be more optimally used to remove noise contributions from the ECG signal at a low SNR. The advantage of the proposed technique is invariance to non-stationary changes in the shape of the ECG signal during recording, as well as the ability to adapt to each individual recording by calculating binary matrices for filtering from the bispectral estimate the signal being processed. This makes the proposed technique adaptive and robust to any changes.

Supplementary Materials: Software code for generation of ECG signals and interferences is available by https://sameni.org/OSET/. Algorithms necessary for implementation of proposed technique are represented in the paper.

***Author Contributions*:** Conceptualization, O.V. and A.T.; methodology, A.T.; software, O.V.; validation, O.V.; formal analysis, A.T.; investigation, A.T.; resources, A.T.; data curation, A.T.; writing—original draft preparation, O.V.; writing—review and editing, A.T.; visualization, O.V.; supervision, A.T.; project administration, A.T.

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Data Availability Statement: Data exploited for experimental study were generated by using https://sameni.org/OSET/.

Conflicts of Interest: The authors declare no conflicts of interest.

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Scientific adviser: Doctor of Technical Sciences, prof. Totsky O.V.

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