FETAL ECG EXTRACTION: AN APPLICATION OF THE ADAPTIVE FILTER

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Abstract. This is the report for the final project of the course *320372 Machine Learning* taught by Prof. Dr. Herbert Jaeger. In this report we use adaptive filter to extract the *Fetal electrocardiogram* (fECG) from the observed *maternal electrocardiogram* (mECG).

Contents

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1. Outline

In this section, we present the schema of extracting fECG from mECG. Our schema contains three steps:

Step 1 Data-prepocessing: given the abdomen signal and thorax signal, we use tricks to clean the noise in the raw data.

Step 2 Filtering: in this step, we apply the Zero-Attracting LMS (ZA-LMS), instead of the traditional LMS, to extract the fECG from mECG.

In the following sections, we provide the motivation, justification and realization for the two steps. Please refer to my code `myFinalScript_Basic` to see the experiments in section 2, 3, and 4 of this report, and refer `myFinalScript_Generalization` for the experiments in section 5.

2. Step1: Data Pre-processing

Define a pair of an abdomen signal and a thorax signal as a *data couple*. In this section, we will fix our data couple as {`abdomen3`, `thorax2`}. In the fifth section, we will treat other data couples.

Recall that the time series data `abdomen3` and `thorax2` are of 20000 dimension, i.e., the time t ranges from 1 to 20000. To look at the data closely, we zoom in and only look at the data ranging from $t = 15001$ to $t = 19000$. One can also pick other ranges of data.

2.1. Pre-processing the `abdomen3`.

(1) Goal: Erase the baseline drifting of the `abdomen3`.
Strategy: We need a high-pass filtered version of `abdomen3`. The simple and naive way to realize this is to let `abdomen3` minus its moving-local-average. For the sake of convenience, let us denote the resulted signal `abdomen3_bc` ("bc" is short for "baseline correction"). The comparison between `abdomen3` and `abdomen3_bc` is shown below.

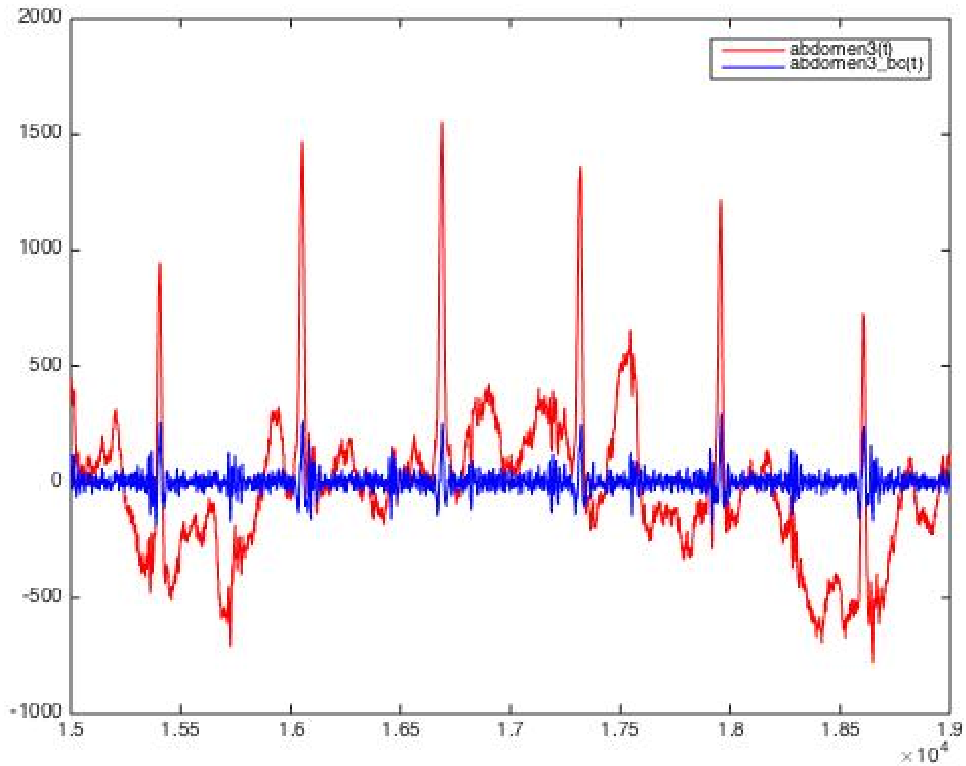

FIGURE 1. `abdomen3` v.s. `abdomen3_bc`, t from 15001 to 19000

Observe that after the minus-moving-local-average treatment, we erased the baseline drifting behaviour of `abdomen3`. However, note that there is still much high-frequency noise in the treated signal. The high-frequency noise motivates us to do further treatment.

(2) Goal: Erase the high frequency noise in `abdomen3`.
Strategy: Design and apply the low-pass filter on `abdomen3_bc`. This is realized by using the `fir1` function, which is provided by the signal processing toolbox of MATLAB. We call the resulting signal `pre_processed_abdomen3`.

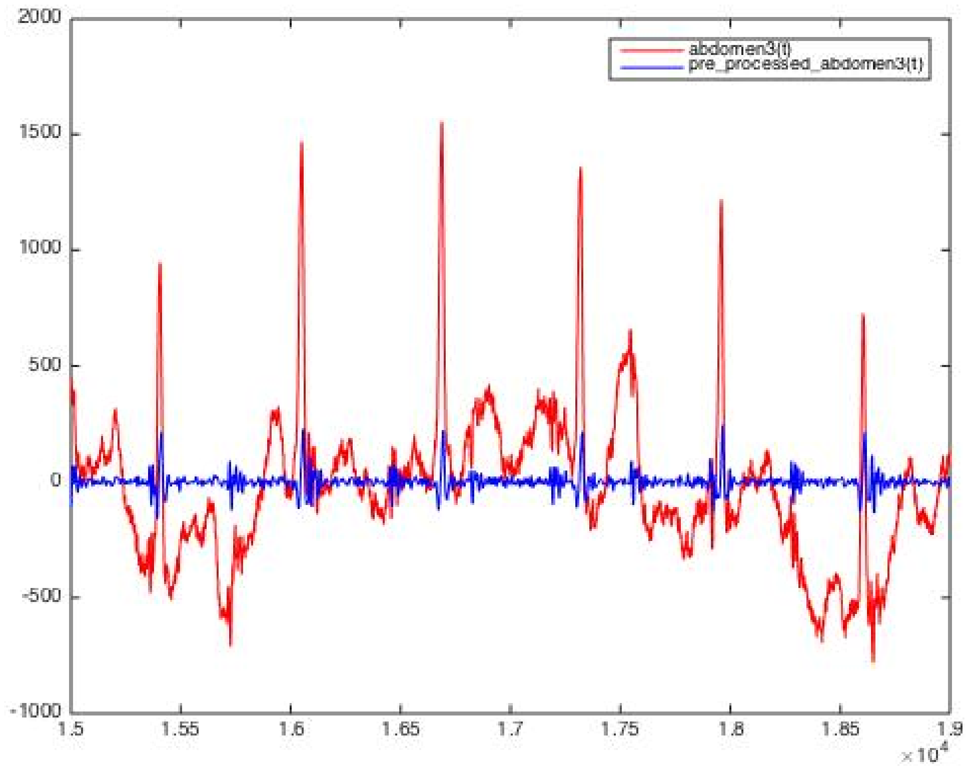

FIGURE 2. `abdomen3` v.s. `pre_processed_abdomen3`, t from 15001 to 19000

Compared with the previous figure, we see that the treated `pre_processed_abdomen3` signal (blue curve) is more well-behaved and clearer in its pattern. Even without applying the denoising filter, one can spot that there is a trace of pulse that is about twice as frequent as the dominating mECG.

2.2. **Pre-processing the `thorax2`.** Before applying the denoising filter, we will pre-process the raw signal `thorax2`. Recall that the ECG contains three stages: P wave, QRS complex, and T wave, as shown in the graph below:

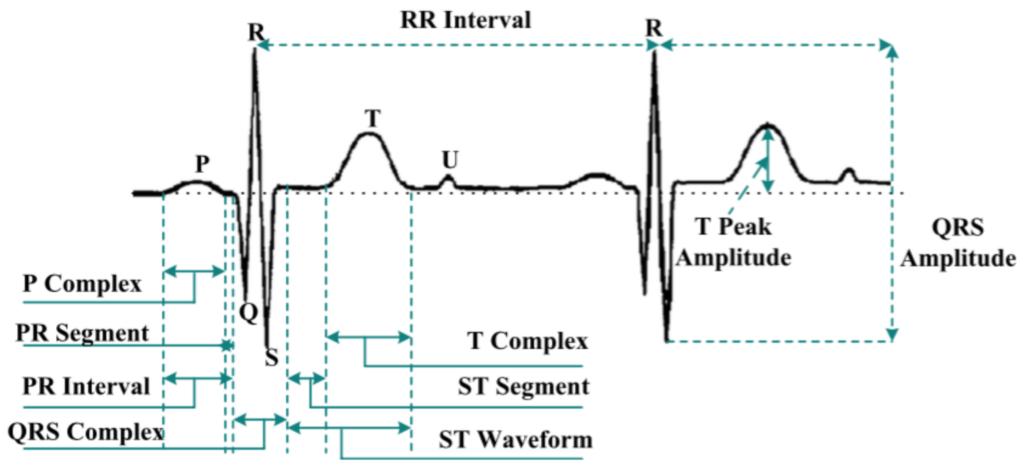

FIGURE 3. The PQRST Complex (Fig.1 in [1])

Among the three stages, the QRS complex is of particular importance, because it associates with the contraction of the ventricles [1]. Particularly, the R-peaks, i.e., the peaks of the QRS complex in an abdominal electrocardiogram signal, provides information on the heart rate [2]. Hence, especially, we want to reconstruct the QRS complex of fECG. To this end, we pre-process the `thorax2` by extracting its QRS complex according to the following algorithm, which is adopted from [3]:

QRS Extraction

Input: data: `thorax2`, threshold ϵ, zero-equalizing-range m.

Initialization: $t = m$

Iteration: Repeat until t = length(`thorax2`)

If $|\texttt{thorax2}(t)| > |\texttt{thorax2}(t-1)|$ *and* $|\texttt{thorax2}(t)| > |\texttt{thorax2}(t+1)|$ *and* $|\texttt{thorax2}(t+1)| > \epsilon$

then Do nothing.

else

$$\texttt{thorax2}(t+m-1) = \texttt{thorax2}(t+m-2) = \cdots = \texttt{thorax2}(t-m+1) = 0$$

end

t= t+1.

Output: The QRS Complex of `thorax2`

In other words, if a data point $\texttt{thorax2}(t)$ is a local minimum or local maximum in its neighbourhood of radius of 1, we keep it; if not, we set all data points in its neighbourhood of radius of M to be zero. Note that the value of M is extremely important – we determine it simply by repetitive experiments.

For the sake of convenience, we give the resulted "QRS complex of `thorax2`" a name: call it `QRS_thorax2`. The comparison between signal of `thorax2` and that of `QRS_thorax2` is shown in the below figure.

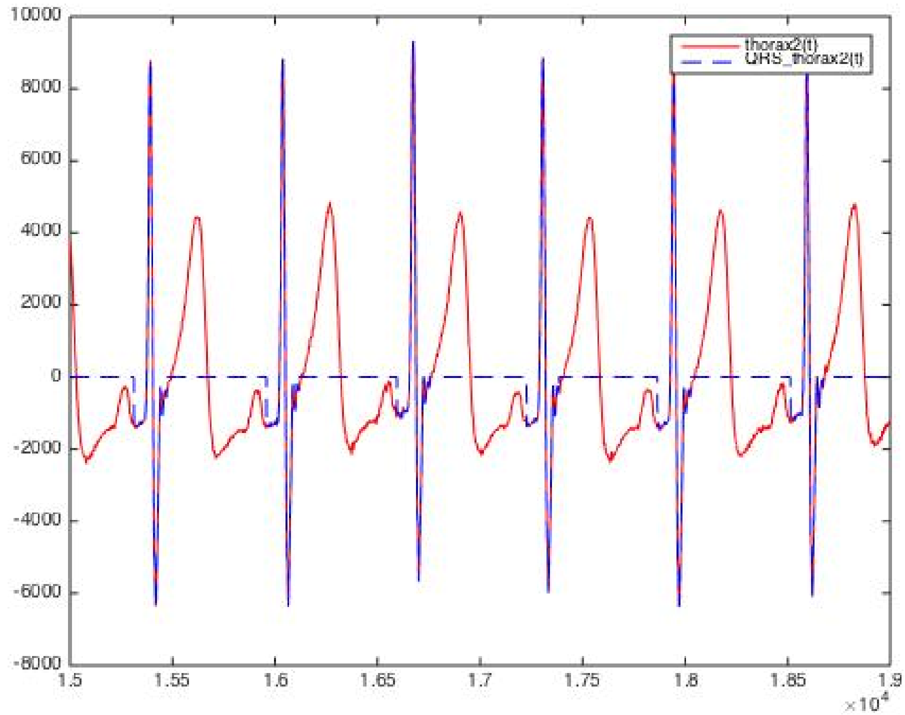

FIGURE 4. The thorax2(t) and QRS_thorax2(t), t from 15000 to 19000

Note that the resulted QRS_thorax2(blue curve) coincides the thorax2(red curve) within the QRS complex, while in P wave and T wave, the blue curve is forced to be 0.

3. Step2: Filtering

In this section, we design a denoising filter that extracts the fECG.

It is essential to observe that, the QRS_thorax2 is a "sparse" signal, in the sense that it contains a limited amount of non-zero entries. We expect that the learned_QRS_thorax2, which is the signal predicted by the denoising filter, is also sparse. To this end, instead of using the traditional LMS filter, we use Zero-Attracting LMS (ZA-LMS). (I am not sure in which paper the ZA-LMS was originally proposed, but a good introduction is provided in section 2.2 of [4].)

Basically, the ZA-LMS modifies the tap-weights updating stage by adding a zero-attracting term. The ZA-algorithm is outlined as follows:

ZA-LMS

Input: $\mathbf{d}$, L, $\mathbf{x}$, ρ, μ.
Initialization: $n = 1$, $\mathbf{w}$ is a zero vector
Iteration: Repeat until $n >$ length($\mathbf{y}$)
$\mathbf{y}(n) = \sum_{i=0}^{L-1} \mathbf{w}(i)\,\mathbf{x}(n-i)$
$\mathbf{e}(n) = \mathbf{d}(n) - \mathbf{y}(n)$
$\mathbf{w}(n+1) = \mathbf{w}(n) - \rho\,\mathrm{sgn}(\mathbf{w}(n)) + \mu\,\mathbf{e}(n)\,\mathbf{x}(n)$
$n = n + 1$
Output: Prediction signal: $\mathbf{y}$, Error signal: $\mathbf{e}$

Note that $\rho\,\mathrm{sgn}(\mathbf{w}(n))$ is the zero-attracting term, whose strength is controlled by ρ. Intuitively, according to [2], the zero-attracting-term will speed-up convergence when the majority of coefficients of $\mathbf{w}$ are zero, i.e., the system is sparse. This feature is exactly what we need in our scenario.

We plug in our pre-processed data into the ZA-LMS algorithm. Specifically, we set `prep_rocessed_abdomen3` = $\mathbf{d}$ and `QRS_thorax2` = $\mathbf{x}$. ρ, μ, L are tuned to be 1e-10, 0.9e-9, and 150 respectively. Consequently, the filter produces the $\mathbf{y}$ and $\mathbf{e}$, where $\mathbf{y}$ is the `Learned_QRS_thorax2` signal and the $\mathbf{e}$ is the `Extracted_fECG_32` signal (the index"32" here states that the signal is extracted based on from the data couple {`abdomen3`,`thorax2`}).

Following the above denoising scheme, we get the following experiment result:

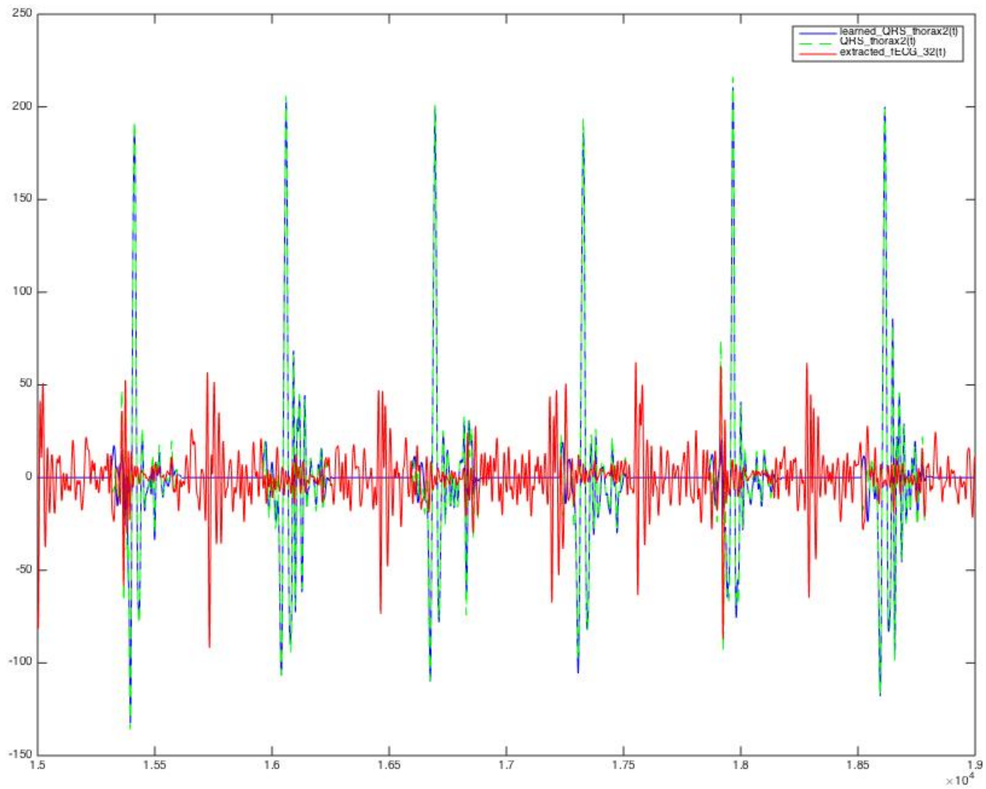

FIGURE 5. `learned_QRS_thorax2`(blue) v.s. `QRS_thorax2` (green and dotted) v.s. `extracted_fECG_32`(red)

Note that, by using ZA-LMS, we encourage the `Learned_QRS_thorax2` (the blue line) to be sparse while staying with `QRS_thorax` (the green and dotted line) as close as possible.

4. Fetal ECG Extraction Result

We now compare the resulted post-processed extracted fECG with `abdomen3` and `thorax2`. (Note that they are re-scaled and shifted for the illustration purpose).

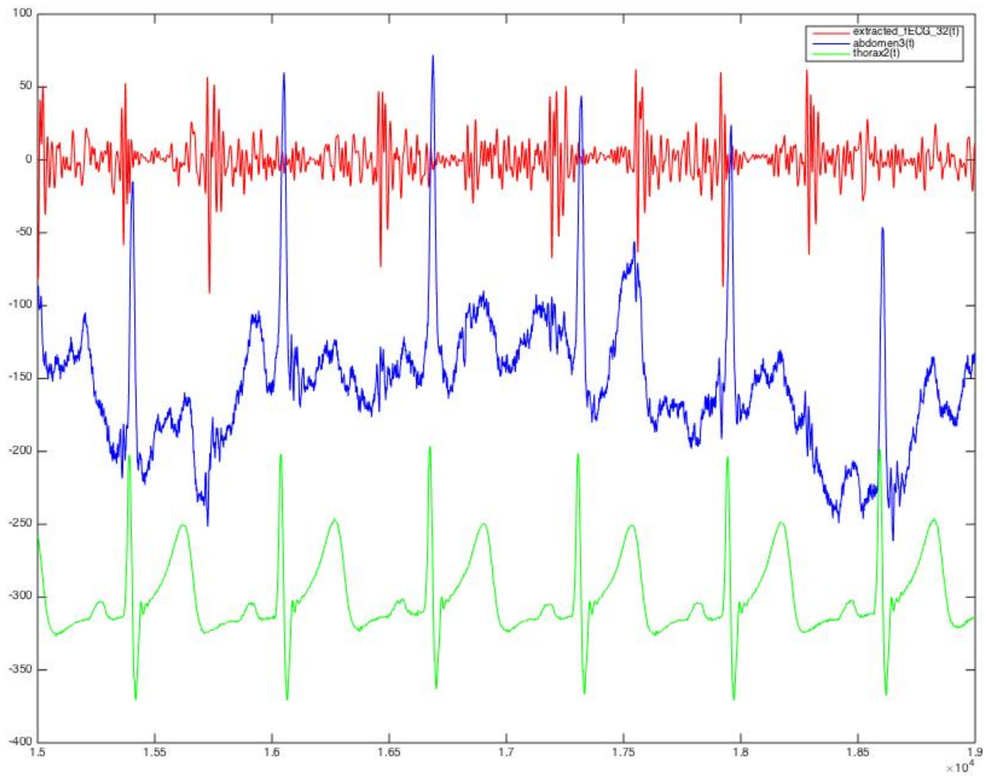

FIGURE 6. `extracted_fECG_32` v.s. `abdomen3` v.s. `thorax2`

The result looks pretty good!! The extracted red line is indeed "roughly periodic with a period length about half as long as the mother's heartbeat", as expected!!

5. Generalization: Experiments in Other Data Couple

Following the exactly same routine with minor adjustments in parameters, we are able to extract the fECG based on the data couple {`abdomen1`, `thorax2`}, {`abdomen2`, `thorax2`}, {`abdomen1`, `thorax1`}, {`abdomen2`, `thorax1`}, and {`abdomen3`, `thorax1`}. The results from each of the these couples are shown below. Please refer my code `myFinalScript_Generalization` for details.

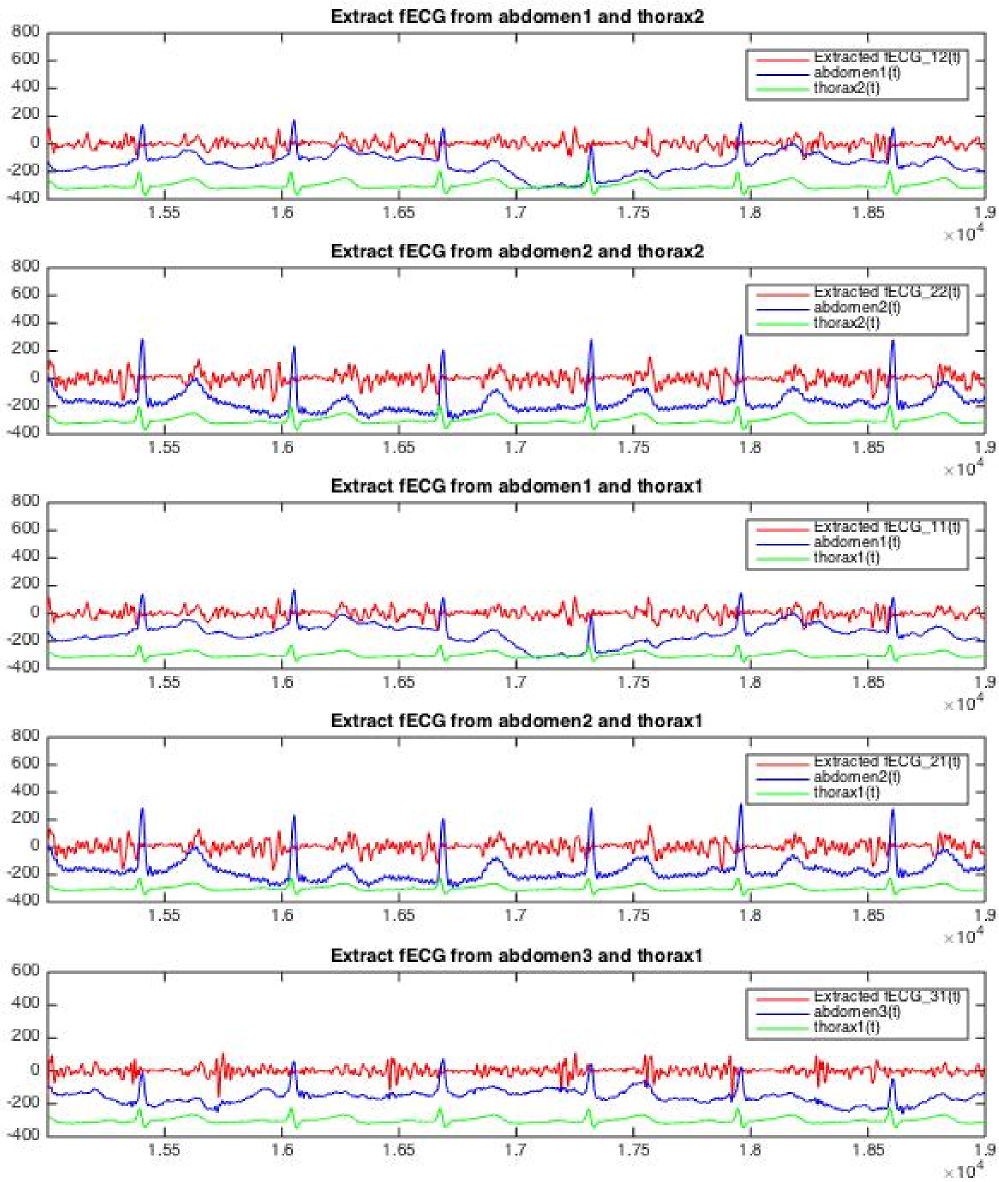

FIGURE 7. Extracted fECG from generalized data couple

From the above figures, we can spot the fECG signals, though it is much weaker and less patterned compared with our illustration in the previous section.

6. Summary and Outlook

In this report, we carried out a two-step schema to extract fECG effectively by an adaptive filter from maternal abdomen and thorax ECGs. Particularly, instead of using the traditional LMS filter, we propose to use the ZA-LMS filter, which, to my knowledge, was not used in the previous literature.

Recall that ZA-LMS uses the assumption that the `learned_QRS_thorax2` is sparse. It is nature to ask the question that, besides the information of "sparsity", shall we also use the information of "structured"? Indeed, observing the `learned_QRS_thorax2`, one shall see that not only it has a small amount of non-zero entries, but also its non-zero entries are located in some identified ranges, namely, the ranges that its teacher signal `QRS_thorax2` has non-zero entries. Hence for the future work, I suggest that we can design the LMS filter that exploits the "block sparsity". Frustratingly, according to the "9-of-10-ideas-you-come-up-with-shows-in-arxXiv theorem," I found that the similar filter has already been designed by researchers in [5]. But implementing, adapting, and examine this filter in the fECG scenario seems doable.

References

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[2] Prasanth, K., Baby Paul, and Arun A. Balakrishnan. "Fetal ECG Extraction Using Adaptive Filters." International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering 2.4 (2013): 1483-1487.

[3] Fetal ECG Extraction and Analysis from Composite Maternal ECG using an Adaptive Noise Canceller (in Chinese) http://www.masys.url.tw/AU/Research/Publications/2011-ICAIT-ChenCH.pdf

[4] Chen, Yilun, Yuantao Gu, and Alfred O. Hero III. "Sparse LMS for system identification." Acoustics, Speech and Signal Processing, 2009. ICASSP 2009. IEEE International Conference on. IEEE, 2009.

[5] Jiang, Shuyang, and Yuantao Gu. "Block-Sparsity-Induced Adaptive Filter for Multi-Clustering System Identification." Signal Processing, IEEE Transactions on 63.20 (2015): 5318-5330.