Blind Source Separation

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Abstract

Blind Source Separation is a type of Source Separation where we have little or no idea about the sources and mixing system and our goal is to reconstruct the original signals. There are many methods which we can employ to reconstruct the original signals using Principal Component Analysis, Dependent Component Analysis and Independent Component Analysis. In this work, we implemented the Independent Component analysis which reconstruct the original signals by mixing the original signals using some mixing system and did some experiments by tweaking the hyper parameters.

1. Introduction

The process of recovering the original signals from the mixture signals is known as the Source Separation. The scenario where it mostly used is in the cocktail party where you have a lot of sources and noise, and we know only the mixture signals which we have captured through the microphones. The goal is to reconstruct the original signals using these signal mixtures.

Blind Source Separation is a type of Source Separation where we have little or no idea about the sources and mixing system and our goal is to reconstruct the original signals. There are many methods which we can employ to reconstruct the original signals using Principal Component Analysis, Dependent Component Analysis and Independent Component Analysis. Depending on the problem and mixing system , we can employ the algorithm but Blind Source Separation is originated for Audio Processing. And in this work, we are trying to reconstruct the original signals using the mixture signals.

Independent Component Analysis (ICA) is a special case for the Blind Source Separation which can unveil the hidden factors and can reconstruct the original signals using mixed signals. For ICA to be working, it assumes hat these original signals are mixed in some linear combination of the mixing system. It also assumes that all these sources are mutually independent and non-gaussian.

2. Methodology

Lets us suppose that we have signal u1, u2, n source signals each of length t which is denoted by Matrix U (n x t) and have m x t matrix of mixed signals where (m ¿= n) of length t consisting of different mixtures of source signals U where X = AU where A is m x n. The goal is to recover the original source U matrix where we have no idea about the A matrix.

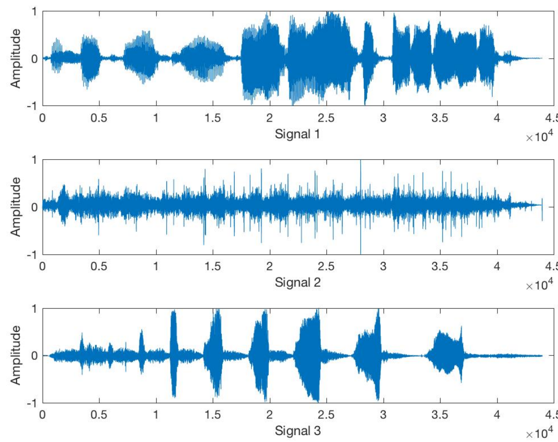
Our task is to find out the W matrix (which is the inverse of A matrix) that recovers the original source signal. For the task, we try to minimize the mutual information between the signals and for that we will use the gradient descent algorithm. We start with the initial guess of the matrix with some random value and compute the initial estimate of the initial estimate of the source signal, Y = WX. Then we calculate the Z matrix using sigmoidal function on Y as it helps us in traversing the gradient of maximum information separation. Next, we calculate the error matrix, ΔW using our current guess W, Y, η and Z. Then, we update our matrix W to W + ΔW. And, we continue this process until the error converges.

2.1. Algorithm

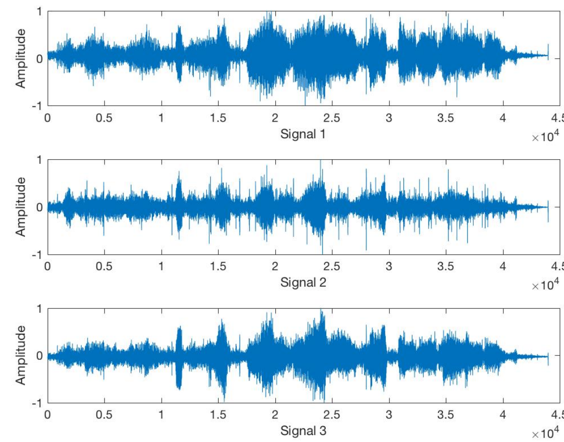
These are the steps in the ICA algorithm which we follow to retrieve the original signals from the mixed signals.

1. Assume **X = AU**
2. Initialize the (**n** by **m**) matrix **W** with small random values.
3. Calculate **Y = WX**.

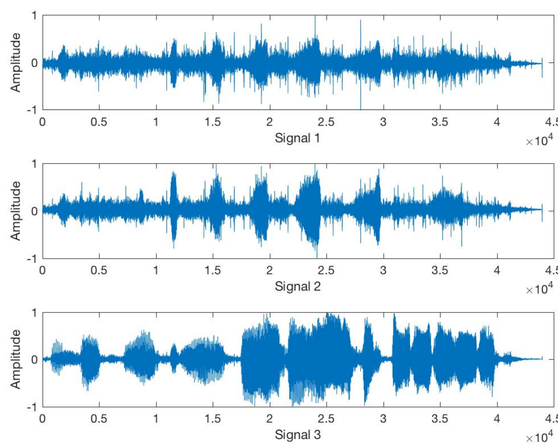
   Y is our current estimate of the source signals.
4. Calculate **Z** where $z_{i,j} = g(y_{i},_{j}) = 1/(1+e\text{-}y_{i},_{j})$ for $i \in$ [1..n] and $j \in$ [1..t] (where t is the length of the signals). This helps us traverse the gradient of maximum information separation.



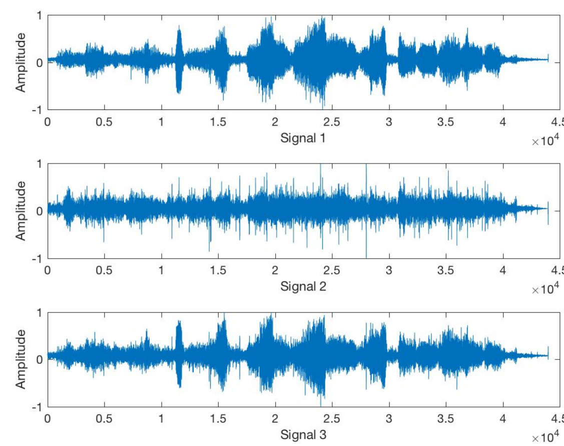
(a) Original Signals



(b) Reconstructed signal using $\eta = 0.001$



(c) Reconstructed signal using $\eta = 0.01$



(d) Reconstructed signal using $\eta = 0.001$

Figure 1: Reconstructed the original signal by varying the learning rate η in the range [0.001 - 0.1]

5. Find $\Delta\mathbf{W} = \eta(\mathbf{I} + (\mathbf{1\text{-}2Z})\mathbf{Y}^{\mathbf{T}})\mathbf{W}$ where η is a small learning rate.

6. Update $\mathbf{W} = \mathbf{W} + \Delta\mathbf{W}$ and repeat from step 3 until convergence.

3. Experiments

To better understand the ICA algorithm, we did the bunch of experiments. This section will give you the details of all the experiments which we have done in order to asses the performance of the algorithm.

3.1. Varying the Learning Rate

In this experiment, we fix the number of iterations to 10,000 and vary the learning rate from 0.001 - 0.1. From the figure 2, we can see that for learning rate = 0.001, amplitude varies from [-0.6,-0.8] whereas the original signal varies from [-0.8, 1]. Similarly is the case with learning rate =0.1 which is varying from [-0.4,0.8]. However, if we choose the learning rate = 0.01, we can see that it varies in the same range as the original signal and have almost the same amplitude at the same time.

This is happening because if you choose learning rate very small, then it will take long time to converge because of the fixed number of iterations. It may possible that it hasnt reached the optimal stage. But if we choose the learning rate very high, then it may miss the optimal condition and reach to some other stage which is clearly seen from plot 4 in fig 2. However, if we choose our learning rate in good range, then it will reach to the optimal range in less iteration and we can reconstruct the signal.

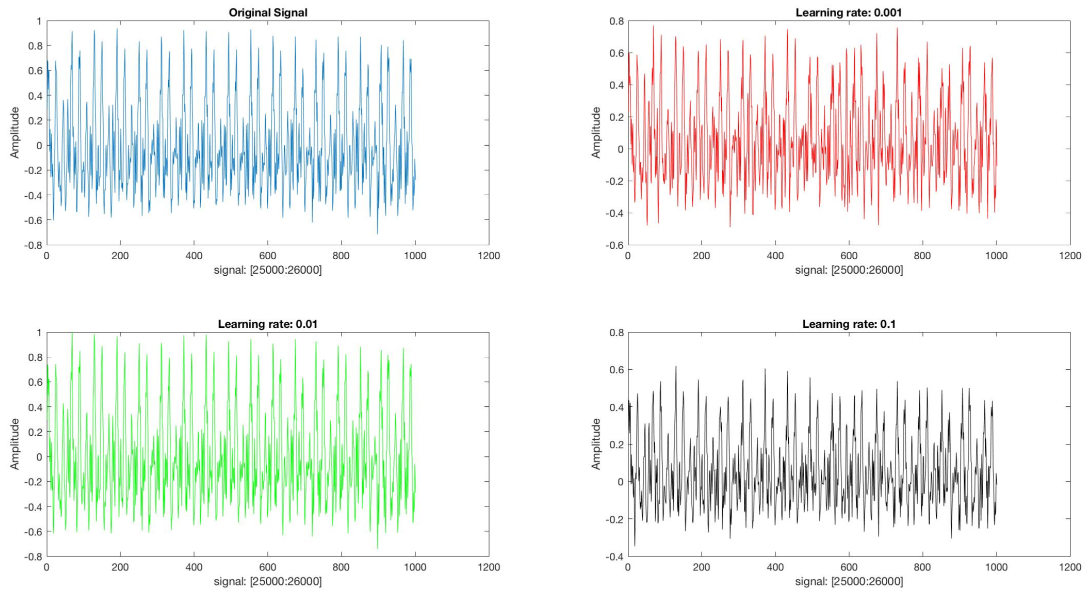


Figure 2: A small part of reconstructed signal of signal 1 from Fig1 using η = [0.001 - 0.1] from t = [2000-3000].

3.2. Varying the Number of Iteration

In this experiment, we fixed the learning rate to 0.01 and varied the number of iterations from [100 - 1,000,000]. The figure 3 shows the small part of the reconstructed signal of Signal 1 from Fig 4, we can see that for iteration = 100, amplitude varies from [-0.6, 0.6] where as the original signal varies from [-.04, 0.4]. Similarly is the case for iteration = 1000, 10000. However, if we use number of iteration = 10,000, we can see that it varies in the same range as the

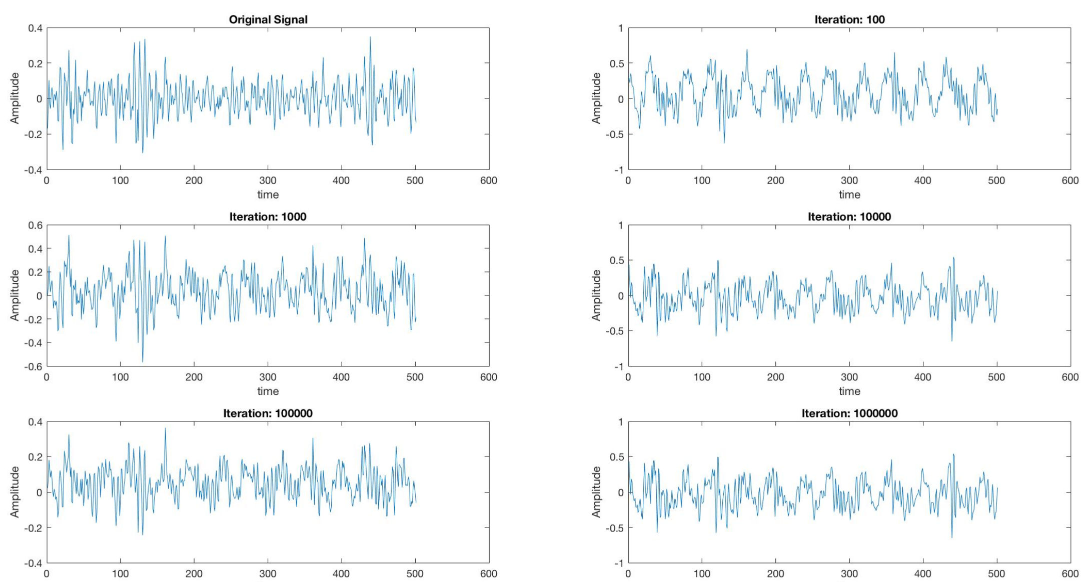
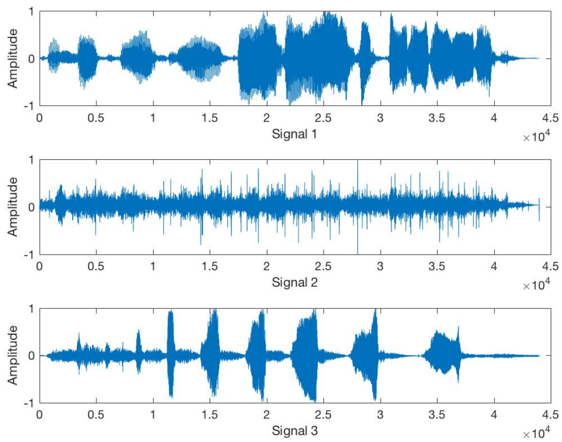
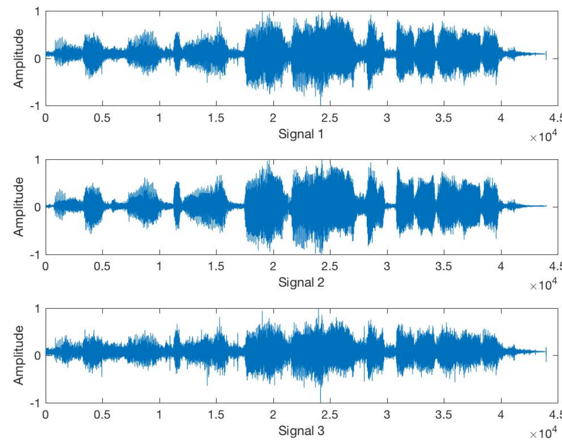


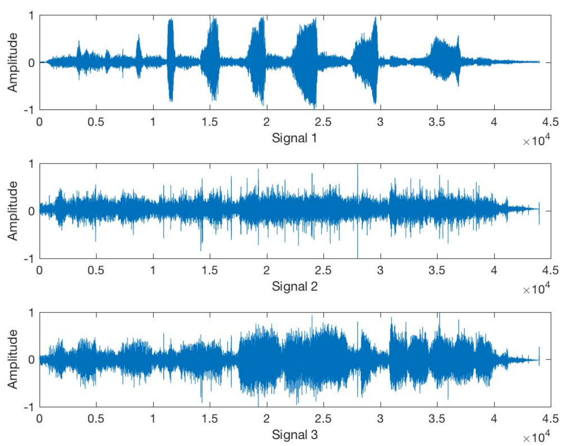
Figure 3: A small part of reconstructed signal of signal 1 from Fig4 using iteration = [100 - 1000,000] from t = [2000-3000].



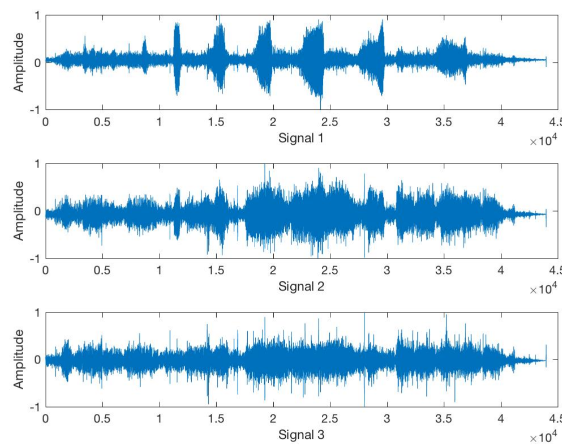
(a) Original Signals



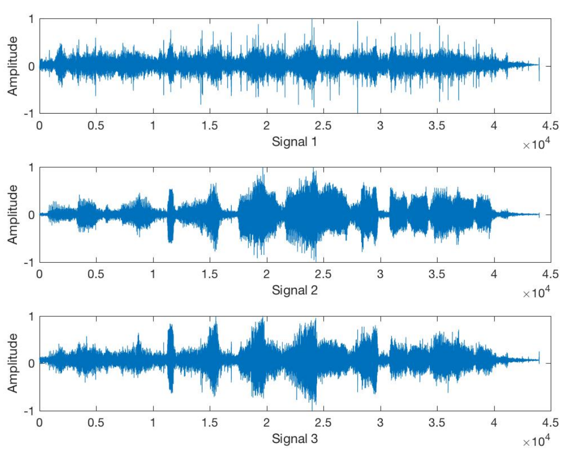
(b) Reconstructed signal using Iteration = 100



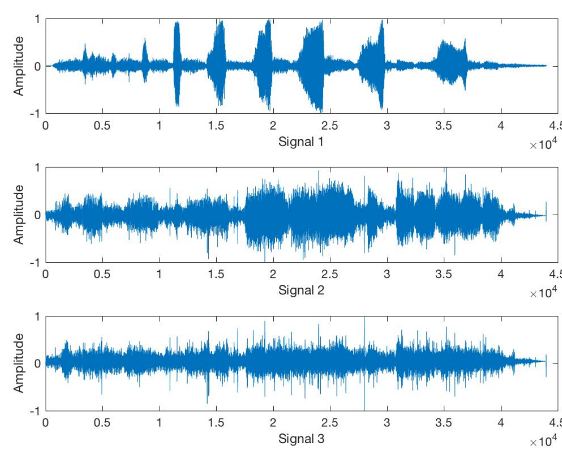
(c) Reconstructed signal using Iteration = 1000.



(d) Reconstructed signal using Iteration = 10000



(e) Reconstructed signal using Iteration = 100000



(f) Reconstructed signal using Iteration = 1000000

Figure 4: Reconstructed the original signal by varying the number of Iterations in the range [100 - 1,000,000]

original signal and have almost the same amplitude at the same time.

This is happening because of the addition of very less number of Δ W since running for less number of iterations which won't lead us to converge to the optimal stage . But if we choose the number of iteration in some good range, then it will reach to the optimal range and we can reconstruct back the original signals which can be clearly seen from the Fig 4 representing the complete reconstructed signal.

3.3. Varying the dataset size

In this experiment, we fixed the learning rate to 0.01 and the number of iterations = 100,000 and varied the size of the signal from t = [1-10,000/40,000]. From the figure 5 which shows the small part of the reconstructed signal of signal 1, we observe that algorithm performs extremely well for

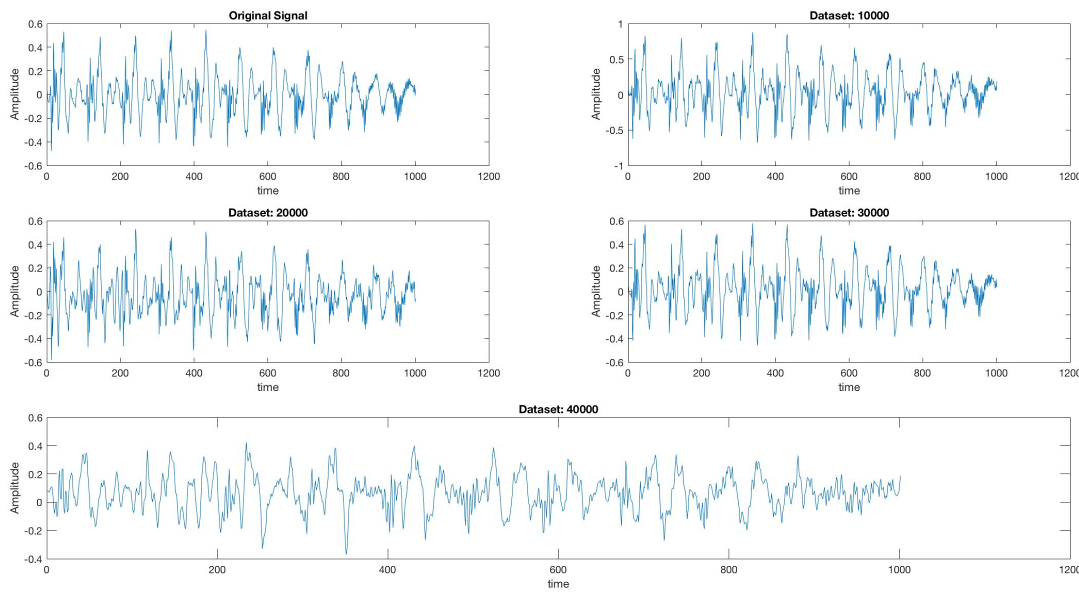
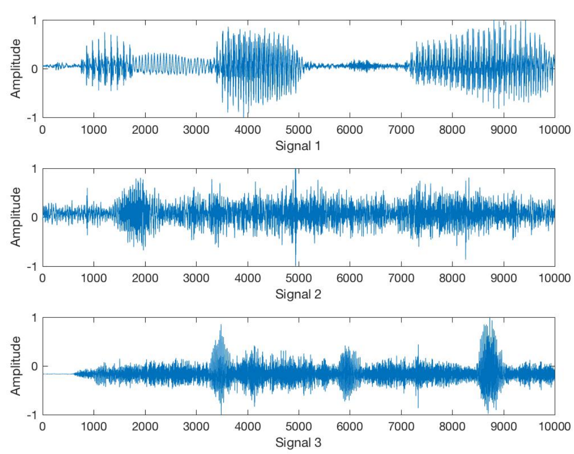
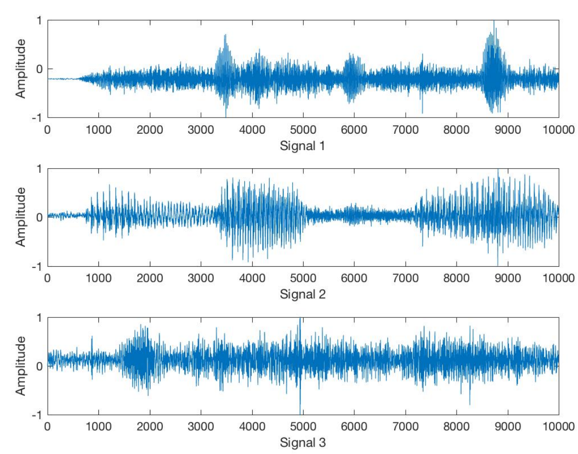


Figure 5: A small part of reconstructed signal of signal 1 from Fig6 and 7 by varying t from [1-10000/40000], fixing η = 0.01 and iteration = 100,000.

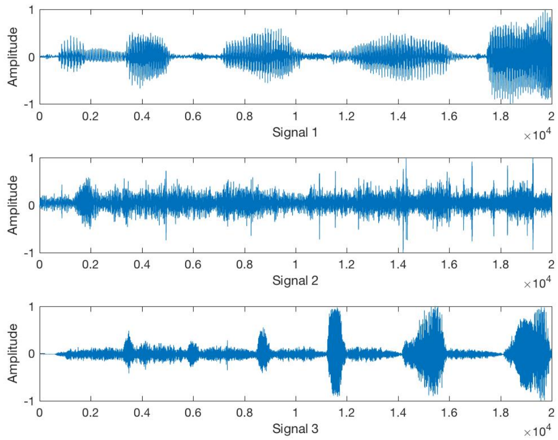


(a) Original Signals using t = [1-10000]

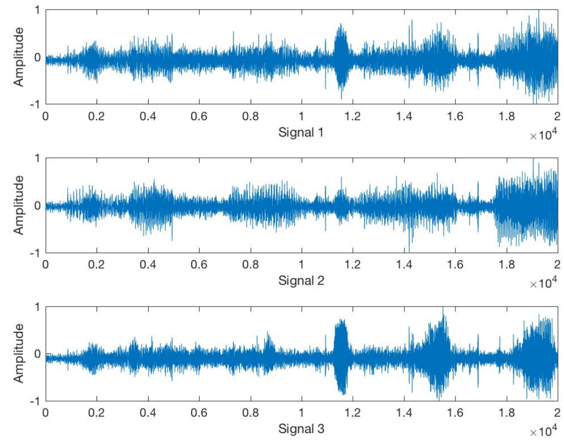


(b) Reconstructed Signal using t = [1-10000]

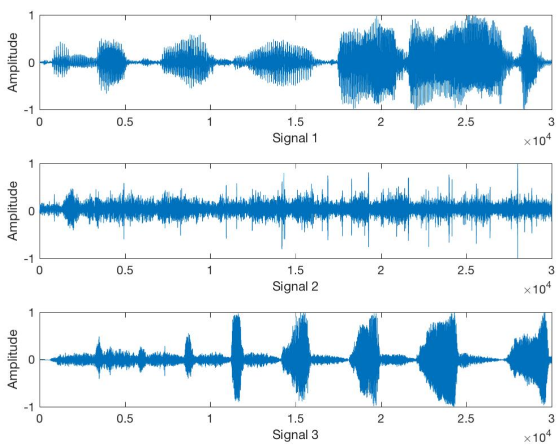
Figure 6: Reconstructed the original signal by varying the dataset time in the range [10,000 - 40,000]



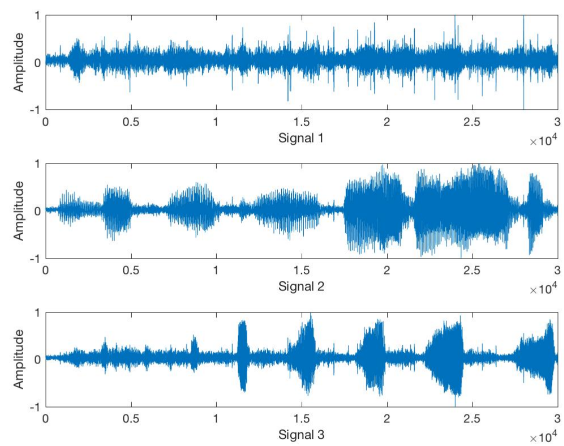
(a) Original Signals using t = [1-20000]



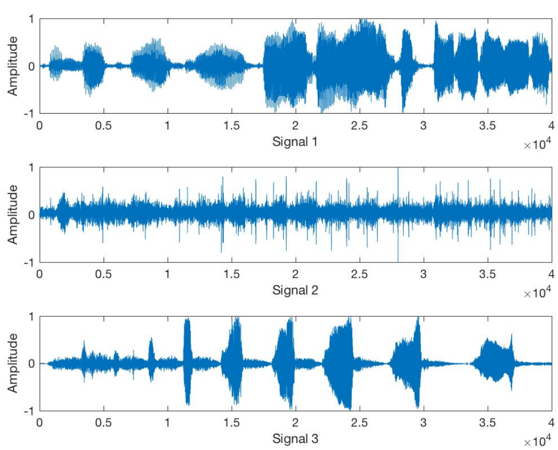
(b) Reconstructed Signal using t = [1-20000]



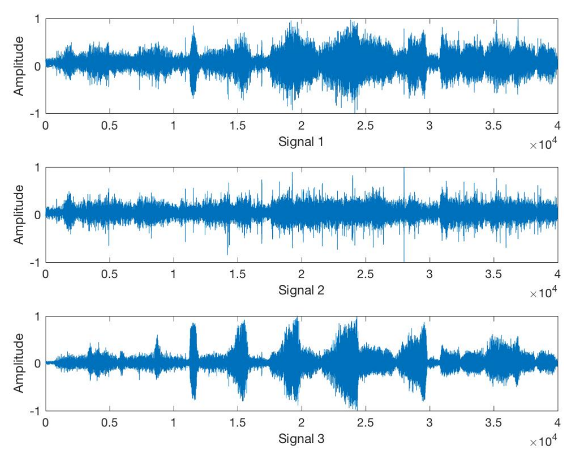
(c) Original Signals using t = [1-30000



(d) Reconstructed Signal using t = [1-30000]



(e) Original Signals using t = [1-40000]



(f) Reconstructed Signal using t = [1-40000]

Figure 7: Reconstructed the original signal by varying the dataset time in the range [10,000 - 40,000]

the smaller dataset, almost retrieves back the original source signal and reasonably well for larger dataset.

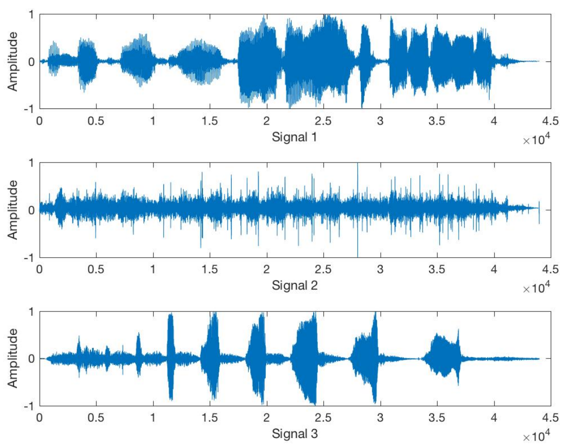
3.4. Performance comparison with Balanced and Overdetermined system

In this experiment, we tried to estimate the 3 Original signals from the 3 mixed signals (Balanced system), 5 and 8 mixed signals (Overdetermined system) which is shown in Fig 8. We observed that there is not huge difference between the reconstructed signals for the balanced and over determined system.

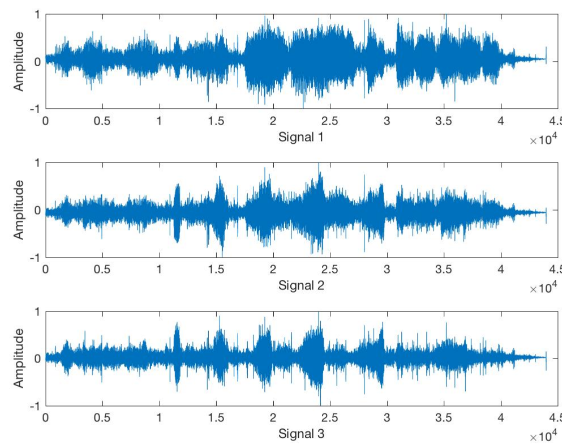
3.5. Varying the Signal Selection

In this experiment, we tried the different number and combination of original signal for mixing and tried to reconstruct them. We fixed the learning rate $\eta = 0.01$ and number of iterations = 100,000. From the fig 9 and 10, we can see that we are able to generate the original signals by varying the original signals. This is happening because the original source signals are independent of each other which is the basic necessity of the ICA.

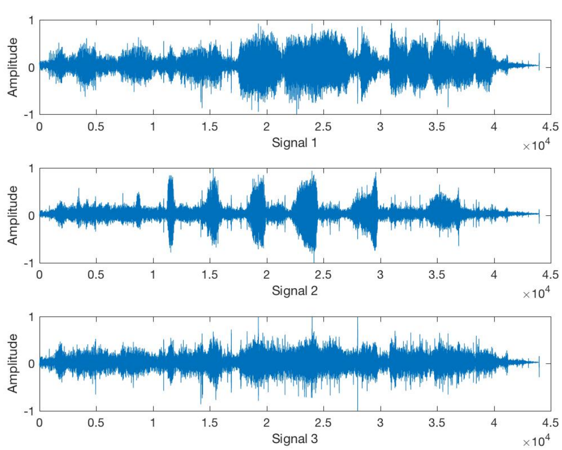
The important point to notice here is that if we choose signals 2 and 3, we are able to reconstruct both 2 and 3 as shown in fig 9a, 9b. But if we mixed the signals 2,3 and 4, we are not able to reconstruct the signal 3 as show in fig 9c, 9d. Same is the case if we mixed the signals 2,3,4 and 5 as show in fig 9e, 9f. We are not able to reconstruct the signal 3 and 5 . We checked the correlation between these signals and they are independent. We don't know the exact solution but it seems that signal 2 is correlated to other signals in some different fashion may be in Fourier domain.



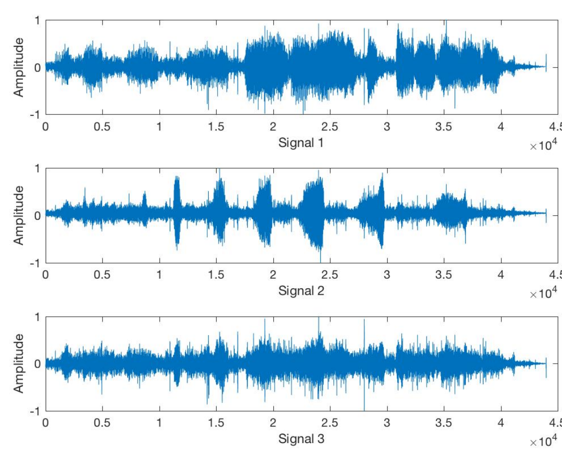
(a) Original Signals



(b) Reconstructed Signal using 3 mixture signals

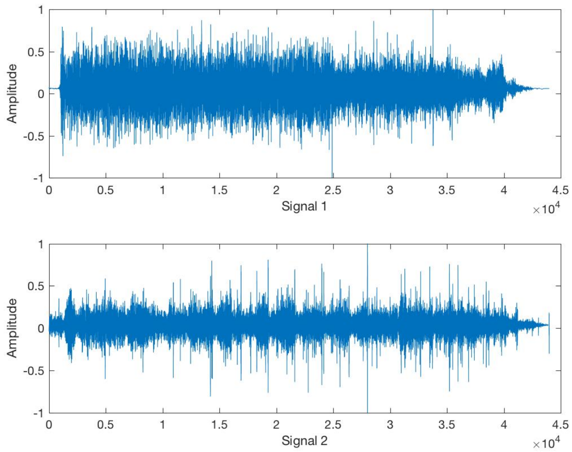


(c) Reconstructed Signal using 5 mixture signals

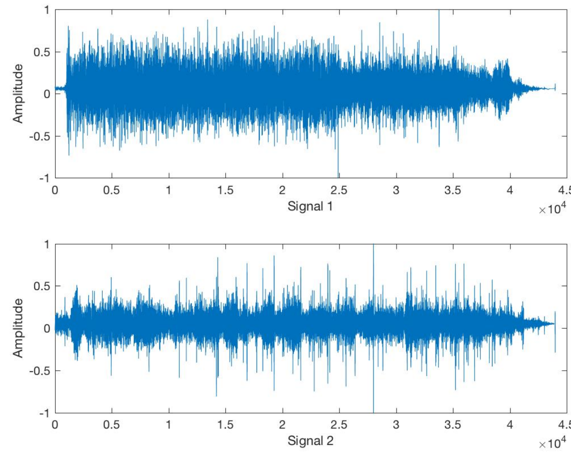


(d) Reconstructed Signal using 8 mixture signals

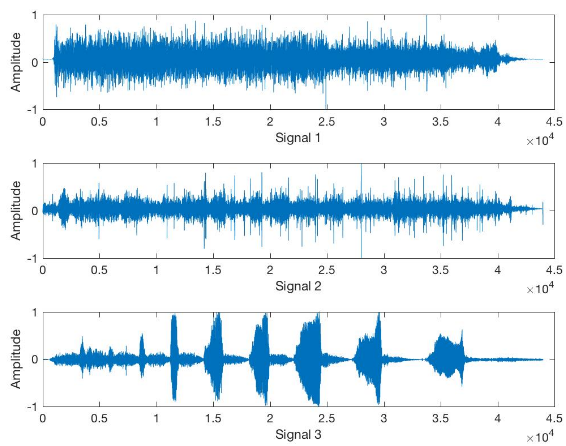
Figure 8: Reconstructed the original signal by fixing the 3 original signals and varying the number of mixed signals.



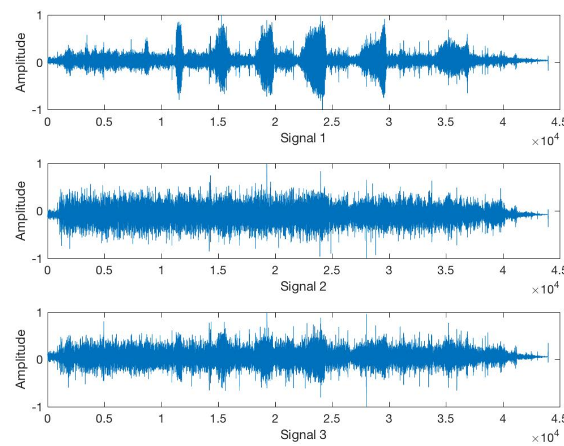
(a) Original Signals: 2, 3



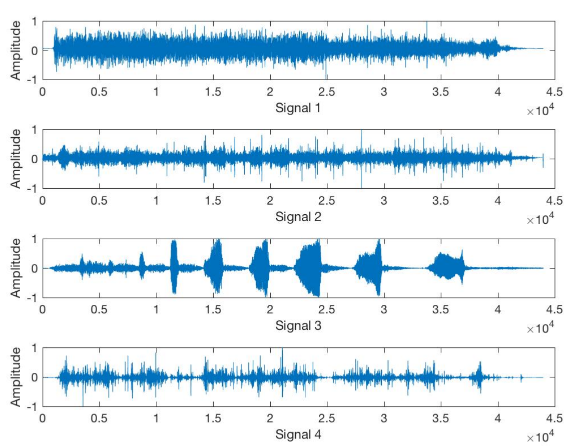
(b) Reconstructed Signal



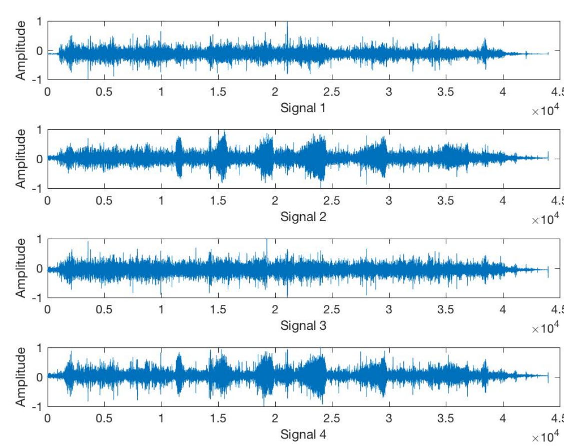
(c) Original Signals: 2, 3, 4



(d) Reconstructed Signal

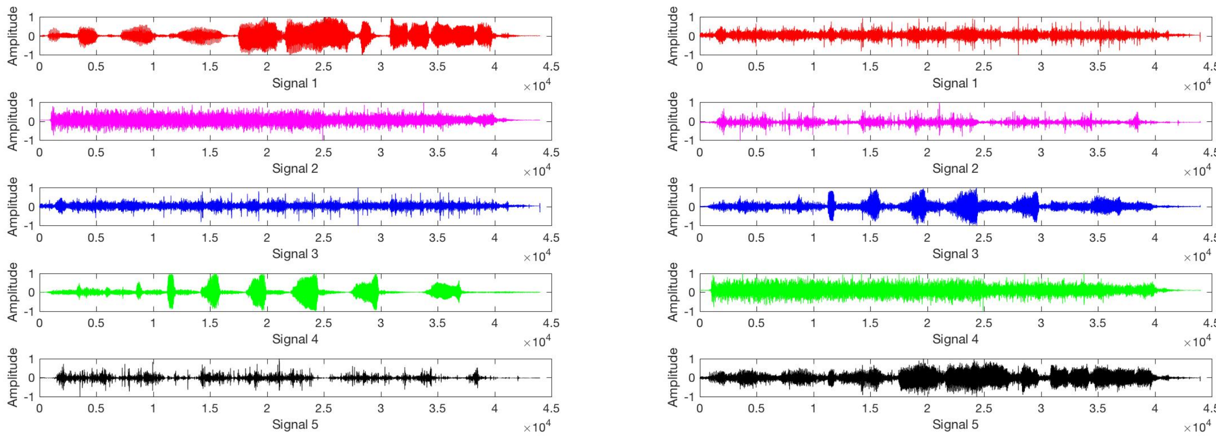


(e) Original Signals: 2, 3, 4, 5



(f) Reconstructed Signal

Figure 9: Reconstructed the original signal by varying the number and combination of original signals.



(a) Original Signals: 1, 2, 3, 4, 5

(b) Reconstructed Signal

Figure 10: Reconstruction of all the 5 Original Signals using η = 0.01 and iteration = 1,000,000.

4. Conclusion

In this work, we implemented the Independent Component analysis for the blind source separation, which reconstruct the original signals by mixing the original signals using some mixing system. From the experiments, we can say that Independent Component Analysis can be used for the reconstruction of the original signals provided they are independent, non-Gaussian and mixed in linear fashion. We also see that learning rate, number of iteration have high impact on the source signal reconstruction, however, it's not much affected by the other parameters like balanced, overdetermined system and dataset time length.

5. Discussion

We are considering sound signals are coming at the same time, however, in real scenario, signals propagate at different rates or may be coming after reverberating from the walls, thus, it doesnt reach to microphones at the same time. Second, we are considering that there exists no noise in the mixing signals. We should consider the noise also. To future work, we would like to consider these points.