Common Spatial Pattern with Deep Learning for Fetal Heart Rate Monitoring

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***Abstract*—In this paper, the problem of monitoring the electrical pulse of the fetal heart using non-invasive electrocardiogram (ECG) signal is studied. To overcome challenges like the overlap between maternal and fetal heart components and noise in the mother's abdomen signal, we propose a new single-channel signal processing technique to detect the fetal QRS (fQRS) events. We first propose a modified sample entropy technique to filter out noisy and complex signal components. Then, common spatial pattern (CSP) technique is employed to find a new sub-space with reduced overlap among maternal and fetal patterns. Then, a one-dimensional convolutional neural network is trained to detect the fQRS events from the abdominal ECG. The obtained results on several well-established datasets are promising and confirm the effectiveness of the proposed approach.**

***Index Terms*—Electrocardiography, common spatial pattern, deep learning, sample entropy, QRS event**

I. Introduction

Today, heart problems in newborn babies are the leading cause of death due to pre-existing defects in fetus [1]. Hence, fetal heart monitoring is considered one of the most important clinical checks at different stages of pregnancy. Electrocardiogram (ECG) recording, which measures the electrical signals produced by the human heart, is widely used as a non-invasive method for heart disorder diagnosis. Numerous heart diseases can be diagnosed by studying the shape of the ECG signal and its frequency contents. QRS complex is the most visible part of a typical ECG which is a combination of the graphical deflections lasting between 80-100 seconds in adults (Figure 1) [2]. While ECG is usually captured by placing some electrodes on an adult's chest, it cannot be easily captured from the fetus heart. Instead, fetal ECG (FECG) can be obtained by placing electrodes on the mother's abdomen. This type of recording provides abdominal ECG (AECG) which is a mixture of maternal and fetal ECG signals, plus noise. Therefore, it requires post-processing to be cleaned and separated. AECG suffers from issues such as mixing with different noises, maternal muscle movement [3] and respiratory activity as well as fetal movement. Performing signal processing and/or machine learning algorithms on abdomen recordings can significantly enhance the quality of the extracted information associated with the fetus's heart. Several techniques, including adaptive filters, blind source separation (BSS), and template subtraction (TS) have been used for extracting FECG components from the abdominal signals [4], [5]. These methods are generally complex, not accurate, and have convergence issues. Although TS method is less computationally expensive, it requires knowledge about the exact maternal QRS location which is not always available [6].

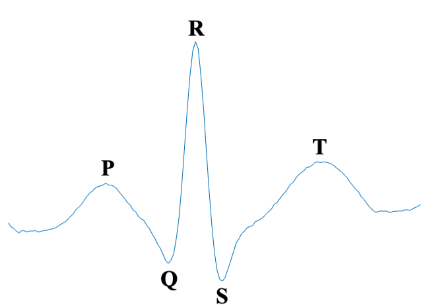

Fig. 1. QRS complex cycle in a small segment of a sample ECG signal.

Recently, the deep learning approach has been dominantly reported with promising performance in this context [7]–[9]. For example, Zhong et al. [8] proposed a method using deep learning to detect complex fetal QRS in a single channel ECG data without cancelling MECG signals. A three-layer neural network was used as a classifier in this paper. In another work, Lee et al. [10] developed a deep network based on a two-dimensional CNN with seven convolutional layers for detecting fetal ECG peak in AECG signal on four-channel raw ECG signals. Vo et al. [11] provided a model using deep learning to detect fetal QRS complexes with four-channel ECG signals. Their deep learning model is based on ResNet and one-dimensional octave convolution to reduce memory and computational cost. In general, deep learning methods have considerably improved the accuracy of fetal QRS detection compared to traditional approaches. However, they still require further improvement in terms of accuracy, parameter selection, and complexity. Most related studies on the extraction of fetal ECG require access to the associated maternal ECG (or at least the exact location of maternal QRS). This is a limiting factor as maternal ECG is not often available and maternal QRS detection is a complex task with error. This can significantly reduce the performance of FECG component extraction.

The above-reviewed methods use raw abdominal ECG signals to detect fetal QRS events. Unlike other studies, Lo et al. [12] used time-frequency representation to train the deep learning model. They used short-time-Fourier-transform (STFT) to prepare the features for training. Their deep learning model contained two-dimensional convolutional layers to extract spatial features from time-frequency images. Zhang et al. [13] used template subtraction based on principal component analysis (PCA) to extract FECG from AECG signals. They preprocessed signals using a Butterworth bandpass filter in order to remove noises and artifacts. K-means clustering with the feature of max-min pairs was used to find fetal and maternal QRS. Finally, fQRS was extracted using template subtraction based on PCA.

In this paper, we address fetal QRS wave detection using a deep learning approach. Our major contributions are: *i*) applying a modified signal quality metric (called Sample Entropy) to the raw AECG signals to remove unwanted noisy components, *ii*) utilising the common spatial pattern (CSP) method (as a feature mapping technique), for the first time with ECG signals, and *iii*) employing a one-dimensional convolutional neural network (1D-CNN) for fQRS detection.

The rest of the paper is organised as follows. In Section II, the details of the datasets used in the study are provided. In Section III, the proposed approach is described. Section IV is devoted to the experimental results. Finally, the concluding remarks are given in Section V.

II. Datasets

Three datasets, all belonging to PhysioNet[1], are used in this study. The first one is Non-invasive Fetal ECG (NIFECG1)–The PhysioNet Computing in Cardiology Challenge 2013 [14]. It includes 75 AECG recordings. The sampling rate of the signals is 1000 Hz and each recording includes 4 channels and has 60 seconds of data [15].

The second dataset is called the Non-Invasive Fetal ECG Database (NIFECG2) [14]. It includes 55 recordings with 1000 Hz sampling rate. Each recording includes 3 or 4 abdominal and 2 thoracic signals, filtered by a bandpass filter between 0.01 and 100 Hz. All recordings are 60 seconds long. This dataset is used for testing the proposed method to make sure that the method is not personalized for the PhysioNet Computing in Cardiology Challenge 2013 dataset.

A third dataset, called FECG Synthetic Database (FECGSYNDB) [14], [16], is also used in this study. This dataset is a large collection of non-invasive fetal ECG (NI-FECG) simulated signals including both adult and fetal. It comprises 10 subjects, 7 cases, 5 different SNR levels (0, 3, 6, 9, and 12 dB), and 5 repetitions. The sampling frequency is 250 Hz and each signal includes 34 channels (32 abdominal and 2 maternal ECG reference channels). There are 3 separate signals for each record – the MECG, the FECG, and noises (noise1 and noise2). In our experiments, we have picked up a sub-set of signals with two different SNR levels (0 and 12 dB) from this dataset.

III. Proposed Approach

The proposed method for fQRS detection consists of four major steps: *i*) pre-processing, *ii*) windowing, *iii*) data transformation, and *iv*) deep learning. Pre-processing includes bandpass filtering and signal quantification. Data transformation includes feature extraction using CSP. In the final stage, deep learning is used for training and classification. The block diagram of the proposed fQRS detection is shown in Figure 2 and details of these steps are explained in the following.

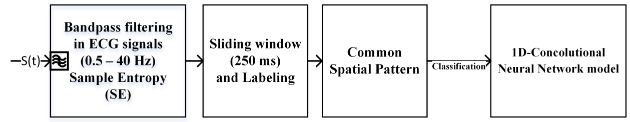

Fig. 2. Overall procedure of the proposed fQRS detection based on the proposed combination of CSP and 1D-CNN.

A. Pre-processing

The challenges of analysing FECG signals are twofold; 1) they form a mixture of maternal and fetal heart rate information, and 2) they are normally contaminated by a variety of other physiological signals and noise. Therefore, pre-processing is considered an essential step to mitigating the amount of noise and artifacts. The valid frequency range of ECG signals to be preserved is within 0.05 and 100 Hz. However, most types of noises that exhibit during ECG acquisition overlap with this frequency range. To obtain a reliable and precise data analysis of fetal ECG, a sequence of pre-processing algorithms must be applied to the raw data. In this paper, two main approaches are adopted to mitigate the effects of noises and artifacts in the ECG signals.

1) Filtering: Power-line noise (50/60 Hz), and baseline drift (low-frequency noise 0-1 Hz) are two types of typical noise in ECG signal [17] that can be removed using band-pass filtering. However, we must make sure that no information about maternal and fetal signals is destroyed. Hence, we design and apply a Butterworth bandpass filter with cut-off frequencies between 0.5 and 40 Hz, to reduce the effect of these noises. Using this filter, unwanted frequencies are removed from ECG signals.

2) Sample Entropy: Sample Entropy (*SaEn*) is a generic metric used for estimating the complexity of time-series signals [18]. It is an effective tool to estimate the quality of a signal with respect to the waves it is composed of. Thanks to the regularity of ECG signals, Zhong et al. [8] demonstrated that removing signal channels with low regularity (as a result of strong non-ECG components) can increase the accuracy of diagnosing fQRS. Hence, it can be inferred that *SaEn* is a technique for data purification. In the following, we describe an improved version of *SaEn* to determine and remove noisy ECG channels.

Let us consider time series $\mathbf{s}$ (e.g. a channel of filtered AECG) with N samples as $\mathbf{s} = [s(1), s(2), ..., s(N)]$. We partition $\mathbf{s}$ into $N-m+1$ small segments of length $m < N$ with $N-m$ overlapping samples. Each segment is defined as $\tilde{\mathbf{s}}_i^m = [s(i), s(i+1), ..., s(i+m-1)]$ where $1 \leq i \leq N-m+1$. By definition, the sample entropy is computed via:

$$SaEn = -\ln\left(\frac{\sum_{i=1}^{N-m} Q_i^m(r)}{\sum_{i=1}^{N-m+1} P_i^{m+1}(r)}\right) \tag{1}$$

[1]https://physionet.org/about/database/

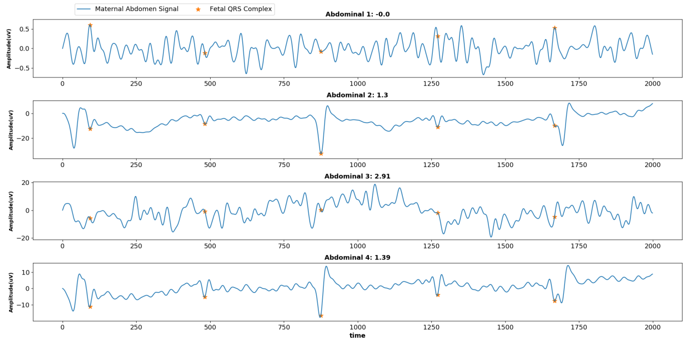

Fig. 3. An example of signal quality evaluation related to record 42 of NIFECG1. Channels 2 and 4 have the sample entropy less than threshold ($r = 1.5$) and therefore are kept for the next processing stage. The values on top of each plot are the calculated *SaEn*.

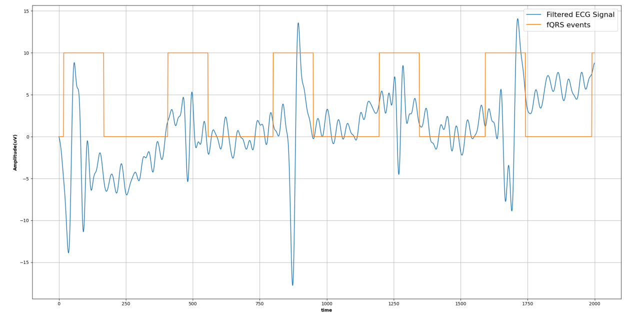

Fig. 4. The square signal associated with fQRS events in the ECG signal. Where the yellow signal is set to 1, fQRS has occurred. Related to abdominal 4th of subject 42 of NIFECG1.

where N, m, and r correspond to signal length, embedded dimension, and threshold on Euclidean distance d (defined below), respectively. $Q_i^m(r)$ and $P_i^{m+1}(r)$ are the number of template vector pairs having a distance less than threshold r defined as:

$$Q_i^m(r) = \sum_{i,j=1}^{N-m} 1 : d[\tilde{\mathbf{s}}_i^m, \tilde{\mathbf{s}}_j^m] \leq r, i \neq j \tag{2}$$

$$P_i^{m+1}(r) = \sum_{i,j=1}^{N-m+1} 1 : d[\tilde{\mathbf{s}}_i^{m+1}, \tilde{\mathbf{s}}_j^{m+1}] \leq r, i \neq j \tag{3}$$

where $d[a, b]$ is the Euclidean distance between two vector a and d and is equivalent to $max(|s(i+k)| - |s(j+k)|) : 0 \leq k \leq N-m$. The process of calculating *SaEn* is performed for two embedded dimensions, i.e., m and $m+1$, and repeating the required steps to calculate $Q_i^m(r)$ and $P_i^{m+1}(r)$ and finally the *SaEn* measure using (1).

Figure 3 shows 2-second acquired AECGs of channels 1-4 from subject no. 42 in NIFECG1. Also, the calculated *SaEn*'s for these channels are provided on top of each signal. Based on the work in [8] and our empirical evaluations, we selected data length ($N = 500$), embedded dimension ($m = 2$), and threshold ($r = 1.5$), to calculate *SaEn*. By definition, signals with *SaEn* $< r$ should be qualified as appropriate (i.e. *simple*). Applying this rule to Figure 3 classifies only channel 3 (with $SaEn_3 = 2.91$) as *complex*. However, it is clearly observed from this figure that channel 1 (with $SaEn_1 = 0$) has also severe noise that can fail fQRS detection, and it should be classified as complex. We have analysed all AECG channels and have found significant cases like this. The reason for this issue is obvious; $SaEn = 0$ is equivalent to $Q_i^m = P_i^m$ where segments are of equal size in the corresponding signal. Thus, it should be classified as *complex* and not *simple*. In order to exclude this case from the *SaEn* purification process, we modify the Sample Entropy rules as follows so that all signals with zero *SaEn* will be removed from the pipeline for further processing. The proposed modified *SaEn* rule is:

Definition 3.1 (Modified SaEn): The signal S is classified as simple if and only if $0 < SaEn \leq r$.

3) Sliding Window and Labeling: As already mentioned in Section II, each recording in the datasets of interest includes raw abdominal signals along with annotations of the associated fQRS. However, the annotations cannot be directly used during the training phase. In fact, we require vectors of binary values (labels of fetal and non-fetal samples) associated with each training signal. In what follows, we describe our approach to automatically generating labels associated with annotation files. The annotation files include specific sample locations where fQRS occurred. We need to define the intervals where fetal (f_event) or maternal (m_event) heartbeats occurred. Hence, we divide all ECG signals into segments of equal size and then associate these numbers with exact locations of fQRS occurrence. This is performed by applying a sliding window on every single abdominal signal that successfully passed the Sample Entropy stage. The length of the sliding window is empirically set at 250 samples (equivalent to 250 ms). This has been achieved in a coarse-to-fine manner and after several tries and errors. All windows have the same length and are slid over the entire length of the abdomen signals. In order to make sure maternal and fetal events are well preserved during the process, we consider a 50% overlap between all the neighbouring windows. In any given segment, if an fQRS has occurred (according to the annotation file) in the middle of the window (i.e. 75 samples before and after the start of the window), that window is labelled as 1 (f_event). Otherwise, the window is labelled as 0 (M_event). The output will be a squared wave as shown in Figure 4 illustrating two windows with and without an fQRS.

B. Common Spatial Pattern

The mixed nature of FECG and MECG within abdominal signals makes time-domain detection of fQRS challenging. One general approach is to transform input signals into a domain where separable features can be obtained. CSP transforms the data representation space to reduce the complexity of the model, increase data discriminability, and avoid overfitting. It aims to learn spatial filters to minimise the variance of one class and, at the same time, maximise that of another class for the given data. This technique has been extensively applied to Electroencephalogram (EEG) signals and Brain-Computer-Interface (BCI) applications [19], [20].

In this paper, we employ CSP to obtain a separable feature space for fetal and maternal events. To the best of our knowledge, this is the first study in which the use of CSP for fQRS classification is reported. We adopt CSP algorithm in this work to differentiate between fetal ECG signals and other parts of the signal and ultimately improve the classification accuracy. To do this, we apply CSP to the windowed signals obtained in the previous step where two classes of FECG and MECG were labelled. By performing this step, we expect to find the filters that create the greatest difference in terms of variance between different classes. To perform a two-class CSP, consider matrix $\mathbf{S}$ of size $M \times N$ to represent M-leads and N samples ECG signals. There are two classes $C \in \{c_0, c_1\}$ in this problem where c_0 and c_1 correspond to f_event and m_event, respectively. The normalized covariance matrix for both class C is calculated via:

$$\mathbf{\Theta}_C = \left(\frac{1}{V}\right)\sum_{i=1}^{V} \frac{\mathbf{S}_{iC} \times \mathbf{S}_{iC}^T}{trace(\mathbf{S}_{iC} \times \mathbf{S}_{iC}^T)} \tag{4}$$

where $\mathbf{\Theta}_C$ is the covariance matrix for class C, V is the number of segments, T is transpose operation, and $trace(\mathbf{A})$ is the sum of the elements of the original diameter of the matrix $\mathbf{A}$. $\mathbf{S}_{iC} \in \mathbb{R}^{M \times k}$ is i-th segment of ECG data with k samples in class C. After that, the matrix of eigenvalues and the diagonal of normalized eigenvectors matrix is calculated:

$$\mathbf{CC} = \sum_{i=1}^{C} \mathbf{\Theta}_C = \mathbf{U}_0 \mathbf{\Sigma} \mathbf{U}_0^T \tag{5}$$

where $\mathbf{\Sigma}$ and $\mathbf{U}_0$ are the matrices of eigenvalues and the diagonal of normalized eigenvectors, respectively. In order to map the data to new space with $\mathbf{U}_0$ vectors, the whitening matrix is computed via (6) and is transformed via (7):

$$\mathbf{G} = \mathbf{\Sigma}^{-1}\mathbf{U}_0^T \tag{6}$$

$$\mathbf{D}_C = \mathbf{G}\mathbf{\Theta}_C\mathbf{G}^T = \mathbf{U}\Psi_C\mathbf{U}^T \tag{7}$$

where $\sum_{c \in C} \mathbf{\Psi}_c = \mathbf{I}$. $\mathbf{U}$ and $\mathbf{\Psi}$ are the matrix of eigenvalues and the diagonal matrix of eigenvalues, respectively. $\mathbf{D}_C$ includes the largest eigenvalues for one of the classes and the smallest eigenvalues for another class. Finally, the transformation matrix is applied to each segment of ECG data as:

$$\mathbf{B}_{iC} = (\mathbf{U}^T\mathbf{G})^T \mathbf{S}_{iC}^T \tag{8}$$

where $(\mathbf{U}^T\mathbf{G})^T \in \mathbb{R}^{M \times M}$ and $\mathbf{B}_{iC} \in \mathbb{R}^{M \times k}$. Each row of $(\mathbf{U}^T\mathbf{G})^T$ represents a spatial filter, and each column of $(\mathbf{U}^T\mathbf{G})^T$ represents a spatial pattern. Algorithm 1 shows the pseudocode of CSP we applied to ECG signals.

Algorithm 1: Proposed CSP-FECG algorithm.

Input: A set of I segments of ECG multi-channel signals $\mathbf{S} \in \mathbb{R}^{M \times N}$ for two class $C \in \{c_0, c_1\}$

Output: A transformed version of $\mathbf{S}$.

For $i = 1$ to I do

Consider $\mathbf{S}_{iC} \in \mathbb{R}^{M \times k}$ where $\mathbf{S}_{iC}$ is the i-th segment of k samples an ECG signal belonging to class C.

Compute the normalized covariance matrix for both class C via (4)

Compute the composite covariance matrix: $\mathbf{CC} = \sum_{j=1}^{C} \mathbf{\Theta}_C = \mathbf{U}_0\mathbf{\Sigma}\mathbf{U}_0^T$

Obtain whitening matrix $\mathbf{G}$ that can map data to new space with $\mathbf{U}_0$ vectors, $\mathbf{G} = \mathbf{\Sigma}^{-1}\mathbf{U}_0^T$

Compute whitening transform

$$\mathbf{D}_C = \mathbf{G}\mathbf{\Theta}_C\mathbf{G}^T$$

Dialyze $\mathbf{D}_C$ in order to share common eigenvalues,

$$\mathbf{D}_C = \mathbf{U}\Psi_C\mathbf{U}^T$$

Compute transformation matrix $\mathbf{Z}$, $\mathbf{Z}_C = (\mathbf{U}^T\mathbf{G})^T$

Finally, apply transformation matrix $\mathbf{Z}$ on each segment of ECG data, $\mathbf{B}_C = \mathbf{Z}_C\mathbf{S}_{ic}^T$

End for

C. Proposed Deep Learning Model

The abdominal ECG signals in our proposed pipeline were transformed to a reduced sub-space using CSP. In this step, these signals are used to train the neural network for classification. A one-dimensional convolutional neural network (1D-CNN) model is proposed for this purpose which is described next.

In our model, there are two convolutional layers with 16 and 32 units, respectively, followed by a fully connected (dense) layer with 128 units. Also, each convolutional layer is followed by a MaxPooling layer and a LeakyReLU activation function. This model is used for fetal ECG diagnosis. Figure 5 shows full architecture of the proposed deep learning model. The input of the proposed network is the real-valued matrix (B_C) containing the output of CSP algorithm (See Algorithm 1). The data is then fed to a one-dimensional CNN structure. In the CNN structure, for each convolutional layer, the dilation rate is used. The main ingredients of dilated CNN are causal convolutions. The convolutional layer with dilation d skips $d-1$ inputs. The dilated convolution can expand the input without using pooling and the output has a wide range of information. This type of convolution is used for problems that require more dependence on the information sequence [21]. The kernel size is 3 for all layers. The kernel and bias in each layer of the proposed CNN model are initialised by random uniform and random normal, respectively. Kernel and

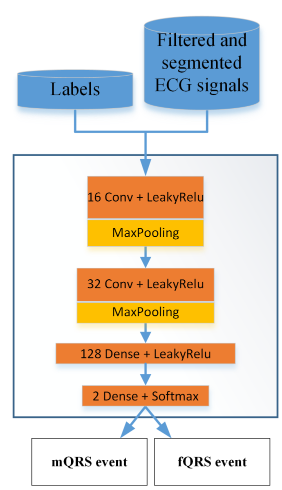

Fig. 5. The proposed deep learning model to detect fQRS event.

TABLE I
THE COMPARISON OF FQRS DETECTION ACCURACY WHEN SEVERAL FEATURE MAPPING TECHNIQUES WERE USED WITH THE PROPOSED DEEP LEARNING MODEL.

Feature mapping	NIFECG1	NIFECG2
CSP - PCA	95.0%	90.0%
CSP - STFT	95.4%	89.4%
CSP - CWT	94.2%	90.0%
PCA only	60.0%	95.7%
CSP only	**97.0%**	**98.0%**
Raw data	86.0%	93.2%

bias initialisers are used to set the initial random weights of layers. The random uniform generates tensors with a uniform distribution and the random normal generates tensors with a normal distribution. LeakyReLU is a leaky version of a Rectified Linear Unit (Relu) which is obtained as follows:

$$f(x) = \begin{cases} \alpha x, & x \leq 0 \\ x, & x \geq 0 \end{cases} \tag{9}$$

where α is the number between 0 and 1 and x is summation of the weights (w) and the inputs (a) plus bias (b) as ($\Sigma_i a_i w_i + b$).

The maxpooling layer is used in our model which downsamples the input representation by taking the maximum value over the maxpooling window. The pool size of maxpooling window is 2 for all maxpooling layers. Finally, a Dense layer with 128 neurons extracts the final features and is fed to the classifier layer. The network benefits from softmax classifier which classifies the data as either fetal or maternal QRS.

IV. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed approach, several experiments were implemented. In the first experiment, we aim to assess and compare the performance of the proposed model when various feature mapping methods, as well as raw data, are used. During this experiment, the datasets NIFECG1 and NIFECG2 are divided into train, test, and validation subsets. We used a 10-fold cross-validation method to evaluate our proposed method. The accuracies were calculated at each setting in the proposed deep learning model with two datasets, namely NIFECG1 and NIFECG2. The number of empirically selected CSP components in this experiment was 100. The results of this experiment are given in Table I.

As shown in Table I, the highest accuracy in classifying fQRS events was obtained when CSP was used in the detection algorithm's pipeline for both datasets. The accuracies are 97% and 98% with datasets NIFECG1 and NIFECG2 (see section II), respectively. These results show that the CSP algorithm could find a well separable subspace for the two classes (i.e. fetal QRS and maternal QRS) such that the proposed model has classified the data with high accuracy. Further, Table I compares the accuracy obtained using CSP algorithm against other relevant methods and combinations like PCA, STFT, and continuous wavelet transform (CWT), and when raw data are used for fetal event detection. It is clearly observed that CSP has a superior performance compared to other feature

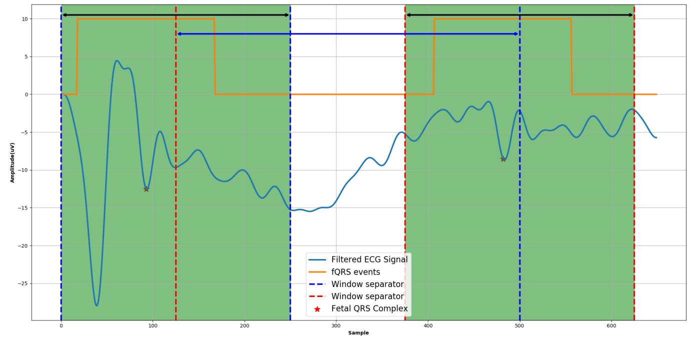

Fig. 6. The sample of AECG, FECG, and MECG signals in dataset FECGSYNDB. The AECG signal was generated by combining FECG, MECG, and a noise.

extraction methods. The number of PCA components was selected at 30 in this experiment. For STFT, Hamming window of length 36 with 256 points was used.

PCA algorithm is commonly used to select the best features as well as to provide feature reduction. According to Table I, the obtained accuracies when PCA was used with NIFECG2 is as high as 95.7%. However, this performance is significantly dropped to 60% with NIFECG1. This indicates that feature reduction, which is done by PCA, is highly dependent on the dataset and may cause information loss in detecting fQRS. To further verify this result, we have conducted an experiment to apply CSP prior to PCA. As the results of Table I suggest, although the performance has been improved, the proposed deep learning method could not classify data as well as the case when CSP alone is used. This means that all features are important to detect fQRS in ECG signals and PCA should not be used for feature reduction. Thus, PCA was excluded for the remaining experiments in this paper.

Another experiment was conducted to evaluate and compare the effects of time-frequency representation on classification accuracy. In this implementation, STFT and CWT are applied to the output of CSP in the algorithm hierarchy. STFT and CWT transform signals into time-frequency representation and generate pictures from raw signals. As shown in Table I, time-frequency representations have less accuracy than CSP alone. As seen from Table I, the highest accuracy belongs to CSP algorithm. However, the accuracy in some cases is much less with NIFECG1 compared to NIFECG2. We believe the reason for such large difference is that all signals in dataset NIFECG2 are smoother than those in dataset NIFECG1.

Figure 6 shows an example result of applying the proposed deep learning model on the FECGSYNDB dataset to detect fQRS on a test signal. Dotted lines (blue and red) show the start and end of each window in this signal. Each window has a 50 per cent overlap with the previous and next window as mentioned in the previous section. The Highlighted areas in green are classified as f_event class using the proposed model. As shown in this figure, fQRS falls in the range [-75, +75] samples inside the window.

[2] ADFECGDB refers to the Abdominal and Direct Fetal ECG Database accessible via https://physionet.org/content/adfecgdb/1.0.0/

TABLE II
THE COMPARISON OF DIFFERENT METHODS.

State-of-the-arts	Datasets	Classifier	Accuracy
Zhong et al. [8]	NIFECG1	1D-CNN	77.38%
Vo et al. [11]	NIFECG1	1D-CNN	91.82%
Lee et al. [10]	NIFECG1	1D-CNN	92.70%
Lo et al. [12]	ADFECGDB[2]	1D-CNN	90.00%
Huque et al. [22]	NIFECG1	HMM	97.10%
Liao et al. [23]	NIFECG1	SVM	84.53%
Venkatesan et al. [24]	MIT-BIH	SVM	96.00%
Proposed method	NIFECG1	1D-CNN	97.00%
Proposed method	NIFECG2	1D-CNN	98.00%

In the final experiment we compare the performance of the proposed approach with state-of-the-art techniques. The accuracies of fetal event detection using different methods are tabulated in Table II. Zhong et al. [8] used one-dimensional CNN model, Vo et al. [11] used 2 blocks residual network and GRU (gated recurrent units) layers on multi-channel ECG signals, Lee et al. [10] used a deep neural network based on CNN with 7 convolutional layers on multi-channel ECG signals. These three references used raw data to feed their models for classifying the fQRS event but the preprocessing steps were different. Lo et al. [12] used STFT for transfering raw ECG signals into time-frequency representation. They used band-pass filter and sample entropy (see Section 2) to remove noises and artifacts but all of them obtained low accuracies. Traditional models like support vector machine (SVM), linear discriminant analysis (LDA), neural network (NN), and the work in [23] - yield low accuracy. Among the state-of-the-art methods, the proposed model obtains highest accuracy with both datasets. These observations verify that combination of CSP method and deep learning model resulted in a high accuracy.

V. CONCLUSION

In this study, fetal QRS event detection from abdominal ECG using a deep learning model was proposed. For fetal QRS detection, common spatial pattern was employed prior giving the data to the proposed 1D-CNN classifier. The advantage of this stage is creating a new feature space in which the variances are optimal for classification by the deep model. The results of our extensive experiments with three well-framed datasets confirm the effectiveness of the proposed methods. Our experiments show that combination of CSP and deep learning has significantly improved the fQRS detection performance compared to related works. As the future work, we aim to design a suitable deep network, e.g. based on auto-encoder models, to fully extract the fetal ECG components from the abdominal signals.

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