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ICA Based Source Separation

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Abstract— Independent Component Analysis is a statistical and computational method for finding underlying factors or components form multivariate (multidimensional) statistical data. What distinguishes ICA from other method is that it looks for components that are both statistically independent and non-Gaussian. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear mixtures of some unknown latent variables and the mixing system is also unknown. The latent variables are assumed non-Gaussian and mutually independent and they are called the independent components of the observed data.In this paper FastICA algorithm is used to separate various types of signals.

Index Terms— Independent Component Analysis, FastICA

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1 Introduction

Independent Component Analysis is a signal processing technique whose goal is to express a set of random variables as linear combinations of statistically independent component variables. To define ICA, assume n linear mixtures $x_1 \ldots x_n$ of $\boldsymbol{n}$ independent

$$x_j = a_{j1}s_1 + a_{j2}s_2 + \ldots + a_{jn}s_n, \text{ for all } j. \quad (1)$$

Now, ignoring the time index t, in the above mixing model, each mixture x_j and each independent component s_k can be assumed as a random variable. Defining the ICA model in matrix notation,

$$x = As \quad (2)$$

Where, **x** is the random vector with elements that are the mixtures $x_1 \ldots x_n$ and **s** is the random vector with elements $s_1, \ldots s_n$, and **A** is the mixing matrix with elements a_{ij}. The statistical mode in eq.(2) is called independent component analysis, or ICA model. Sometimes we need the columns of matrix A; denoting them by a_i, the model can be written as,

$$x = \sum_{i=1}^{n} a_i s_i \quad (3)$$

The mixing matrix is assumed to be unknown. Here, all we observe is the random vector x and we aim to estimate both **A** and **s** using it. The ICA estimation is done under two important assumptions, (i) the components s_i, are statistically independent and, (ii) the independent components must have non-Gaussian distributions. For simplicity, it is also assumed that the mixing matrix is square. Then, after estimating the matrix A, we can obtain the independent components by:

$$s = Wx \quad (4)$$

Where, **W** is the demixing matrix and can be calculated by the inverse of **A**.

2 Methodology

There are several types of ICA algorithms among which the FastICA has been used in this work. Basically, it consists of two steps, the preprocessing step and the FastICA algorithm itself. The preprocessing consists further of two steps known as centering and whitening. The centering step is done by subtracting the mean of the observed data x, so as to make x a zero-mean variable. A whitening step is done to remove the correlation between the components of the observed data. One popular method for whitening is to use the eigenvalue decomposition (EVD) of the covariance matrix of the mixed signal. The final step is the FastICA algorithm which is briefly summarized as follows:

1. Choose an initial (e.g. random) weight vector **w**.
2. Let $\mathbf{w}^+ = E\{\mathbf{x}g(\mathbf{w}^T\mathbf{x})\} - E\{g'(\mathbf{w}^T\mathbf{x})\}\mathbf{w}$
3. Let $\mathbf{w} = \mathbf{w}^+ / \|\mathbf{w}^+\|$
4. If not converged, go back to 2.

The term *converge* in step 4 above refers to the condition that the value of **w** in the current iteration is same as the previous **w** value. ***E*** denotes the expectation. The function $g(.)$ can be chosen either as:

$$g(u) = \tanh(a_1.u) \text{ or } g(u) = u.\exp(-u^2/2),$$

Where, a_1 is any value that fulfils $1 \leq a \leq 2$.

3 Results and Discussions

We have taken sine, square and triangular wave of different frequencies, with different harmonics and different combinations, these signals are mixed in a random proportion to get

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the mixed signals and then are extracted back using the algorithm. Some speech signals are also taken into consideration. The order in which the outputs are recovered could not be predicted. The variances of the source signals are assumed to be equal to one.

We have taken six combinations of different signals, mixed them and then separated them using the FastICA algorithm. The joint distributions of the signals are also analysed. The type of signals taken, number of samples taken and the type of functions used are mentioned in a table below.

3.1 Simulation result1:

Signals used	sine wave, square wave
Number of samples taken	10000
Functions used	tanh(*u*), 1-tanh²(*u*)

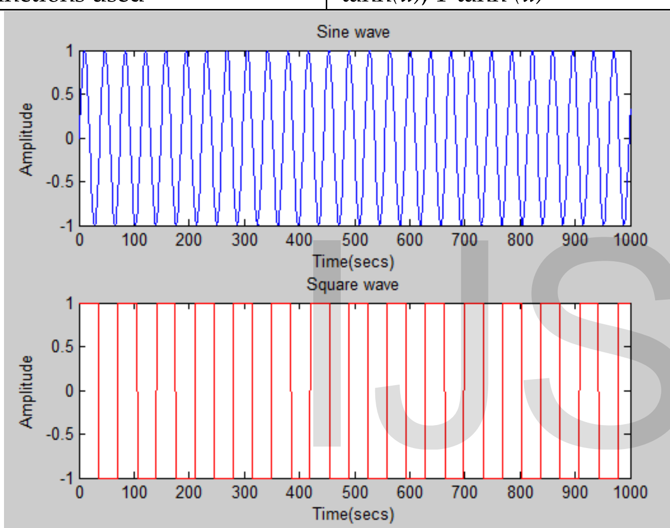

Figure 3.1(a): Original signals taken in first simulation

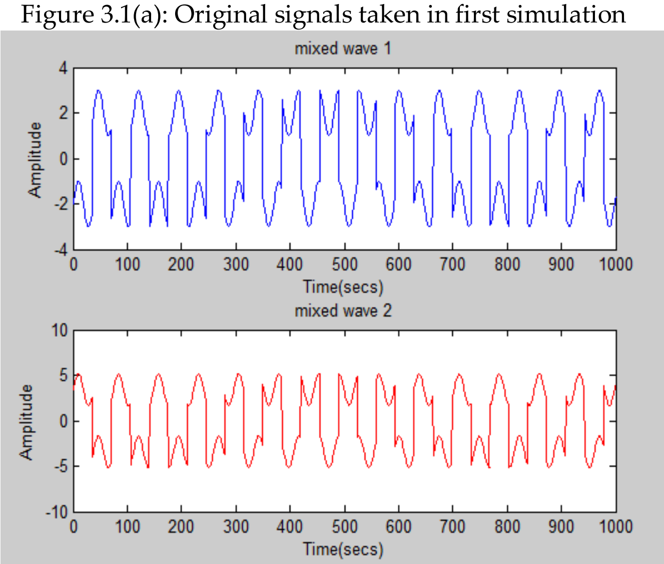

Figure 3.1(b): Mixed signals in first simulation

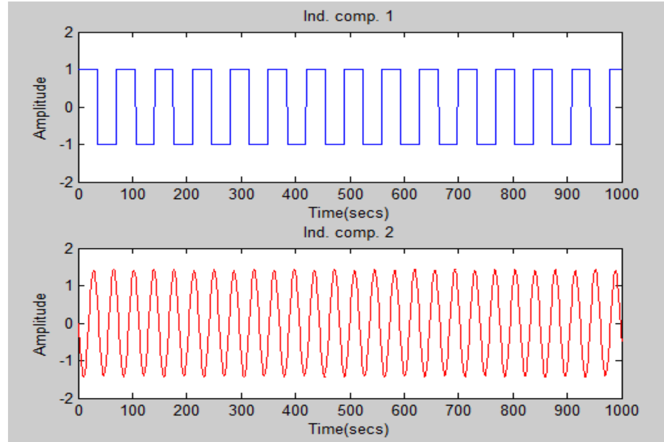

Figure 3.1(c): Recovered signals in first simulation

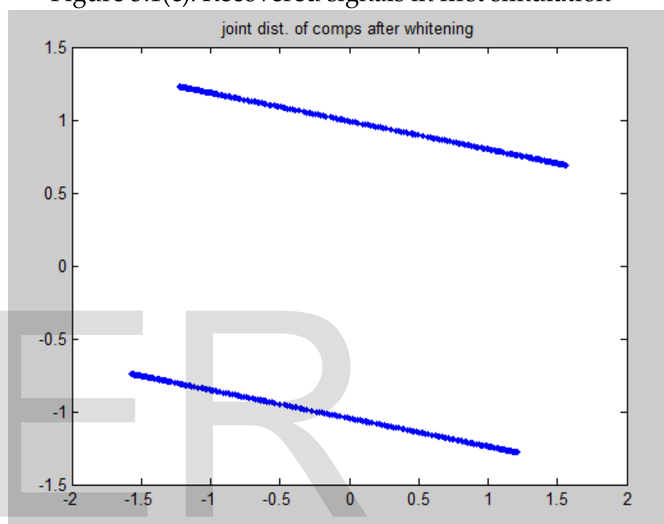

Figure 3.1(d): Joint distribution of signals in first simulation

3.2 Simulation result2:

Signals used	sine wave, square wave, 7th harmonics of sine wave
Number of samples taken	10000
Functions used	tanh(*u*), 1-tanh²(*u*)

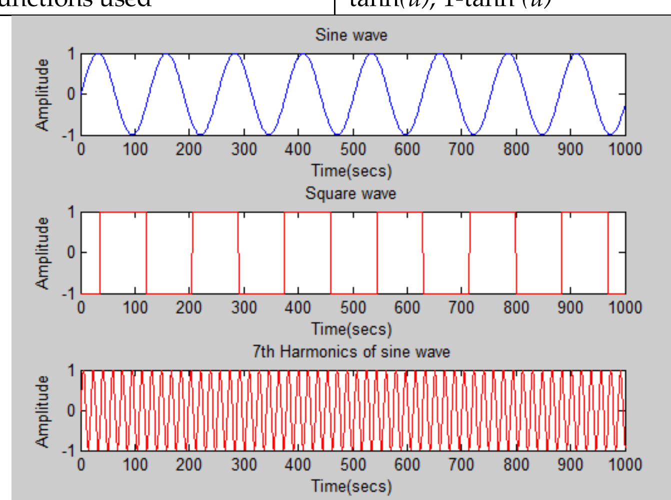

Figure 3.2(a): Original signals taken in second simulation

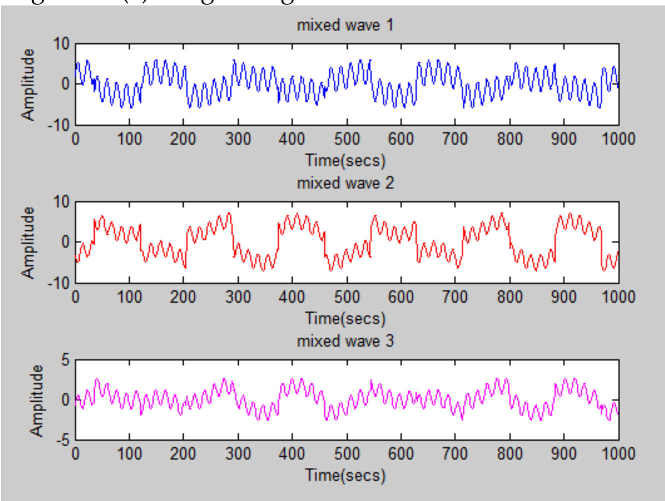

Figure 3.2(b): Mixed signals in second simulation

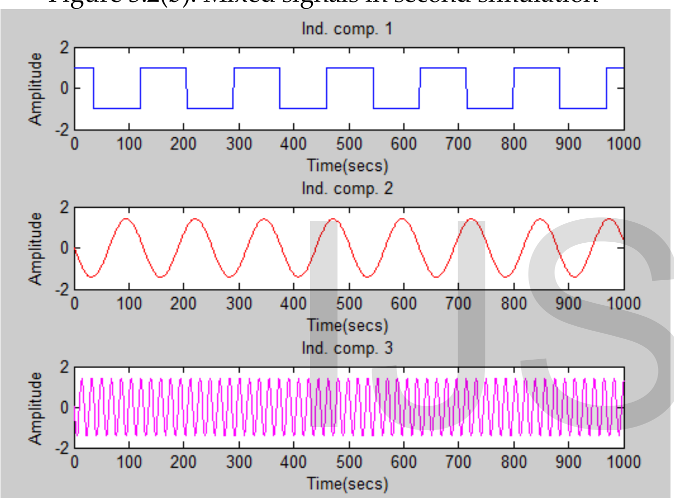

Figure 3.2(c): Recovered signals in second simulation

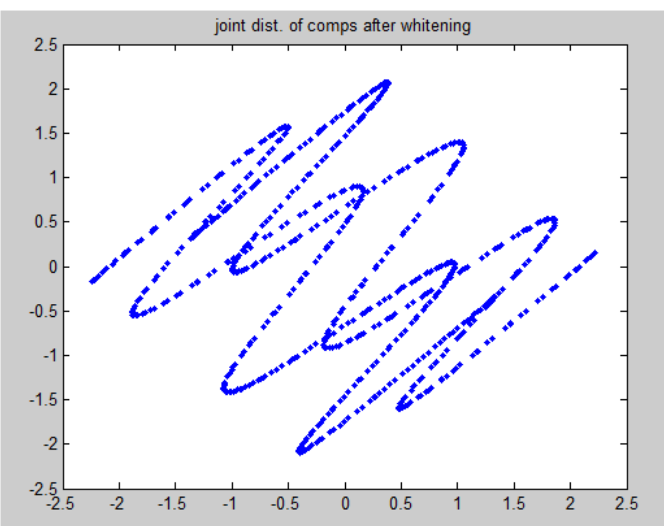

Figure 3.2(d): Joint distribution of signals in second simulation

3.3 Simulation result3:

Signals used	5^{th} harmonics of sine wave, 3^{rd} harmonics of square wave
Number of samples taken	10000
Functions used	$\tanh(u)$, $1-\tanh^2(u)$

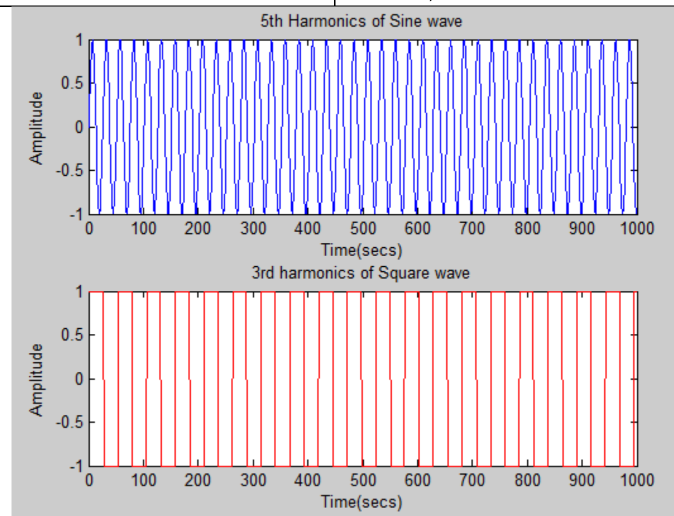

Figure 3.3(a): Original signals taken in third simulation

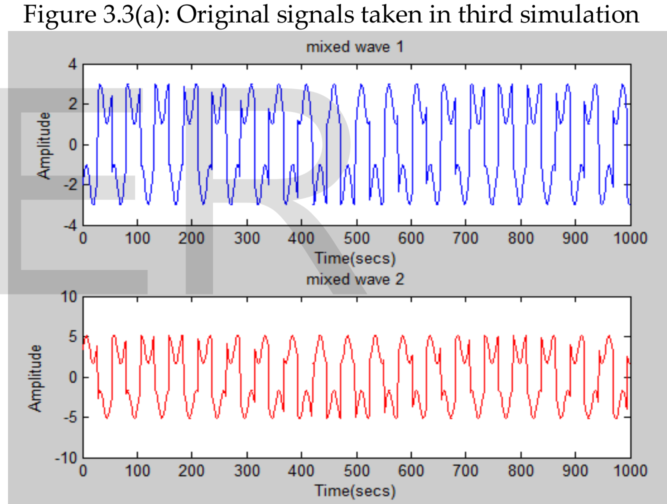

Figure 3.3(b): Mixed signals in third simulation

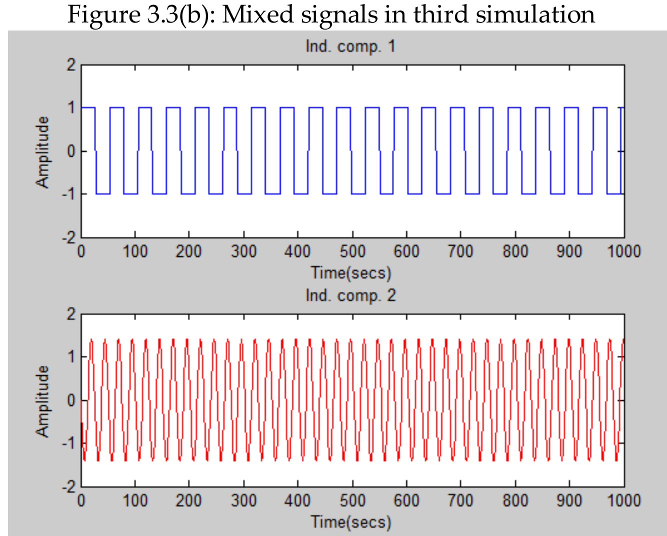

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Figure 3.3(c): Recovered signals in third simulation

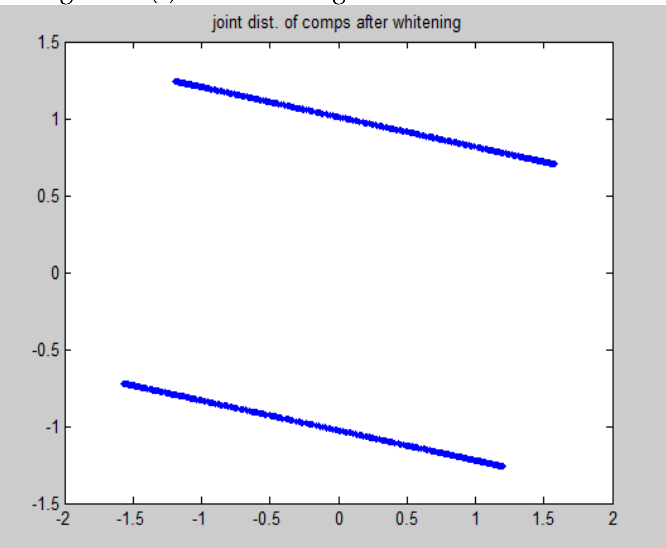

Figure 3.3(d): Joint distribution of signals in third simulation

3.4 Simulation result4:

Signals used	Two different speech signals
Number of samples taken	500000
Functions used	tanh(*u*), 1-tanh²(*u*)

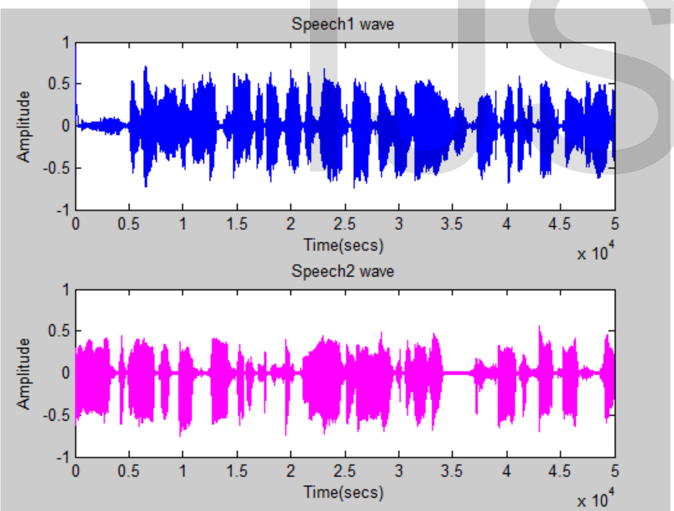

Figure 3.4(a): Original signals taken in fourth simulation

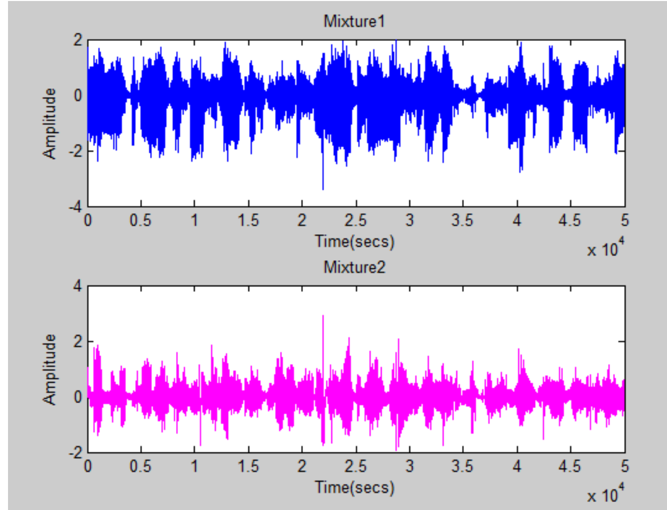

Figure 3.4(b): Mixed signals in fourth simulation

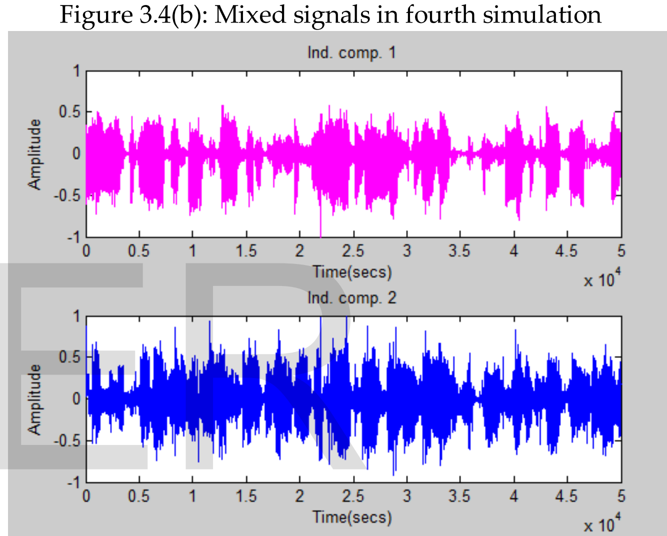

Figure 3.4(c): Recovered signals in fourth simulation

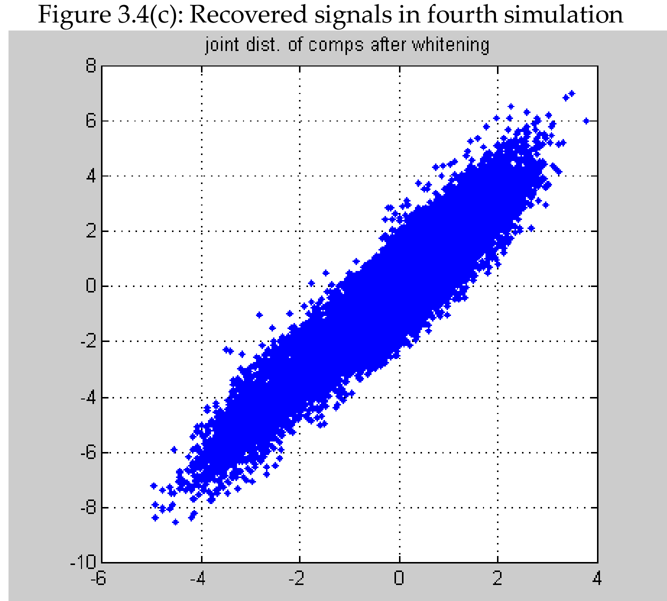

Figure 3.4(d): Joint distribution of signals in fourth simulation

3.5 Simulation result5:

Signals used	Sine, square and triangular wave
Number of samples taken	10000
Functions used	tanh(u), 1-tanh$^2(u)$

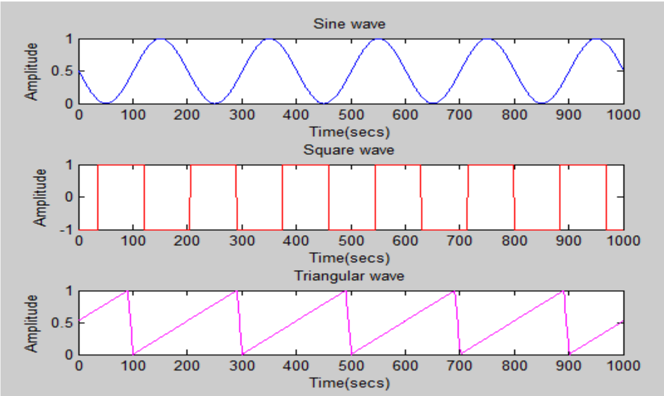

Figure 3.5(a): Original signals taken in fifth simulation

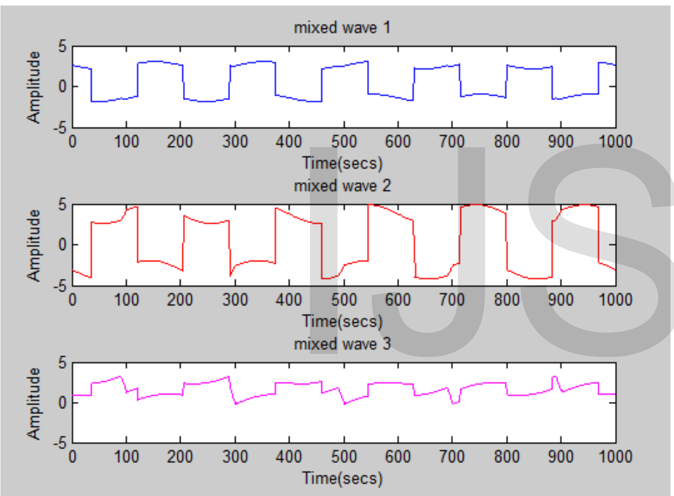

Figure 3.5(b): Mixed signals in fifth simulation

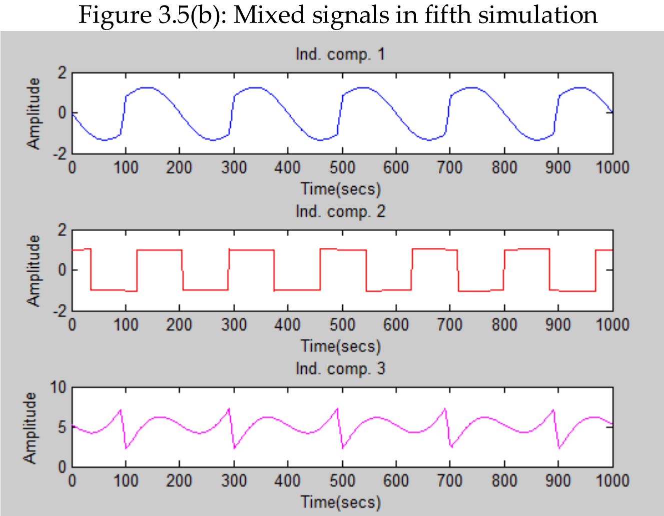

Figure 3.5(c): Recovered signals in fifth simulation

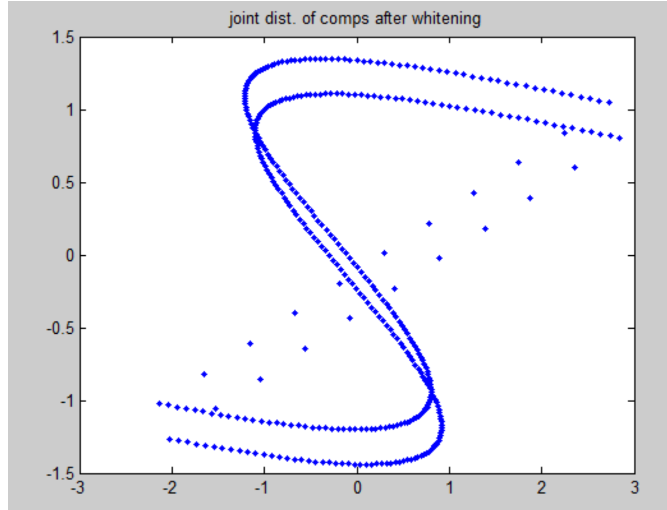

Figure 3.5(d): Joint distribution of signals in fifth simulation

4 Conclusion

In this paper, various mixed signal separation using the FastICA algorithm is shown .The result shows that the Fast ICA algorithm is an effective tool for denosing of mixed signal. The error signal between the original and recovered signal decreases by increasing the number of iterations.

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