Independent Component Analysis for Separation of Speech Mixtures: A Comparison Among Thirty Algorithms

Ali Al-Saegh
Computer Engineering Department
University of Mosul
Mosul, Iraq
ali.alsaegh@uomosul.edu.iq

Abstract: *Vast number of researches deliberated the separation of speech mixtures due to the importance of this field of research. Whereas its applications became widely used in our daily life; such as mobile conversation, video conferences, and other distant communications. These sorts of applications may suffer from what is well known the cocktail party problem. Independent component analysis (ICA) has been extensively used to overcome this problem and many ICA algorithms based on different techniques have been developed in this context. Still coming up with some suitable algorithms to separate speech mixed signals into their original ones is of great importance. Hence, this paper utilizes thirty ICA algorithms for estimating the original speech signals from mixed ones, the estimation process is carried out with the purpose of testing the robustness of the algorithms once against a different number of mixed signals and another against different lengths of mixed signals. Three criteria namely Spearman correlation coefficient, signal to interference ratio, and computational demand have been used for comparing the obtained results. The results of the comparison were sufficient to signify some algorithms which are appropriate for the separation of speech mixtures.*

***Index Terms*—Comparison of algorithms, blind source separation (BSS), independent component analysis (ICA), Signal to .interference ration (SIR), Spearman correlation coefficient**

I. INTRODUCTION

Mixed speech recordings are indeed not clear to listeners and hence this considered a problem for those listeners, this problem is known as the cocktail party problem. Whereas different speech signals coming simultaneously from different speakers are received and combined, by several microphones, into several mixed signals. Since nowadays voice plays an energetic role in many different applications such as in distant communications, therefore, it is of great importance to seek for a solution for such a problem and recover the original speech signals.

A mathematical model called independent component analysis (ICA) [1] is one of the computational techniques which are used for solving the pointed out problem throughout estimating the independent components i.e. original speech signals. The more general technique of ICA is the blind source separation (BSS), sometimes called blind signal separation, which tries to estimate the original signals from their observed mixture data depending on several assumptions about the mixing process. The word "blind" means that very little, if nothing, of information about the original sources is available. In addition to the problem of mixed speech signals, BSS and ICA have been intensively used for solving problems in different fields like in convoluted mixtures of images, psychometric measurements, stock market indicators, and artifacts removal from EEG recordings [1], [2].

Specifically, the problem of separating mixed speech signals using ICA has been widely investigated in different studies. Recently, Douglas and others proposed in [3] two spatio-temporal algorithms for separating convolutive mixtures, these algorithms are extension to the FastICA algorithm. Pedersen and others [4] combined independent component analysis (ICA) and binary time-frequency masking for under determined blind source separation using an instantaneous mixing model which assumes closely spaced microphones. Zhang and Ching suggested in [5] a short-time based ICA algorithm for estimating the original sources from noisy mixed speech signals. Their supposition is that nothing is known about the noise covariance. Prasad and others proposed in [6] a fixed-point ICA algorithm for estimating original sources by non-Gaussianizing the time-frequency series of speech in a deflationary manner. Chien and Chen have advanced in [7] a nonparametric likelihood objective function for estimating components as independent as possible.

Yet, the appropriate ICA algorithm(s) to be adopted for the purpose of separating mixed speech signals is of great importance. In [8] a study for comparing just two algorithms namely fastICA and gradient algorithms has been published. This study shows that gradient is more efficient than fastICA in quality of separation, while fastICA is better than gradient in the means of computational demand and the number of required iterations for convergence.
To this end, the aim of this paper is to compare the performance of 30 ICA algorithms in separating mixed speech signals then signifying some algorithms to be used for this purpose. The comparison is based on appropriate criteria, where they are either utilizing the contained information within the estimated components or the computational demand of the algorithms. Moreover, the robustness of the algorithms in separating both different number of mixed signals and different number of samples were also investigated.

The rest of this paper is structured as follows: Section II describes the basics of the ICA mathematical model; Section III lists the ICA algorithms used in the comparison, describes the analyzed data, and gives a brief depiction for each of the comparison criteria. The results are presented in Section IV, then Section V concludes this paper.

II. Independent Component Analysis (ICA)

Independent component analysis (ICA) [1] is a mathematical model for estimating underlying components, they are assumed non-Gaussian, from intensive observed mixed data with the aim of estimating components as independent as possible. The observed signals are assumed to be formed by mixing the original source signals in a prescribed manner [9]. The estimated underlying components which hopefully represent the original source signals are called independent components (ICs). The process of mixing original signals and unmixing them is illustrated in Fig. 1. It is assumed that there are three microphones recording (mixing) three speech signals, then the observed (mixed) signals are passed throughout an ICA algorithm for estimating the ICs.

The ICA mathematical model can be written as:

$$x_i(t) = \sum_{j=1}^{n} a_{ij} s_j(t) \qquad (1)$$

for $i = 1, \ldots, n$, where $x_i(t)$ represent the observed mixtures which are the linear combinations of n random variables $s_i(t)$. The constant coefficients a_{ij} are the weights of mixing the original voice signals, each of these coefficients is influenced by the

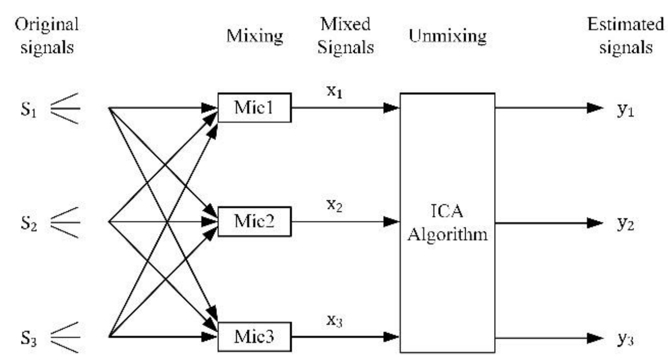

Fig. 1: Mixing and unmixing basic model. Three original speech signals s_1, s_2, s_3 are recorded by three microphones. Then the recorded mixtures x_1, x_2, x_3 are separated using an ICA algorithm to give back the estimated signals y_1, y_2, y_3.

distance between the source and the microphone. Hence, determining their values involves knowing the properties of the physical mixing system which is not so easy in general, therefore, they are unknown in this case. Moreover, the original source signals are unknown because recording them separately is impossible for the microphones. So the task is represented by recovering the original signals using the observed mixtures only. Inverting the linear system of equations given in (1) is the way to find a solution for the task if the mixing coefficients are known. These coefficients can be estimated using ICA which assumes that the original signals are statistically independent at each time point (t), this assumption is nearly the case in vast majority of the real world practical situations.

Usually, the ICA model is represented in vector-matrix notation as:

$$x = As \tag{2}$$

where the vector x contains the observed mixtures, vector s contains the original sources, and A is the matrix that contains the mixing coefficients.

After estimating the mixing matrix A using an ICA algorithm, the unmixing matrix becomes $W = A^{-1}$, then the underlying variables (separated signals or ICs) $y_i(t)$ are achieved by:

$$y = Wx \tag{3}$$

Estimating the ICs is accomplished using different ICA algorithms based on different approaches, such as maximization of non-Gaussianity, maximum likelihood estimation, minimization of mutual information, tensorial methods. All of them utilizes an objective function (sometimes called cost function) which gives an indication about the goodness of the attained estimation, this indication is considered as a condition for the convergence.

III. Materials And Methods

A. Simulation Premises

- Algorithms

Thirty of available ICA algorithms were compared. All of them are available for free and were written in Matlab. Details about the algorithms can be found in the given references. Without particular order, the compared ICA algorithms are: icaMS, icaML, FBSS, EGLAD, infomax, flexICA, sfanalICA, ICA_EBM, SUT, A-CMN, acsobiro, AMUSE, RADICAL, fast_RADICAL, EFICA, BEFICA, ERICA, OGWE, COMBI, fastICA, fastICAter, FOBI, JADE, JADEOP, QJADE, evd, evd24, SONS, SOBI, pearson_ICA [1], [10]–[18].

- Comparison Criteria

Three comparison criteria have been used in order to compare the performance of the different algorithms. Two of them utilize the obtained estimated signals while the other is for quantifying the computational demand.

- Analyzed Data

In this comparison the "Telephone based speaker identification data set from India" [19] has been used. All files of this data set are in WAV format. Only 8 files from the data set have been used, where 4 of them are for males and the other 4 files are for females. The choice of this data set is arose because of the big similarity within the recordings, whereas all of them are speech only without any distinct samples like music. Hence, this strengthens the comparison.

- Simulation

A mixing matrix was randomly generated in order to mix a number of the speech signals. Then one of the intended tests is the robustness of ICA algorithms against separating different number of mixed signals, wherein each time the algorithms were forced to separate a number of mixed signals different from the number in the other times. Likewise, another test is the robustness of ICA algorithms against separating different lengths of mixed signals, wherein each time the algorithms were forced to separate a number of mixed signals with a specific number of samples different from the number in the other times.

B. Comparison Criteria

The following three comparison criteria have been used for comparing the performance of the algorithms:

- Spearman Correlation Coefficient Criterion

In order to measure the amount of presence of one original source signal within each estimated signal, the Spearman correlation coefficient criterion [20] verifies to be an appropriate choice. Since, it is able to compare between the original source signal and the estimated independent component whereas it is not reliant on the absolute amplitude but instead on the shape of the signal. For simplicity, this criterion will be denoted as (SCC) in this paper. The formula for calculating SCC is:

$$r = 1 - 6\sum \frac{d^2}{N(N^2-1)} \tag{4}$$

where d is the difference in statistical rank of the corresponding signal, N is the signal length, and r is the correlation index. Regardless of the sign which is not in scope here, SCC presents 0 in case of highly uncorrelated two signals i.e. signals are not matched, in contrast it presents 1 for those highly correlated signals i.e. signals are matched. In other words, the more zeros are presented the better is the performance of the algorithm.

- Signal to Interference Ratio Criterion

Since the mixing matrix is known, therefore, signal to interference ration (SIR) [10] is another suitable criterion for measuring the performance of the ICA algorithms. The formula for calculating SIR is:

$$\text{SIR} = \frac{1}{N}\sum_{i=1}^{N}\left[\sum_{j=1}^{N}\frac{|P_{ij}|}{\max_j |P_{ij}|} - 1\right] \tag{5}$$

where $P = WA$, if $A = W^{-1}$ then P turns out to be the identity matrix, otherwise it is coarsely a permutation matrix; N is the number of original/estimated signals. SIR quantifies the distance of the obtained permutation matrix from the optimum. The lower the SIR value, the better the separation; with zero describing a perfect separation i.e. the algorithm has a good performance. Whilst SIR is the ratio of signal power of the estimated IC and total power of the interfering signals, accordingly henceforth it is favored to measure the SIR in decibels (dB). Thus the results of SIR will be presented as $10 \log \text{SIR}$ (dB).

- Computational Demand

Since an ICA algorithm is a statistical procedure and its results predominantly affected by its random initialization, objective function, and inherent number of iterations that terminate or not with a correctly estimated IC; consequently, another very important measure for the comparison of algorithms is the elapsed time taken by each of the algorithms. On account of that, the elapsed CPU time represents a measure of the computational demand needed by an algorithm for estimating the ICs. Matlab’s built in function permits to get back the spent CPU time for estimating those components only and excluding probable inspirations of simultaneously running external processes. As it is inferred, the less the elapsed time, the better the performance of the algorithm. The computer system that is employed for this work is equipped with an Intel Core2 Due CPU of 2 GHz, 3 MB L2 Cache, 3 GB of DDR2 400MHz physical memory, and running Windows 7 Ultimate 64-bit and Matlab 2009a.

IV. RESULTS

For the purpose of examining the robustness of the algorithms, each of the used algorithms was executed seven times. Whereas the first execution was applied for separating two mixed signals, the second execution was applied for separating three mixed signals, and so on. In this paper, all results are presented as images divided into small rectangular areas. Each one of these areas gives an indication about the performance of an algorithm for separating a number of signals at a specific condition. This way of visualization permits to investigate the results returned by all of the algorithms for separating different signals.

Fig. 2 and Fig. 3 show attained results of SCC after executing all of the algorithms for separating 8 mixed signals each of them consists of 50000 samples. For each algorithm, the 56 SCCs which are represented as small rectangular areas within a single row in Fig. 2 denote the correlation of each one of the source signals with all of the estimated

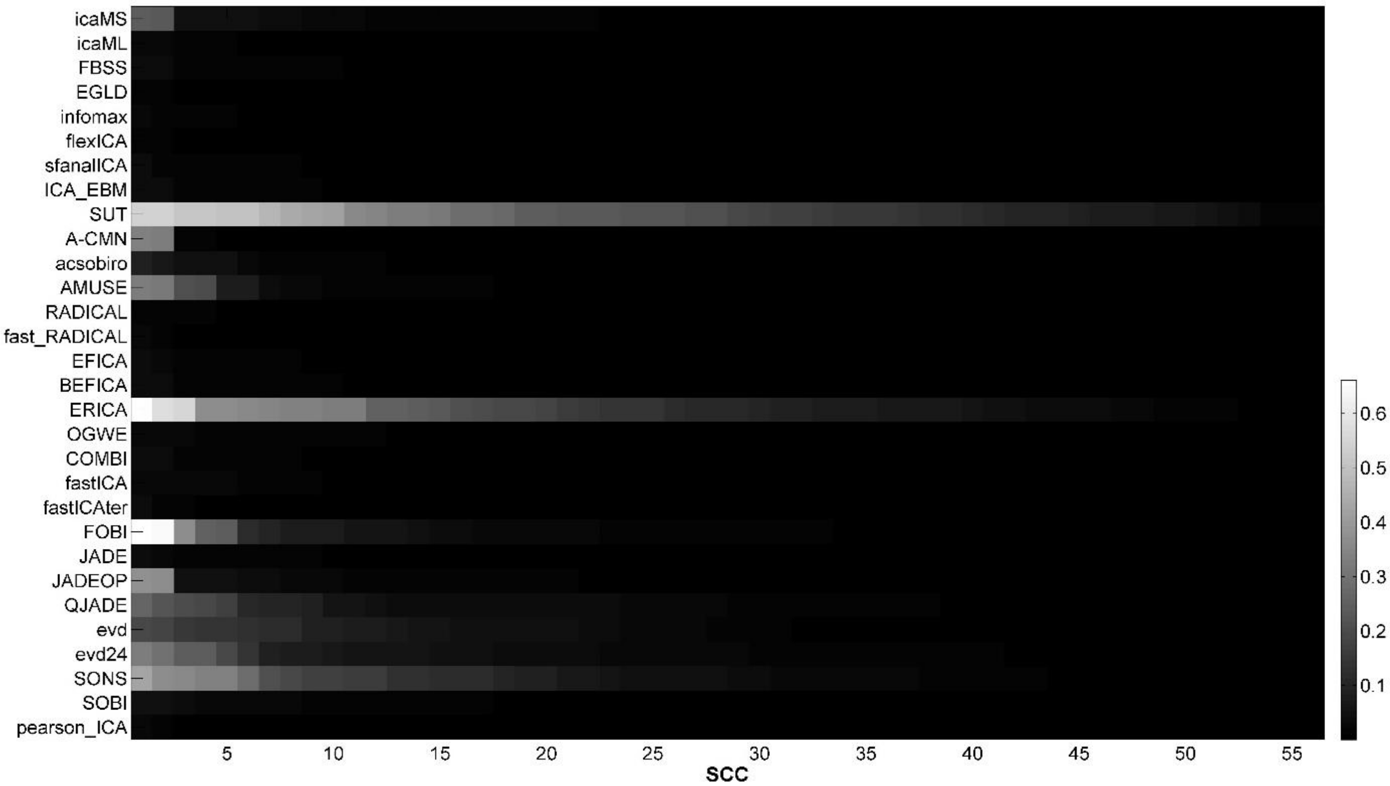

Fig. 2: SCC-algorithm plot. Each row is composed of 56 small rectangles indicating by their colors the correlation degree of each source signal with all of the estimated "unmatched" signals. The algorithm achieves the best separation if all rectangles within its corresponding row are black. Oppositely, the algorithm gives the worst separation if all rectangles within its corresponding row are white. For example, EGLD delivered very good results whereas SUT delivered bad results.

"unmatched" signals (for each source signal there is only one estimated signal that is matched with and seven signals unmatched with). Here, it is supposed that SCC is equal or near to 0 as nearly nothing from the estimated signal is contained within the source signal that is unmatched with. Also for each algorithm, the 8 SCCs which are represented as small rectangular areas within a single row in Fig. 3 denote the correlation of the source signals with their corresponding estimated "matched" signals. Here, it is supposed that SCC is equal or near to 1 as nearly whole of the estimated signal is contained within the source signal that is matched with. Since the estimation process that is carried out by an ICA algorithm is up to a permutation, therefore, the order of the estimated signals is not necessary and hence their SCCs are shown in the figures in ascending order from left to right.

Accordingly, more black rectangular areas within a single row in Fig. 2 with more white rectangular areas within a single row in Fig. 3 means that the algorithm achieved better separation. So, it is evident from both figures that the performance of SUT, ERICA, FOBI, and SONS is the worst whereas they were incapable of estimating the original sources accurately. Moreover, the majority of the estimated signals which are unmatched with their source signals were returned with a high degree of correlation. On the contrary, EGLD, flexICA, fast_RADICAL, pearson_ICA, and fastICAter have overcome the other algorithms. A slightly lower achieved, but as yet very good, performance is returned by these algorithms: icaML, FBSS, infomax, sfanalICA, ICA_EBM, RADICAL, EFICA, BEFICA, COMBI, fastICA, and JADE. It is clear that these algorithms were capable of estimating the original sources accurately, in addition almost all of the estimated signals have a very low degree of correlation with the unmatched source signals. Although other algorithms were capable of estimating the original sources accurately but the estimated signals in their cases show some

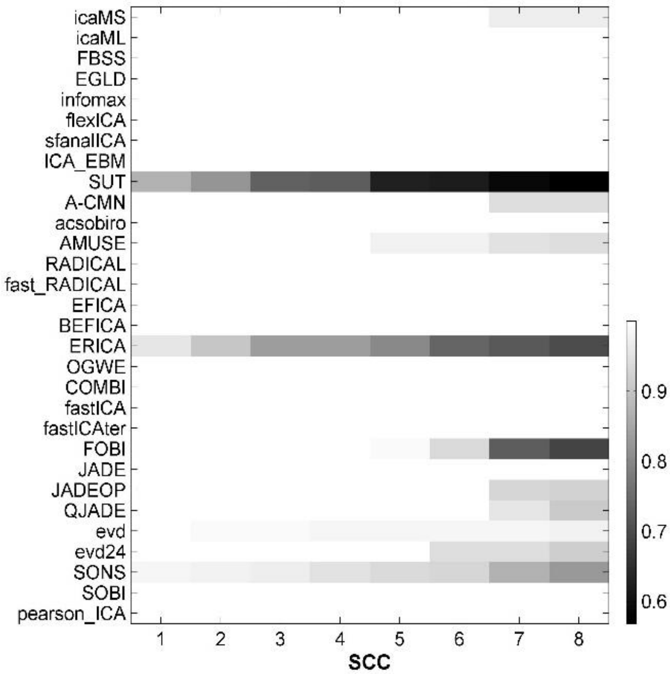

Fig. 4: SCC-algorithm plot. Each row is composed of 8 small rectangles indicating by their colors the correlation degree of the source signals with their corresponding estimated matched signals. The algorithm achieves the best separation if all rectangles within its corresponding row are white. Oppositely, the algorithm gives the worst separation if all rectangles within its corresponding row are black. For example, EGLD delivered very good results whereas SUT delivered bad results.

correlation with the unmatched original source signals.

Fig. 4 shows attained results of SIR as a function of the number of mixed signals. Where for each algorithm, SIR has been computed for separating 2,3,4,5,6,7,8 mixed signals each one of the mixed signals consists of 50000 samples; then results are displayed as small rectangular areas within a single row in the image. In the figure, the black color of a rectangle for a specific number of mixed (or separated) signals and algorithm indicates that the algorithm achieved the best separation, while the white color indicates that the algorithm failed to separate the mixed signals. Therefore, as an overall evaluation, it is obvious that FBSS, ICA_EBM, EFICA, BEFICA, and COMBI achieved better results than the other algorithms. Whilst SUT, and ERICA again failed to achieve sufficient performance. The numerical results of this test are listed in Table I.

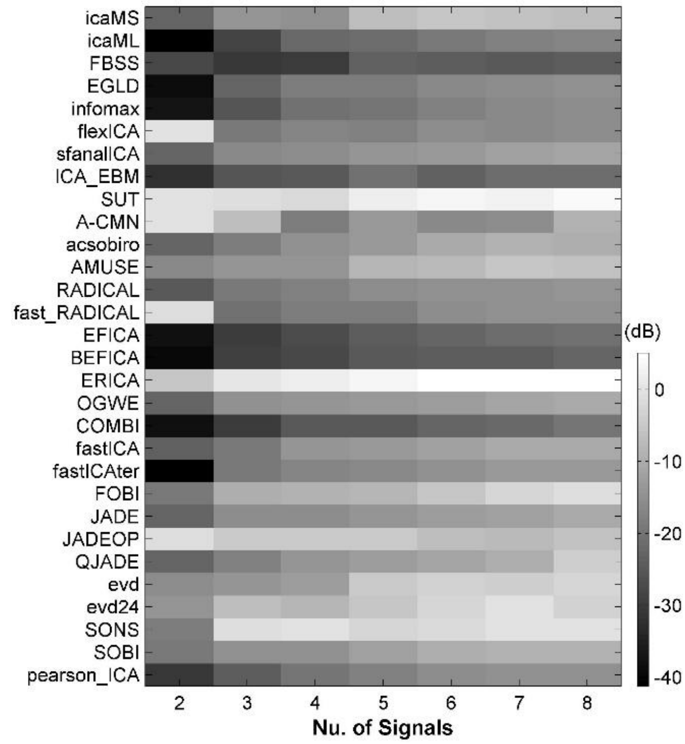

Fig. 3: Number of signals-algorithm plot of SIR criterion, mixed signals consists of 50000 samples. The black color of a rectangle indicates that the algorithm is able to separate the specified number of mixed signals, whilst the white color indicates the case of failure.

Also, the performance of the algorithms has been tested against the number of samples of mixed signals by computing SIR for different number of samples. Fig. 5 shows attained results of SIR for separating 3 mixed signals. Once again, the black color of a rectangle for a specified number of samples and algorithm indicates that the algorithm achieved the best separation, while the white color indicates that the algorithm failed to separate the mixed signals. Hence, it is clear that FBSS, EFICA, BEFICA, and COMBI achieved better results than the other algorithms. Whilst SUT, ERICA, and SONS again failed to achieve sufficient performance. The numerical results of this test are listed in Table I.

The elapsed CPU time which gives an indication about the computational demand for each algorithm is given in Table I. The given time is in seconds, this represents the required time for separating 8 mixed signals each consists of 50000 samples. It is clear that RADICAL requires the maximum elapsed time

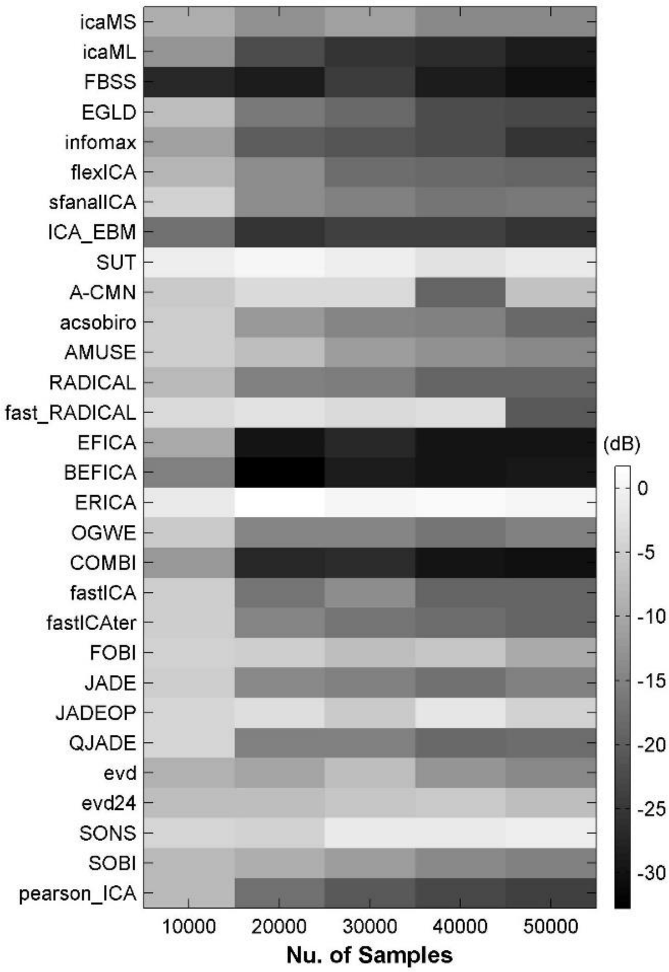

Fig. 5: Number of samples-algorithm plot of SIR criterion for separating 3 mixed signals. The black color of a rectangle indicates that the algorithm is able to separate the mixed signals that each is consisting from the specified number of samples, whilst the white color indicates the case of failure.

compared to other algorithms, while FOBI requires the minimum elapsed time. Generally, taking into consideration the results returned by all used comparison criteria, it may be concluded that COMBI, BEFICA, and EFICA are the best three algorithms among the used ones for separating speech mixtures, whereas these algorithms outperformed other algorithms besides their low computational demand (elapsed time). The other three algorithms: ICA_EBM, FBSS, and icaML have also given back good results while they require large elapsed time especially FBSS and icaML.

V. CONCLUSION

Thirty ICA algorithms based on different approaches have been used for separating speech mixtures. Then a comparison of their performance has been accomplished based on different criteria. Thus, some of the algorithms have been considered appropriate for separating speech mixtures while the others were not. Among those appropriate ones are COMBI, BEFICA, and EFICA; the performance of these three algorithms was the best. These algorithms were able to separate mixed speech signals and return pure signals similar to the original ones. In addition, these three algorithms do not require very good computer resources because their computational demand is low. On the other hand, SUT, ERICA and SONS show bad results; the returned separated signals from these algorithms were not clear to hear where each of the signals contains some parts from other signals.

TABLE I: Results of SIR for different number of signals, SIR for different number of samples, and elapsed time.

Algorithms	Signal to Interference Ratio (SIR) (dB)												Elapsed Time (sec.)
	Number of Signals							Number of Samples ($\times 10^3$)					Number of Signals
	2	**3**	**4**	**5**	**6**	**7**	**8**	**10**	**20**	**30**	**40**	**50**	**8**
icaMS	-23	-14	-15	-7	-5	-6	-7	-10	-13	-11	-14	-14	1.631
icaML	-41	-29	-22	-21	-19	-18	-17	-12	-22	-26	-26	-29	17.845
FBSS	-28	-31	-30	-24	-24	-25	-24	-27	-29	-25	-29	-31	83
EGLD	-38	-23	-18	-18	-16	-15	-15	-7	-16	-18	-22	-23	46.228
infomax	-38	-25	-20	-20	-17	-17	-16	-11	-20	-21	-22	-25	5.725
flexICA	0	-19	-17	-17	-16	-16	-15	-8	-14	-18	-19	-19	11.646
sfanalICA	-23	-16	-16	-14	-13	-12	-11	-5	-14	-15	-17	-16	156.165

ICA_EBM	-32	-26	-25	-21	-23	-22	-21	-17	-26	-24	-24	-26	3.601
SUT	-1	-1	-1	2	3	2	4	-1	0	0	-2	-1	0.045
A-CMN	0	-7	-19	-14	-16	-15	-9	-6	-3	-3	-19	-7	58.185
acsobiro	-23	-18	-15	-13	-10	-9	-9	-5	-12	-15	-16	-18	1.147
AMUSE	-16	-14	-14	-8	-7	-5	-6	-5	-7	-11	-13	-14	0.041
RADICAL	-25	-19	-18	-15	-15	-15	-14	-8	-15	-16	-19	-19	13270.281
fast_RADICAL	-1	-20	-18	-18	-16	-15	-15	-4	-2	-4	-3	-20	298.21
EFICA	-38	-30	-27	-24	-22	-22	-20	-10	-30	-27	-30	-30	0.88
BEFICA	-39	-29	-28	-25	-24	-24	-23	-15	-33	-29	-30	-29	1.352
ERICA	-5	0	2	3	5	5	5	-1	2	0	1	0	0.098
OGWE	-23	-15	-14	-13	-13	-11	-10	-5	-14	-15	-17	-15	0.564
COMBI	-38	-30	-25	-25	-23	-22	-20	-12	-27	-27	-30	-30	0.199
fastICA	-24	-19	-14	-14	-12	-11	-11	-5	-17	-14	-19	-19	0.744
fastICAter	-41	-19	-17	-16	-15	-13	-13	-5	-15	-17	-18	-19	1.052
FOBI	-20	-10	-9	-8	-5	-3	-1	-5	-5	-7	-6	-10	0.038
JADE	-23	-15	-15	-14	-13	-12	-11	-5	-14	-15	-17	-15	0.613
JADEOP	-1	-5	-5	-5	-7	-7	-6	-4	-3	-5	-2	-5	0.656
QJADE	-23	-18	-14	-13	-11	-10	-4	-4	-15	-15	-19	-18	0.695
evd	-16	-14	-12	-4	-4	-4	-2	-9	-10	-7	-12	-14	0.152
evd24	-14	-7	-8	-5	-2	-1	-3	-7	-7	-6	-6	-7	0.332
SONS	-19	-1	0	-3	-2	0	0	-4	-5	-1	-1	-1	0.344
SOBI	-19	-15	-15	-12	-10	-9	-9	-8	-9	-12	-14	-15	0.11
pearson_ICA	-31	-24	-20	-18	-15	-15	-15	-8	-18	-20	-23	-24	2.349

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