The non-adaptive methods do not use any adaptive system for signal processing and only work with one or more records that contain components that need to be processed. Thus, in fECG signal processing, these methods do not need electrodes placed at the maternal chest as with adaptive methods and only use electrodes placed at the maternal abdomen. The non-adaptive methods have constant coefficient values and the system does not adapt to the existing circumstances but performs work for which it is intended [2]. These methods are very fast and accurate, but their disadvantage is that they are time invariant in nature compared with the adaptive methods. For interference elimination in aECG signal, the non-adaptive methods use either single channel signal sources, which are implemented by many methodologies, or multichannel signal sources, which are processed by blind source separation techniques (BSS) [1–3,6].

In this paper, Section 2 deals with non-adaptive methods that use single channel signal sources for extraction of fECG signal. Then, Section 3 deals with non-adaptive methods that use multichannel signal sources for extraction of fECG signal. Section 4 shows the possibility of creation hybrid algorithms, in Section 5, discussion is provided, and, in Section 6, conclusions are provided.

2. Single Channel Signal Sources

Many methods use only single channel signal sources. This group of methods includes methods based on wavelet transform (WT), correlation technique (CT), subtraction technique (ST), averaging technique (AT), filtering techniques (FT) such as finite impulse response (FIR) and infinite impulse response (IIR) filtering, Wiener filtering (WF), fixed filtering such as low-pass filtering (LPF) and high-pass filtering (HPF), de-shape short time Fourier transform (STFT) and nonlocal median (NM), single channel BSS (SCBSS), template subtraction (TS), sequential total variation denoising (STVD), empirical mode decomposition (EMD), etc. All of these methods will be discussed below. Table 2, at the end of Section 2, shows a comparison of the different single channel methods.

2.1. Wavelet Transform

There are many types of wavelet transform such as discrete wavelet transform (DWT), complex wavelet transform (CWT), pitch synchronous wavelet transform (PSWT), etc., and the choice depends on the application and the type of the input signal [51]. These methods provide information in time and frequency domains, so they are very effective in non-stationary signals or multiple component signals. Wavelet transform is basically a convolution operation of the signal and wavelet function [52]. This method decomposes a signal into a detail signal, which contains the upper half of frequency components, and into an approximation signal, which contains the lower half of frequency. This decomposition can be performed again on the approximation signal and then will create the second detail and approximation signal. They are also used for creation of a hybrid method as preprocessing [5].

Hassanpour et al. [51] used DWT for estimation of fECG. Their algorithm consisted of two steps. In the first one, they used a two-level WT to extract fECG and mECG and, in the second one, they used a Savitzky–Golay smoothing filter (SGSF) on fECG signal to attenuate the effect of the noise. This filter is a LPF, well adapted for smoothing noisy data. The type of wavelet of DWT is the same in shape as the heart beat wave and its energy spectrum is around low frequencies. They used three pieces of synthetics data, where mECG were ten times stronger than the energy of fECG, and real data from the database developed by De-Moor [53], which were 10 s long and with a 250 Hz sampling rate. They concluded that this method has promising results for fECG extraction.

Bhoker et al. [52] used DWT for extraction of fECG and then for detection of R-peaks. In the first step, they used WT for decomposing into fECG and mECG and, in the second step, the fetal R-peaks are detected from the extracted fECG signal. For estimation, they used the data from physionet NI-fECG database [54,55], which were 10 s long and with a sampling rate of 1 kHz with 16-bit resolution. They used 15 different signals containing two thoracic and three to four abdominal signals filtered by a 50 Hz notch filter. The estimation of fECG was conducted by subtraction of the extracted mECG from aECG because the energy of mECG in aECG was much higher than the energy of fECG, and DWT

- Overall performance—this parameter reflects the robustness of the method used, and it can be divided into three groups:
  - Low—methods suitable primarily for NI-fECG preprocessing, these methods are not able to extract fECG, but only remove some specific types of interference, e.g., baseline wandering, power line interference, and so on (improvement $\leq$5 dB; based on fECG extraction from synthetic records).
  - Medium—methods suitable for advanced preprocessing eliminating most of the interference in NI-fECG (e.g., power-line interference, myopotentials, and electromyographic interference, isoelectric line fluctuations, motion artifacts, etc.). These methods partly suppress the maternal component allowing detection of the fQRS complex and thus fHR determination; further morphological analysis is not possible (improvement $\leq$20 dB; based on fECG extraction from synthetic records).
  - High—the most powerful comprehensive NI-fECG processing methods that provide information on fHR, and fECG morphology—PR, QT, ST intervals and so on (improvement $\geq$20 dB; based on fECG extraction from synthetic records).
- SNR improvement—this parameter takes into account the improvement of SNR, can be divided into three categories: low, medium, and high. It should be noted that the SNR parameter objectively determines the efficacy of the method with regards to the reference; however, in terms of the clinical use, the used SNR as a parameter may be very misleading. The methods that show excellent SNR improvement can be very inaccurate in fQRS complex detection.
- Computational cost—this parameter evaluates the demands of the methods in terms of computational complexity; the categories are low, medium, and high.
- Real-time—parameter defining whether the method can be used in online mode (real-time) from the point of view of its feasibility using currently available hardware devices in clinical practice.
- Implementation complexity—this parameter, divided into three categories low, medium, and high, evaluates the overall complexity in terms of its deployment in clinical practice. The complexity of hardware and software must be economically viable for the public health system to be available to all pregnant women.

Table 2. Comparison of the different single channel methods.

Method	Overall Performance	SNR Improvement	Computational Cost	Real-Time	Implementation Complexity
WT	Medium	Medium	Low	Yes	Medium
CT	Low	Low	Low	Yes	Simple
ST	Low	Low	Low	Yes	Simple
AT	Low	Low	Low	Yes	Simple
FT	Low	Low	Low	Yes	Simple
STFT & NM	Medium	Medium	Medium	No	Medium
SCBSS	Medium	Medium	Medium	No	Complex
TS	Medium	Low	Low	No	Medium
STVD	Medium	Medium	Medium	No	Complex
EMD	Medium	Medium	High	No	Medium

3. Multichannel Signal Sources

This group of methods includes mainly methods based on BSS, which is very promising and developing work in biomedical signal processing and not only for fECG extraction. Fetal ECG is obtained by means of estimation of independent sources for fetal cardiac bioelectric activity [2]. These methods are used to extract unobserved signals (sources). The sources are assumed to be statistically independent of a known mixture of these signals [57]. Blind source separation is divided into methods based on higher-order statistical (HOS) information, which is performed by independent component analysis (ICA), and methods based on second-order statistics (SOS), which is performed by singular value decomposition (SVD), PCA or period component analysis (πCA). However, there are

Akbari et al. [99] used πTucker method for fECG extraction and compared it with ICA-based methods. For the evaluation, they used synthetic data and real data from database adfecgdb [10,47–50], which contains five records from different women that are 5 min long with a sampling frequency of 1 kHz and with 16-bit resolution. The results showed good performance of this. This method needs only 20 iterations for a satisfactory error in the extracted fECG.

3.15. Multivariate Empirical Mode Decomposition

This method is based on EMD, which is a fully data-driven method for nonlinear and non-stationary real-world signals. It divides the signal into a finite set of IMFs. The first step of this method comprises elimination of the noisier noisy channels based on comparison of similar indexed IMFs, which were found by MEMD. Then, denoising of the remaining noisy channels is performed by eliminating the similarly indexed IMFs. Finally, an mECG signal is eliminated from aECG signals and fECG signal is detected by CWT [100].

Gupta et al. [100] used the MEMD method on real data for extraction of fECG. They used data from the database adfecgdb [10,47–50], which contains five records from different women that are 5 min long with a sampling frequency of 1 kHz and with 16-bit resolution, and from another database [101], which contains one record from a mother in gestational age of 40 weeks and the sampling rate of this record was 1 kHz. They came to the conclusion that MEMD had high value of the cross correlation between the detected and true fHR signals, so this method can be used for fHR monitoring.

3.16. Summary of Multichannel Methods

Table 3 compares different multichannel methods. For the relevant comparison of all the introduced methods, the same assessment criteria as in Table 2 was used. It can be stated that most multichannel methods achieve better results than single-channel methods.

Table 3. Comparison of the different multichannel methods.

Method	Overall Performance	SNR Improvement	Computational Cost	Real-Time	Implementation Complexity
ICA	Medium	Medium	Medium	No	Medium
SVD	Low	Low	Low	Yes	Simple
PCA	Low	Medium	Low	Yes	Simple
πCA	Medium	High	Low	No	Simple
SA	Medium	Medium	Medium	No	Medium
BA	Medium	Medium	Low	No	Simple
ZA	Medium	Medium	Low	No	Simple
SM	Medium	Medium	Medium	No	Simple
QIO	Medium	Medium	Medium	No	Medium
PEVD	Medium	Medium	Medium	No	Medium
FCM	Medium	Medium	Medium	Yes	Simple
CS	Medium	Medium	Medium	Yes	Medium
MCSM	Medium	Medium	Medium	No	Simple
πTucker	Medium	Medium	Low	No	Simple
MEMD	Medium	Medium	Medium	No	Medium

4. Hybrid Methods

A large number of studies address the possibility of combining either adaptive methods with one another, non-adaptive methods with one another, or combinations of adaptive and non-adaptive methods together in order to create hybrid methods. Very often, non-adaptive methods, such as preprocessing, are used for adaptive algorithms. The non-adaptive methods partially separate the components and make extraction easier for the adaptive system. This section is dedicated to these hybrid methods, which improve accuracy compared to the use of only one method. Table 4, at the end of Section 4, shows the comparison of the different multichannel methods.

dynamics and the nonlinearities of the mECG, is estimated. This combination uses a single channel signal source, so it requires simpler hardware and makes long term recordings of the fECG possible. For the evaluation, they used a synthetic signal, which is generated from two completely different ECG signals, and real data from the database by the courtesy of prof. L. De Lathauwer [77] consisting of eight real recordings (five abdominal, three thoracic) with 12-bit resolution, 1 min long and with a sampling rate of 500 Hz, and a dataset recorded in AI-Wasl Hospital in Dubai. They came to the conclusion that this combination is very effective and capable of extracting fECG from a single lead.

4.9. PN and SGSF

Ayat et al. [112] developed a two-tier technique for fECG extraction from a single abdominal record. First, a SGSF is applied for mECG estimation from aECG signal by suppressing the fECG component which can be observed as noise of the overlapping frequency contents with the wanted mECG signal, and, then, this mECG is nonlinearly aligned with the abdominal signal using polynomial networks (PN) to extract the fECG. They compared this new technique with SVD method and used synthetic data, which is created by one set of real normal resampled data and added to the other real normal ECG signals, and real data from the ECG physionet challenge 2013 database [50] and from a dataset recorded in AI-Wasl Hospital in Dubai. They came to the conclusion that this new combination of SGSF and PN provides better results than SVD method and removes the requirement for PN that use one abdominal and one thoracic signal.

4.10. Summary of Hybrid Methods

Table 4 compares different hybrid methods. For relevant comparison of all the investigated methods, we used identical assessment in previous cases (Tables 2 and 3). Generally, hybrid fECG processing methods outperform the rest of the introduced non-adaptive methods.

Table 4. Comparison of the different hybrid methods.

Method	Overall Performance	SNR Improvement	Computational Cost	Real-Time	Implementation Complexity
ICA-EEMD-WS	High	High	High	Yes	Complex
ICA & AF	High	Medium	High	No	Complex
ICA & PF	High	Medium	High	No	Complex
π-ICA	Medium	Medium	Medium	No	Medium
ICA & PCA	Medium	Medium	Medium	Yes	Medium
ICA & SVD	Medium	Medium	Medium	Yes	Medium
BA & ZA	High	Medium	Low	No	Simple
SVD & PC	Medium	Medium	Low	No	Medium
PN & SGSF	Medium	Medium	Medium	No	Medium

5. Discussion

The fetal ECG reflects the electrical activity of the fetal heart and carries a huge amount of information. Unfortunately, current technologies are able to sense and identify only a fraction of them. The fetal heart rate and its variability are the only parameters that can be obtained with sufficient accuracy at the moment (see [113,114]). However, the latest science and research suggests that the NI-fECG contains other, yet unexploited, clinically relevant data, see [115]. These are, for example, the morphology and the length of the individual NI-fECG elements, the dynamic behavior of the NI-fECG, etc. Today's diagnostic devices are able to extract this features only by invasive approach [116,117] using a transvaginal fetal scalp electrode. However, this method can only be used after the rupture of the amniotic fluid. This invasive fECG monitoring approach makes it possible to apply the latest method to determine hypoxia based on fHR in combination with ST segment analysis (ST segment analysis using T/QRS), see [118]. However, due to its invasiveness, this method is associated with many disadvantages, such as the risk of introducing infection or significant fluctuations in the isoelectric line. The aim is to create a non-invasive variant of this method that does not endanger the mother or the fetus and could be used for pre-natal diagnosis.

Morphological analysis of the ECG generally involves a large number of different methods. These include QRS complex analysis (in particular its shape and duration), the R/S ratio (vectorcardiography), the PR/fHR ratio (inverse correlation between PR interval and fHR that changes in hypoxic states), P wave morphology/absence, PR interval, QT interval, and ST segment. An emphasis has been recently placed on the T/QRS ratio used in the above-mentioned ST segment analysis.

The comparison of non-adaptive methods summarized in Tables 2–4 offered an overview of the advantages and disadvantages of the introduced methods in terms of their overall performance, SNR improvement, computational cost, real-time, and implementation complexity. To assess the methods from the clinical point of view, we provide additional evaluation criteria illustrating the applicability in the fetal monitoring, more precisely for fHR determination and morphological analysis. In Table 5, the additional parameters are denoted and described as follows:

- fHR (R-R)—this evaluation parameter classifies the effectiveness of the investigated methods from in terms of the fHR determination based on the fetal R-R interval. There are four categories for the assessment:
    - Inaccurate—the methods are not sufficient to remove artifacts and noise sufficiently to enable the R–R interval detection; the NI-fECG processed by these methods cannot be used for fHR monitoring.
    - Moderately accurate—these methods sufficiently suppress most common interference and thus make RR interval detection possible. However, the noise is not completely eliminated and thus there are many false-detected and undetected significant complexes, i.e., sensitivity (Se) $\leq$ 80%, positive predictive value (PPV) $\leq$ 90%, accuracy (ACC) $\leq$ 80%, total probability of correct detection of beats (F1) $\leq$ 85%.
    - Accurate—these methods allow accurate detection of fHR, i.e., Se $\leq$ 85%, PPV $\leq$ 95%, ACC $\leq$ 85%, F1 $\leq$ 90%.
    - Very Accurate—these methods enable a very accurate determination of fHR and, in this case, it is a full replacement of the conventional CTG [31,40,119], i.e., Se $\leq$ 95%, PPV $\leq$ 95%, ACC $\leq$ 95%, F1 $\leq$ 95%.
- Morphological analysis (T/QRS; QT)—this parameter classifies the efficacy of the investigated methods from a deeper morphological analysis of fECG. The following categories were created for the evaluation:
    - Insufficient—these methods cannot estimate fECG in a sufficient quality for morphological analysis.
    - Moderately accurate—these methods enable morphological analysis; however, only in the case of some tested real data, the efficacy is significantly affected by gestational age, fetal position, SNR, and so on. Therefore, these methods could not be used for long-term monitoring of T/QRS ratio or QT interval.
    - Promising—these mostly hybrid methods have great potential to be used for fECG morphological analysis.
- Dataset—in this column, we provide the source of the data that was used in the studies. Databases with fECG recordings are an important part of this research. A major problem is their insufficient quantity that would be available to the scientific community. Without the databases, i.e., real recordings, the scientists can hardly verify the methods for extracting fECG and thus improve diagnostic quality contrary to the standard ECG of adults.
- Technical aspects—the last column includes the technical details of each study, e.g., number of electrodes, heterogeneity of the patient population, conditions and gestational ages, as well as data quality (duration (T), sampling frequency (Fs), amplitude resolution (res), gestational age (GA), number of electrodes (channels), type of records, and number of records).

Table 5. Comparison of non-adaptive methods of fECG extraction from the point of view of obtaining clinical information.

Method	fHR (R-R)	Morphology Analysis (T/QRS; QT)	Dataset	Technical Aspects
WT [51,52,56,58] Section 2.1	Moderately accurate	Insufficient	De-Moor [53]; NI-fECG [54,55]; U. Nottingham [57]	3 synt. records [51]; T = 10 s; Fs = 250 Hz [53]; T = 10 s; Fs = 1 kHz; res = 16 b; GA = 21–40 weeks; 55 real records [54,55]; T = 60 s; Fs = 300 Hz; res = 12 b; data = 15 real records [57]
CT [57,59] Section 2.2	Inaccurate	Insufficient	—	Old method; Without tech. specification [59]
ST [60,61] Section 2.3	Inaccurate	Insufficient	—	Old method; Without tech. specification [60,61]
AT [62] Section 2.4	Inaccurate	Insufficient	—	Old method; Without tech. specification [62]
FT [64–66] Section 2.5	Inaccurate	Insufficient	MIT-BIH [67]	T = 15 s; Fs = 1 kHz; 15 real records [64] Fs = 500 Hz [65]; T = 0.5 h; Fs = 360 Hz; res = 11 b; 48 real records [67]
STFT & NM [68] Section 2.6	Accurate	Insufficient	fecgsyndb [69]; adfecgdb [10,47–50]; ECG physionet challenge 2013 [50]	T = 300 s; Fs = 250 Hz; res = 16 b; 1750 synt. records; 34 channels [69]; T = 300 s; Fs = 1 kHz; res = 16 b; GA = 38–41 weeks; 5 real records; 5 channels [10,47–50]; T = 60, 600 and 3600 s; Fs = 1 kHz; res = 12 b; 4 channels; 175 real records [50]
SCBSS [70] Section 2.7	Accurate	Insufficient	MIT-BIH [67]	1 synt. record [70]; T = 0.5 h; Fs = 360 Hz; res = 11 b; 48 real records [67]
TS [45,71] Section 2.8	Moderately accurate	Insufficient	adfecgdb [10,47–50]	T = 300 s; Fs = 1 kHz; res = 16 b; GA = 38–41 weeks; 5 real records; 5 channels [10,47–50]

Table 5. *Cont.*

Method	fHR (R-R)	Morphology Analysis (T/QRS; QT)	Dataset	Technical Aspects
STVD [72] Section 2.9	Accurate	Insufficient	fecgsyndb [69]; ECG physionet challenge 2013 [50]	T = 300 s; Fs = 250 Hz; res = 16 b; 1750 synt. records; 34 channels [69]; T = 60, 600 and 3600 s; Fs = 1 kHz; res = 12 b; 4 channels; 175 real records [50]
EMD [5,73] Section 2.10	Accurate	Insufficient	—	Without tech. specification [5,73]
ICA [74,75] [78–82] Section 3.1	Accurate	Moderately accurate	Katholieke U. Leuven [76]; de Lathauwer [77]; NI-fECG [54,55]; ICALAB toolbox [83]; De-Moor [53]	T = 10 s; Fs = 250 Hz; res = 12 b; 8 real records [76]; T = 300 s; Fs = 500 Hz; 8 channels[79]; T = 60 s; Fs = 500 Hz; res = 12 b; 8 channels [77]; T = 10 s; Fs = 1 kHz; res = 16 b; GA = 21–40 weeks; 55 real records [54,55]; T = 10 s; Fs = 250 Hz [53]
SVD [85] Section 3.2 PCA [88] Section 3.3	Inaccurate Moderately accurate	Insufficient Insufficient	— —	T = 60 s; Fs = 500 Hz; 8 channels [85] T = 10 s; Fs = 500 Hz; 8 real records [88]
πCA [88] Section 3.4	Very accurate	Moderately accurate	—	Fs = 500 Hz; 8 synt. records [88]
SA [89] Section 3.5	Accurate	Moderately accurate	—	20 real records [89]
BA [90,91] Section 3.6	Moderately accurate	Insufficient	De-Moor [53]	T = 10 s; Fs = 250 Hz [53]
ZA [92] Section 3.7	Moderately accurate	Insufficient	De-Moor [53]	4 synt. records [92]; T = 10 s; Fs = 250 Hz [53]
SM [93] Section 3.8	Accurate	Moderately accurate	De-Moor[53]	T = 10 s; Fs = 250 Hz [53]
QIO [94] Section 3.9	Accurate	Moderately accurate	ECG physionet challenge 2013 [50]	T = 60, 600 and 3600 s; Fs = 1 kHz; res = 12 b; 4 channels; 175 real records [50]

Table 5. *Cont.*

Method	fHR (R-R)	Morphology Analysis (T/QRS; QT)	Dataset	Technical Aspects
PEVD [95] Section 3.10	Accurate	Moderately accurate	MIT-BIH [67]; ECG physionet challenge 2013 [50]	T = 0.5 h; Fs = 360 Hz; res = 11 b; 48 real records [67]; T = 60, 600 and 3600 s; Fs = 1 kHz; res = 12 b; 4 channels; 175 real records [50]
FCM [96] Section 3.11	Accurate	Moderately accurate	—	T = 7 s; Fs = 500 Hz; 2 real records [96]
CS [97] Section 3.12	Accurate	Moderately accurate	adfecgdb [10,47–50]; ECG physionet challenge 2013 [50]	T = 300 s; Fs = 1 kHz; res = 16 b; GA = 38–41 weeks; 5 real records; 5 channels [10,47–50]; T = 60, 600 and 3600 s; Fs = 1 kHz; res = 12 b; 4 channels; 175 real records [50]
MCSM [98] Section 3.13	Accurate	Moderately accurate	—	3 real records [98]
πTucker [99] Section 3.14	Moderately accurate	Insufficient	adfecgdb [10,47–50]	T = 300 s; Fs = 1 kHz; res = 16 b; GA = 38–41 weeks; 5 real records; 5 channels [10,47–50]
MEMD [100] Section 3.15	Accurate	Moderately accurate	adfecgdb [10,47–50];	T = 300 s; Fs = 1 kHz; res = 16 b; GA = 38–41 weeks; 5 real records; 5 channels [10,47–50] 1 real record [101]
ICA-EEMD-WS [102] Section 4.1	Very accurate	Promising	NI-fECG gen. [103]; MIT-BIH [67]; adfecgdb [10,47–50]	Fs = 1 kHz; 500 synt. records [103]; T = 0.5 h; Fs = 360 Hz; res = 11 b; 48 real records [67]; T = 300 s; Fs = 1 kHz; res = 16 b; GA = 38–41 weeks; 5 real records; 5 channels [10,47–50]

Table 5. *Cont.*

Method	fHR (R-R)	Morphology Analysis (T/QRS; QT)	Dataset	Technical Aspects
ICA & AF [104] Section 4.2	Very accurate	Promising	MIT-BIH [67]; De-Moor [53]	T = 0.5 h; Fs = 360 Hz; res = 11 b; 48 real records [67]; T = 10 s; Fs = 250 Hz [53]
ICA & PF [105] Section 4.3	Very accurate	Promising	—	4 real records; 4 channels [105]
π-ICA [107] Section 4.4	Very accurate	Moderately accurate	De-Moor [53]	T = 10 s; Fs = 250 Hz [53]
ICA & PCA [108] Section 4.5	Accurate	Moderately accurate	ECG toolbox [108]; de Lathauwer [77]	8 synt. records; 5000 samples [108]; T = 60 s; Fs = 500 Hz; res = 12 b; 8 channels [77];
ICA & SVD [109] Section 4.6	Accurate	Moderately accurate	—	2 synt. records [109]; T = 600 s; Fs = 300 Hz; 1 real record [109]
BA & ZA [110] Section 4.7	Very accurate	Promising	De-Moor [110]	T = 10 s; Fs = 250 Hz [110]
SVD & PC [111] Section 4.8	Moderately accurate	Insufficient	de Lathauwer [77]	1 synt. record [111]; T = 60 s; Fs = 500 Hz; res = 12 b; 8 channels [77];
PN & SGSF [112] Section 4.9	Accurate	Insufficient	ECG physionet challenge 2013 [50]	1 synt. record [112]; T = 60, 600 and 3600 s; Fs = 1 kHz; res = 12 b; 4 channels; 175 real records [50]

For the reasons listed above, the major challenge nowadays is to enable morphological analysis from the non-invasively recorded signal. Some of the studies proved that it is possible, mainly using advanced hybrid non-adaptive methods [102,104,105,110]. It should be noted that specific technical aspects are associated with the morphological analysis, mainly the sampling frequency that should be higher than 500 Hz that is generally used for the fHR monitoring. Some of the databases available thus offer insufficient data for such tasks [53,57,67,69,76,77,93]. Additionally, the deployment of the electrodes for the morphological analysis is not yet standardized, but it is certain that it influences the results significantly. Therefore, we suggest that a new database should be created specifically for these purposes; it should include large values of electrodes deployed across the maternal abdomen, the sampling rate should be sufficiently high (2 kHZ or above), and it should, if possible, also include data from the fetal scalp electrode to be used as a gold standard for evaluation.

6. Conclusions

This article focuses on introducing different types of non-adaptive methods of signal processing. There are many applications where these non-adaptive methods can be utilized. They are used more often in the area of extraction fECG, but also in the area of fPCG or electroencephalography signal processing, voice recognition, image identification, etc. There is a large number of non-adaptive methods of signal processing and the choice of which one is used will depend on the type of signal we want to process and the result that we are trying to achieve. The most widely published methods of processing virtually all signal types are ICA, PCA and WT due to their efficiency, great accuracy and the speed of the algorithms.

Based on the extensive overview presented herein, we conclude that hybrid methods, such as ICA-EEMD-WS [102], ICA & AF [104], ICA & PF [105], and BA & ZA [110], seem to be the most promising non-adaptive methods for NI-fECG signal processing. The authors believe that the application of selected NI-fECG methods will lead to the development of a completely new diagnostic method using non-invasively recorded fHR data (fHR based on detection of NI-fECG R-R interval) to determine the fetal hypoxic state in combination with non-invasively obtained T/QRS ratio, i.e., enable non-invasive fECG ST segment analysis. Introducing this novel non-invasive diagnostic method into clinical practice should lead to a significant reduction in unnecessarily performed cesarean sections for suspected hypoxia.

7. Ethics Statement

The study protocol was approved by the Ethical Committee of the Silesian Medical University, Katowice, Poland (NN-013-345/02). Subjects read the approved consent form and gave written informed consent to participate in the study.

Funding: This article was supported by the Ministry ofEducation of the Czech Republic (Project No. SP2018/170). This work was supported by the European Regional Development Fund in the Research Centre of Advanced Mechatronic Systems project, project number CZ.02.1.01/0.0/0.0/16_019/0000867 within the Operational Programme Research, Development and Education.

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

References

1. Martinek, R.; Kahankova, R.; Jezewski, J.; Jaros, R.; Mohylova, J.; Fajkus, M.; Nedoma, J.; Janku, P.; Nazeran, H. Comparative Effectiveness of ICA and PCA in Extraction of Fetal ECG From Abdominal Signals: Toward Non-invasive Fetal Monitoring. *Front. Physiol.* **2018**, *9*. [CrossRef] [PubMed]
2. Jagannath, D.; Selvakumar, A.I. Issues and research on foetal electrocardiogram signal elicitation. *Biomed. Signal Process. Control* **2014**, *10*, 224–244. [CrossRef]
3. Sameni, R.; Clifford, G.D. A review of fetal ECG signal processing; issues and promising directions. *Open Pac. Electrophysiol. Ther. J.* **2010**, *3*, 4. [CrossRef] [PubMed]