A Review of Recent Advances and Future Developments in Fetal Phonocardiography

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(Methodological Review)

***Abstract*— Fetal phonocardiography (fPCG) is receiving attention as it is a promising method for continuous fetal monitoring due to its non-invasive and passive nature. However, it suffers from the interference from various sources, overlapping the desired signal in the time and frequency domains. This paper introduces the state-of-the-art methods used for fPCG signal extraction and processing, as well as means of detection and classification of various features defining fetal health state. It also provides an extensive summary of remaining challenges, along with the practical insights and suggestions for the future research directions.**

***Index Terms*—Fetal phonocardiography, fPCG extraction, non-invasive fetal monitoring, signal processing.**

I. Introduction

FETAL phonocardiography (fPCG) is a monitoring technique used to assess fetal well-being during pregnancy and childbirth. It is a graphical record of fetal heart sounds (fHS) measured on the surface of the mother's body. In essence, it is a modern form of auscultation technique, which is one of the oldest techniques of fetal surveillance. The great advantage of fPCG is that it provides additional diagnostic information on some congenital heart diseases that cannot be obtained by other monitoring methods, such as cardiotocography (CTG), fetal electrocardiography (fECG), magnetocardiography (fMCG) [1]. It allows, for example, early detection of extrasystoles, murmurs, bigeminal and trigeminal atrial contractions, intrauterine growth retardation and other abnormal cardiac functions [2], [3]. Moreover, this method is entirely passive, low-cost and suitable for continual fetal heart rate (fHR) and maternal heart rate (mHR) monitoring [4].

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The signal is recorded by probes that can detect the mechanical vibrations caused by the fetal heart. Among the most popular sensing probes are microphones [5], but there are also other means of sensors based on optical fibers [6], accelerometers [7], or other alternatives [8]. However, besides the desired fPCG signal, the probes also record variety of unwanted signals that affect the resulting signal quality.

The factors affecting the quality of the fPCG signal include biological effects of the maternal body (signals appearing as artifacts produced by surrounding organs and tissue, body motion, respiratory activity, uterine contractions) and also technical aspects, such as ambient noise or artifacts generated by other devices. The fPCG signal also varies for different gestation age (stage of pregnancy) or fetal position, which may change during a single measurement. In addition, the intensity of the interfering signals is higher than the fetal one and they overlap with the desired signal in the time and frequency domains, which makes accurate extraction of the fetal component challenging. If the data collection systems and signal processing methods were improved, fPCG-based monitoring could become the future of electronic fetal monitoring removing most of the current limitations in fetal telemonitoring and e-health [9], [10].

Over the years, many researchers have been introducing methods for fPCG signal processing and extraction. There have also been some attempts to provide an overview of this topic [11], [12]:

- The paper of Kovacs *et al.* published in 2011 [11] provides a great introduction to the topic and practical insights by one of the most well-known groups focused on fPCG. Their paper offers the reader important details about anatomy and physiology of the fetal heart, thorough description of the fetal heart sounds, their origin, clinical use, and additional features needed for diagnostics of congenital heart defects. On the other hand, the paper does not cover the topic in terms of signal processing and analysis methods introduced by other authors and offers only limited amount of references (26), which are now quite out-of-date.
- In the second available review published in 2017 [12], the authors presented an overview of the existing fetal monitoring methods and highlighted their benefits, limitations and means of use. The paper provides an extensive survey of the fHS characteristics in both time and frequency

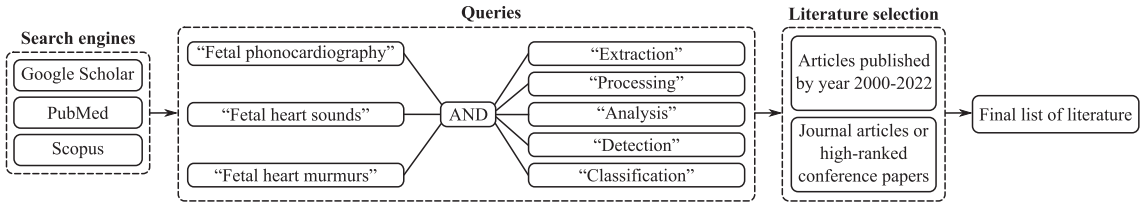


Fig. 1. Illustration of the search phrases and selection criteria used in the search strategy.

domains, and insights in modelling of fPCG signal and associated noise. Compared to the previously mentioned review, the authors in [12] provided a thorough summary of available literature covering signal processing and also classification algorithms proposed by other researchers. However, the paper lacks a thorough objective comparison of given methods and practical examples and recommendations.

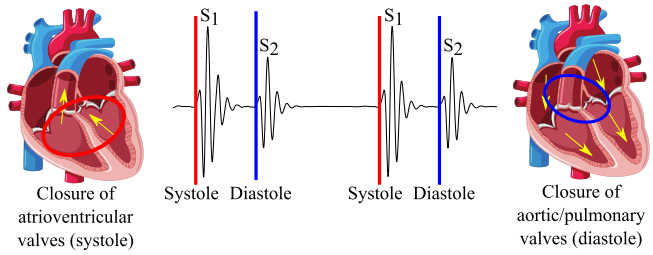
The review introduced herein provides an extensive critical review of the available techniques in fPCG signal processing and analysis and tries to add useful and practical information that was missing in the previous reviews. It includes clinical insights, practical challenges, and recommendations on sensor placement or evaluation metrics so it may be of use particularly for the early-stage researchers interested in fPCG monitoring. Finally, it summarizes remaining challenges and reveals recent advances in this area along with several promising directions of future research.

Google Scholar, PubMed, and Scopus search engines were used to find relevant references. The selection criteria for the references to be included involved phrases combining terms from the field of fetal phonocardiography: "Fetal phonocardiography," "Fetal heart sounds," and "Fetal heart murmurs" with terms from the field of signal processing: "Extraction," "Processing," "Analysis," "Detection," and "Classification" A total of 15 queries were created and used in the literature search, as indicated in Fig. 1. Research articles that were published before 2000 and most conference papers were excluded from the search. Thus, only journal articles and high-ranked conference papers published between 2000–2022 were used.

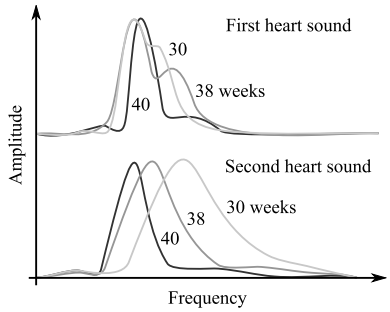
A. Fetal PCG Signal Characteristics

The fetal heart produces narrow frequency band acoustic signals of low intensity caused by its transmission through the maternal tissue. These sounds are generated by the opening and closing of heart valves and blood flow [13]. We distinguish four heart sounds (HSs) in both adult and fetal PCG, while the third and fourth sounds are practically undetectable [3]. As illustrated in Fig. 2, the first HS (S1) is generated by the closure of the mitral and tricuspid valves during systole. The second HS (S2) is generated by the closure of the aortic and pulmonary valves during diastole.

In general, S1 has a higher amplitude, lower frequency, and longer duration than S2. The systolic time interval occurring between S1 and S2 sounds is generally shorter than diastolic (between S2 and S1). Fetal and maternal HSs can be considered as almost periodic, narrowband signals. The frequency of fHS



(a) Illustration of the fPCG signal origin and feature characteristics in time domain.



(b) Frequency characteristics of the S1 and S2 sounds for different stages of pregnancy (30, 38, and 40 weeks).

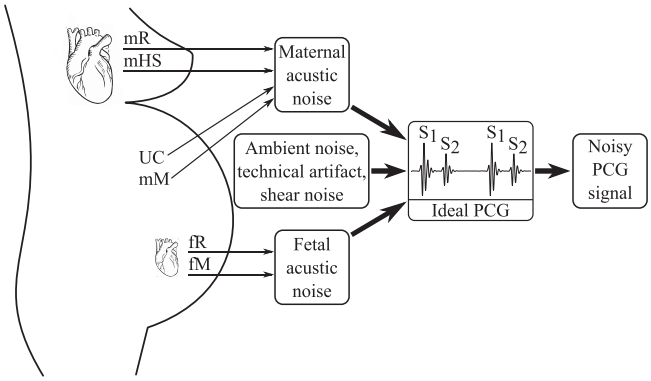
Fig. 2. Example of the fPCG signal in time and frequency domain [14].

is in the range from 20 to 110 Hz and maternal HS (mHS) is in the range from 10 to 40 Hz [11], [12]. Fig. 2(a) shows an example of the fPCG signal in time domain illustrating its origin while Fig. 2(b) depicts its frequency spectra of both S1 and S2 sounds corresponding to different stages of pregnancy. However, in the clinical practice, it is nearly impossible to distinguish the individual sounds S1 and S2 in such an interference signal without professional experience [15].

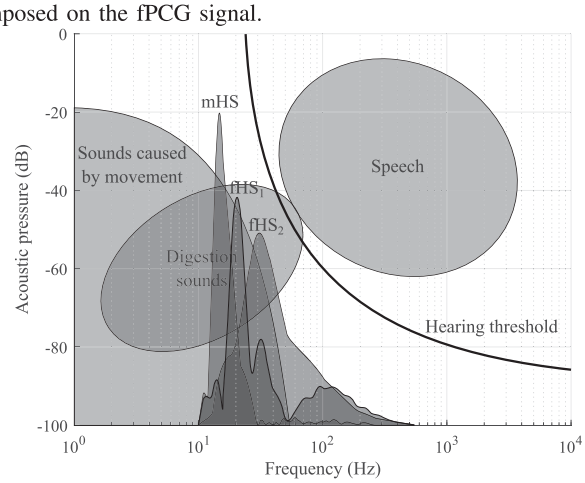
For this reason, methods for automatic identification of the individual fHSs have been presented in the past. They were mainly based on the thresholding and conditioning according to the physiological properties of the heart cycle [16], [17], but also other alternatives proved to be effective, such as those using spectrogram [18] or a combination of scalogram and physiological properties of fPCG [19].

Unlike in fPCG research, advanced methods have been tested in adult PCG based mainly on artificial intelligence and machine learning [20]. Very promising results were achieved with the automated identification of S1 and S2, for example, when using deep neural networks [21], [22] or support vector machines [23], [24].

Other important features of fPCG signal are murmurs, manifesting as abnormal HSs. Their identification contributes to



(a) Block diagram illustrating and summarizing the signals superimposed on the fPCG signal.



(b) Frequency characteristics of the S1 and S2 sounds for different stages of pregnancy (30, 38, and 40 weeks).

Fig. 3. Examples of the noise present in the fPCG monitoring in time and frequency domains [27], [28].

the early detection of congenital heart defects. The presence of heart murmurs is in most cases associated with a pathology that changes the blood flow from laminar to turbulent causing the tissue vibrations [25]. Pathological murmurs can be detected after the first trimester, i.e. in the 12th week of pregnancy. For murmurs, the intensity and frequency are always determined [11], [25]. The detection of murmurs is further discussed in Section III-D.

B. Noise Definition

As illustrated in Fig. 3, in fPCG based monitoring, we face the problem of the occurrence of a large number of interfering signals, which are sensed along with the desired fPCG signal. As defined in [26], the most significant types of interference include following signals:

- *Sensor and background noise (SBN)* - this category includes the noise that is not produced by the fetal or maternal body. These types of interference are random white Gaussian broadband signals. They occur at all frequencies during recording and lead to significant changes in the acquired signal.
- *Shear noise* - is caused by the sensor movement during recording.
- *Ambient noise* - is the external noise originating from the environment (for example, sum of speech, acoustic noise caused by electronic appliances, and other sounds). The noise can be minimized by careful positioning the measuring device and ensuring its contact with the subject's skin [26].

Acoustic noise produced by fetal body - corresponds to the various activity of the fetal body (both physiological and pathological). Besides outputs such as fetal cough, hiccups, or organs' activity, main categories include:

- *Fetal respiration (fR)* - although the fetal lungs are functional only after birth, they produce respiratory movements. Fetal respiration is a low-frequency periodic signal with a range of inspiratory and expiratory pressure components in the range from 0.3 to 1.5 Hz.
- *Fetal motion artifacts (fM)* - arise from the movement of the limbs or the head of the fetus in the frequency range from 0 to 25 Hz. These artifacts include hiccups or respiratory movements of the fetus' lungs, which are already described above.

- *Acoustic noise produced by maternal body* - maternal respiratory artifacts, maternal digestive sounds, mHS, uterine contractions or maternal motion (mM).
- *Maternal respiration (mR)* - is a low-frequency signal generated by the maternal breathing. This noise covers the frequency band from 0.2 to 0.5 Hz [29].
- *Maternal heart sounds (mHS)* - are sounds generated by the activity of the maternal heart. However, when related to the fetal monitoring, its definition is not as simple as that. For example, in [28], the authors describe mHS as a regular periodic signal known as a maternal pulse derived from the sound of blood flow in maternal arteries covering the frequency band 8–25 Hz and having a higher amplitude than fHS, fR, and mR. Contrary, in [30], the authors interpreted mHS as umbilical cord sounds. Moreover, in [27], the authors interpreted mHS as the signal derived from aortic/placental sounds with a frequency range up to 10 Hz. Finally, in [29], the authors interpret mHS as a periodic pulse wave originating from the sound of aortic blood flow, where the frequency range is between 10 and 50 Hz.
- *Uterine contraction (UC)* - is type of interference occurring in the abdominally sensed PCG signal (aPCG) and is caused by the uterine muscles contracting during the labor but also before it. The frequency, intensity and duration of UCs are highly related to the week of pregnancy. They generally occur 2–5 times every 10 minutes and their duration varies from 15 to 70 s.

Possible artifacts can then be eliminated by selecting a suitable filtration method and its optimal setting, more in Sections III and IV-A, respectively. The frequency ranges of the individual disturbances are illustrated in Fig. 3(b). The above-mentioned types of noise and their parameters are also summarized in Table I.

TABLE I
SUMMARY OF THE FPCG SIGNAL COMPONENTS AND ARTIFACTS [12], [26]

Component	Frequency range (Hz)	Time duration	Relative amplitude	Effect on aPCG signal
fHS	15–110	Continuous	SBN, fR, < **fHS** < mHS, mR, fM	- S1 and S2 sounds
fM	0–25	1–3 s	SBN < **fM** < fR, fHS ,mHS, mR	- changes in fHR, broadband noise superimposed on fPCG
fR	0.3–1.5	Continuous	SBN < **fR** < fHS, mHS, mR, fM	- baseline fluctuations and deviations in fPCG signal
mHS	10–50	Continuous	SBN, fR, fM, mR < **mHS**	- overlap with fHS in time and frequency domain, - unwanted morphological changes in fPCG
mR	0.2–0.5	Continuous	SBN, fR, fHS, fM < **mR** < mHS	- baseline wander - fHR variations
UC	0.2–0.5	15–60 s	–	–
SBN	Broadband	Continuous	**SBN** < fR, fHS, mHS, mM	- change in mean value and variation of fPCG

II. SIGNAL QUALITY ASSESSMENT

The main focus of this review is on methods for signal processing and analysis in fPCG. These methods will be introduced and discussed in detail in Section III. However, to properly evaluate and compare their effectivity, we first need to introduce associated metrics and available open-access datasets used for the experiments.

A. Evaluation Metrics

The quality of the fPCG signal extraction can be evaluated *subjectively* or *objectively*. The subjective assessment can be performed visually by evaluating the fPCG morphology and the amount of the artifacts and/or noise remaining. In the case of fPCG, it can also be evaluated by listening to the signals. In contrast, objective evaluation is carried out by means of evaluation metrics that use an information provided by an ideal reference signal (in case of synthetic signals) or reference annotations (in case of real records). Following objective signal quality indices have been used among the literature:

- *Signal-to-noise ratio (SNR)* - is used to evaluate the ratio between the useful signal and the noise, its unit is the decibel (dB). The usual practice is to calculate the SNR of the input (unfiltered) signal, and the output (filtered) signal, i.e. SNR_{in} and SNR_{out}, respectively. The difference between those values tells us about the success of the filtration. The following equations are used to determine the SNR_{in} and SNR_{out} [31]:

$$SNR_{\text{in}} = 10\log_{10}\frac{\sum_{m=1}^{M-1}\left(s_{\text{ref}}(m)\right)^2}{\sum_{m=1}^{M-1}\left(s_{\text{in}}(m)-s_{\text{ref}}(m)\right)^2}, \quad (1)$$

$$SNR_{\text{out}} = 10\log_{10}\frac{\sum_{m=1}^{M-1}\left(s_{\text{ref}}(m)\right)^2}{\sum_{m=1}^{M-1}\left(s_{\text{filt}}(m)-s_{\text{ref}}(m)\right)^2}, \quad (2)$$

  where M is the number of samples of the reference signal (s_{ref}), the input signal containing interference (SNR_{in}) and the signal after filtering using the specific method (s_{filt}). It is important to note that the SNR parameter can only be used in case of artificial recordings since the reference (ideal) signal is available. In the case of real records, the reference usually refers to the heart beat annotations, not a signal, and thus (1) and (2) could not be used.

- *Mean Square Error (MSE)* - is metric derived from the square of Euclidean distance (see (3)). Its value is always a positive; the higher the value, the higher the error (i.e. lower the filtration quality).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(s_{\text{filt}}(i)-s_{\text{ref}}(i)\right)^2. \quad (3)$$

- *Root Mean Square Error (RMSE)* - is a parameter that indicates the degree of difference between the ideal fPCG values and estimated ones. The closer the RMSE value is to zero, the more accurate the filtration result is.

$$RMSE = \sqrt{MSE} = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\left(s_{\text{filt}}(i)-s_{\text{ref}}(i)\right)^2}. \quad (4)$$

- *Percentage RMS Difference (PRD)* - is one of the quality indicators often used in ECG compression [32]. It is therefore useful in assessing the visual quality (morphological accuracy) of the output signal in comparison with the reference.

$$PRD = \sqrt{\frac{\sum_{i=1}^{N}\left[s_{\text{ref}}(i)-s_{\text{filt}}(i)\right]^2}{\sum_{i=1}^{N}s_{\text{ref}}(i)^2}}\cdot 100. \quad (5)$$

- *Correlation coefficient* - this parameter reflects the relationship between the original signal and the filtered one. The value of the correlation coefficient ranges from 0 to 1 and shows the similarity of the shape of these two signals. A higher correlation coefficient means a lower deformation of the signal shape after filtering.
- *Statistical evaluation of HS detection* - accurate detection of S1 (or S2) sounds, corresponding to the individual heart beats, is crucial for the fHR determination. Following indices can be used to assess this: Sensitivity (SE), Accuracy (ACC), Positive Predictive Value (PPV), and F1 score, which is a harmonic mean of SE and PPV. The parameters are defined as follows:

$$ACC = \frac{TP}{TP+FP+FN}\cdot 100, \quad (6)$$

$$SE = \frac{TP}{TP+FN}\cdot 100, \quad (7)$$

$$PPV = \frac{TP}{TP+FP}\cdot 100, \quad (8)$$

TABLE II
SUMMARY OF AVAILABLE FPCG DATABASES

Name	Type	Device	Pregnancies	Twins	Recordings	Fs
SFPDB	Synthetic	Generator	–	–	37	1 kHz
SUFHSDB	Real	Digital JABES Electronic Stethoscope	109	7	119	16 kHz or 44.1 kHz
FPCGDB	Real	Fetaphon Monitoring System by Pentavox	26	–	26	333 Hz

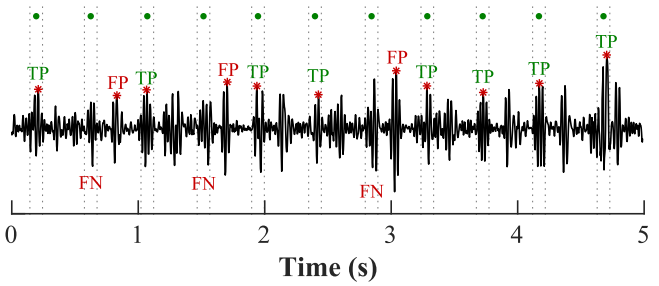


Fig. 4. Example of the parameters (TP, FP, FN) used for statistical evaluation on a real fPCG signal. The reference annotation values are marked as green dots with the interval of ± 50 ms around it is indicated by a dashed line; the values detected on the filtered signal are marked as red dots.

$$F1 = 2 \cdot \frac{PPV \cdot SE}{PPV + SE} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} \cdot 100, \tag{9}$$

where TP (true positive) represents the correct detection of S1 (or S2), FP (false positive) indicates an incorrect indication of the presence of S1 (or S2), and FN (false negative) corresponds to the missed S1 (or S2). As illustrated in Fig. 4, TP, TN, and FP can be determined in case of both synthetic and real recordings. In both cases, the annotations regarding HS position must be available. A true positive (TP) value is then defined as a *correctly* detected S1 sound, which had to be detected in given time interval (most often ± 50 ms) before/after the corresponding S1 sound in the reference recording (annotations). In synthetic recordings, these reference annotations can be acquired by automatic detection from the *ideal* signal. In real signals, these annotations must be provided by the authors of the database. Most often, they are created by manual selection of the heart beats by several independent experts (to ensure reliability) or by comparing it with other signal considered as gold standard, for example *invasive* (direct) fetal ECG signal [33].

B. Available Databases

The unified publicly available databases to test and evaluate the fPCG extraction methods are an essential part of the fPCG research. Unfortunately, the number of databases containing fPCG recordings is still very limited. Currently, there are only three databases available at *PhysioBank* containing *real* data and one database containing *synthetic* data. The real data can be found in *Fetal PCGs database* [34] and *Shiraz University Fetal Heart Sounds Database* [34], [35], while the synthetic ones in *Simulated Fetal PCGs database* [3], [34]. A short description of the available databases is given below and summarized in Table II.

1) *Shiraz University Fetal Heart Sounds Database (SUFHSDB)* - contains fetal and maternal PCG recordings from 109 pregnant women from 16 to 47 years old (mean $\pm$ SD: 29.3 ± 5.8 years) with Body Mass Index (BMI) from 19.5 to 38.9 (mean $\pm$ SD: 29.2 ± 4). The signals were acquired with a digital JABES Electronic stethoscope (GS Technology Co. Ltd., South Korea) [35]. The data set includes 7 cases of twin pregnancies. In these cases the data were collected twice according to the locations advised by the gynecologist. Audacity cross-platform audio software was used for recording and editing the signals on a PC. In summary, 99 subjects had one signal recorded, three subjects had two signals and seven cases of twins were recorded individually, resulting in total of 119 total recordings, each about 90 s long. The sampling rate was generally 16 kHz with 16-bit ADC and a few recordings at 44.1 kHz. The data was recorded in wide-band mode of the digital stethoscope, with a frequency response of 20 Hz to 1 kHz. This data set also provides maternal PCG data (mPCG): in total of 92 mPCG signals from 91 subjects (90 subjects had one mPCG signal recorded while one had two recordings carried out).
2) *Simulated Fetal Phonocardiograms Database (SFPDB or simfpcgdb)* - this data set is a series of artificial fPCG signals simulating various scenarios (e.g. physiological and pathological fetal states) and recording conditions, generated by a simulator introduced in [3].
Simulated PCGs were generated as a sequence of frames, each including simulated S1 and S2 sounds. The fetal HSs were corrupted by noise and artifacts at various levels, such as mHSs, maternal body organs sound (due to maternal digestion, respiratory muscular movements, placental blood turbulence), fetal movements, surrounding environment and additive white Gaussian noise.
3) *Fetal PCGs Database (FPCGDB)* - includes series of 26 physiological fPCG recordings from different pregnant women in the final stages of pregnancy (gestational week between 31 and 40). The recordings were acquired by a portable PCG device (Fetaphon Monitoring System by Pentavox). The data were digitized with a sampling frequency of 333 Hz at 8-bits ADC. These signals were used to design a fPCG simulator and to develop and test algorithms for fHR extraction [3].

In general, the synthetic data are important especially in the initial stages of the research and development. A simulator generating fPCG signals is able to simulate the physiological and pathological conditions of the fetus by simply adjusting system

TABLE III
OVERVIEW OF BAND-PASS FILTERS USED FOR FPCG PRE-PROCESSING

Authors, year, source	Filter order	Bandwidth	Data source
Zhang *et al.* (2018) [4]	6th	20–200 Hz	UBabycare device
Fuadina *et al.* (2019) [36]	Not specified	30–80 Hz	Synthetic data from [3]
Tomassini *et al.* (2019) [37]	3th	20–120 Hz	Synthetic and real data from [3, 35]
Dia *et al.* (2019) [38]	Not specified	20–200 Hz	Cardio-microphone (MLT201, ADInstruments)
Vican *et al.* (2021) [39]	8th	50–150 Hz	Microphone Behringer ECM8000

parameters. Pathological records are particularly important for the development because they enable to test the methods in unexpected conditions. However, in the clinical practice, it is often impossible to acquire them since the measurement is stopped when a pathology is detected (i.e. the unborn is endangered) and the delivery is ended surgically via Caesarean section. The disadvantage of *real* recordings compared to *synthetic* ones is also the absence of a reference signal which makes the evaluation of the filtration accuracy more challenging.

III. FETAL PCG SIGNAL PROCESSING AND ANALYSIS

As mentioned in I-B, the fPCG signal sensed on the maternal abdomen can obtain various type of noise. To obtain all of the diagnostically important information, there are several steps that need to be undertaken. These steps are as follows and will be introduced and extensively discussed in the following subsections:

1) *Pre-processing* – noise suppression in the pre-processing stage usually involves linear filtration (low pass, high pass or notch filters) to acquire only the desired frequency bands.
2) *fPCG extraction* – in order to obtain a high quality fPCG signal, a number of studies have been presented dealing with methods for fPCG extraction (see III-B).
3) *HS detection* – the fHSs are detected in the filtered fPCG signal. Some authors introduced extensive fPCG extraction systems that already involve specific algorithms for fPCG signals detection while others used separate detectors to obtain fHSs for evaluation purposes (see III-C).
4) *Feature extraction and classification* – involves extraction of other features besides fHSs and additional analysis (see III-D).

A. Pre-Processing

Pre-processing is an essential part of signal processing. It is used to remove the components of the signal, which correspond to noise, and thus enhance the quality of the desired signal. The unwanted components to be removed include, for example, broadband noise signals, motion artifacts, or breathing activity (see Section I-B).

For fPCG pre-processing, band-pass filter is usually used to preserve only the useful frequency range of the signal. Most of studies use Butterworth filter but its order and the signal bandwidth that is retained varies slightly across studies from 20 to 200 Hz, see Table III. However, some studies use other techniques for pre-processing such as Wiener filter [40], wavelet transform [41] or moving average.

B. Extraction Methods

Before any analysis can take place, it is necessary to extract the fPCG signal from the composite abdominal mixture. Many methods have been introduced and their accuracy is often evaluated using fHR calculation or other metrics, see Section II-A. Herein, we provide an overview and comparison of the most popular methods for fPCG signal extraction from the composite aPCG signal.

1) *Spectral subtraction* - restores spectrum magnitude of the wanted signal in an additive noise through subtraction of the average noise spectrum from the noisy signal. The noise spectrum is usually acquired and updated from the periods when there is only noise but no signal. This method assumes that noise is a stationary process and the noise spectrum does not change too much between the update periods [12].

- Chen *et al.* [42] created a device with simplified spectral subtraction and amplitude modulation technique for elimination of noise from fPCG signal and for fHR real-time monitoring. They tested this approach in 41 subjects in 37th to 38th week of pregnancy. Their device could clearly detect fHS in 75% of the subjects, which is significantly lower comparing to the Doppler technique. Thus, as the authors concluded, their device can be used as a supplementary tool, but not as substitution for the ultrasound device.

2) *Fourier transform (FT)* - FT is used to convert the signal from time to frequency domain. The FT-based filter attenuates or amplifies specific frequency components according to the given purpose. The process is finalized by the inverse FT, where the signal is reconstructed with the changes applied [43]. The FT is commonly used in the biological signal processing, however, it is not really suitable for fPCG processing. There is only one paper focused on this issue available:

- Mittra *et al.* [18] used a simple Short Time FT (STFT) method for analyzing fPCG signal in the time-frequency domain. They showed STFT based spectrograms and concluded that this method can become an important diagnostic tool in prediction of the prenatal anomalies.

3) *Wavelet transform (WT)* - is a frequently tested and very effective method able to suppress noise when its setting is optimized for given purpose. Contrary to the FT, WT treats frequency logarithmically which corresponds to the acoustic perception of the human body and therefore is more suitable for the analysis of the sound-related signals [44]. It decomposes the input signal into a set of wavelets – a wave-like oscillations with two basic

properties: scale, which relates to the signal's frequency, and location, which defines its position in time. In the WT-based filtering, one should pay attention to selecting suitable set of the parameters, such as the wavelet base (e.g. *Daubechiens* or *Coiflets*) or level of decomposition [33]. Moreover, the effectiveness of WT-based filter can be further increased by combining this algorithm with other filtration methods.

- Song *et al.* [45] developed a passive acoustic device for real-time fHR monitoring. The fHS were detected using the WT, de-noised and reconstructed. The *Coiflet* wavelet base and five levels of decomposition were used for the filtration, when the level most corrupted by noise was not used for the reconstruction. The device was tested on 41 pregnant women (37th to 40th week of pregnancy). They concluded that *Coiflet* WT significantly improves SNR so that fHR can be determined even in a noisy environment.
- Chourasia *et al.* [46] designed a new WT-based algorithm optimized for fPCG signals. This method uses a quadratic mirror filter bank designed accordingly to the fPCG signal characteristics involving low and high-pass filtration in the decomposition phase and the reconstruction phase. The basic features of this method comprise speed in convergence from infinity to 0, regularity, and orthogonality. This method has a small number of coefficients in high-pass subbands and, in the low-pass subband, it allows intact signal singularities, transitions, and edges. Their results show that this method outperforms the existing wavelet bases and preserves physiological information contained in the original fPCG signal.
- Kovacs *et al.* in [47] presented a complex heuristic method for the fPCG extraction and reliable fHR variability evaluation using a combination of autocorrelation (AT) technique, WT, and matching pursuit (MP). The functionality of the algorithm was tested on 25 real fPCG signals sensed directly on the abdomen of pregnant women at 34 weeks of gestation. The signals were further adjusted with a band-pass filter in the range of 25–100 Hz and resampled to a sampling frequency of 333 Hz. The overall accuracy ranged from 92.9 to 98.5%.
- Varady *et al.* [9] introduced the fTCG extraction method based on WT. The proposed method was tested on real records measured by an electronic stethoscope developed by the author. The sensed signals were evaluated subjectively by a cardiologist by listening. The authors do not report any statistical results.
- Vaisman *et al.* introduced an adaptive wavelet transform (AWT) as a method for fPCG signal processing in [10]. To test the method, they used real fPCG records obtained from 14 pregnant women in the 36–40th week of pregnancy. The overall accuracy of the method was evaluated based on the ability of the method to fit fHR trace. The results showed an accuracy of 94–98.5%, including highly disturbed cases.
- Koutsiana *et al.* presented a system using WT and fractal dimension (WT-FD) method in [16]. The efficiency of the WT-FD method in fHS extraction was tested on 19 artificial fPCG signals generated for the purpose of this study, with additive noise up to (3 dB), and on signals from the SIMFPCGDB database. The results showed promising performance in identifying the correct location and morphology of fHS and achieved an overall accuracy of 89%.
- Strazza *et al.* proposed PCG-Delineator as an algorithm for detection S1 and S2 sounds [17]. This method is based on WT and uses a *Coif4* mother wavelet with 7 levels of decomposition. To verify the functionality of the proposed system, 37 fPCG signals from the SIMFPCGDB database were used. The performance of the algorithm was evaluated according to the statistical parameters SE and PPV. The results show that the accuracy of S1 detection was on average 88% according to the SE parameter and 91% according to the PPV parameter. For the S2 detection, the values of the SE and PPV were 77% and 99%, respectively.
- Tomassini *et al.* provided comparative analysis of WT-based filters in [37]. They tested three wavelet bases (*Coif4*, *Db4*, and *Sym8*), two threshold rules (*Soft*, *Hard*), and three threshold algorithms (*Universal*, *Rigorous* and *Minimax*). Using these parameters and their combinations, they created in total of 18 different fPCG filters. Individual filters were tested on 37 simulated records from the SIMFPCGDB database and 119 real records from the SUFHSDB database. Their performances were evaluated using the SNR parameter and also by the reliability in estimating fHR from the filtered fPCG signal. According to the authors, the best results (for both groups of tested data) were obtained by combining the *Coif4* wavelet base with the *Soft* thresholding rule and the *Universal* thresholding algorithm, as it was able to maintain the fHR value with respect to the reference ($Ref_{fHR} = 138.7$, $SIM_{fHR} = 139.6$, $SU_{fHR} = 140.5$), see Table IV.
- Faradisa *et al.* in [48] dealt with the filtering of the fPCG signal using a WT-based filter on the data from the SUFHSDB database. The authors tested different types of wavelet bases (*Coif3*, *Sym5*, and *Db6*), thresholding (*Soft*, *Hard*) and the type of thresholding algorithm (*Universal*, *Minimax*, *SURE*). The filtration efficacy was evaluated using the MSE parameter. Contrary to Tomassini *et al.* [37], the authors achieved the best results (lowest value of MSE) when applying the *Coif3* wavelet with the *SURE* thresholding algorithm and the *Hard* threshold parameter.
- Strazza *et al.* tested a new extraction method based on WT multi-level decomposition in [49]. The filtering was carried out using *Coif4* base with 9 levels of decomposition (called PCG-Decompositor), and *soft*-thresholding denoising technique (STDT) on 119 real fPCG records from the SUFHSDB database. The efficacy of the method was evaluated in terms of SNR, RMSE and the ability of the method to estimate the value of fHR with respect to the CTG reference. The authors state that there was a significant increase in SNR after the application of the PCG-Decompositor. In addition, when comparing with the method based on STDT, the PCG-Decompositor shows a lower dispersion (RMSE $= 0.7$ dB) than the STDT

TABLE IV
COMPARISON OF THE AVAILABLE FPCG EXTRACTION METHODS

Authors, year, source	Filtration method	Data source	Results of experiments
Varady *et al.* (2001) [9]	WT + Adaptive coefficient thresholding	Two electret microphones	–
Chen *et al.* (2006) [42]	Spectral Subtraction + AM modulation	Panasonic microphone omni-directional	fHS detection accuracy 75%
Song *et al.* (2006) [45]	WT	Acoustic sensor	–
Jimenes and James (2008) [58]	FastICA	PCG piezoelectric transducer (TK701T, Nihon Kohden)	–
Mittra *et al.* (2009) [18]	STFT	Self-made electronic stethoscope (piezoelectric sensor)+ reference microphone and simulated pathological data	RMS-real S1: 16.7 S2: 12.6 / RMS-pathological S1: 10.4 2: 9.4
Warbhe *et al.* (2010) [56]	EMD-SVD-FEICA	Microphone	–
Kovacs *et al.* (2011) [47]	AT-WT-MP	Fetaphon-2000	ACC of S1 detection (%) 92.9–98.5
Balogh *et al.* (2011) [62]	WVD	Self-made electronic stethoscope	SE of S1 detection (%) 90
Vaisman *et al.* (2012) [10]	AWT	Electret microphone encapsulated in conical interface	ACC of S1 detection (%) 94–98.5
Chourasia *et al.* (2012) [63]	NMF	Own simuated and real data sensed by wireless data acquisition system	SNR sim. (dB) 23.55 / SNR real (dB) 21.42
Zahorian *et al.* (2012) [64]	FIR filter + Autocorrelation	Piezopolymer pressure sensor	Energy LF (mV^2) 1281.36 / VF energy (mV^2) 2627.64
Cesarelli *et al.* (2013) [3]	BPF-TEO	Own simulated dataset	ACC of S1 detection (%) 68–99
Chourasia *et al.* (2013) [46]	WT: own wave-Soft-Rigrsure WT: own wave-Soft-Minimax WT: own wave-Soft-Sqtwolog	Own simulated dataset	MSE 0.49 0.55 0.56
Samieinasab *et al.* (2015) [35]	SCBSS	SUFHSDB (50 recordings)	ACC of S1 detection (%) 83–100
Potdar *et al.* (2015) [61]	LMS NLMS DLMS RLS QRD-RLS	Not specified	SNR (dB) / MSE 1.36 / $1.79 \cdot 10^{-6}$ 1.34 / $4.51 \cdot 10^{-6}$ 1.51 / $1.81 \cdot 10^{-6}$ 20.69 / $4.86 \cdot 10^{-7}$ 0.0025 / $1.09 \cdot 10^{-2}$
Tang *et al.* (2016) [65]	CFS	SIMFPCGDB	Accuracy rate (%) 81–92.3
Koutsiana *et al.* (2017) [16]	WT-FD	Own simulated dataset/SIMFPCGDB	Accuracy rate (%) 89
Martinek *et al.* (2017) [6]	LMS NLMS	Own simulated dataset	SNR (dB) / PPV (%) / SE (%) / RMSE 7.77 / 94.24 / 98.08 / 0.033 7.88 / 97.15 / 98.41 / 0.030
Strazza *et al.* (2018) [17]	PCG-Delineator	SIMFPCGDB	SE of S1 detection (%) 88 / SE of detection S2 (%) 77 PPV of S1 detection (%) 91 / PPV of detection S2 (%) 99
Kahankova *et al.* (2018) [60]	LMS DLMS	Own simulated dataset	SNR (dB) / PRD (%) 2.682 / 14.843 2.586 / 15.247
Tomassini *et al.* (2019) [37]	WT: Coif 4-Soft-Universal WT: Db 4-Soft-Universal WT: Sym 8-Soft-Universal	SIMFPCGDB / SUFHSDB	fHR (bpm) / SNR (dB) ref. 140.2/140.5 / ref. 0.7/15.6 138.7/139.6 / 25.9/22.9 139.2/139.1 / 26.3/22.9 138.6/139.4 / 25.9/22.9
Strazza *et al.* (2019) [49]	STDT PCG-Decompositor	SUFHSDB	fHR (bpm)(ref. 140.5) / RMSE (dB) 146.6 / 1.2 140.6 / 0.7
Dia *et al.* (2019) [38]	NMF	Cardio-microphone (MLT201, ADInstruments)	Accuracy of fHR detection (%) 84–91
Faradisa *et al.* (2020) [48]	WT: Sym 5-Hard-SURE WT: Coif 3-Soft-SURE WT: Coif 3-Hard-SURE	SUFHSDB	MSE 0.000227 0.000204 0.000150
Tomassini *et al.* (2020) [19]	AdvFPCG-Delineator PCG-Delineator	SIMFPCGDB / SUFHSDB	fHR (bpm) (ref. 140-140/135-149) 139-140/138-145 140-141/135-145
Huimin *et al.* (2020) [66]	EMD-LWT-HT	SUFHSDB	fHR (bpm) 99–180
Martinek *et al.* (2020) [54]	EMD EEMD AWT	Own simulated dataset	ACC of S1 detection (%) 46.55–100 89.02–100 97.37–100
Vican *et al.* (2021) [39]	EMD-RF EMD-LR EMD-Linear SVC EMD-MLP	Microphone Behringer ECM8000	Accuracy of S1 detection (%) 74.13 68.45 68.31 71.12

(RMSE $= 1.2$ dB), which confirmed the effectiveness of the new PCG-Decompositor method.

- Tomassini *et al.* proposed the AdvFPCG-Delineator in [19] and tested it on two publicly available databases (37 records from SIMFPCGDB and 119 records from SUFHSDB). The performance of the proposed method was evaluated in terms of the accuracy in determining the fHR value, which was calculated from the interval S1-S1 (or S2-S2) and compared with the CTG reference. The authors also compared this new method with the previously created PCG-Delieator introduced in [17], which differs only in the absence of scalogram calculation. The authors state that the application of AdvFPCG-Delineator enabled the identification of S1 and S2 in the resulting fPCG signal. Compared to the PCG-Delineator proposed earlier, the accuracy of fHR determination was increased from 92.8 to 99.9% for SIMFPCGDB data and from 83.5 to 99.4 % for data from the SUFHSDB database.

4) *Empirical mode decomposition (EMD)* - is a filtering technique suitable for non-stationary and nonlinear signals. The input signal is decomposed into so-called *intrinsic mode functions* (IMFs) representing a certain frequency band [50]. The principle of the method is based on the detection of the upper and lower envelope of the signal by detecting local maxima and minima. Subsequently, the mean of envelopes is calculated, which is further subtracted from the input signal. As with the WT, its optimal setting is crucial for this method. According to the results achieved by several authors [51]–[53], this method can very well suppress low-frequency interference.

- In [54], Martinek *et al.* proposed the study comparing different extraction methods: the EMD, ensemble EMD (EEMD), and adaptive wavelet transform (AWT) methods for fPCG signal extraction. The methods were tested on a synthetic dataset created for the purpose of this study containing one ideal reference (*true* fPCG signal) and 12 composed aPCG signals corresponding to 12 different virtual sensing probes on maternal abdomen [55]. The extraction was evaluated by determining the accuracy of S1 sound detection and fHR determination. The accuracy of the tested methods was determined using the SNR, ACC, SE, and PPV parameters. The authors state that the best results were achieved when applying the AWT method, which achieved average values of parameters ACC $= 99.34\%$, SE $= 99.49\%$, PPV $= 99.85\%$ and F1 $= 99.67\%$.
- Warbhe *et al.* introduced a single-channel method combining EMD, singular value decomposition (SVD), and efficient version of ICA (EFICA) [56]. The combination of all methods was tested on real records and led to efficient extraction of fPCG from noisy signals. Although the authors did not publish statistical results, they stated that they could clearly identify the S1 and S2.

5) *Blind source separation methods* - blind source separation (BSS) enables to separate linearly independent source signals from a set of linear and instantaneous mixed signals based on the statistical analysis of the signal. The benefit is that the system needs no information about the source signals or the mixing process [57]. Among the most well-known and widely used BSS methods are, for example Principal component analysis (PCA) or Independent component analysis (ICA):

- Jimenez and James [58] proposed FastICA algorithm for extraction of fHS from single channel aPCG called SCICA. Firstly, an appropriate matrix of delays was constructed, then multiple independent components were calculated, and, finally, the components were projected back onto the measurement space and grouped using K-means method (i.e. the components associated to fHS were chosen). The experiments on three single-channel aPCG from pregnant women between the 36–40th week of pregnancy were used to evaluate the methods. The results show that this method clearly identified fHS from input signals. The paper introduces a thorough explanation and discussion of this extraction method. However, an overall evaluation of the achieved results is missing.
- Soysa *et al.* [40] used the Wiener filter for preprocessing of fPCG signal, PCA for extracting an accurate fHS and a subspace separation technique for fHS abnormality detection. In preprocessing, they used a subspace-Wiener filter which proved to be useful to achieve better results - PCA then performs better in fHS analysis and reveals more information. By selecting appropriate subspace eigenvector pairs, the subspace tool was able to detect the abnormalities of fHS. This approach can provide a lot of information hidden in fPCG signal.

6) *Adaptive filters*, which are self-learning filters changing their parameters depending on the change in the parameters of the input signal, are also very popular. These types of filters allow filtering interference from the useful signal if it changes its parameters over time or its parameters are not known in advance [59].

- The least mean square (LMS) and delayed least mean square (DLMS) filters for fPCG extraction were presented in [60]. The author tested the extraction systems on synthetic dataset to optimize the filter settings using the objective parameters (filter length M and step size μ). Their results show that the tested LMS-based algorithms work efficiently when set in the range of $M \in <70, 130>$ and $\mu = 0.015$–0.1, while for $\mu > 0.5$ the system became unstable. However, the authors also state that these findings need to be confirmed on the real fPCG signals.
- The LMS and normalized LMS (NLMS) algorithms were also tested in study [6]. The testing was performed on synthetic recordings and evaluated using the signal quality indices (SNR and RMSE) and objective metrics (SE and PPV) to assess its ability to determine fHR. The authors concluded that NLMS algorithm outperformed the latter algorithm in determining the fHR, while the LMS algorithm achieved better results according to the SNR and RMSE.
- Algorithms based on LMS and RLS based methods were tested in [61]. The quality of fPCG extraction was evaluated using the SNR and MSE metrics. The authors

point out the advantages of the LMS algorithm, such as its simplicity in a stationary environment and its robustness. On the other hand, the RLS algorithm is more suitable for non-stationary environments with a high degree of convergence, but at the cost of higher complexity. The authors did not specify the dataset used to conduct the experiments.

7) *Wigner ville distribution (WVD)* - is a time-frequency transformation tool which provides good localizations for all the times and frequencies simultaneously. This method loses phase information, so WVD is not commonly used for signal de-noising. In fPCG analysis, WVD is set for characterizing fHS by their instantaneous frequencies [62].

- Balogh *et al.*, 2011 [62] used WVD for identification of murmur and for investigation of the splitting interval of S2 sound. They concluded that WVD is reliable even in case of noisy records and that this method can identify murmurs or extract discriminative features with high precision.

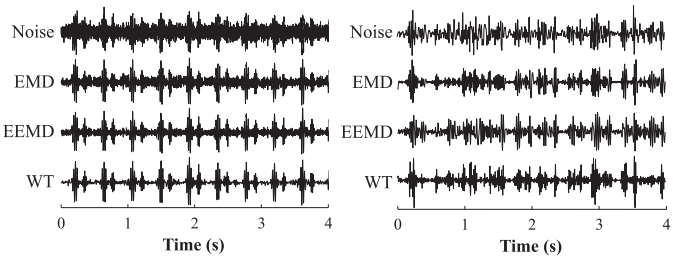
8) *Non-negative matrix factorization (NMF)* - this method utilizes the non-negative matrix factorization algorithm and serves for removal of unwanted noise from the processed signal. It is not an effective method for signal processing but can be used as a classifier for de-noised signals [63].

- Chourasia *et al.* [63] used NMF for fPCG de-noising. They tested the effectiveness of this method on simulated and real-time fPCG signals and concluded that this method improves SNR in the range of 12 to 30 dB, so this method is useful for assessment of fetal well-being.
- In [38], N. Dia *et al.* proposed a new method based on NMF. To verify the proposed algorithm, the authors used their own records, which were obtained from four pregnant women between the 38th and 39th week of pregnancy. Signals were recorded using a cardiomicrophone located on the mother's abdomen. In two subjects, the CTG signal was recorded simultaneously with the fPCG signals so it could be used as a reference. The fPCG signals were sampled at 1000 Hz and preprocessed with band-pass filter in the range of 20–200 Hz. The performance of the proposed system was verified by the accuracy of determining the fHR value with respect to the CTG reference only for the first 2 records.

9) *Combination of different techniques* - each method is associated with certain advantages and limitations. Therefore, many authors proposed systems that consisted of more than one signal processing methods to increase the quality of the fPCG extraction:

- Zahorian *et al.* [64] developed a dual transmission model of fHS. They applied autocorrelation technique for the determination of fHR from fPCG signal. They concluded that the properties of the resulting signal depend on the fetal position. The experiment on 12 patients showed that this model is suitable for fHR determination.
- In [3], the authors focused on the development of an fPCG signal generator, which will allow simulating various physiological and pathological conditions of the fetus, but also testing the algorithm of fHR extraction from fPCG. The developed extraction algorithm is based on a combination of band-pass filter (34–54 Hz), Teager Energy Operator (TEO) and a non-linear time operator for the detection of S1. The authors state that the accuracy of the proposed extraction method according to the ACC parameter is between 68–99%.
- Tang *et al.* [65] proposed a method of cyclic frequency spectrum (CFS) for fHR monitoring using the frequency of repetition of HS, which can be extracted from peaks in the cyclic frequency spectrum without detection of sound pulses and noise reduction. Simulated signals from the SIMFPCGDB database were used to test CFS performance. The evaluation of the performance of the proposed method was performed on the basis of the statistical parameter ACC.
- Huimin *et al.* [66] introduced a combination of EMD and lifting wavelet transform (LWT) methods to suppress the fPCG noise. Subsequently, the spectrum of the signal envelope was obtained by Hilbert transform (HT), and the resulting fHR values were obtained by the cepstrum method. The method was tested on 20 real records obtained from women between 30 and 40 weeks of pregnancy. The authors did not publish statistical results, only stated that the determined value of fHR was accurate.
- Samieinasab and Sameni [35] proposed a single-channel fPCG extraction method based on single channel blind source separation (SCBSS) combining EMD, NMF, and clustering algorithms. The method was tested on 50 real records and the concurrently measured CTG trace was used as a reference. The accuracy of the algorithm in determining fHR was 83–100% with respect to the reference.
- A combination of EMD and machine learning techniques has been reported by Vican *et al.* in [39]. The algorithms were tested on fPCG data recorded on 7 subjects in third trimester with a microphone and evaluated using simultaneously recorded fHR trace by means of portable Doppler device. The EMD method was used to extract signal features (statistical and spectral), which were used together with conventional audio features for subsequent estimation and classification and S1. Random forest (RF), logistic regression (LR), linear support vector classifier (SVC) and multilayer perceptron (MLP) were used for classification. The most effective was the combination of EMD and RF, which achieved an accuracy of 74.13% in the S1 detection.

Objective comparison of the results of these studies is relatively difficult, since there are currently not enough suitable databases with fPCG records of a good quality with proper annotations of fHSs. Therefore, many authors use synthetic data for their experiments, however, the results acquired in synthetic data significantly differ from those obtained in real data experiments, see example of the analysis in Fig. 5. Another problem when comparing these results is that the authors use different evaluation parameters. Some authors do not even evaluate their results by mean of objective statistical parameters and provide only graphical outputs of extracted fPCG signals in the results.



(a) Simulated signals. (b) Real signals.

Fig. 5. Example of the filtration carried out using the same systems (EMD, EEMD, and WT).

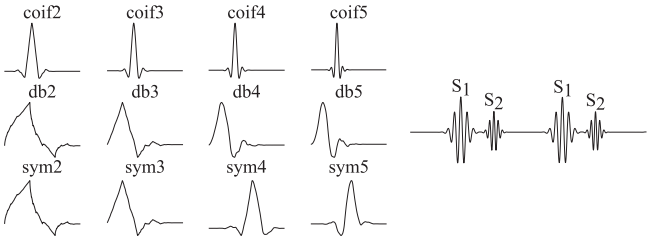


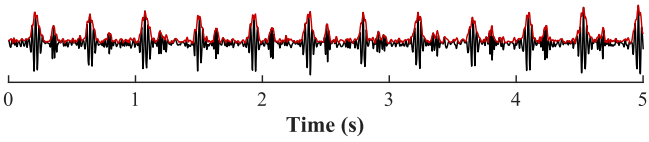
Fig. 6. Example of different mother wavelets (*Coiflets*, *Daubechiens*, *Symlets*) in comparison with the fPCG signal shape.

According to the literature review, the greatest development in the field of fPCG signal extraction was achieved by WT-based methods. The authors of the above studies agree that if this method is optimally set, it can effectively filter out the disturbed PCG signal, which can then be used to determine the variability of the fetal heart rate. In most cases [17], [37], [49], [67], the studies conclude that the most appropriate is the use of a 4th order *Coiflet*, since it is the closest one to the morphology of the desired signal, see Fig. 6. However, the methods of individual authors differ in the levels of decomposition, the type of thresholding and the thresholding algorithm used.

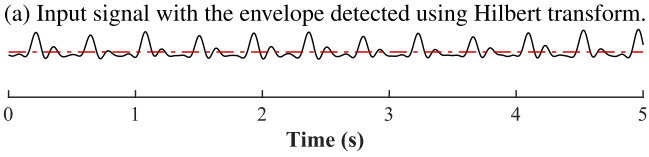
When evaluating the results obtained with *synthetic* and *real* data, following can be stated:

- All the methods tested on the *synthetic* data reduce the noise contained in the signal to some extent. The filtered signal can then be used to determine the fHR.
- The quality of the extracted signal from *real* data depends on their quality, the location of the measuring probes, the gestation age and position of the fetus and the effects of the artifacts. If the input signal contains a significant amount of noise, it is almost not possible to eliminate it completely. The extraction of the fPCG signal is thus more difficult, and this may cause incorrect determination of the instantaneous fHR and the course of the fHR over time.

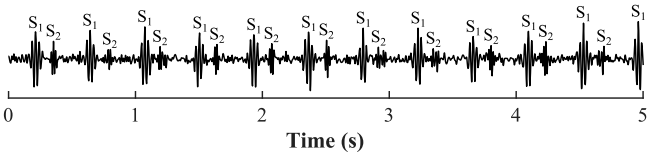
If we compare the results of experiments reported by Tomassini in [19], [37] and by Strazza in [49], where the authors used the same evaluation parameters and the same dataset from the SUFHSDB database, we can state that the PCG-Decompositor method described in [49] achieved the best results compared to the reference. However, the other tested methods of these authors did not perform significantly worse and deviated a maximum of ± 3 bpm from the reference value.



(a) Input signal with the envelope detected using Hilbert transform.



(b) Smoothed envelope using FIR filter (LPF with cut-off frequency 40 Hz) together with a set threshold for detection of S1 and S2.



(c) Input signal with the fHSs above threshold detected.

Fig. 7. Steps of fHS detection using the detector based on Hilbert transform.

C. Heart Sounds Detection

Once the fPCG signal is extracted, fHS detection can be performed to obtain information about fHR and other important clinical parameters. Accurate detection of fHS is a critical factor in determining fHR. Contrary to R-peak detection in ECG signal, which is more prominent and easier to distinguish by a detector, HS detection is more challenging even in the filtered data [68]. The detectors need to be tailor-made for the given purpose – some authors [47], [55] deal only with the detection of the S1, while others deal with the detection of both S1 and S2, e.g. [17], [19], [69]–[71]. Both approaches are sufficient to determine fHR.

Among the simplest detection algorithms are based on creating an envelope and searching the local maxima in the signal. As an illustration, we provide the outputs of a detector based on the Hilbert transform (see Fig. 7), consisting of several steps:

- *Envelope creation* - the envelope of the input fPCG signal is obtained using the Hilbert transform. The estimated envelope is then smoothed using a low-pass FIR filter (see Fig. 7(a));
- *Thresholding* - a threshold calculated as 20% of the amplitude of the 5th highest peak in the signal envelope is determined (see Fig. 7(b)); local maxima (peaks) exceeding this threshold are determined.
- *Classification* - decision algorithm is introduced to remove redundant peaks based on a minimum distance of 100 ms between the detected peaks. Finally, the classification of S1 and S2 based on the physiological condition that the systolic interval between S1 and S2 is shorter than the diastolic interval between S2 and S1 (see Fig. 7(c)).

Currently, a relatively large number of studies are focused on accurate detection of S1 and S2 in the adults' PCG signal. An extensive summary of all possible HS detection techniques can be found e.g. in [72], [73]. Fortunately, most of these advanced

TABLE V
SUMMARY OF FPCG FEATURE EXTRACTION AND CLASSIFICATION METHODS

Authors, year, source	Method	Purpose	Data type	Data source
Kovács et al. (2009) [80]	Correlation method	Cardiac murmurs detection	Real	Telemedicine fetal monitor in comparison with ECHO and CTG
Kovács et al. (2010) [47]	Combination of multistage autocorrelation, WT, concordance and an individual model-based correlation algorithm	Cardiac murmurs detection	Real	Fetaphon-2000
A. T. Balogh (2012) [25]	Analysis of systolic envelope properties	Detection and classification of cardiac murmurs for diagnosis of congenital heart diseases	Real	Fetaphon-2000
Kovács et al. (2020) [82]	Segmented Structures with Frequency Splitting	Fetal Breathing Movement Detection	Real	Acoustic sensor

methods can also be used to detect fHS in the extracted fPCG signal. These include for example methods based on energy detection and analysis [69]–[71], [74], [75], duration-dependent hidden Markov model (DHMM) [76], Hilbert transform [77], Gaussian regression [78], or EEMD algorithm in combination with the kurtosis features [79].

D. Feature Extraction and Classification Methods

As mentioned above, the fPCG method as an additional monitoring technique is of great importance in the early diagnosis of some fetal heart diseases that are not normally detected during pregnancy. These are mainly heart murmurs. However, PCG also allows the indication of other abnormalities of fetal heart function, e.g. heart rhythm irregularities such as extrasystole, arrhythmias, bradycardia and tachycardia. In the case of fPCG, one is also able to detect fetal breathing movements by selecting 0.7–1.2 Hz spectral components of the rhythm repetition rate [80], [81]. Such monitoring is important since the absence of fetal breathing movements is associated with intrauterine growth restriction [82].

Several types of methods for the detection and classification of cardiac murmurs have been investigated in PCG monitoring in adults. The aim of the studies was to verify and subsequently design a system for automatic classification of cardiac signals from the PCG signal. For example, methods based on the principle of detection based on fractal features [83]–[85], or methods based on the principle of neural networks were tested, see [86], [87]. In [29], the authors test the detection of cardiac murmurs caused by mitral regurgitation, mitral stenosis or aortic regurgitation from the PCG signal using the adaptive-neuro fuzzy inference system (ANFIS) and Hidden Markov Model (HMM) based classifiers. In [88], DWT and Shannon entropy were used for segmentation as a property in a classifier based on the ANFIS algorithm. Furthermore, detection based on dynamic parameters of various time-frequency representations was introduced in [89], [90]. In [91], screening of murmurs in newborns using the WT and the K-means clustering method is proposed. There are a number of other publications on the classification of murmurs, see [92]–[95]. All these studies deal with PCG recordings of children and adults. These techniques can only be partially used to extract fHS, as there are large differences between fetal and postnatal PCG signals, which is a limitation. The main differences include, in particular, much narrower bandwidth of the fetal PCG signal due to attenuation caused by maternal tissues and the lower SNR.

Under normal circumstances, we distinguish only two HS in the fPCG signal due to the action of the valves (S1 and S2). In the case of certain morphological abnormalities, murmurs appear as a result of turbulent blood flow. The detection of a murmur is very difficult because noise from multiple sources damages the sound signal of the fetus' heart at low intensity. The automated murmur detection method relies on the fact that if a murmur is present, it occurs in almost all cardiac cycles, usually at a similar point in time, duration, and envelope shape, while noise does not correlate with heart rate. Table V provides an overview of following publications dealing with the issue of detection and evaluation of cardiac murmurs from the fPCG signal:

- In [80] (2009), Kovács *et al.* dealed with perinatal screening of heart murmur using fPCG. Signals were obtained from a total of 820 pregnant women in the 28th - 40th week of pregnancy. One group of data was measured using a telemedicine fetal monitor at home and the other one after a planned examination by fetal echocardiography. In both cases, a 20-minute CTG recording was also performed. The measured signals were then analyzed by a signal processing program based on multiple cycles of the recorded signal in order to find the signal shapes that are systematically repeated at the same time intervals (e.g. between wave S1 and S2). The search is based on the correlation method. During the screening, 43 occurrences of murmurs were detected out of all 820 cases. Their causes were subsequently identified using ECHO and subsequent infant examination. The results showed that a large proportion of the murmurs found were innocent murmurs (28 of 43 cases), but there were also murmurs caused by ventricular septal defect, murmurs due to atrial septal defect, or murmurs due to aortic or mitral stenosis. The authors state that fPCG is a suitable tool for the detection of heart murmurs and severe heart defects in perinatal age.
- Kovács *et al.* [47] (2010) presented a heuristic method for evaluating fHS simultaneously with the combination of the multistage autocorrelation method, WT, concordance and an individual model-based correlation algorithm. In this study, more than 3,000 acoustic signals were recorded with a Fetaphon-2000 phonocardiographic CTG device.

The authors used 25 random records and applied the above methods and their combinations. The individual methods show quality results, but their combination provides the highest hit rate at the expense of higher computational requirements. The authors conclude that this combination can achieve reliable HR and murmur detection even in the case of noisy recordings.

- A. T. Balogh (2012) in [25] presents the principles of detection of heart murmurs in the fetuses and preterm infants with ductus arteriosus. The fetal audio signal was recorded using the telemetry fetal monitoring system using Fetaphon-2000 device to collect aPCG signals introduced in [47]. The measurement was also supplemented by the simultaneously recorded CTG trace. A heuristic method using the principles of correlation or WT was developed for fPCG extraction. Fractal characters are used to classify murmurs. The proposed method therefore uses the cyclostationarity of the signal. The algorithm calculates the envelope of the systolic segment based on local extremes. Analysis of certain envelope properties (such as shape, maximum and average value, maximum and average rate of change) allows more accurate murmur detection. The author further states that despite the verification of this method as a possible detector of heart murmurs, further research is needed to quantitatively improve the sensitivity and specificity of the proposed method.
- Finally, in [82], Kovács *et al.* proposed an algoritm for fetal breathing movement detection. To analyze the individual episodes, the authors split the frequency band into single test frequencies. To differentiate the desired features from the disturbing signals (e.g. hiccups, body rotation and limb movements), the starting points of the fetal breathing movements are characterized by an approximation process.

The fPCG feature extraction and classification is an important topic because it could open up new possibilities for prenatal coronary heart disease screening for comprehensive fetal examinations, especially in the low-risk population. In addition, the equipment needed to record fPCG is inexpensive and therefore readily available. Although methods of detecting heart disease can be applied in the second half of the second trimester at the earliest, early detection of possible cardiac pathologies could contribute to a well-prepared delivery and early postnatal treatment.

IV. Discussion

The aim of this section is to summarize and discuss further challenges and future directions in the field of fetal phonocardiography. The main challenges can be summarized as follows:

- *Optimization of the methods* - there are several remaining signal processing problems associated with high amount of undesired signals with overlapping frequency bands, and low magnitude of the fetal signal compared to the surrounding noise. Although many authors achieved promising results, there are still considerable number of limitations of each method. This can be overcome when the methods are either combined or optimized for given purpose yet taking into consideration variable nature of the noise associated with fPCG signal. This problem is further discussed in Section IV-A.
- *Sensor placement* - varying sensor placement on mother's abdomen due to changes in fetal position. The incorrect probe placement is also closely correlated with attenuation of detected sounds as it passes through the environment (fetal fluid, uterine contractions, fetal limbs, etc.). This challenge is further discussed in Section IV-B.
- *Lack of databases* - the lack of quality data to train and test the methods is one of the main reasons for slow progress in this field, as discussed in Section II-B. It is the main drawback for the development of the methods based on artificial intelligence or machine learning. These methods require high amount of input data to train a successful model and also to test them. These methods have the potential to improve the accuracy of the classification of the fetal pathological states, which is a great challenge in the today's clinical practice, see Section III-D.

A. Algorithm Optimization

Algorithm optimization is a process in which parameters affecting the quality of filtration are set so that the obtained signal extraction results are as accurate as possible. It should be noted that the optimal setting is different for each signal and depends on many criteria such as: the type of method used, the sampling frequency or the location of the sensors for sensing the signal. Optimal parameters can be found, for example, by heuristic methods, manual search, or grid search [33]. So far, only a small number of publications dealing with the issue of optimization of filtration parameters during fPCG signal extraction have been published. A more detailed description of selected publications dealing with the issue is below.

- In [60], a method for optimizing LMS-based algorithms (LMS and DLMS) for fPCG extraction is presented. The experiments were performed on synthetic data generated by a generator introduced in [96]. The SNR (%) and PRD (%) parameters were used to evaluate the filtration quality. The optimal choice of the size of the filter parameters (M and μ) for both tested algorithms was performed by means of a network search. First, the value of the parameter μ was optimized. During this step, the value of the parameter M was set to a constant value $M = 100$, while the value of the parameter μ ranged from 0.0001 to 1. Subsequently, the values of SNR and PRD were calculated. When the SNR value was the highest, the optimal setting of the parameter μ was obtained. The optimization of the parameter M proceeded in the same way. The optimal value of the parameter M was determined for μ and the variable from 1 to 500. After finding the optimal solution, the extraction of the fPCG signal was performed. The results showed that both optimized algorithms were able to effectively suppress the parent component. The authors state that the subject of further research will be the verification of the optimized system on real data.

- In [67], a study dealing with the optimal setting of the filter for fPCG signal extraction using the WT is presented. The optimal choice of parameters depends on several factors, namely the type of wavelet, the level of decomposition, the threshold method and the type of thresholding. Only *Haar*, *Daubechies*, *Symlets* and *Coiflets* orthogonal wavelets were used for testing since they allow the use of a fast algorithm. Decomposition levels from 1 to 10 and 4 threshold rules were tested for each wavelet. Although there was no evidence that a single wavelet was best suited to suppress the parent component, there were some wavelets that were slightly better than others. Experimental results showed that *Coif4*, *Coif5*, *Db11*, *Db14*, *Db20*, *Sym9*, *Sym11*, and *Sym14* showed better results. The use of five levels of decomposition proved to be adequate. Soft thresholds definitely outperformed hard ones, and of the 4 threshold selection rules, minimax and SURE achieved the best results. In the future, the authors want to test the conformity monitoring method as a possible method of fPCG extraction.

Currently, optimizing filter parameter settings is not a fully explored topic. Many publications on the extraction of fPCG or fHS signals from aPCG signals sensed from the surface of the mother's abdomen use various filtering methods. However, most authors do not deal with the issue of optimization or do not mention it. For most publications, testing is performed randomly, using a number of methods and alternatives, from which the one that achieves the best results is subsequently selected (see [37], [48]).

However, the optimization of individual parameters could also take place in a similar way as we suggest in [97] during fECG signal extraction, when the optimal optimization is searched using a 3D optimization graph so that variable values are set for individual parameters in a certain range after e.g. 0.1 steps. Based on the F1 parameter, the best setting for the given record was then searched.

As already mentioned, the research in the field of optimization of fPCG signal extraction algorithms has not been sufficiently undertaken. However, available studies suggest that it could significantly contribute to increasing the accuracy of fPCG signal extraction and thus the determination of fHR, which is an essential indicator in clinical practice. Therefore, we see the potential to test the optimization of individual filtration methods that are used to extract fPCG from aPCG.

B. Sensor Placement

As mentioned above, the location of the aPCG signal from the surface of the mother's abdomen varies during pregnancy depending on the position of the fetus. The sensor deployment will to some extent also affect the quality of the extraction of fPCG and fHR. The sensor placement has not yet been standardized. In general, it is not possible to precisely determine the optimal position of the sensor, as it depends on the variable position of the fetus. As a result, the sensor is usually located based on the experience of a physician. Generally, fPCG signal of the best quality can be detected where the fetal back is in direct contact with the mother's abdomen [98]. Conversely, when the fetal signals are recorded from the locations on the maternal abdomen that are further from the fetal heart, their intensity is much lower and quality worse. Although this solution allows us to obtain relatively good signals, it means having different sensor positions for different women at various stages of pregnancy. However, there are some guidelines available for the physicians, as illustrated in Fig. 8.

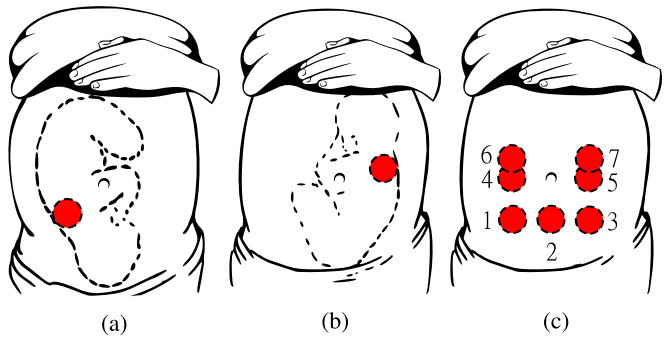


Fig. 8. Optimal placement of the sensor according to the fetal position. (a) Example of the vertex position. (b) Example of the Breech position. (c) Deployment according to stage of pregnancy: Early stage (12–24 weeks, position 1, 2, and 3), Middle stage (24–32 weeks, position 1, 3, 4, 5), Late stage (32–40 weeks, positions 1, 3, 6, 7).

One of the possible solutions is creating a universal device using multiple sensors for fPCG monitoring, from which only the best ones are selected. We now provide an overview of studies dealing with the position of sensors when capturing their own data.

- J. Zuckerwar *et al.* (1993) [99] gradually proposed three options for the placement of piezopolymer pressure sensors for monitoring fHS. In the first version, the authors used only one sensor located in the lower abdomen of the mother. The second version already contained three sensors placed linearly next to each other. The third version contained a seven-member array of sensors.
- M. Samenisab *et al.* (2015) [35] sensed aPCG signals using only one sensor located on the underside of the maternal abdomen. Specifically, it was an electronic stethoscope JABES. The position of the sensor was variable depending on the current position of the fetus in the uterus. The data measured in this way were subsequently published for the needs of other scientific teams so that they could test their methods and extraction systems on them, e.g. for the determination of fHR. Today, these signals are contained in the SUFHSDB database.
- The problem with the location of the sensors was solved by A Khandoker *et al.* (2018) [100] by creating a four-channel fPCG monitor using 4 audio transducers placed on the mother's abdomen in a cross. Thus, this system provides at least one quality aPCG record without affecting the position of the fetus in the uterus. The functionality of the system was tested on 15 pregnant women with a gestational age of 33–40 weeks. Cardiac activity recordings with fPCG and fECG were compared and very promising results were obtained.

- Y. Yao *et al.* (2020) [101] presented the PARIS monitoring system for the continuous sensing of fHS, which are further converted to fHR. In this case, fHS are sensed by three acoustic sensors located on the mother's abdomen in the shape of a triangle. The authors state that the application of three sensors is quite sufficient to obtain a quality fPCG signal. A convolutional neural network (CNN) is then used to locate the signal source, which determines in which of the nine regions the fetal heart is located. The measuring system was subsequently tested on 16 pregnant women aged 22 to 44 years. The results of the experiments show that PARIS makes it possible to measure the fHR with an average error of 4.3 beats per minute.

Limited number of studies have been focused on the issue of optimizing the location of sensors for sensing high-quality fPCG signals. From Table IV summarizing the overview of fPCG extraction methods and their results, it can be observed that a relatively large group of authors tested their proposed methods on their own real data. However, most of them do not indicate how the signal sensors were arranged. That is why we certainly see the potential for further research here.

V. Future Directions

Several studies have already shown that non-invasive fPCG or fECG are a very effective alternatives to the Doppler-based CTG ([35], [102]–[105]). These methods provide additional information to fHR, which cannot be obtained by conventional CTG monitoring, such as detection of abnormalities in fetal heart function (murmurs, split effect, extrasystoles, arrhythmias), prediction of congenital heart and developmental defects, or determination of fetal position in the uterus. However, both fetal ECG and PCG have a number of disadvantages. For example, NI-fECG signals are difficult to detect between the 28th and 32nd week of pregnancy, when vernix caseosa forms around the fetus [33]. The quality of the fPCG signal is affected by surrounding acoustic sounds and the location of the fetus relative to the sensor. The results are also significantly affected by BMI, because the sensitivity of the sensors is proportional to the thickness of the patient's abdominal wall [33]. These and other problems of non-invasive fetal monitoring could be solved by a combining of individual monitoring techniques. An interesting idea is to combine the fECG and fPCG measurement since both waveforms manifest the same phases of the cardiac cycle. The combination of fPCG-fECG methods would be extremely also advantageous for its feasibility and low cost. This could have huge benefits not only in home care but also in future clinical practice. Several authors have already addressed this issue:

- In [106], Ruffo *et al.* considered the idea of using a combined fECG-fPCG system for fetal monitoring. They provided several examples of extracted fECG and fPCG signals obtained by combined monitoring. The authors state that by monitoring the time interval between e.g. the P wave in fECG and the S1 wave in fPCG, it is possible to obtain information on fetal circulating impedance. By monitoring the variable time period, it would then be possible to identify the endangered fetus. As this is only a proposal for the possibility of using such a combined method, there are no more detailed descriptions of the experiments performed (e.g. description of the data on which the system was verified, or the location of sensors or filtering methods for signal conditioning).
- In [102], Gobillot *et al.* introduced a preliminary study on non-invasive fetal monitoring using PCG and ECG. The signals were sensed by electrophysiological sensors (ECG) and microphone acoustic sensors (PCG) simultaneously with CTG recording. The aim of this study was to increase the reliability of fHR monitoring and to verify the use of this non-invasive multimodal monitoring technique in clinical practice. The system was tested on 7 pregnant women between the 24th and 39th week of pregnancy with normal BMI. These results show the feasibility of this approach, but further development is needed before it can be used in everyday obstetric practice. The future goal of the authors is to develop a reliable robust device that connects ECG and PCG in order to effectively monitor fHR.
- This approach is used in the commercially available device called Invu (NUVO Inc.), the first remote monitoring system approved by the the United States' Food and Drug Administration. This system contains 4 acoustic and 8 electrical sensors located in a wearable belt (see Fig. 9. In [107], Mhajna *et al.* tested this system on 147 volunteers with gestational age from 35 to 40 weeks. The aim of the study was to compare the fHR and mHR data obtained by Invu with the CTG traces measured simultaneously. The raw data from each Invu wearable belt sensor is sent to the mobile device via Bluetooth for analysis. It consists of data validation, signal pre-processing and interference filtering, HR detection from fECG and fPCG independently of each other, and fusion of acquired heartbeats from fECG and fPCG signals to calculate fHR and mHR curves. Statistical parameters of correlation mean difference and Bland-Altman analysis were used to compare the output from the Invu and CTG systems. The results showed that there was a significant correlation between fHR from Invu and CTG ($r = 0.92$). Estimation of mHR using Invu also performed well in comparison with CTG, where the degree

Fig. 9. Example of a commercially available device based on concurrent PCG and ECG monitoring: Invu sensor band by Nuvo [108].

of correlation between the two signals was found to be $r = 0.97$. The authors state that although the fHR and mHR outputs were sensed by the Invu system using different methods, the results were very similar to the outputs obtained with current standard monitoring techniques.

These studies show that the system using a combination of fPCG and fECG is functional and is a promising alternative to the CTG method. This combination not only provides even more accurate information on the current state of the fetus (than when this information is captured by different methods independently), but also increases the sensitivity and specificity of the monitoring technique, especially in cases where fECG-only fHR monitoring is not completely possibly due to the formation of sebum on the surface of the fetal body.

Furthermore, there is the possibility of continuous monitoring of fHR (e.g. 24-hour recording) for the detection of fetal arrhythmias or recording of other heart disorders even in the early period of pregnancy. The music of the distant future is no longer the development of a reliable device that will serve for the so-called eHealth, or in the home environment as a simple home monitor fHR (as an Invu device). Combinations of other methods, such as fPCG with fMCG, do not appear to be tested or have not been published. However, it is possible that the use of fMCG for these purposes is not entirely attractive due to the size of the equipment, the price or the complexity of the equipment required [106].

VI. Conclusion

Fetal phonocardiography is a promising method for fetal monitoring which is both non-invasive and passive. This makes it suitable for continuous monitoring of heart rate variability compared to the techniques currently used in the clinical practice. Moreover, it provides information about mechanical activity of the fetal heart, that is not contained in the other rising method, fetal electrocardiography. The greatest issue associated with this method is the interference from various sources, overlapping the desired signal in the time and frequency domain. As summarized herein, there have been many attempts to solve this issue and great amount of advanced signal processing methods introduced in the past decade. The most successful and prevalent method for fPCG signal extraction and processing is the wavelet transform, but other methods also achieved promising results. So far, very few methods based on artificial intelligence or machine learning have been tested in the field of fPCG. This is caused mainly due to lack of data that these methods require. Nevertheless, these methods could achieve good results especially in classification tasks. The future research should focus on combining individual methods of fetal monitoring (such as fetal electrocardiography) and signal processing and thus minimizing their limitations and enabling accurate automatic detection of abnormalities and classification of fetal health in clinical practice but also in home monitoring.

Appendix A
List of Abbreviations

ACC	accuracy.
ANFIS	adaptive-neuro fuzzy inference system.
aPCG	abdominal phonocardiography.
AT	autocorrelation.
AWT	adaptive wavelet transform.
BMI	body mass index.
BSS	blind source separation.
CFS	cyclic frequency spectrum.
CNN	convolutional neural network.
CTG	cardiotocography.
dB	decibel.
DHMM	duration-dependent hidden Markov model.
DLMS	delayed least mean square.
EEMD	ensemble empirical mode decomposition.
EFICA	efficient version of independent component analysis.
EMD	empirical mode decomposition.
F1	harmonic mean of sensitivity and positive predictive value.
FD	fractal dimension.
fECG	fetal electrocardiography.
fHR	fetal heart rate.
fHS	fetal heart sounds.
fM	fetal motion.
fMCG	fetal magnetocardiography.
FN	false negative.
FP	false positive.
fPCG	fetal phonocardiography.
FPCGDB	fetal phonocardiograms database.
fR	fetal respiration.
FT	Fourier transform.
HMM	hidden Markov model.
HS	heart sounds.
HT	Hilbert transform.
ICA	independent component analysis.
IMF	intrinsic mode function.
IUGR	intrauterine growth retardation.
LMS	least mean square.
LR	logistic regression.
LWT	lifting wavelet transform.
mHR	maternal heart rate.
mHS	maternal heart sounds.
MLP	multilayer perceptron.
mM	maternal motion.
MP	matching pursuit.
mPCG	maternal phonocardiography.
mR	maternal respiration.
MSE	mean square error.
NLMS	normalized least mean square.
NMF	non-negative matrix factorization.
PCA	principal component analysis.
PPV	positive predictive value.
PRD	percentage root-mean-square difference.
RF	random forest.
RMSE	root mean square error.
S1	first heart sound.
S2	second heart sound.
SBN	sensor and background noise.

SCBSS	single channel blind source separation.
SE	sensitivity.
SFPDB	simulated fetal phonocardiograms database.
SNR	signal-to-noise ratio.
STDT	soft-thresholding denoising technique.
SUFHSDB	Shiraz university fetal heart sounds database.
SVC	support vector classifier.
SVD	singular value decomposition.
TEO	teager energy operator.
TP	true positive.
UC	uterine contraction.
WT	wavelet transform.
WVD	Wigner ville distribution.

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