A Review of Signal Processing Techniques for Non-Invasive Fetal Electrocardiography

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(Methodological Review)

***Abstract*—Fetal electrocardiography (fECG) is a promising alternative to cardiotocography continuous fetal monitoring. Robust extraction of the fetal signal from the abdominal mixture of maternal and fetal electrocardiograms presents the greatest challenge to effective fECG monitoring. This is mainly due to the low amplitude of the fetal versus maternal electrocardiogram and to the non-stationarity of the recorded signals. In this review, we highlight key developments in advanced signal processing algorithms for non-invasive fECG extraction and the available open access resources (databases and source code). In particular, we highlight the advantages and limitations of these algorithms as well as key parameters that must be set to ensure their optimal performance. Improving or combining the current or developing new advanced signal processing methods may enable morphological analysis of the fetal electrocardiogram, which today is only possible using the invasive scalp electrocardiography method.**

***Index Terms*—Fetal electrocardiography, noninvasive fetal (foetal) monitoring, signal processing, electronic fetal monitoring, fetal heart rate, morphological analysis.**

I. Introduction

FETAL heart rate (fHR) monitoring in its early form was based on the auscultation methods, i.e. intermittent observations of the fetal heart sounds [1]. Progress in electronics and computers science brought to the introduction of the first fetal monitors based on phonocardiography in the middle of the 20th century [2]. Yet these inventions were still challenged by the need to automatically distinguish between the maternal and fetal heart sounds [3]. Consequently, in 1953, the first attempt was made to continuously monitor fHR by means of non-invasive fetal electrocardiography [4]. In the following decade, invasive monitoring tools were introduced, including the intrauterine catheter [5], fetal scalp electrode [6], and cancellation system [7], which are still in use. These innovations brought to a better appreciation and understanding of a wealth of information about the fetal health state that can be extracted from the signals, such as fHR and uterine contractions [8], [9]. Based on these observations, in 1969, Huntingford and Pendleton published the first classification system of fHR [10].

Almost simultaneous to the development of fetal electrocardiography (fECG), the ultrasonic fetal cardiotocography (CTG),[1] a non-invasive method for simultaneous monitoring fHR and uterine contractions was introduced [11]. The popularity of this noninvasive method grew as it was accepted by the medical community throughout the 1960s with the first commercially available model (Hewlett-Packard 8020A) introduced into delivery rooms in 1968 [12]. Some practitioners noted the virtual disappearance of fetal death in labor following its introduction [13]. However, despite great expectations, application of CTG in clinical practice did not result in a rapid reduction of undiagnosed fetal hypoxia or a decrease in the incidence of cerebral palsy [14], [15]. This may be attributed to the fact that the first monitors were rather unreliable and suffered from considerable inter- and intra-observer disagreement since the data were difficult to interpret [16].

Additionally, in late 1970s and 1980s, several studies [17]–[23] suggested that CTG was one of the factors responsible for the significant rise of Caesarian section (C-section) rates. However, some authors have pointed out that introduction of the CTG is only one of the factors causing this rise [24], [25]. Other suggested causes [24], [25] were new obstetrical methodologies

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[1]In English-speaking countries, particularly in the United States, the term used instead of CTG is electronic fetal monitoring (EFM), the name given in the 1960s to describe this new technology. However, nowadays use of this term may be misleading. Therefore in 2015, the consensus promoted by the International Federation of Gynecology and Obstetrics agreed that cardiotocography is the term that best describes this monitoring technique. In this paper, the term EFM will only be used for the electronic fetal monitoring in general.

introduced in the late 1970s, which added previous C-section or obstructed labour to the indications for a C-section.

Fig. 1 shows the trend of the C-section rate (per 100 deliveries) and perinatal mortality ratio (per 1000 live births) in the US between 1965 and 2017 (based on [22], [26]–[29]). While no causal effect is implied here, it can be noted that the rise in the C-section rate was steepest after the introduction of CTG to clinical practices. In parallel, perinatal mortality decreased significantly after CTG was introduced. However, it has not significantly decreased in the past 30 years, while the C-section rate has continued to increase gradually. There is little evidence of a positive correlation between C-section rates and perinatal outcomes [30]. According to the World Health Organization (WHO) *Statement on Caesarean Section Rates* [31], this rate should be between 10-15%. Moreover, WHO states that rates higher than 10% are not associated with reductions in maternal and newborn mortality rates. It is therefore understandable why Simsek *et al.* [32] found the current Cesarean birth rates alarmingly high. Taken together, there remains a pertinent need for precise automated systems that can interpret CTG traces or more contextual information than the sole estimated fHR tracing [33].

More accurate fetal monitoring can be achieved by *internal* electronic fetal monitoring, where the fHR is determined using signals measured by a fetal scalp electrode (FSE) [34]. Moreover, in 2007, the Swedish company Noeventa Medical (Molndal, Sweden) introduced the innovative STAN S31, a fECG device which is attached to the FSE and can trace the changes in individual elements of the ECG waveform. In addition, it performs automatic ST segment analysis, which improves the ability to identify fetal hypoxia [35].

Non-invasive fetal electrocardiography (NI-fECG) is among the most promising alternative method for continuous fetal monitoring, which may provide unique physiological information for identifying fetal distress that cannot be obtained by the most prevalent method of electronic fetal monitoring, CTG. The main reason is that the fECG signal carries valuable information, such as pathological states (myocardial ischemia, intrapartum hypoxia, or metabolic acidosis) manifesting as changes in the morphology of the fECG waveform (ST segment, QT interval), that cannot be accessed from the CTG because of the nature of its measurements. Moreover, both mother and fetus are not exposed to any kind of radiation. Furthermore, uterine contractions can be monitored by sensing the electrical activity on the maternal abdomen [41]. This method is known as electrohysterography and it has a great potential for uterine activity monitoring [42]. Therefore, NI-fECG is theoretically capable to supersede CTG [43].

(a)

(b)

Fig. 2. Examples of CE or FDA-certified commercially available NI-fECG-based devices. a) Monica AN24, Monica Novii Wireless Patch System [37], MERIDIAN M110 Fetal Monitoring System; b) PUREtrace [38], Nemo Fetal Monitoring System [39].

Over the last decade, the first commercially available devices for fHR monitoring based on NI-fECG were approved by the Food and Drug Administration (FDA), namely the Monica AN24 (2012) and Monica Novii Wireless Patch System (2014) (Monica Healthcare Ltd., Nottingham, UK), MERIDIAN M110 Fetal Monitoring System (2017) (MindChild Medical, Inc., North Andover, MA, USA), and PUREtrace (2017) (Nemo Healthcare, Veldhoven, the Netherlands). In October 2018, Nemo Healthcare released the Nemo Fetal Monitoring System, which is CE-certified and is now available for commercial sale and clinical use in Europe. The available NI-fECG devices differ in the ways that they are physically applied on the body and the number of electrodes they use (see Fig. 2). While Monica AN24 uses five individual electrodes (4 sensing and 1 common electrode), the other NI-fECG devices utilize a disposable patch system, which incorporates electrodes that can record both ECG and electromyography (EMG) signals.

The signal recorded on the maternal abdomen is composed of a mixture of fetal ECG signal, maternal ECG (mECG) and noise. In addition, the amplitude of the maternal signal is usually much stronger than the fetal one and both have a similar frequency content, challenging the separation of the fetal and maternal signals in both time and frequency domains. Thus, accurate extraction for morphological analysis of the fECG waveform can be challenging [36]. A number of researchers have been focusing on finding the best method for fECG signal extraction. In this paper, we aim to introduce the most promising signal processing techniques used to improve the monitoring capabilities of NI-fECG.

In contrast to adult ECG-related research, there exists a lack of open access fECG databases for robust quantitative evaluation of extraction algorithms. While several researchers introduced synthetic signal generators to produce data for their experiments [44]–[46], the results obtained often differ from those obtained from signals from clinical practice.

While previous reviews on fECG have been published [47]–[52], [47]–[52], this paper provides a critical review of recent advances in NI-fECG signal processing techniques. In addition, it reviews the most promising techniques and current challenges in fECG signal processing and analysis, including practical challenges, optimal system settings, and preprocessing requirements. An inventory of open-access databases and source codes is also provided.

II. Continuous Fetal Monitoring in Clinical Practice

The most common form electronic fetal monitoring (EFM) in clinical practice, CTG, is based on concurrent measurement of the fHR and uterine contractions, using a Doppler-based ultra-

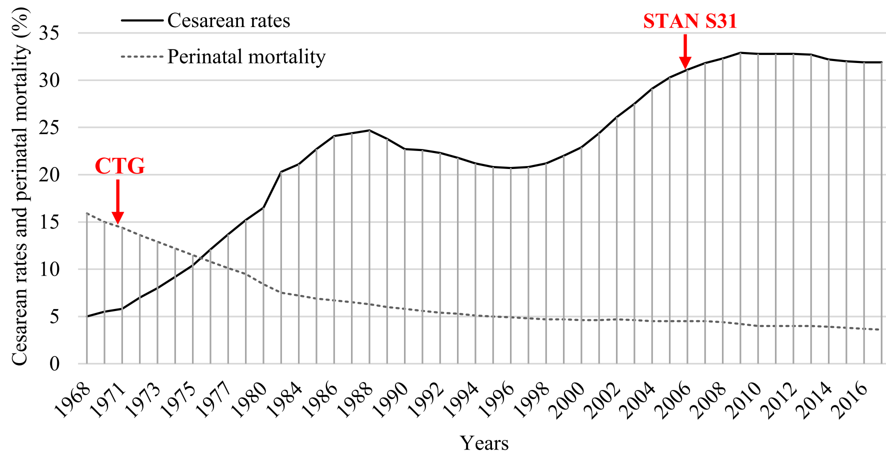

Fig. 1. Cesarean rates and perinatal mortality in the United States from 1965 to 2017, Cesarean section rates per 100 births (%), Perinatal mortality ratio per 1000 live births (20 weeks, through 7 days) based on [22], [26]–[29].

sound transducer and pressure sensor, respectively [1]. The technique, however, requires high physician skills and experience in positioning the transducers. In addition, it is quite vulnerable to both fetal and maternal motion and loses its sensitivity when used with patients with a high body mass index (BMI) [53], [54]. Moreover, since both sensors are attached to the maternal abdomen by means of elastic belts, maternal mobility is limited which is inconvenient especially during labor. Further, some studies have reported low reliability of the technique [53]–[56]. For example, Sartwelle *et al.* [55] report on its problematic false-positive profile, limiting its reliability, especially as legal evidence. This is supported by other studies that investigated the agreement in the decision-making about operative intervention between expert obstetricians [57], [58]. Nonetheless, TG remains the standard of care worldwide, partly due to lack of a superior non-invasive monitoring technique [59], [60].

There are also some practical issues that need to be kept in mind when monitoring the fetus using NI-fECG. Although the fetal heart can be heard without amplification and recorded using NI-fECG as soon as the 20th weeks of gestation, the commercially available devices, such as Monica Novii Wireless Patch System, are only indicated for use from week 37. One of the reasons for this is the gradual disappearance of the vernix caseosa coat after week 37 [62], which has been reported to reduce the effectiveness of NI-fECG recording [61].

For example, Keenan *et al.* showed that volume conductor asymmetry results in significant changes in fECG waveform amplitude and morphology (over 70% errors in the observed T/QRS ratio) [64]. Therefore, this method is most effective in the later stages of pregnancy, especially during the labor [50].

Fetal magnetocardiography (fMCG), an alternative method for prenatal surveillance, involves registration of magnetic fields arising from conduction currents generated by the fetal heart. The morphology of the recorded signal is identical to that of the fECG signal (i.e., QRS complex, P wave, and T wave) but has better signal-to-noise ratio (SNR). Several studies proved that fMCG is a useful tool for early diagnosis of fetal arrhythmias and congenital heart defects [65], [66]. However, fMCG remains an experimental method since it requires careful shielding, skilled technical support, and expensive equipment, which is not widely available [67].

A. Fetal Heart Rate Estimation

All of the currently used monitoring techniques utilize fHR as the main parameter to assess the fetal health state during labor. However, CTG only provides a time-averaged fHR. Other methods, namely fECG, fetal phonocardiography (fPCG) and fMCG, enable beat-to-beat heart rate variability analysis, providing more diagnostically significant information as compared to CTG [68].

There are several factors that need to be considered when monitoring fHR. The sampling frequency often varies based on the technique used. NI-fECG sampling frequency is usually relatively high (around 1 kHz) [69], [70]. Xuan *et al.* investigated the impact of the sampling frequency on the output signal quality [71] and suggested that 900 Hz is a suitable sampling frequency for fHR monitoring based on fECG. Similarly, Behar *et al.* [47] concluded that a minimum 1 kHz sampling frequency should be used to ensure adequate quality. Indeed, most of the available databases use this sampling frequency. Another factor is the peak detector algorithm used and its influence on the accuracy of the fHR variability. A variety of approaches to detect fetal QRS complexes have been proposed, e.g., Christov's beat detection [72] and matched filtering [73], fetal RS slope detection by a dedicated adaptive procedure [74], expectation weighting [75], and echo state recurrent neural network [76]. Yet, no objective comparisons between the methods have been conducted to date; to objectively compare the performance of various fetal QRS detectors, the algorithms must be tested using the same NI-fECG database.

B. Morphological Analysis

Morphological analysis of the fECG waveform in the clinical setting is currently only possible using invasively recorded fECG data. Morphological analysis of the fECG waveform in the clinical setting is currently only possible using invasively recorded fECG data. Such analysis was first enabled by the STAN S31, which traces the changes in individual elements of the ECG waveform such as P wave, QRS complex, and T wave. Using the individual R waves, the fHR is continuously calculated, subsequently also providing the beat-to-beat variability. Moreover, this device can perform an ST analysis (STAN) using the acquired ST segment and T:QRS ratio. Other analysis options include T-wave alternans (TWA) [77], or abnormal cardiac repolarization analysis [66]. Zhao *et al.* [66] used fMCG to detect and analyze fetal T-wave characteristics, such as QT interval in the normal fetus, and subsequently, to define T-wave abnormalities associated with fetal arrhythmia.

The drawbacks of this method are risk of infection, decreased comfort of the patient, and the necessity for membrane rupture and uterine penetration, limiting its use to the labor stage only [78]. For these reasons, the method is often criticized and its benefits are questioned [79]–[82].

These limitations can be overcome by the use of external fECG monitoring. However, accurate fECG waveform needs to be extracted in order to access equivalent morphological information as obtained using invasive monitoring. According to authors' best knowledge, a very few authors have achieved this goal so far. Niknazar [83] *et al.* reconstructed the fECG waveform by extended state Kalman filtering from single-channel recordings. Su *et al.* [84] successfully extracted fECG signal for both fHR and morphological analysis using a novel algorithm based on the optimal-shrinkage and the nonlocal Euclidean median under the wave-shape manifold model. Behar *et al.* [85] extracted the complete fECG waveform using Bayesian filtering framework based on the extended Kalman filter. The same author demonstrated accurate fECG extraction using an approach introduced by Andreotti *et al.* [87] and proved the feasibility of the NI-fECG as a supplementary method to diagnose fetal arrhythmias [86].

Enabling fECG morphological analysis could open new diagnostic opportunities:

- Monitoring ECG for ST segment deviation is used in adults to diagnose myocardial ischemia. In fact, at present, it is the only practical method for continuous non-invasive monitoring of ischemia episodes in adults [88]. In current fetal monitoring, ST analysis scores biphasic ST segments, which may be an indicator of the severity of hypoxia [89]. Nonetheless, ST analysis is clinically carried out using invasive monitoring by FSE. Interestingly, Clifford *et al.* [90] compared the fHR and ST change extrapolated from FSE data with those recorded non-invasively using abdominal electrodes and suggested that they are clinically indistinguishable.
- It is known that the QT segment reflects ventricular repolarization, where shortening of the QT interval is associated with intrapartum hypoxia and metabolic acidosis in adult ECG [91]. Conversely, prolongation of the QT interval is considered a risk factor for sudden cardiac death [92], [93]. It is noted that this method is not without challenges. Indeed, the manufacturer of a popular patient monitor model [94] emphasizes that for ST segment monitoring, their algorithm depends on determination of the end point of the S wave. Therefore, any sudden change, such as increased heart rate, can lead to shortening of the QT interval and consequently generate erroneous ST segment values.
- The feasibility of NI-fECG as a supplementary diagnostic method for fetal arrhythmias has been demonstrated [86], [95]. However, the quality of the fECG extraction and P-wave is critical for characterization of certain arrhythmias.

III. Assessment of Fetal ECG Extraction Performance

When applying any signal processing method for fECG, it is essential to devise tests that provide an assessment of its performance. In the following subsections, we introduce the most commonly available methods for filtration quality assessment, applicable to synthetic as well as real data, and provide a list of available fECG signal databases.

A. Evaluation Methods

Undoubtedly, optimal evaluation of a fECG processing method should use real data. However, simulated data are often used for initial testing and evaluation of devised algorithms. This enables testing of algorithm design assumptions [96]. Quality evaluation using simulated data can therefore benchmark various algorithms, while the *actual* signal is used as the reference (or *gold* standard) later compared with the estimated data. In contrast, the only way to measure *true* fECG signals is by means of a FSE. However, this signal does not fully correspond to the fetal component in the composed abdominal signal, since it changes its properties due to the dispersion of the waveforms that are sensed at different locations. For instance, this distortion is manifested as *dispersion* of the QT interval or QRS complex. Therefore, the FSE signal is considered a strong reference for the fHR assessment and an acceptable one for morphological parameters, sometimes denoted as a *silver* standard [47]. Practically speaking, the morphological features being investigated in the FSE signal (ST segments, QT intervals) must be manually annotated by a panel of experts (ideally, at least three [91]). In the following subsections, we introduce the most common parameters used to evaluate the quality of the filtration.

1) Evaluation Using Real Data: Various evaluation and scoring statistics have been used in research publications. Up until 2013, there was no suitable large public databases or defined quality assessment methodologies available. To address these issues, the Oxford research team, led by Clifford and Behar, initiated an international competition entitled *'The PhysioNet/Computing in Cardiology Challenge 2013'* (henceforward, 'Challenge 2013') [36]. This competition involved 91 open-source algorithms from 53 international teams and contributed significantly to the development of methods for evaluation of proposed algorithms.

Other researchers suggested the use sensitivity (Se), positive predictive value (PPV), their harmonic mean F_1, and accuracy (Acc). These parameters are defined by the classification of the detected fetal QRS complexes: true positive (TP), false positive (FP), and false negative (FN), i.e. correctly identified, incorrectly detected (extra) and missed QRS complexes, see Equations (1)–(4).

$$Se = \frac{TP}{TP + FN}. \tag{1}$$

$$PPV = \frac{TP}{TP + FP}. \tag{2}$$

$$F_1 = 2 \cdot \frac{PPV \cdot Se}{PPV + Se} = 2 \cdot \frac{TP}{2 \cdot TP + FP + FN}. \tag{3}$$

$$Acc = \frac{TP}{TP + FP + FN}. \tag{4}$$

2) Evaluation Using Synthetic Data: The scoring statistics defined in section III-A1 can be used for both synthetic and real data. For synthetic data, there are also other evaluating statistics available, which utilize the *known reference* fECG signal that is available as a reference. These parameters include statistics, such as signal to noise ratio (SNR) [97]–[99], root-mean-square error (RMSE) [97], [100], and percentage root-mean-square difference (PRD) [97], [100].

Besides the benefit of a more objective evaluation, the synthetic data enable modelling of different stages of pregnancy, fetal position based on the fetal vectorcardiogram, pathologic states. Four of the artificial fECG signal generators were introduced by Sameni *et al.* [101], Behar *et al.* [44], [45], Martinek *et al.* [46], and Keenan *et al.* [64].[2]

Despite the advantages provided by synthetic data, they fail to compete with thorough performance evaluations using real data. Nonetheless, when an algorithm is considered for practical medical applications, it is necessary to prove the capability of the algorithm in recovering the main clinical features used for fetal monitoring, such as the fHR, ST and QT intervals, for which reference annotations may be challenging or impossible to obtain.

B. Available Fetal ECG Signal Databases

Before the Challenge 2013, the following databases were available: A database for identification of systems (DAISY), Non-Invasive Fetal Electrocardiogram Database [102] (NIFECGDB), Abdominal and Direct Fetal Electrocardiogram Database [103] (ADFECGDB). The DAISY was the first database, constructed to increase the reproducibility of the results reported in scientific papers, includes data of various categories. The fetal recordings are included in the Biomedical Systems section of the database and categorized as *"Cutaneous potential recordings of a pregnant woman"*. The recordings consist of five abdominal and three chest channels from a single fetus, with duration of 10 s, which were sampled at 250 Hz. The dataset contains the recording of only one fetus, the sampling frequency is low, the length of the segments is insufficient, and the NI-fECG is relatively easy to separate.

Following Challenge 2013, a new dataset consisting of one-minute recordings sampled at 1 kHz, was made available by PhysioNet [104]. Each recording includes four abdominal signals. The data were contributed by different institutions and are divided into two sets: Set A and Set B. Since then, a number of researchers who have participated in the Challenge 2013 evaluated their algorithms using the following protocol. New algorithms should be trained on Set A (training set) and evaluated using Set B (validation set) to ensure objective assessment and comparison with other results. The final algorithms were evaluated on the hidden test-c, which was not made available to participants. It is still possible to carry out the evaluation on the hidden test-c.[3] However, the dataset has some limitations, e.g., each record is only 1 minute-long and the chest leads are not included, rendering it useless in evaluation of adaptive extraction systems.

The algorithms must be tested on as much data as possible. Following are databases publicly available on PhysioNet [104]:

- The Abdominal and Direct Fetal ECG Database (ADFECGDB) [103] includes a total of 5 recordings from 5 different subjects in labor (38–41 weeks of gestation) recorded using the KOMPOREL fetal monitoring system (ITAM, Zabrze, Poland). Each record includes four abdominal signals and one signal form FSE, which serves as the reference for fQRS annotations. The length of each signal is 5 minutes, totaling 25 minutes of data sampled at 1 kHz. The unique advantage of this database is that it has the reference scalp ECG available [105].
- The Non-Invasive Fetal Electrocardiogram Database (NIFECGDB) contains a total of 55 recordings from a single subject (21–40 weeks of pregnancy). Each record includes four abdominal and two thoracic signals of variable length (minimum length is 1 minute and 54 seconds, while maximum is 46 minutes and 20 seconds). Recordings were sampled at 1 kHz [104].
- The 2013 PhysioNet/Computing in Cardiology Challenge Database consists of 447 min of data from five different databases, which are divided into the following sets in PhysioBank ATM:
  - Challenge 2013 Training Set A (Challenge/2013/set-a) consists of 25 recordings, each including four abdominal ECG signals sampled at 1 kHz. The fQRS annotations are publically available.
  - Challenge 2013 Test Set B (Challenge/2013/set-b), which includes 100 recordings of abdominal ECGs sampled at 1 kHz. Unlike training Set A, test Set B is not publically available [36].
- The Fetal ECG Synthetic Database (FECGSYNDB) [87] includes synthetic signals generated generated using the FECGSYN simulator [45]. The dataset includes simulated signals from 10 different pregnant subjects. For each subject, there are 5 different noise levels, 7 different noise

[2]Code is available online at: http://www.fecgsyn.com

[3]In case of interest, the algorithms should be sent to Challenge organizers (challenge@physionet.org).

TABLE I
EXISTING PUBLICLY AVAILABLE DATABASES OF NI-fECG RECORDINGS

	Average duration	Fs (Hz)	Number of recordings	Signals	Reference R peak annotations	Number of fetuses
DaISy [102]	10 s	250	1	5 aECGs, 3 mECGs	No	1
ADFECGDB [103]	5 min	1000	5	4 aECGs, 1 FSE	Yes	5
Challenge 2013 Set A [36]	1 min	1000	75	4 aECGs	Yes	unknown
Challenge 2013 Set B [36]	1 min	1000	100	4 aECGs	No	unknown
FECGSYNDB [87]	1 min	1000	5	4 aECGs, 1 mECG	Yes	10*
NIFECGDB [104]	1.9 to 46.3 min	1000	55	4 aECGs, 2 mECGs	No	1
NIFEADB [86]	10 to 13 min	500 or 1000	26	4 or 5 aECGs, 1 mECG	No	26

*synthetic signals, 10 simulated pregnancies
aECGs - abdominal ECG signals
mECGs - chest (maternal) ECG signals
FSE - reference signals from fetal scalp electrode

cases (e.g., uterine contraction, fetal movement, etc.), and five recordings (repetitions) for each combination of settings available, totaling 1750 synthetic fECG signals. Moreover, the database contains the reference chest and noise signals [87].

- The Non-invasive Fetal ECG Arrhythmia Database (NIFEADB) provides a series of recordings from 26 fetuses; 12 arrhythmic and 14 normal (based on the fetal echocardiography, which was used as a reference diagnostic method). For each recording, a set of 4 or 5 abdominal channels and 1 chest maternal channel were recorded. The average length of each NI-ECG record is 13 minutes 3 seconds and 10 minutes 6 seconds arrhythmic and normal rhythm cases, respectively. The sampling frequency is either 500 Hz or 1 kHz. Detailed diagnosis information as well as gestational age of each fetus can be found in the companion reference [86]. The database is suitable for testing algorithms designed for automatic detection of abnormal rhythm events. Data were recorded using the Cardiolab CS software (KhAI Medica, Ukraine) [106], [107].

Table I summarizes the available open-access databases. Overall, the total length of available data is modest and thus, construction of a large NI-fECG database following the standards of *big data* remains one of the major unmet needs in the field [108]. Such a database must include signals from both abdominal and chest electrodes. In case of recording performed during labor, reference recordings by means of FSE might be necessary, in particular for the purpose of the morphological analysis of the NI-fECG signal. The length of the signals should be at least 5 minutes and preferably more as the heart rate variability of adults is traditionally analyzed over 5 minute windows [109]. The sampling frequency is recommended to be at least 1 kHz and with quantization of 16 bits. Ideally, to enable tests of automated analysis of fECG recordings, the database should document the health outcomes at delivery.

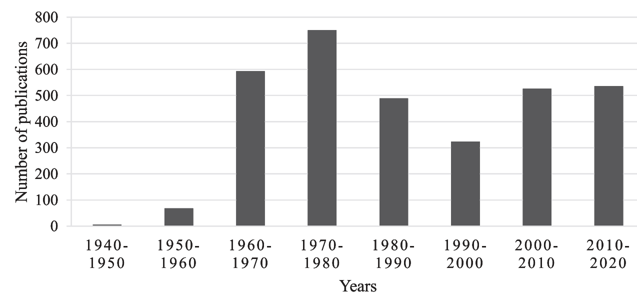

Fig. 3. Number of publications on fetal electrocardiography in the US National Library of Medicine.

IV. ALGORITHMS FOR fECG SIGNAL EXTRACTION

According to PubMed (US National Library of Medicine), 3301 articles focusing on fECG (both invasive and noninvasive) have been published since 1940 (see Fig. 3).

In this review, the algorithms are divided into two categories: algorithms that require only abdominal electrodes (Abdominal electrode-sourced (AES) methods) and algorithms that require both abdominal and chest electrodes (Combined source (CS) methods). The principles of this categorization are illustrated in Fig. 4. This terminology was selected in order to minimize the confusion and inconsistency caused by different nomenclature.

The CS system, which includes an adaptive algorithm, requires a minimum of one abdominal electrode and one for chest recording. Adaptive noise cancelling methods are based on the theoretical assumption that abdominal and chest channels contain the same noise. Practically, this is true for the mECG (which is considered the main source of *noise*) but less accurate for electromyography noise, which might be location-dependent.

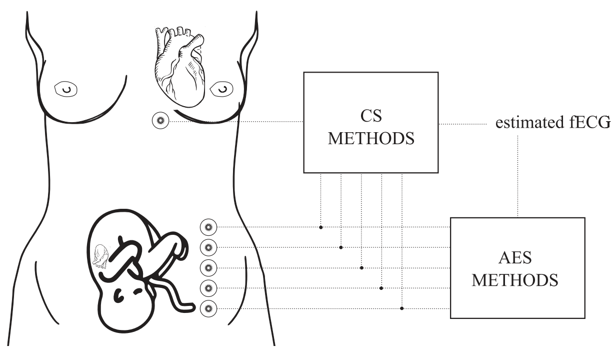

Fig. 4. Illustration of a multi-lead extraction system. The Combined Source (CS) methods, are the systems that require the chest lead to learn the maternal ECG signal in order to subtract it from the composite abdominal ECG (aECG) signal, usually, via an adaptive filtering technique. Conversely, Abdominal Electrodes Sourced (AES) methods only use abdominal leads.

Adaptive techniques are well suited for the maternal component cancellation, which is the main and most challenging contaminant in the abdominal mixture [110].

A. Abdominal Electrodes Sourced Methods

One category of AES methods involves designs working in the time domain and reliance on quasi-periodic, time-uncorrelated fECG and mECG signals, which are used to generate an mECG template which is subsequently subtracted from the abdominal ECG signal. These techniques include a variety of template subtraction methods [111], [112], Kalman filtering [113] or wavelet transform [114].

A second category of AES methods can be classified as spatial techniques. This approach is based on separating fetal signal by using the information about the spatial distribution of the source signals. The most well-known and most frequently used spatial methods, traditionally denoted blind source separation (BSS) methods, include principal component analysis (PCA) [115], independent component analysis (ICA) [116], or nonlinear state-space projections [117]. Their advantage lies in their ability to detect and extract typical ECG-patterns, e.g. extra systoles [116], is a crucial factor in medical diagnosis and treatment. At the same time, they usually require a large number of abdominal channels, which causes discomfort to the mother and thus makes their clinical utilization challenging. Conversely, the temporal methods are much easier to implement in clinical practice [118], [119].

1) Template Subtraction Methods: In fECG extraction, the template subtraction (TS) method is a generic name that is broadly applied to approaches that extrapolate fetal ECG by subtracting the template (maternal component) from the input signal mixture (aECG recording). The main drawback of this technique is that its the accuracy significantly depends on the quality of the mQRS detection [120], [121]. One of the challenges is accurate location of the fetal R waves overlapping with the maternal ones to avoid the amplitude and phase distortion. For implementation in clinical practice, it is crucial that unexpected ECG-patterns be detectable [122]. Therefore, the parametric formulation of the quasi-periodicity of a regular heart rate pattern would hamper the detection of events such as extra systoles [116].

The mother template can be estimated using different approaches. Behar *et al.* [123] used Martens [112] approach (therein denoted as $\mathrm{TS_m}$) and built the mECG template cycle centered on the mother R-peak, with a duration of 200 ms for the P wave, 100 ms for the QRS complex, and 400 ms for the T wave. This approach, however, suffers from discontinuities since the choice of these interval durations is empirical. It was suggested that variable interval lengths, dictated by maternal heart rate, would significantly improve the efficacy [123]. The improved $\mathrm{TS_m}$ addresses this need by scaling the average mECG complex for each individual mECG cycle with a multiplication *constant* to decrease the mismatch between the template and the mECG complex.

In another approach described by Vullings *et al.* [124], and referred to as weighted averaging of mECG segments (WAMES), the mECG signal is dynamically divided into separate segments, generating an individual estimate for each mECG segment. The estimation is carried out using the linear combination of offset-compensated, time-shifted, and scaled corresponding segments in preceding mECG complexes. The authors built the template ECG by weighting the 7 previous cycles, where the weights are selected to minimize MSE between the estimate and the actual mECG complex. To ensure adaptation to the non-stationary nature of the mECG morphology, the template is updated every cycle.

Finally, Kanjilal [125] used a PCA-based TS approach which obtains the principal components using singular value decomposition (SVD) along with the analysis based on the singular value ratio spectrum. To separate the mECG component, the data matrix is designed so that each row corresponds to one mECG cycle and the maternal R-peaks occupy the same column. mECG suppression is achieved through selective separation of the decomposed components. When the maternal component is suppressed, the residual signal contains the fetal component and the noise. For extraction of the fetal component, the data matrix is designed so the consecutive rows contain the fetal ECG cycle with the peak value lying in the same column. The SVD is then performed on this matrix and the principal component corresponding to the fECG is obtained.

Moreover, Lee *et al.* [126] used this method, denoted as TS_{PCA}, along with the total variation denoising. The algorithm first filters the aECG using total variation denoising. Then, the mECG is subtracted by means of TS_{PCA}, and finally, total variation denoising is applied to the residual signal and fECG is estimated. These additional steps significantly improved performance.

Additionally, in the method introduced by Liu *et al.* [127], the fetal R wave was detected by a single abdominal lead by combining the template matching approach and the RR time-series smoothing.

2) Kalman Filtering: The standard KF approach is built for linear systems. However, many practical systems have a nonlinear nature. The KF can be applied to a linearized version of

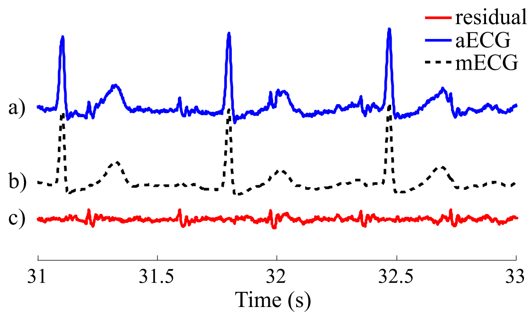

Fig. 5. Kalman Filtering. a) An example of the abdominal ECG signal composed from both maternal and fetal component; b) mother template to be subtracted from the composite signal; c) residual signal containing fetal component and some noise. Adapted from from Behar *et al.* [123].

these systems with loss of optimality. The extension to non-linear systems is known as extended Kalman filter (EKF), and can be used to filter the maternal component by considering fECG as noise [113]. The maternal component is subsequently subtracted from the abdominal mixture and subsequently, the residual signal will contain the fetal ECG and some noise, as illustrated in Fig. 5. Of note, the EKF method is an advanced type of TS approach since the estimated mECG cycle is subtracted from each individual heart beat [128]. As in the case of other TS approaches, EKF has the same drawback of requiring precise mQRS detection, which is associated with susceptibility to noise in the chest or abdominal mECG recording. However, in contrast to the other TS techniques which cancel the mECG cycle within a given window length, the EKF places limitations on the lengths of P, QRS and T waves. Therefore, it continuously attempts to estimate the mECG.

Vullings *et al.* [129], compared the performance of EKF to that of KF with fixed process noise covariance, which needs to be estimated *a priori*. This requires detailed information on the ECG signal dynamics [129]. The comparison showed that when the process noise covariance is chosen optimally for fixed KF, its performance is equivalent to the adaptive EKF. Moreover, EKF is capable of quickly adapting the noise estimation to match the filter's output to the new input. This is suitable for long-term monitoring [129]. Conversely, due to less flexible estimation of the Kalman gain, the fixed Kalman filter needs some time to adjust its output.

Before implementing the filter, one must choose the properties of covariance matrices, and means of estimation of the Gaussian parameters. Sameni *et al.* [113] built process and observation noise covariance matrices (Q_k and R_k, respectively) as a compromise between the convergence rate and stability, based on the level of nonstationarity of the input signal. While for stationary noises the diagonal elements of Q_k are relatively small, for highly nonstationary noises, they are large. As for R_k, it should be chosen by considering the desired output noise variance. Moreover, since noise sources are assumed not to correlate with each other, both matrices can be simplified to diagonal. Behar *et al.* [128] proposed to multiply the R_k and Q_k covariance matrices by gain terms. The values of G_R and G_Q are determined by searching for optimum performance from a training dataset.

The Gaussian parameters can be automatically estimated by randomly initializing the Gaussian parameters to the identified P, QRS and T waves of the template data. Sameni [113] used a non-linear curve fitting approach to find the Gaussian parameters minimizing the root mean squared error (RMSE) between the template and the cardiac cycle mapped by the Gaussian functions. Behar *et al.* [128] used the RMSE as the stopping criterion; this process was repeated until reaching the best set of Gaussian parameters. Another parameter that influences the performance of the KF method is the number of Gaussian parameters used. An evaluation using synthetic data showed that the more functions used, the better the mean fitting error, but at a cost of computation time [128].

Zaunseder *et al.* [118] compared EKF effectiveness with the template subtraction method based on an event synchronous canceller which performs coherent averaging of the cardiac cycles to construct a time varying beat template. The authors concluded that the EKF-based system achieves significantly higher accuracy. Andreotti *et al.* [130] and [131] used a KF-based method based on EKF followed by a backward smoothing stage, labeled as extended Kalman smoother (EKS). The system processes the signal as follows: average maternal beat is obtained by wrapping the single beat and is subsequently approximated by Gaussian kernels. Finally, in order to obtain acceptable estimations, the Kalman gain is then used to correct the observed signals on a sample basis, considering the system dynamics. The algorithm was presented at Challenge 2013 and won the one of the closed-source events.

The advantage of EKF is that when subtracting the evaluated maternal signal, no discontinuity is generated due to the phase mapping. On the other hand, using the EKF can be problematic in cases when maternal and fetal beats overlap because of the adaptive nature of the filter. Therefore, when performing the subtraction, the fetal beats will be partially cancelled along with the maternal component.

3) Wavelet Transform: Wavelet transforms (WT) have received a lot of attention in the areas of signal and image processing like data compression or noise reduction [132]. In comparison with the traditional noise reduction methods based on Fourier analysis, wavelet based analysis offers time-frequency representation of signals and thus can be applied even in the cases where the frequency spectrum of useful signal and noise overlap, such as fECG ("signal") and mECG("noise"). There are several wavelet denoising techniques, which vary according to the application and type of input signal, such as discrete (Daubechies) wavelet transform (DWT), complex wavelet transform (CWT), stationary wavelet transform (SWT), pitch synchronous wavelet transform (PSWT), and undecimated wavelet transform (UWT) [133].

In some cases, especially for simple synthetic data, the extraction can be carried out using WT decomposition alone. However, in case of real data, this approach is limited due to significant cross-over between the useful signal and the noise in the spectral domain [36]. Thus, WT methods are usually combined with other methods such as adaptive filtering [134], or blind source separation methods [134]. Additionally, since the energy of the maternal component in aECG signal is significantly higher than the fetal component and can be estimated more precisely using DWT, the estimation of fECG is performed by subtracting mECG from the abdominal signal [135]. Moreover, WT was also successfully utilized in wavelet transform based QRS detectors [136], [137].

Since the wavelet transform is widely used for fECG signal processing, we provide some fundamental information about WT-based system settings derived from fECG processing literature. For WT-based fECG signal processing, the following parameters must be selected carefully:

- *Suitable Wavelet Basis*
  The choice of mother wavelet is very important since it has a significant impact on the results of filtration. Usually, it is recommended to choose a wavelet base which is morphologically similar to the processed signal, as it allows to filter the higher frequencies of the signal. For fECG signal processing, following wavelet bases have been used frequently in the literature:
  – Daubechies (e.g., [138]–[141]),
  – Symlet (e.g., [142], [143]),
  – Quadratic Spline (e.g., [114], [144]),
  – Complex Frequency B-Spline (e.g., [145]),
  – Biorthogonal (e.g., [146], [147]).
  Besides the above-mentioned wavelets, Daamouche *et al.* [148] introduced a wavelet design method which adopts the polyphase representation and formulates the optimization problem within a Particle Swarm Optimization (PSO) framework. The presented results have demonstrated that the method is more accurate in comparison with two other commonly used wavelets (i.e., Daubechies and Symlets), but significantly more computationally demanding. Contrary, for fPCG extraction, the more suitable wavelet family may be the coiflets, particularly *coif4*, according to a study in 2009 by Chourasia [149]. This wavelet family has also been used in case of fECG processing, but only for the high frequency noise reduction [144].
- *Thresholding Rules and Parameters*
  The most important types of thresholding are the *hard* thresholding and the *soft* thresholding defined by Equation (5) and (6), respectively. The hard thresholding sets the samples lower than the threshold to zero and the rest of the values remain unchanged whereas for soft thresholding, the non-zero coefficients are decreased towards zero.

$$R_{\mathrm{H}}(\omega) = \begin{cases} 0 \text{ for } \omega < \lambda, \\ \omega \text{ for } \omega \geq \lambda \end{cases}, \tag{5}$$

$$R_{\mathrm{S}}(\omega) = \begin{cases} 0 \text{ for } \omega < \lambda, \\ \mathrm{signum}(\omega)(\omega - \lambda) \text{ for } \omega \geq \lambda \end{cases}, \tag{6}$$

  where λ is the thresholding constant size defined by the threshold rules; ω represents the wavelet coefficients; R_{H} and R_{S} is the resulting signal from hard and soft threshold function, respectively. Four different thresholding rules can be selected in Matlab Wavelet Toolbox (by MathWorks, Natick, Massachusetts, USA):
  – rigrsure – based on the principle of Stein's Unbiased Risk Estimate (SURE).
  – sqtwolog – Fixed (Universal) threshold defined as

$$\lambda = \sqrt{2 \cdot logN}, \tag{7}$$

  where N is the signal length.
  – heursure – defined as combination of SURE and fixed threshold.
  – minimaxi – based on minimax principle.

$$\lambda = 0.3936 + 0.1829 \cdot \frac{log\ n_j}{log\ 2}, \tag{8}$$

  where j is the level of decomposition, and n_{j} is the coefficient vector length at each decomposition level j.
  For fECG pre-processing, it is recommended using the Matlab Wavelet Toolbox wavelet *sym4* with adaptive threshold and hard thresholding [150]. The thresholding rules and parameters can be combined and modified such as by Casillo *et al.* [140].
- *Level of Decomposition*
  Generally, determining the levels that a signal should be decomposed to depends on several attributes or characteristics of the signal such as whether the signal is biological or synthetic, signal length, and sampling frequency. Hence, the researchers have opted for different decomposition levels, based on their assessment of the signal attributes.
  For instance, Hassanpour *et al.* [138] suggested using second level of decomposition to extract fECG and mECG, and consequently, a Savitzky-Golay smoothing filter to reduce the remaining noise. Contrary, Chouakri *et al.* [142] used decomposition at Level 4 by Symlet wavelet. Moreover, Castillo *et al.* [140] removed the baseline wandering based on following equation:

$$L = \log_2(F_0) \tag{9}$$

  where F_0 is the maximum frequency component of the signal. This expression for the calculation of the level of decomposition L is based on the detailed analysis carried out by Sharma *et al.* [151].

Fig. 6 shows an example of wavelet decomposition applied on the real aECG signal (aECG3, recording r01, ADFECGDB [103]) using the wavelet *Db4* and the five levels of decomposition. It can be noticed that the approximation coefficient *a5* corresponds to the maternal component in the input aECG signal. In case of the detail coefficients, the last two of them (d_4 and d_5) include the fetal component. Thus, fECG estimate could be obtained by minimizing the noisy detail coefficients at levels 1, 2, and 3 by means of the thresholding methods in the reconstructed signal. It should be noted that the morphology of such fECG signal will be deformed and thus could not be used for morphological analysis.

The wavelet transform is a useful tool for fECG signal processing. The main advantage of the WT-based techniques over the conventional Fourier methods is the use of localized

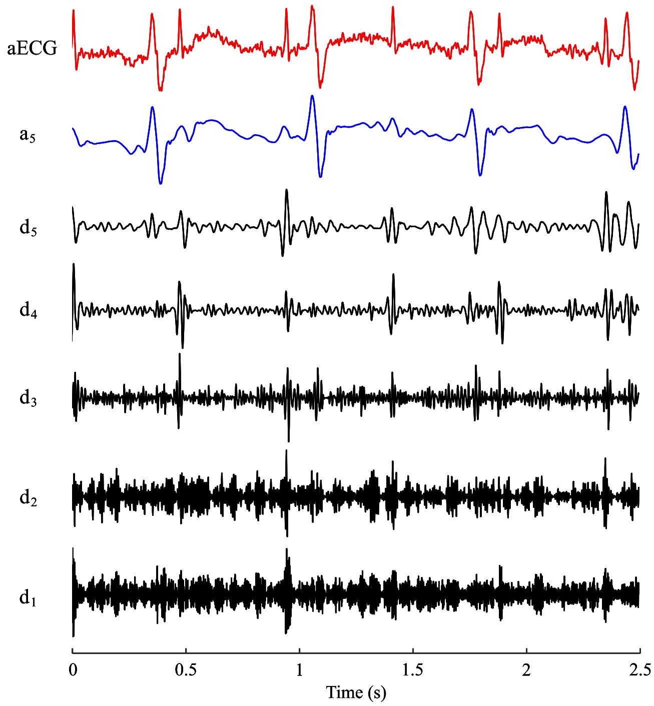

Fig. 6. An example of the wavelet decomposition applied on the aECG signal from ADFECGDB using db4 wavelet on 5 decomposition levels resulting in depicted detail coefficients $d_1 - d_5$ and approximation coefficent a_1.

basis functions and the faster computation speed. The spatially localized basis function allows analyzing of the real situations in which the signal contains discontinuities and sharp spikes. However, it causes deformation of the signal morphology (P and T waves) and thus, it is more suitable for the fHR monitoring rather than morphological analysis.

4) Blind Source Separation Methods: Using blind source separation (BSS) methods, fetal ECG is obtained by means of the estimation of independent sources for fetal cardiac bioelectric activity [48]. These methods are used to extract unobserved signals (sources). Sources are assumed to be statistically independent and the mixture to be linear and instantaneous [152].

In fetal ECG processing, a set of n individual source signals $s(t) = (s_1(t), s_2(t), \ldots, s_{\mathrm{n}}(t))^{\mathrm{T}}$ represents the source signals of the fetal and maternal hearts which linear mixtures are sensed on the maternal abdomen (aECG) and denoted $x(t) = (x_1(t), x_2(t), \ldots, x_{\mathrm{m}}(t))^{\mathrm{T}}$ defined as

$$x(t) = A \cdot s(t), \tag{10}$$

where A is the mixing matrix. In most cases, such as in Fig. 7, n equals m. The input signals can be recovered using un-mixing matrix B, where the output signals (estimated input signals) $\hat{s}(t) = (\hat{s}_1(t), \hat{s}_2(t), \ldots, \hat{s}_{\mathrm{n}}(t))^{\mathrm{T}}$ can be calculated as

$$\hat{s}(t) = B \cdot x(t), \tag{11}$$

where B is the un-mixing (transfer) matrix. It should be noted that the transfer coefficients are subject to a large uncertainty [116]. Therefore, using BSS methods, one can only obtain a rough estimate of the signals.

The BSS methods can be divided into various approaches based on statistical techniques deployed to extract the signal, e.g. ICA [153], [154], and methods based on second-order statistics, such as SVD [125], PCA [154]. Some authors have proposed semi-blind source separation approaches such as periodic component analysis (πCA) [155], [156].

ICA is among the most applied methods for non-adaptive fECG extraction since its first utilization in this context by De Lathauwer [116]. In general, ICA cannot identify the actual number of source signals, nor a uniquely correct ordering of the source signals, and nor a proper scaling (including sign) for the source signals. Many ICA-based techniques have been proposed as FastICA algorithm [157], joint approximate diagonalization of eigen-matrices (JADE) algorithm [158], multidimensional ICA (MICA) algorithm [159], nonparametric ICA (NpICA) algorithm [160], minimum Renyi's mutual information (MeRMaId) algorithm [161], and orthogonal-group ICA (OgICA) neural algorithm [162], etc.

The performance of BSS-based methods in extraction of fECG from the abdominal mixture depends on several factors such as the number of electrodes, noise, or stationarity of the signal [163]. If the fECG extraction system is designed properly, the BSS algorithms can extract fECG with very good accuracy. The following parameters play a critical role in ensuring a good source:

- *Number of Input Channels*
  Su *et al.* [84] introduced a very promising single channel blind source separation (scBSS) algorithm. The algorithm contained three steps. In the first step, the maternal HR is estimated based on the de-shape short-time Fourier transform. Based on that, the aECG is divided so each part contains one maternal cardiac cycle. In the second step, a metric is designed to compare those individual parts. The proposed algorithm utilizes the optimal shrinkage tool. Its advantage is that the immunity to information not related to the maternal cardiac cycles, such as fECG and noise. With this metric, for each piece, we find other pieces with similar maternal cardiac cycles. Finally, the median of all similar maternal cardiac cycles is evaluated in order to recover the mECG. The fECG is then recovered by repeating these three steps for all parts.
  However, most of the BSS-based techniques use multiple abdominal signals as the inputs to estimate the fECG component in the composed abdominal signal [159]. Conversely, Camargo *et al.* [159] introduced a slightly different approach using an estimated chest ECG signal (estimated using PCA from the aECG signals) as the inputs to MICA algorithm along with the abdominal signals. The authors conclude that this approach increases the effectiveness of the MICA method.
  ICA assumes that components are statistically independent and requires as many electrodes placed on maternal abdomen as the number of independent signal sources. Some authors suggested that the estimation is more accurate when using higher number of electrodes [52]. Andreotti *et al.* [87] introduced a pre-processing step based on eliminating the components with low energy (low

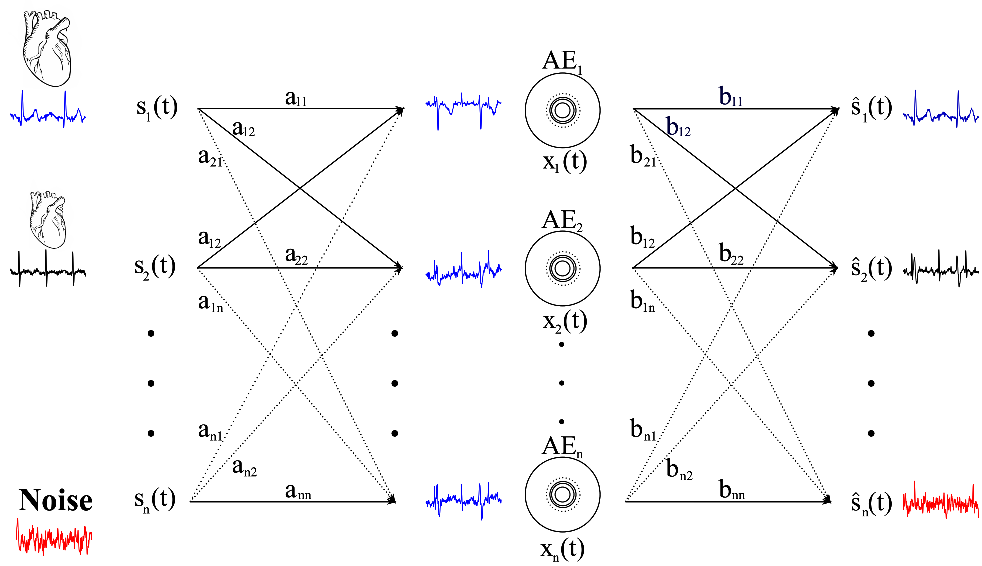

Fig. 7. Basic flowchart of BSS problem in fECG signal processing. It should be noted that the individual source signals $s_1 \cdots s_{\mathrm{n}}$ cannot be measured directly. Using BSS methods, we can obtain estimates of these signals – outputs $\hat{s}_1 \cdots \hat{s}_{\mathrm{n}}$.

eigenvalue) using a dimensionality reduction by means of PCA.

- *Number of Output Components*
  PCA and ICA methods decompose the original signal into their source components. PCA finds the *principal components*, i.e. the statistically most significant components in the input signal. The first principal component has the largest possible variance and thus corresponds to the maternal component [116]. In contrast, ICA decomposes the signal into statistically independent components in no particular order.
- *Norm of the Iterative Step*
  Norm of the iterative step or convergence criterion is the temporal distance between the previous sample and the current sample. The lower the value of the convergence criterion, the greater the accuracy. However, that results in greater computational demands. The convergence criterion is normally set to 10^{-6}. Any lower value does not lead to significantly better results [154].

The advantage of ICA is that it follows the *blind* identification approach and thus there is no need of prior mQRS position. Moreover, in the fECG extraction, ICA has shown to be superior to PCA [154], [164]. The lower power ratio of the weak source to the strong source, the lower is the performance of the PCA [116]. The key factor for greater ICA performance is the number of input channels to enable the reconstruction of different statistically independent source signals. The higher the number of the inputs, the more precise the method is. However, the higher the dimensionality and computational costs [165].

B. Methods Using a Reference Chest Channel

Combined source (CS) methods have been successfully used in reducing noise in variety of the applications such as noise reduction in speech signals or telecommunication [166]. These systems are effective in reducing the noise that can be identified and recorded and thus are used as the reference input to the adaptive system. In case of the fECG signal, the signal considered as the noise is the maternal ECG, which can be recorded by means of electrodes placed on the mother's chest. This signal is assumed to contain no fetal component. The maternal ECG recorded on the abdomen has a lower amplitude and a different morphology than the one recorded on the chest. Therefore, it is not possible to simply subtract it from the abdominal ECG (aECG) signal. An adaptive method (AM) is able to estimate the maternal component contained in the aECG by adjusting the coefficients of the FIR filter based on the error signal $e(n)$, which is the difference between the current output of the FIR filter $y(n)$ and the desired signal given by the reference chest signal. By subtracting this estimated mECG signal, the estimated fECG signal can be obtained as illustrated by Fig. 8.

The general limitation of this method for clinical practice is a need of at least one additional chest electrode that can be discomforting for the patient. The quality of the reference chest signal also strongly influences the results of the fECG extraction. Additionally, the efficacy of these methods is significantly dependent on the configuration of the system [99]. The filter settings must be chosen carefully, since they have a significant impact on the results.

1) Least Mean Squares and Recursive Least Squares Algorithms: The least mean squares (LMS) filter was first introduced by Widrow and Hoff in 1960 and since then has been successfully used for a number of applications, mainly for the purpose of adaptive noise cancelling [166]. The aim is to minimize the *mean square error* between the filter output and the desired signal $y(n)$. Conversely, recursive least squares (RLS) algorithm minimizes the *total squared error* between those signals. Whereas LMS only considers the current error value to adapt its coefficients, the RLS algorithm considers also the previous samples, i.e. the *history* of the signal.

For fECG extraction, these algorithms were used, for example, by Swarnalatha *et al.* 2010 [167]. In their study, the authors

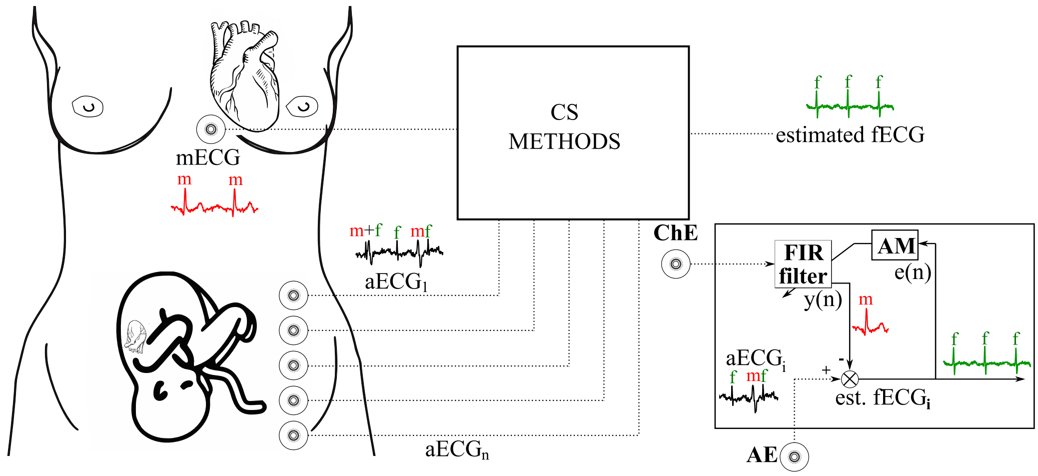

Fig. 8. An example of a multi-lead fECG extraction system using combined source (CS) methods. Chest electrode (ChE) records reference mECG (red). Adaptive system, consisting of CS methods, estimates the maternal component and subtracts it from the abdominal signal (aECG) recorded by means of abdominal electrode (AE) in order to obtain estimated fECG signal (green) and some residual noise. Adaptive system contains an adaptive method (AM) which adjusts the coefficients of the FIR filter based on the error signal $e(n)$.

introduced a novel method called multi-stage adaptive filtering. For fECG extraction, LMS-based algorithms (standard LMS and normalized LMS) and RLS algorithm were combined and the signal was filtered by the cascade connection of those algorithms. According to the authors, the most effective method for fECG extraction is to use the combination of RLS and LMS algorithm. Another example of the LMS algorithm utilization in this field was introduced by Wu *et al.* 2013 [147]. Its effectiveness was enhanced by combining it with wavelet decomposition and the spatially selective noise filtration algorithm [168]. However, these experiments were performed using synthetic data.

Other works such as Behar *et al.* [110], Camps *et al.* [169], Kahankova *et al.* [170], and Martinek *et al.* [171] have tested the performance using real data and shown that this method is not suitable for fECG extraction unless optimized. The optimization of the algorithms lays in choosing the most suitable filter settings. However, not only the optimal setting might vary through the pregnancy, but also it may vary during a single recording. The factors influencing the filtration, and thus the choice of the parameters, include the gestation age [98], fetal position [171], electrode placement [99], sampling rate, etc.

Many authors [99], [169]–[171] have been studying the optimization of the adaptive algorithms. According to majority of the available literature [99], [110], [169]–[171], the main parameters that need to be considered when designing an LMS or RLS-based extraction system are:

- *Filter Length*
  Filter length (M) or filter order (N), where N = M − 1, influences the number of coefficients and also the computational cost. Moreover, it is a function of the signal sampling frequency [110].
- *Step Size*
  Step Size or Convergence Coefficient μ is an important parameter for LMS-based algorithms which controls the stability and convergence rate. The value of the parameter should be chosen carefully. Setting a high value may result in obtaining a very fast optimal solution. However, it is more likely to obtain inaccurate estimates in the case of the occurrence of a large error in the direction of the gradient. Conversely, choosing a small value of μ guarantees high stability of convergence but at the same time, increases the inaccuracy of signal filtering in unsteady environments [99].
- *Forgetting Factor* λ
  This parameter applies for RLS algorithm and defines the proportion of past values to be used for filter coefficients update calculation. Forgetting factor ranges from 0 to 1, the lower value of forgetting factor, the more RLS algorithm considers the recent data (forgets the past ones) and for $\lambda = 1$, all past data contribute equally. In the fECG signal processing literature, the forgetting factor is set in the range between 0.8 and 1 [110]. The results show that the closer to the value 1, the better [99], [110], but that, of course, comes with the increased computational burden.

The optimal parameters can be found by heuristic methods (usually by *manual search*) or by the *grid search*. Another optimization method called the *random search* was introduced by Bergstra *et al.* [172]. This method significantly reduces the computational cost and performs similar or better than the grid search [172], [173].

Adaptive methods offer a relatively high performance if optimized and thus are a great example of the system optimization issue. Fig. 9 shows an example of 3D optimization graph introduced by Martinek *et al.* [99] showing the output SNR as a function of changes in the values of filter order N and the step size μ.

2) Adaline: Adaptive linear network (ADALINE) is an adaptive method for fECG extraction, also known as adaptive linear element. It utilizes neural networks adaptable to nonlinear time-varying properties of the ECG signal.

The main parameters for ADALINE system and suggested settings according to [174]–[177] are:

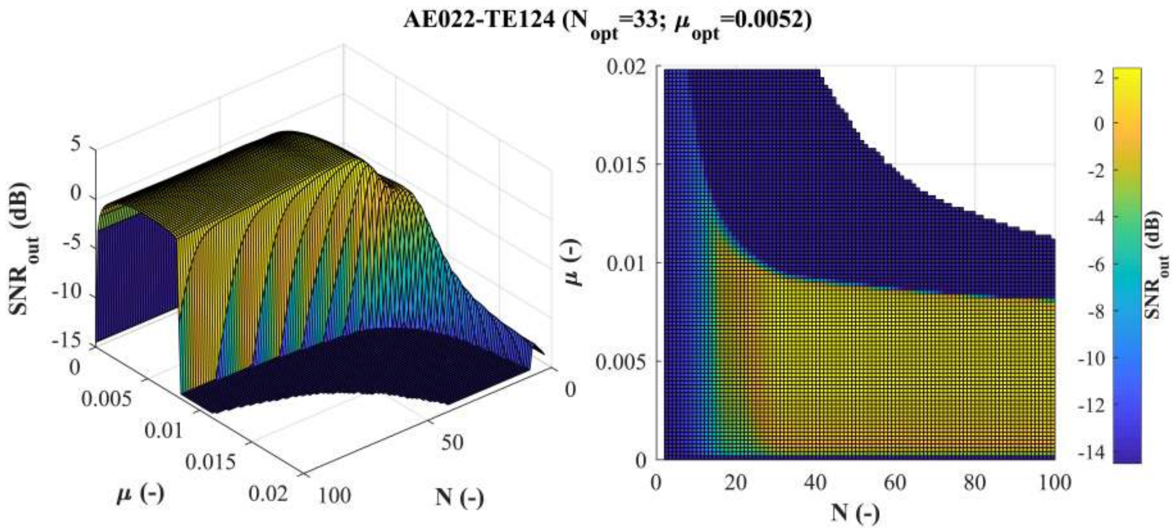

Fig. 9. An example of 3D optimization graph for the LMS algorithm (left); Operating area with the optimal filter settings specified for electrodes AE022-TE124 (right). The yellow part of the graph is the operating area including the optimal filter settings while the blue and white parts of the graph reflect the filter settings where the adaptive system is unstable. Adapted from [99].

- *Momentum,* **HIGH**
- *Learning rate,* **LOW**
- *Initial weights,* **LOW**

In 2010, Jia *et al.* tested the method based on ADALINE for fECG extraction and provided improvement of the network structure which increases its performance [175]. The authors claim that the ADALINE-based system achieves better results while using smaller amount of data for fECG extraction in comparison with the conventional adaptive filtering methods based on LMS or RLS algorithms.

3) Additional Linear Adaptive Methods: In 2010, Zheng *et al.* [178] introduced a single-lead fECG estimation method based on combining R-peak detection, resampling, and a comb filter. A comb filter, with ”teeth” that coincide with the harmonics of the mECG, is applied to the resampled signal. The maternal ECG signal, which is then subtracted from the abdominal signal, is obtained by resampling this filtered signal again; the sampling rate is determined empirically [175]. The result of the subtraction is considered to be a primary estimate of the fECG signal. The performance of the Zheng *et al.* method on both real (MIT-BIH PhysioBank) and synthetic data was compared with two single-lead-based methods, namely singular value decomposition and nonlinear state-space projection [178].

Wei *et al.* [179] describe a simple algorithm for fECG extraction based on adaptive comb filter (ACF) that is able to adjust to changes in the base frequency band that may occur over the recording time. Hence, it is suitable for estimation of the quasi-periodic signals. The experiments showing a high efficacy of the fECG extraction were carried on both synthetic and real signals (DAISY fetal ECG data and Non-Invasive Fetal Electrocardiogram Database from PhysioNet).

Shadaydeh *et al.* [180] presented a new fECG extraction method using adaptive Volterra filters (AVFs). This method uses one chest and one or several abdominal signals. This kind of filter is able to imitate the non-linear relation between the maternal chest and abdominal signals. In case of using several aECG signals, the algorithm utilizes linear combination to create the base signal from all of the recorded abdominal signals. Moreover, to increase the quality of the output signal, a RLS algorithm was used along with the linear combiner and Adaptive Volterra filter.

4) Artificial Neural Networks: Artificial neural networks (ANNs) include soft computing methods that imitate the behavior of a neural network of living organisms. In 2001, Camps *et al.* [169] introduced an interesting variation of the FIR neural network. The same authors in 2004 [181] presented an improved model for the elimination of interference using dynamic neural networks based on both numerical (correlation coefficients) and statistical (ANOVA, variance analysis) methods. In the noise cancellation design, FIR and gamma neural networks are included to provide highly nonlinear dynamic properties to the model. Neural networks were compared with classical adaptive methods (LMS, normalized LMS) on both real and synthetic data. According to this work, neural networks have demonstrably higher efficiency than classical methods, while the best compromise between complexity and efficiency is using the FIR neural network.

Adaptive Neuro-Fuzzy Inference System

Adaptive neuro-fuzzy inference system (ANFIS) represents one of the most popular hybrid neural networks which is used for fECG extraction. It is an adaptive network based on Sugeno fuzzy inference system implemented into five-layered forward artificial neural network. This hybrid combination improves the ability of system to adapt to non-linearity and uncertainty. Elementary ANFIS structure includes two inputs and one output and utilizes a neuro-adaptive learning algorithm (hybrid or back propagation) to determine the relationship between input and output data set [182]. In case of fECG extraction, systems inputs are represented by mECG and aECG signals, while the output signal is the estimated mECG, which subsequently serves as a reference signal for fECG estimation.

Numerous researches including [183]–[186] tuned ANFIS structure by PSO. Due to high level of research using ANFIS tuned by PSO, this combination now seems to be a golden standard in non-linear fECG extraction. Another possible combination is ANFIS and wavelets [133]. In 2010 Swarnalath *et al.* [187], tested three different filtering methods including basic ANFIS and two different combinations of ANFIS and wavelets. The wavelets were positioned before (pre-processing) or after (post-processing) ANFIS and compared with basic ANFIS structure. Research has shown that ANFIS in combination with wavelet in post-processing reached better quality of filtration. In most of researches, fuzzy inference system Takagi Sugeno type 1 is used in ANFIS structure. Hajar Ahmadieh and Babak Mohammadzadeh [188] reached better results with fuzzy inference system Takagi Sugeno type 2 in environments with high uncertainty. Current research also involves ANFIS in telemetry systems. For example, Kumar *et al.* [189] used orthogonal frequency division multiplexing (OFDM), ANFIS and wavelet transformation for telemetry, where mECG and aECG signals are transmitted by OFDM techniques, then the ANFIS and WT are applied on received signals to extract fECG.

The ANFIS-based fECG extraction system requires following parameters to be optimized:

- *Number of Epochs* The higher number of epochs, the better the filtration results. However, with high values, the extraction becomes extremely computationally demanding. Therefore, it is important to find a compromise between these two factors to achieve sufficient results in real time or near real time.
- *Number of Membership Functions (Rules)*
  Assaleh *et al.* [190] used 4 membership functions corresponding to 16 fuzzy rules, 53 nodes, 48 linear parameters, and 24 non-linear parameters. However, in the paper authors chose the parameters heuristically. More objective approach of the optimization is missing in the literature.
- *Shape (Type) of the Membership Function*
  Different Types of membership functions can be used for fECG elicitation such as bell shaped, triangular, Gaussian or trapezoidal. According to [191], the best extraction is achieved using Gaussian or bell-shaped membership functions.

Echo States Networks

Echo state networks (ESNs) are powerful for time series predictions where current state of the reservoir depends on the previous states [192]. For fECG noise cancelling, the reservoirs are initially randomly generated using recurrent neural networks (RNNs). Generally, ESNs are used for RNN training to make parameter estimation for nonlinear dynamical system modelling. The ESN works as a nonlinear medium for the reference signals (mECGs and aECGs) to propagate through. The ESN approach can utilize an adaptive algorithm (such as RLS [110]) as a readout layer, which calculates the output weights of the high-dimensional dynamical response (so-called *"echo response"*) of the reservoir. Subsequently, the reservoir is fixed while the weights of the output neurons are learned and updated. This way, the maternal component contained in the abdominal signal is estimated and can be subsequently subtracted from the original signal to obtain the residual containing fECG component. In non-adaptive approach, the weights are fixed after determining them using an initial training set.

The benefit of the ESN is that it does not require any prior information about the mQRS location, unlike some template-based approaches and at the same time, they can work with some level of uncertainty contrary to linear adaptive algorithms. Moreover, it enables significantly easier parameter estimation than in the case of using RNNs alone. In the context of fECG extraction, ESNs were used by Behar *et al.* [110].

In Fig. 10 $\mathbf{W}$ is a random $M \times M$ sparse matrix with approximately $\Psi \times M \times M$ uniformly distributed non-zero entries, and Ψ is the sparsity of the reservoir. The ESN reservoir connections and input weights are randomly initialised for individual abdominal signal and thus these ESN parameters stay constant.

The output of the illustrated ESN based extraction system is the the residual signal $\hat{s}(n)$, which contains the fECG signal. The input is the chest signal $u(n)$ and the abdominal signal $y(n)$, which is used as the *target* signal. The adaptive algorithm changes the weights in order to obtain the estimated abdominal mECG signal $\hat{\eta}(n)$, which is then subtracted from the abdominal signal $y(n)$ and the residual signal $\hat{s}(n)$ is obtained.

The following parameters should be optimized to ensure a high quality estimation:

- *Size (number) of Units (Neurons) of the Reservoir Weight Matrix* $\mathbf{M}$
  This parameter defines the values of the weights. If the value is too large, the system becomes unstable in case of small deviations from the state defined by the training algorithm. Moreover, this parameter is a function of the signal sampling frequency. Therefore, in case of resampling the data, it should be modified as well.
- *Sparsity of the Reservoir* Ψ
  This parameter describes the connectedness of the nodes and the reservoir. It was not optimized in the fECG literature and was set to 20% in [110].
- *Spectral Radius of the Reservoir Connection Matrix* $\mathbf{W}$
  This parameter affects the stability of the reservoir activations and defines how much the input data influence the reservoir values with respect to time. The higher the spectral radius, the less is the output dependent on recent input data. For fECG extraction, it is recommended to use lower values (0, 0.4) of the spectral radius to ensure better results [110].
- *Input Scaling of the Input Weight Matrix*
  The input scaling defines the reservoir responses degree of non-linearity. The smaller the value, the more linear the system dynamics. In most of the literature, the authors use the value 1 as the input scale, while Behar *et al.* [173] mention that this parameter is not as important as the others.
- *Leakage Rate (Forgetting Factor)*
  The leakage rate determines the significance of the previous state of the neurons. The parameter ranges between 0 and 1, in the latter case the neurons only keep the

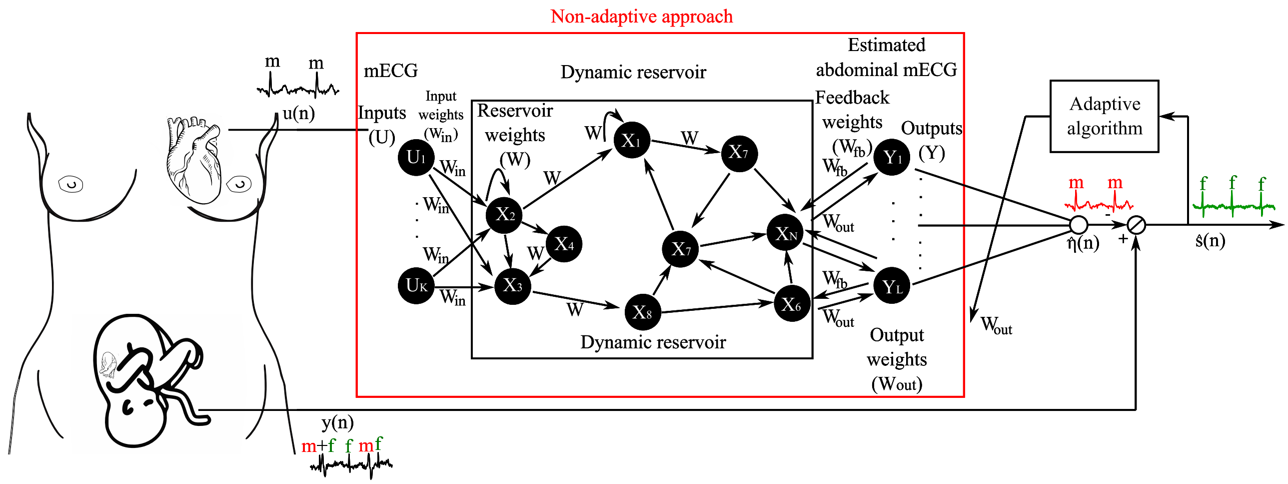

Fig. 10. An example of the fECG extraction system based on ESN. The input is the chest signal $u(n)$ and the abdominal signal $y(n)$; the adaptive algorithm updates the weights in order to obtain the estimated abdominal mECG signal $\hat{\eta}(n)$, which is subtracted from the abdominal signal $y(n)$ to get the residual signal $\hat{s}(n)$ containing the fECG signal.

information about the most recent state. Behar *et al.* [110] tested the influence of this parameter on filtration performance and concluded that the optimal value for this data is 0.4. For both extremes, the system performance decreased, especially for values around 0.

C. Hybrid Methods

In the previous subsections, the most common methods for fECG extraction were introduced. Each of the method has its strengths and weaknesses (for more detail, see Section V. Discussion). The most recent literature on this topic suggests that the performance can be improved by combining different techniques. Examples of such research have been presented by Jaros *et al.* [193], where so-called *hybrid* methods based on combination of both CS and AES algorithms appear to be the most effective methods. This subsection thus introduces some examples of the promising hybrid methods for fECG extraction.

As part of the Challenge 2013, Behar *et al.* [194] tested several approaches and their combinations. The author concluded that the algorithm denoted as FUSE outperformed the rest of the tested methods. The FUSE algorithm was defined as the combination of methods based on ICA, TS and their combinations (ICA-TS, ICA-TS-ICA, TS-ICA). It is important to note that this approach obtained the best scores for events 1 and 2 of the Challenge.

Liu *et al.* introduced an adaptive integrated algorithm based on ICA, ensemble empirical mode decomposition (EEMD), and wavelet shrinkage (WS) denoising, denoted as ICA-EEMD-WS [195]. The EMD is an adaptive technique for analyzing nonlinear and non-stationary signals used for denoising through decomposing the signal into a finite number of intrinsic mode functions (IMFs) [196]. In the first stage, FastICA algorithm separated the noisy fECG from the aECG signal. In the second stage, the noise in this fECG estimate was reduced in three steps. First, the EEMD algorithm decomposed the signal to individual IMFs, which were then sorted using the significance test on noise dominant, useful, and trend IMFs. In the third step, the noise dominant IMFs were denoised using WS and then used along with the useful IMFs to reconstruct the fECG signal.

Another interesting approach was used by Castillo *et al.* [197]. The novel algorithm introduced therein was compared with various approaches including [110], [126], [131], [140], [198] and demonstrated high efficiency of the proposal. The fECG extraction system included three stages: 1) One-step wavelet-based preprocessing; 2) novel clustering-based method for fECG extraction; 3) False positive and false negative correction. The base of the fECG extraction was carried out by means of the novel algorithm, which was comprised of four steps. In the first step, the signal features (amplitude distance between the max-min points and number of samples) were extracted by searching for min-max points, which were assumed as the RS peak since it can be defined as a local maximum followed by a local minimum in the fECG waveform. In the second step, the signal features were selected. The max-min points were subsequently classified into three clusters based on the selected features. The third step involved the clustering classification using which the R peaks were detected. In the final step, the classification was improved by applying some limits on the amplitude and time distance of the data classified as fetal RS-peaks in order to decrease the number of false positive results.

Panigrahy *et al.* [198] tested various combinations of methods such as EKF, EKS, ANFIS, and the differential evolution (DE). The best results were achieved using EKS-DE-ANFIS combination. The algorithm performs five steps to obtain the fECG signal: preprocessing, phase assignment, template estimation, and fECG estimation using DE and EKS with ANFIS logic. The DE algorithm is used to select the optimized mECG parameters. These parameters are necessary to develop the state and measurement equation of the EKS framework, which then estimates the maternal component from the aECG signal. The ANFIS is used to recognize the non-linear relationship between maternal and component in the aECG signal and the mECG signal. The fetal ECG is obtained by subtracting the ANFIS output from the pre-processed aECG signal.

TABLE II
COMPARISON OF THE fECG EXTRACTION TECHNIQUES

	Strength	Limitation	Computational cost	Performance
ICA, PCA	Stable	NoE	Medium	Medium
ESN	Precise	PS	High	High
LMS	Fast	ChE	Medium	Medium
RLS	Stable	ChE	Medium	Medium
ADALINE	Stable	ChE	Medium	Medium
ANFIS	Stable	ChE	High	High
EKF	Stable	MPD	Medium	Medium
WT	Fast	Unprecise	Low	Low
TS	Simple	MPD	Medium	Medium

ChE: Additional chest electrode needed, effectiveness is influenced by the quality of this signal
NoE: number of electrodes, signals from at least four electrodes recorded simultaneously are needed
PS: parameter setting, the number of parameters to be set is high and the performance is low if set incorrectly
MPD: maternal peaks (QRS) detection significantly influences the overall performance

Finally, Jaros *et al.* [199] combined the ICA method with two different adaptive approaches (RLS and ANFIS) and WT. These two hybrid algorithms, therein denoted as ICA-RLS-WT and ICA-ANFIS-WT, combine the advantages of individual methods, i.e. provide accurate fECG estimates using low number of abdominal electrodes. The algorithm performs following three steps: first, ICA is used to estimate the maternal component from the input aECG signals; secondly, the maternal estimate is used as the reference input of the adaptive algorithm, producing the fECG estimate; finally, the output signal is processed by WT to ensure accurate fHR determination. The study on data from clinical practice (extended ADFECGDB database) as well as on Challenge 2013 Set A. The comparison of the fHR wavefors determined using the estimated fECG signals, the FSE reference, and Challenge 2013 annotations proves its accuracy for the non-invasive fHR variability monitoring.

V. DISCUSSION

The comparison of the published methods is challenging since the datasets and evaluation criteria may differ from one publication to another. An objective comparison between algorithms is possible for those who entered the Challenge 2013; the results are summarized in [36]. However, other authors used similar techniques and datasets, such as F_1, Acc, PPV or Se, so it is possible to compare them as well. For example in [197], the authors compared their novel algorithm with a number of other methods (e.g. [110], [126], [131], [140], [198]) either published within the Challenge 2013 framework or after 2013, and demonstrated high efficiency of the proposal. According to Silva *et al.* [200], the hybrid methods (such as [123] and [131]) paticipating in the Challenge outperformed the others that were based on a single method only.

In this section, we aim to summarize the individual methods so that researchers willing to design a new hybrid algorithm understand the strengths and weaknesses of the different approaches.

Table II shows the comparison of all investigated methods. It provides their most significant strength and weakness, computational cost, overall performance of the fHR estimation based on the results reviewed, and the ability to provide fHR analysis. The parameters can be described as follows:

- *Performance* is classified as high, medium, and low. Based on that the methods can be described as follows:
  - *High* – these methods enable a very accurate determination of fHR, i.e. the performance parameters (Se, PPV, Acc, and F_1) $\geq 95\%$.
  - *Medium* – these methods allow moderately accurate detection of fHR, i.e. the performance parameters (Se, PPV, Acc, and F_1) $\geq 80\%$. It may be advantageous to combine these methods with others to achieve higher accuracy.
  - *Low* – the methods are not able to remove artifacts and noise sufficiently to enable the continual fHR monitoring, i.e. the performance parameters (Se, PPV, Acc, and F_1) $<80\%$; these methods need to be used in combination with other methods.

  Computational cost is a crucial factor in designing the extraction system for the continual fetal monitoring since it influences the ability of the system to function in the real time and also long-term. Therefore, one must find a compromise between the performance the method provides and its computational cost. Indeed, methods such as ANFIS and ESN can be problematic in this matter. It is therefore advantageous to combine the methods computationally less demanding with more precise methods in order to create a precise extraction system feasible for clinical practice.

  Strength and Limitation – the Table II includes the main drawback and advantage of each method that will be discussed in detail and illustrated using the examples of output signals of different algorithms below.

Table III summarizes the parameters to be set for a conventional sampling rate (1000 Hz) and electrode placement. Last column of the table provides the sources of codes to implement the fECG extraction system. Based on Table II and Table III, it is evident that each method has its own strengths and weaknesses and thus, the most promising direction seems to be towards hybrid systems that combine multiple algorithms, as suggested in [167], [194].

As mentioned in Table II, the limitation of the TS method is that its overall performance is influenced by the quality of the QRS detection – as measured by the accuracy of detecting R-peaks – since the maternal template is constructed based on the detected R waves. Any false positive or false negative of the maternal QRS detector will affect the fECG estimation and thus need to be adjusted. Fig. 11 shows an example of such a case.

The performance of the BSS methods strongly correlates with the number of the input channels. Fig. 12 shows the influence of number of the input channels on the performance of the ICA method. It can be noted that the higher number of input channels, the more effective the fECG extraction. It is also important to choose reasonably high number of output components. In case of fECG extraction, one should select ideally three or a minimum of two output components to ensure capturing the fetal one [173]. The correspondence of the output channels to

TABLE III
DEFINITION OF THE MOST IMPORTANT PARAMETERS FOR fECG SIGNAL PROCESSING METHODS, CORRESPONDING OPTIMAL SETTINGS, AND LINKS FOR THE ALGORITHM SOURCE CODES AVAILABLE ONLINE

	Parameters	Description	Optimal values	Sources
ICA, PCA	Input	Number of input channels	Minimally 3	fecgsyn*
	Output	Number of outputs components	Minimally 3	
	Iterations	Norm of the iterative step	10^{-6}	
ESN	γ	Input scaling of the input weight matrix	1	fecgsyn*
	ρ	Spectral radius of the reservoir matrix	[0, 1]	
	α	Leakage rate	[0, 1]	
	λ	Forgetting factor of RLS algorithm	0.999	
	Ψ	Sparsity of the reservoir	20%	
	M	Size of the reservoir	[1, 100]	
LMS	M/N	Filter length / Filer order (N=M-1)	[1, 100]	fecgsyn*
	μ	Step size (convergence constant)	[0.001, 0.01]	
RLS	λ	Forgetting factor	[0.9, 1]	fecgsyn*
	M/N	Filter length / Filer order (N=M-1)	[1, 100]	
ADALINE	m	Momentum	[0.5, 1]	[201]
	η	Learning rate	[0.001, 0.02]	
	w_{i}	Initial weights	Small non-zero	
	p	Input space	[20, 30]	
ANFIS	Epochs	Number of epochs	[10, 20]	[202]
	Mf	Number membership functions	6	
	Shape	Type of the Membership function	Gaussian/bell-shaped	
EKF	m	Number of Gaussian kernels (functions)	[5, 9]	fecgsyn*
	Q_{k}, R_{k}	Process noise covariance matrix and measurement noise covariance matrix, size $(3m+2) \times (3m+2)$, diagonal	Estimated from the ECG signal	

*fecgsyn algorithms are available online at: http://www.fecgsyn.com

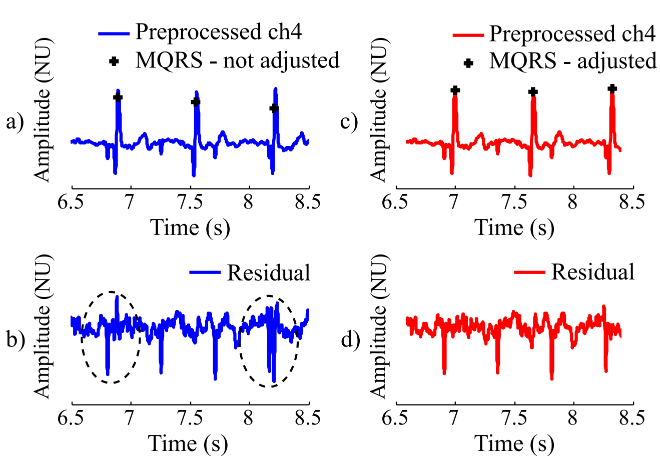

Fig. 11. Influence of the inaccurate mQRS detection on the residual signal reproduced from Behar *et al.* [123]: a) Preprocessed aECG signal (channel 4) with mQRS complexes without adjustment; b) residual signal after the subtraction of maternal template constructed based on the R waves without adjustment – note the maternal residua marked; c) preprocessed aECG signal (channel 4) with mQRS complexes with adjustment; d) residual signal after the subtraction of maternal template constructed based on the adjusted R waves.

fECG is not provided by the algorithm, hence, one cannot be sure which output corresponds to which component. This makes automated detection based on ICA challenging.

The additional chest electrode records maternal ECG directly, so there is a lower chance of signal misinterpretation. However, the efficiency is strongly affected by the quality of the chest signal. Fig. 13 shows how insufficient quality of maternal reference signal can influence the fECG extraction. It is noted that the fHR detection would be difficult and strongly affected by the significant amount of maternal residue.

It is also important to note that most of the currently available techniques are able to determine only fetal heart rate. However, this parameter is currently monitored in the clinical practice using CTG. The NI-fECG is capable to provide more clinical information associated with morphological analysis of the fECG waveform, as mentioned in Section II-B. Enabling fECG morphological analysis of clinically significant parameters (such as QT segment and ST level) could thus open new diagnostic possibilities (such as ST analysis and T:QRS ratio), now only possible using the invasive method [203].

Few authors have achieved good results in this matter. Niknazar *et al.* [83] extracted the fECG by extended state Kalman filtering from single-channel recordings. Su *et al.* [84] were able to extract fECG for both fHR and morphological analysis using a novel algorithm based on the optimal-shrinkage and the nonlocal Euclidean median under the wave-shape manifold model. Another successful attempt to reconstruct the NI-fECG was introduced by Behar *et al.* [85] using a Bayesian filtering framework based on the extended Kalman filter.

However, one should keep in mind the fact that the NI-fECG waveform differs from the one recorded by means of FSE. The reason for this is the signal dispersion caused by the fECG signal propagating from the fetus towards the abdominal electrodes through the maternal volume conductor, which consists of vernix caseosa, amniotic fluids, muscle layers, fat and skin [62]. Clearly, this effect is observable by the changes in the frequency content of fECG as the maternal volume conductor acts as a high-pass filter [61], [204]. Specifically, it affects low frequency features of the fECG waveform, such as the T-wave [62]. According to the experimental results provided by Vullings *et al.* [62], these amplitude and frequency changes only affect the accuracy of the assessed T:QRS ratios; hence, the abdominal electrodes are sufficient.

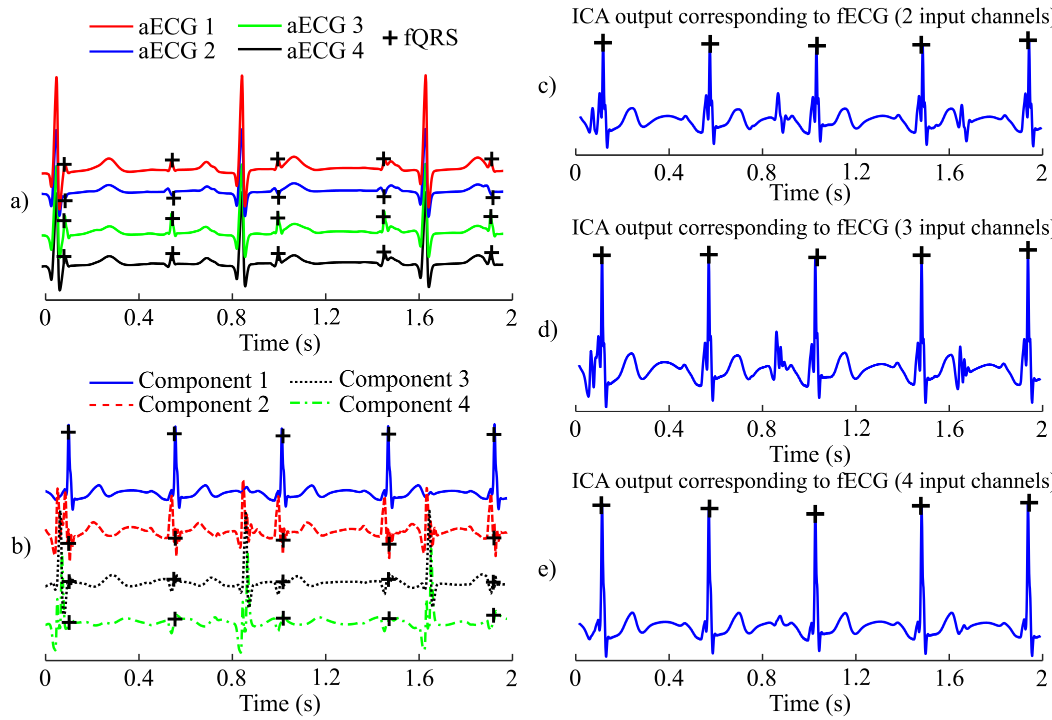

Fig. 12. Application of ICA on four abdominal channels. a) examples of the input abdominal channels aECG1 – aECG4 with the fQRS annotations (+); b) four independent components acquired with ICA using four inputs; c), d), e) output signals corresponding to the main fECG component extracted using ICA from 2, 3, and 4 input channels, respectively. Note that the more input channels, the higher quality of the estimated signal.

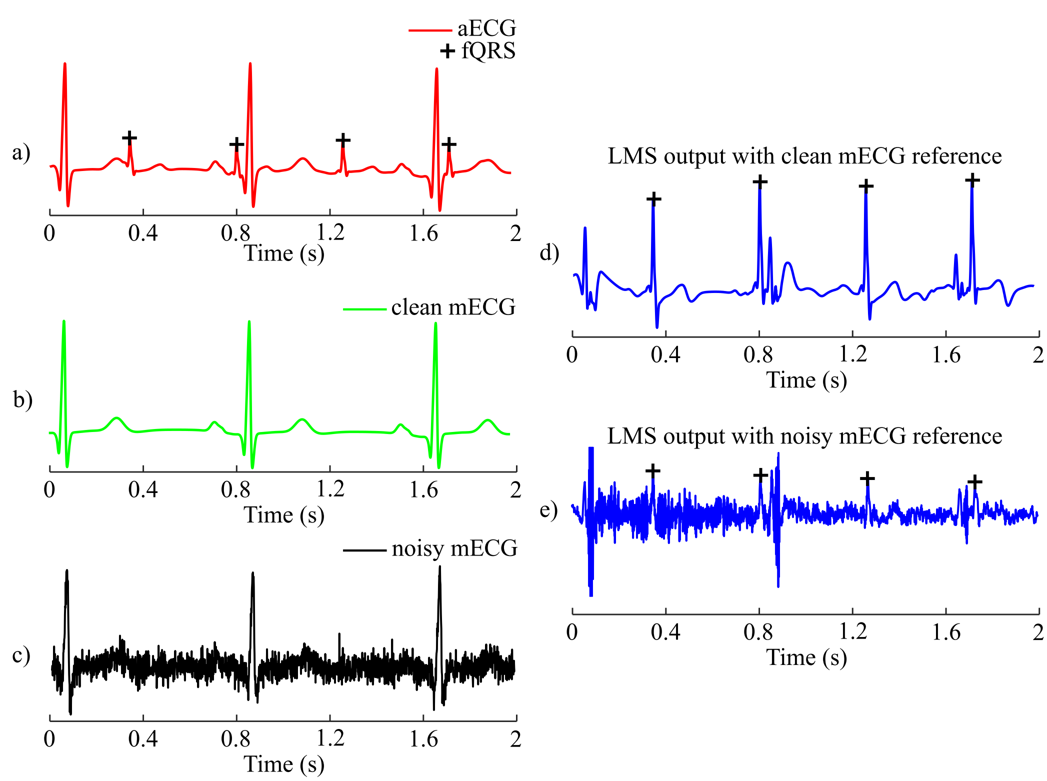

Fig. 13. Influence of the quality of mECG reference input of the adaptive system (filter) using the LMS algorithm; a) an abdominal signal; b) clean mECG reference input; c) a noisy mECG reference input; d) the filter output signal when using a clean mECG reference [as shown in b)]; e) the filter output signal when using a mECG signal of a poor quality [as shown in c)].

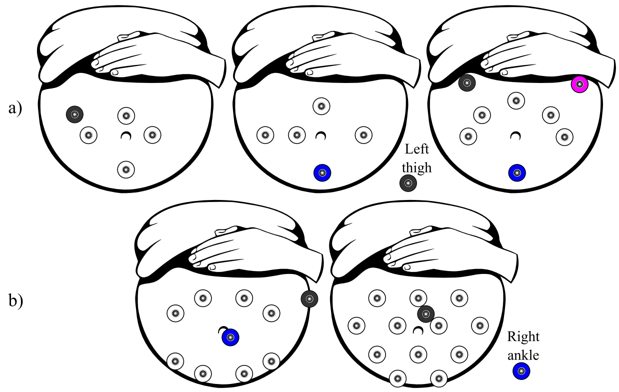

Fig. 14. Examples of the deployment of the measurement electrodes (abdominal – white, and chest – purple), common reference (blue), and the active ground (black): a) from left to right: commercially available device Monica AN24, positioning used in publically available databases ADFECGDB and NIFEADB; b) from left to right: Vullings [62] and Taylor [206].

Finally, we stress the need to unify the electrode placement. There are significant differences in electrode deployment among the databases, different researchers, and also the commercially available devices as illustrated in Fig. 14. While the positioning of the measurement electrodes only influences the magnitude or polarity of the signal, the placement of common reference electrode (blue) and the active ground (black) causes significant changes in the recorded signals since it may help in minimizing both the polarization potential and the maternal component [205]. Therefore, it may significantly influence the performance of the extraction algorithms. The optimal number of electrodes may also differ for each extraction algorithm since BSS methods (such as ICA or PCA) performs better with high number of abdominal inputs, whereas a multi-lead system using an adaptive algorithm requires low number of abdominal electrodes, but at least one chest reference electrode. This review reveals that both theoretical and experimental studies should be performed in order to create a recommendation for electrode placement according to the stage of pregnancy, fetal position, number of fetuses, and the algorithm used for the extraction.

VI. Conclusion

This review paper presented (I) an overview of the advances and current challenges in fetal heart monitoring; (II) a thorough review of promising signal processing techniques for NI-fECG extraction; (III) a detailed description of the open access databases in this field; (IV) highlight of the strengths and limitations of fetal ECG extraction algorithm; and finally (V) a list of the most important parameters for the state of the art algorithms and the corresponding optimal settings.

In this paper, we introduced the most commonly used fetal ECG extraction methods and presented their strengths and weaknesses that make them suitable for different scenarios and types of signals. Based on the up-to-date literature presented in this paper, we may conclude that combining different techniques and creating hybrid systems for fECG extraction might be the most promising direction in reaching an accurate fetal heart rate estimation.

However, it is challenging to see clear into the relative performance of the algorithms to decide which is the most suitable for the needs of fECG extraction. One of the reasons is that for objective assessment of the extraction system performance, it is necessary to provide a large open access database of signals for the tests. However, the currently available databases offer only a limited set of data and they do not follow the same protocol in terms of electrode placement or pre-processing stage. Thus, in most of the papers available, the evaluation provided is insufficient. One of the main challenges is to create a unified and sufficiently large dataset following the standards of *big data*. Moreover, the evaluation of the algorithms should follow the same protocol, be accessed using the same parameters, and tested on the same dataset.

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