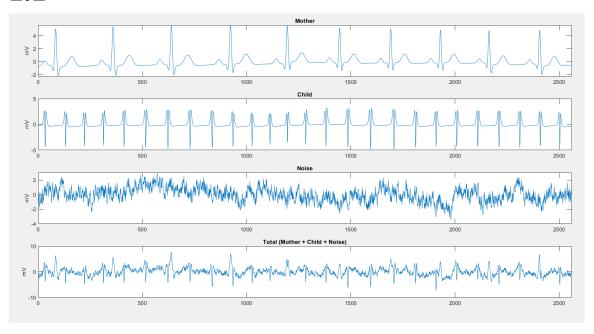
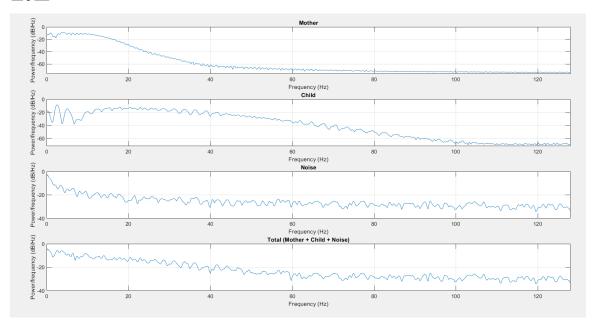
Laboratory of signal processing and medical images

Report Lab 3 Sara Rezanejad – 99101643 MohamadHosein Faramarzi - 99104095 Ali Khosravipour - 99101502



1.2



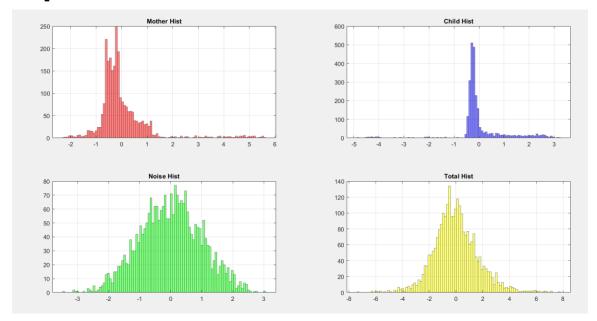
The bandwidth of the mother's ECG is less than that of the fetal heart. The mother almost uniformly has relative frequencies below 0.1, but the fetus has some higher and some lower. In general, there is a significant similarity between the mother's and the fetus's ECG in the frequency domain, so that the two cannot be separated using a filter.

mean_child = -4.250042745469404e-10 mean_mother = -2.466171317508370e-10 mean_noise = -4.769103086402216e-10

The variance of a signal does not directly determine its frequency content, but understanding both concepts helps us analyze and interpret signals effectively. Variance provides information about frequency variation, while frequency content shows the fundamental fluctuations of the signal.

The variance of a signal is related to its frequency content through the power frequency density. The power spectrum shows how the energy of a signal is distributed in different frequencies, and by integrating the power spectrum, it is possible to determine the variance or total power of the signal and show the special relationship between the variance and the frequency content of the signals.

1.4



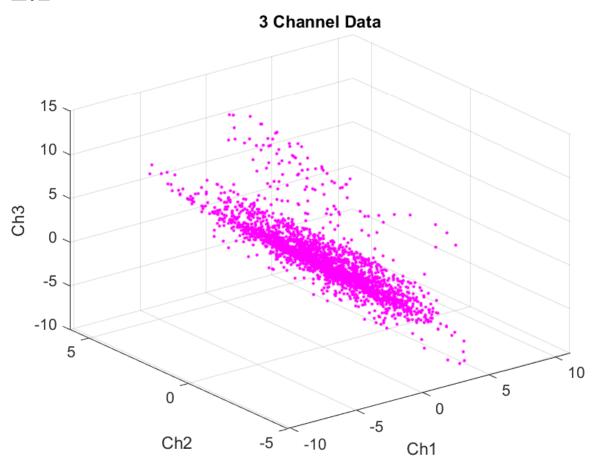
A Gaussian distribution (with a skewness of 3.0) has a mesokurtic shape, meaning that the tail is neither too heavy nor too light.

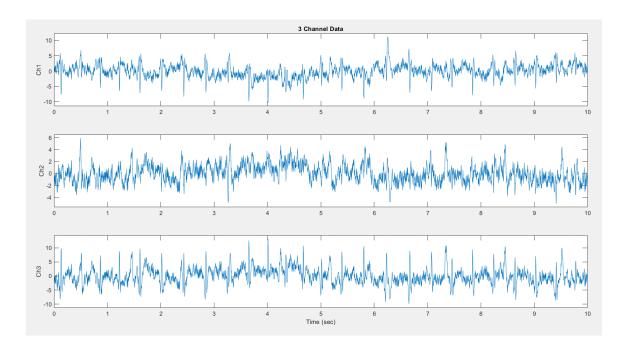
Excessive positive skewness (greater than 3) indicates a leptocortical distribution with heavier tails.

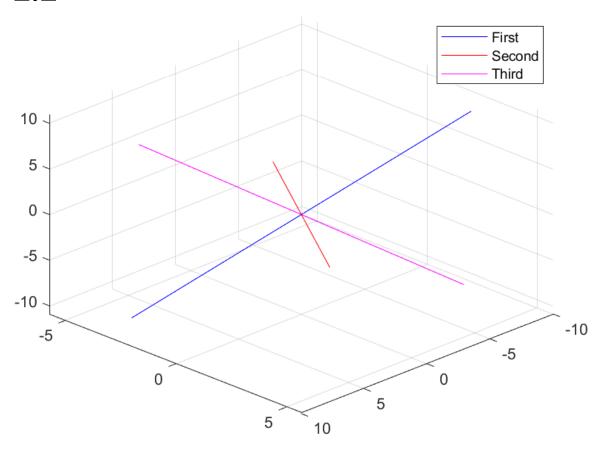
Excessively negative skewness (less than 3) indicates a uniform palette distribution with a lighter tail.

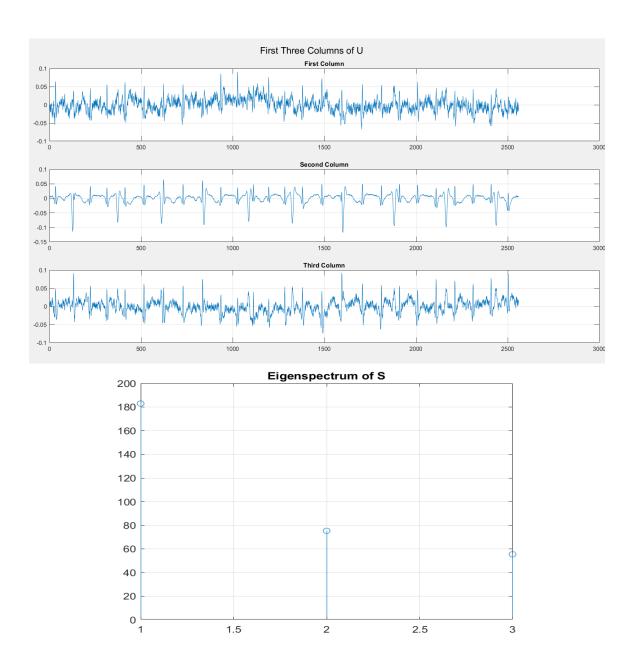
Based on the previously mentioned definitions and Table 1, the skewness values for both the noise signal and the mixture are nearly Gaussian. In contrast, the

mother's signal exhibits strong leptokurtosis, while the fetus's signal is also somewhat leptokurtic.









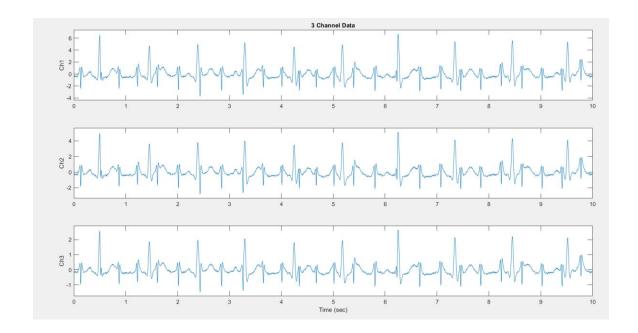
The first column primarily showcases the characteristics of the noise. In the second column, the noise has been eliminated, revealing the combined features of both the mother and fetus. The third column displays the characteristics of the mixture. The second column is preferable because it effectively reduces the influence of noise.

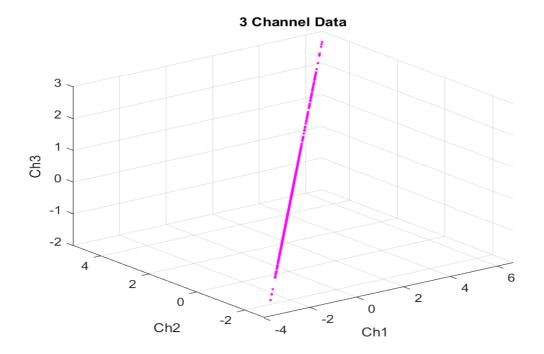
2.4

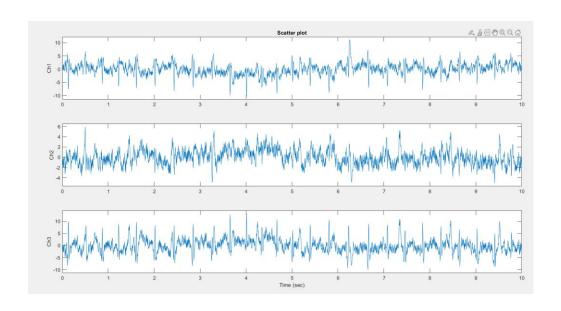
Here the three channels of the fetal sensor are displayed and the effect of SVD decomposition and the corrections made are described. In the first image, the 3D data shows features of the fetal signal that are clearly affected by noise. In the

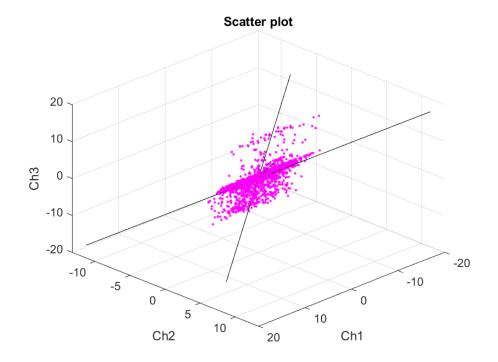
second image, the signals are displayed over time and the fluctuations and patterns in each channel can be seen.

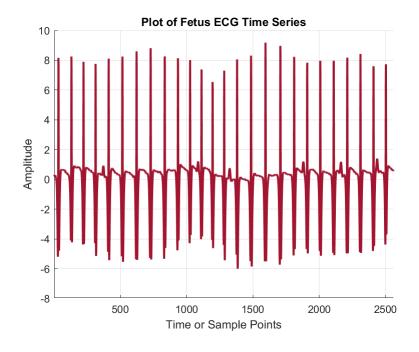
SVD decomposition allows us to separate the embryonic signals from the noise and extract the main features. According to the results, it seems that the recovery of the fetal signal was successful, because after the corrections, distinct and recognizable patterns are observed in the data, indicating the presence of the fetal signal.

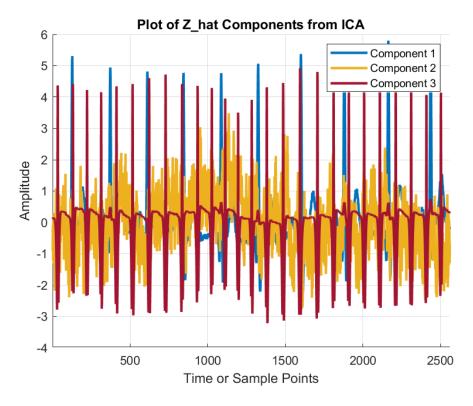






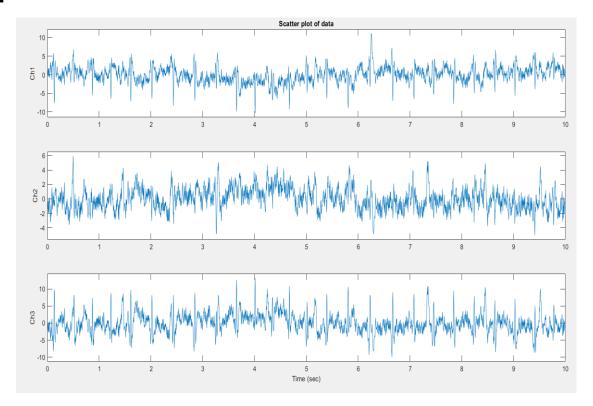




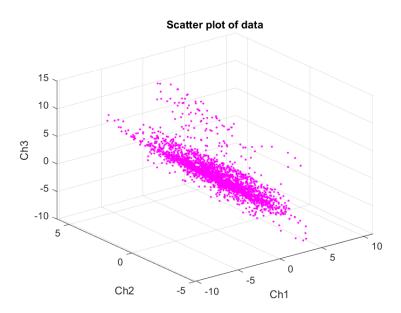


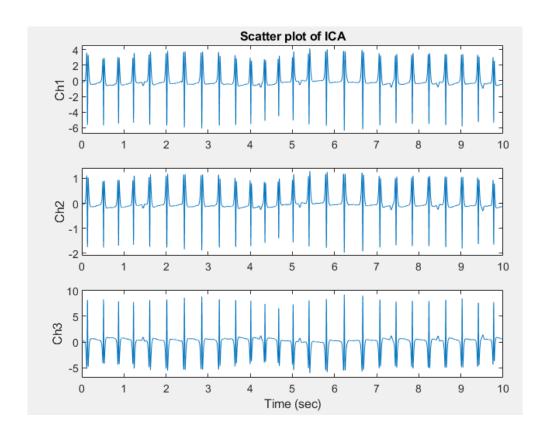
3.4

Based on the similarity of the signals to what we expect from the fetal signal, we can say that the fetal signal is well recovered.

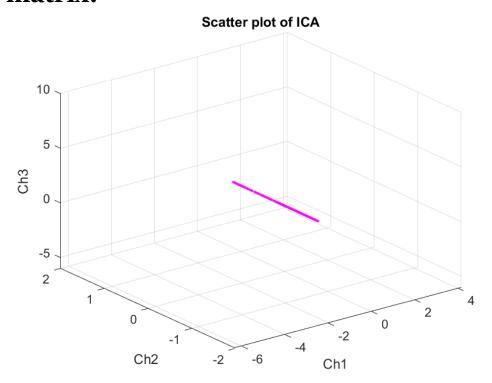


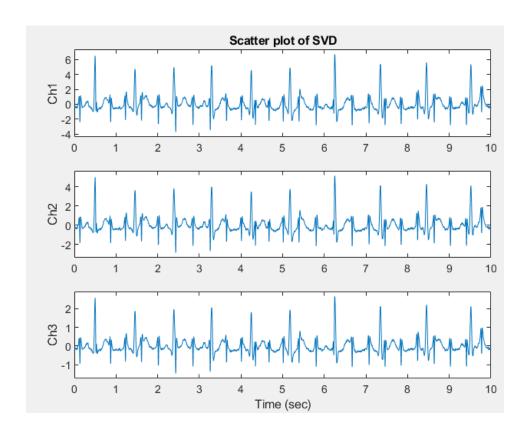
> Scatter plot of the viewing matrix:



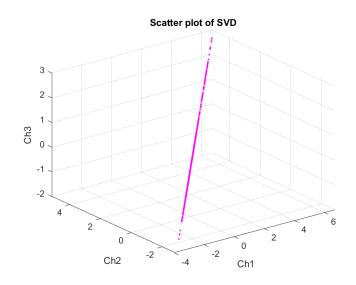


> Scatter plot of the retrieved observation matrix:

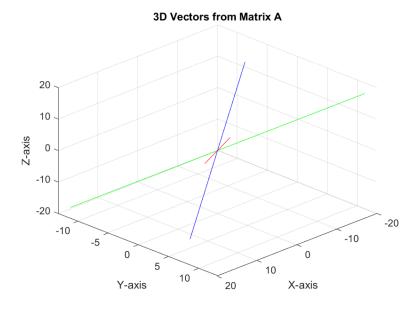




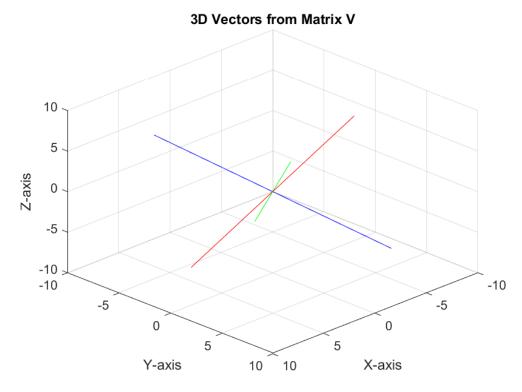
> Scatter diagram of the retrieved observation matrix:



> Matrix W-1



> The columns of the matrix V



angle_A12 = 2.234287837621001

angle_A13 = 1.207448488549260

angle_A32 = 5.326661204078372

 $angle_V12 = 0$

angle_V13 = 1.665334536937735e-16

 $angle_V32 = 0$

 $norm_A1 = 1.635044405269583$

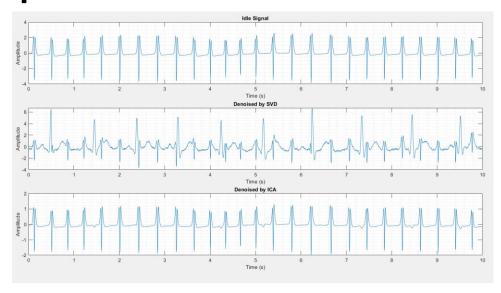
norm_A2 = 2.913460877113846

 $norm_A3 = 2.307861386142267$

 $norm_V1 = 1$

 $norm_V2 = 1$

 $norm_V3 = 1$



It can be seen that the reconstructed signal using ICA method is very similar to our ideal signal. While the signal reconstructed by the SVD method is significantly different from the ideal signal. Therefore, it can be concluded that the ICA method has a better performance.

4.3

icaCorrelation =

1.0000 0.9978 0.9978 1.0000

svdCorrelation =

1.0000 0.4955 0.4955 1.0000

We observed that the correlation between the ICA signal and the ideal signal is 0.9978, which is very close to one. On the other hand, the correlation of the SVD signal has a negative number and its absolute value is less than 0.5. These results confirm our claim that the ICA method is superior.

4.4

Finally, to compare the SVD and ICA methods, the advantages and disadvantages of each are generally as follows:

SVD method (singular value decomposition)

Advantages:

Simple and efficient: SVD is a relatively simple and fast method to perform data analysis.

Numerical stability: SVD has high stability against noise due to its mathematical properties.

Wide applicability: This method works well in many areas, including dimensionality reduction and data compression.

Disadvantages:

Failure to separate independent signals: SVD cannot effectively separate independent signals.

Require special assumptions: In many cases, SVD may require special assumptions about the structure of the data.

ICA method (Independent Component Analysis)

Advantages:

Separation of independent signals: ICA is able to separate independent and non-Gaussian signals, which is very valuable for various applications.

Better performance in the presence of noise: This method performs better in the presence of noise and can recover real information more accurately.

Disadvantages:

Computational complexity: ICA is usually more complex than SVD and requires more computation time.

Sensitivity to initial conditions: ICA results may depend on the initial conditions and how the parameters are chosen.

Conclusion:

In the final analysis, it can be said that the choice between SVD and ICA depends on the type of data and the purpose of the research. SVD is suitable for simple and stable applications, while ICA is more suitable for separating independent signals and solving more complex problems. The appropriate choice should be made based on the specific needs and type of data.

4.5

In the separation of resources, we must first identify their characteristics, then choose the best separation method according to the type of resources.