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A COMPARATIVE ANALYSIS OF INDEPENDENT VECTOR AND COMPONENT ANALYSIS IN TERMS OF PERFORMANCE EVALUATION

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Abstract: In accordance with the energy of the no-stationary mixed signal the weights of the hybrid model between Gaussian and Gaussian will be allocated. On the other hand, in many practical areas of biomedical and engineering, ICA is a newest idea in the statistics and extensively utilized approach for the purposes of BSS. EEG and ECG are multi-channel recordings which represent bodily activities. These multi-channel recording are particularly difficult to understand because of the complicated propagation feature of human tissue. The various methods of the ICA, however, extract signals that may be easily associated with specific bodily function. It was based on a non-Gaussanity technique to discover independent sources, are based on an advanced version of the fast ICA method of Aapo Hyvärinen and Erkki Oja. MATLAB methods have been created based on linear IVA and ICA mathematical models in this thesis. These methods are used to identify the de-mixing matrix for the signal mixture, thereby isolating the words of each source. Laplacian distribution capabilities mean that speech signals in themselves are leptokurtic such that both IVA and ICA could be recognized easily. Subjective and objective quality tests were used to evaluate the increased signals from both IVA and ICA. The average signal-to-noise ratio (SNR) result and mean opinion indicate that the ICA technique is better suited for this task.

Keywords: IVA, ICA, EEG, BSS

I. INTRODUCTION

Principle Component Analysis is a traditional method of signal separation which uses variance for measuring independence [1- 2]. The first and second order moments of the calculated data are used by PCA, which therefore relies heavily on Gaussian features [3]. When all the data is projected on these axes, PCA figures out the range of orthogonal axes in the data. Axis orthogonally is the basis for the freedom of the components of the mixture [4]. Second order moments are considered by PCA only because knowledge on higher order figures is an unavailable. Independent component analysis (ICA) takes advantage of the data's naturally non-Gaussian properties and utilizes higher moments. The mathematical freedom of origins is calculated [5]. The ICA is a data array processing and interpretation technique aimed at retrieving unnoticed signals or origins from detected mixtures, using only the presumption of reciprocal freedom between the signals. ICA is the next PCA generation [6].

The Gaussian GMM mixture model, which caught dependence and prevented permutation, rendered joint frequency modelling from the same source. Various sources were constructed using various model mixtures in Gaussian, which allowed the separation of separate sources between IVA [7]. Three criteria we considered: noiseless, online and noisy independent vector analysis. Noiseless IVA, like most ICA and IVA algorithms, did not expect sensor noise. In the complex world, Online IVA was capable of monitoring and distinguishing moving sources. Noisy IVA took sensor noise into consideration and helps de-noising voice and source isolation to be accomplished. Maximum probability of model parameters was estimated [8]. Effective expectation maximization algorithms for all conditions have been proposed.

In this research work, separate the mixture of the different nature of data into its components sources by using two different model, IVA model & ICA model. Additive White Gaussian Noise could be added in the data before separating it into its components.

II. EXPERIMENTAL SETUP

At first, speech signals have been mixed with noise from other sources to generate a noisy speech mix as it is generated in the actual environment of cocktail party. Subsequently the IVA and then ICA for its separation examined this mixture. The methods that separate this mixture and its implementation technique are discussed. And last individual samples were carefully verified by a well-known signal to noise ratio tool for quality from the algorithm output. We also assessed quality using the subjective Mean Opinion Score technology (MOS). In the matlab simulation environment all these methods and strategies were implemented [9].

In order to simulate the suggested IVA and ICA model for the noisy speech signal and then assess their quality, we have created an environment which will accomplish this step-by-step and gives us both graphical and quantitative data for comparison. We begin with the availability of signals for our surroundings. Every signal that is received is recorded and compiled with all previously received signals, so that the signals might be distinct from each other in a single group. For graphical comparison these signals are identified afterwards. These people are now exposed to a noisy mixture of speech. In order to improve it and separate it from each other, this mixture is next assessed using the IVA's own value decomposition method as well as by noise. The IVA is distinguished by different speech waveforms for the best comparison.

III. RESULTS AND DISCUSSION

Each case consists of a combination of expression, an IVA algorithm, an ICA algorithm and finally a SNR quality measurement process. We not only compared IVA and ICA strategies but also used ICA algorithm parameters such as deflation and symmetric approach and nonlinearity cases to compare each of them with IVA and determine what would be the best case for our work. Cases are defined on the basis of ICA methods which means the reduction of functions and functions associated with the purpose using a different algorithm to alter the IC's acceptable IC matrix in the next phase of these cases and their graphical and numerical effects have been discussed in detail. Each case is modeled after 2 to 6 speech combinations and then compared.

3.1 Independent Vector Analysis (IVA) versus ICA Deflation

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We use the ICA's rapid deflation method and the nonlinearity power case, mimicking other combinations of speech signals. Figure 4.1 shows the first two waveform waveforms and the audio signal to be added as WGN. When these signals are mixed with Gaussian white noise and passed Independent Vector Analysis (IVA) and then ICA, it gives us waveforms of figure 1 and 2 as a separate waveform. Now when we compare ourselves in appearance with the original forms of wave 4.1, it is clear that

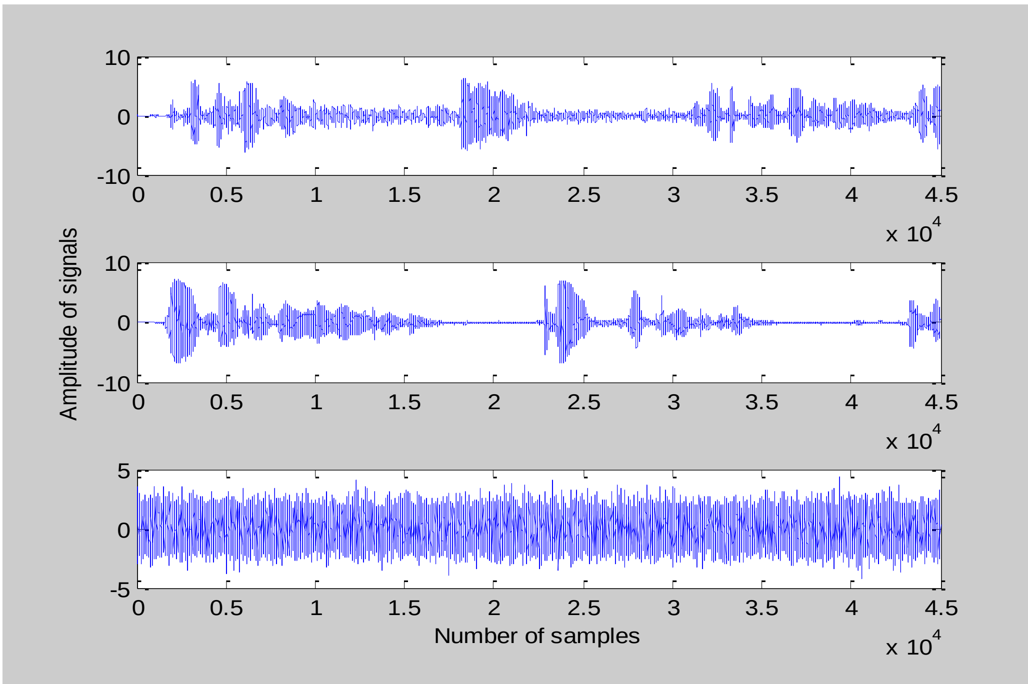

Figure 1: Comparative analysis of speech signal and sound waveform.

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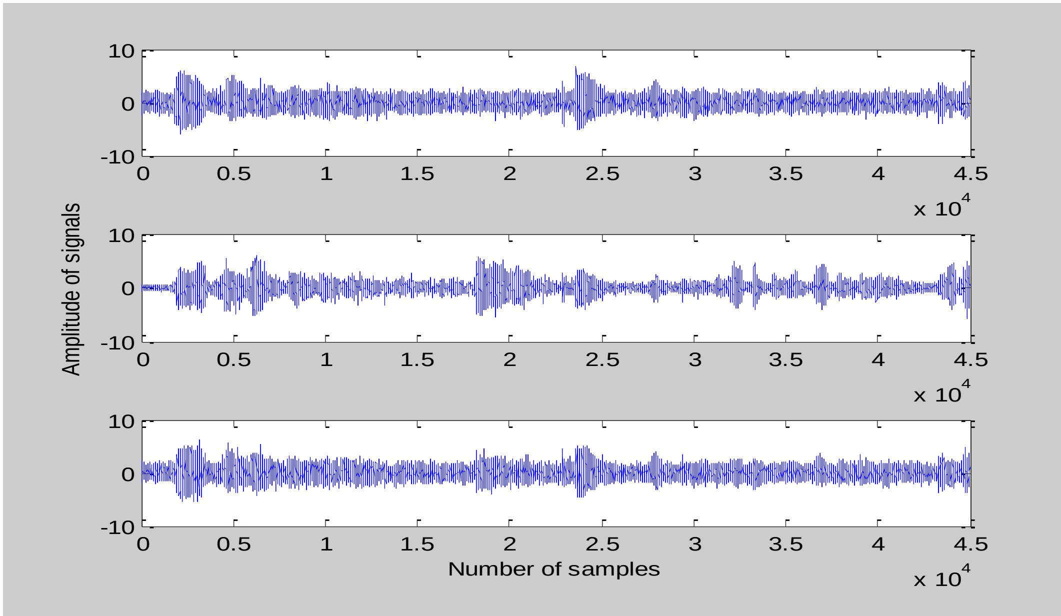

Figure 2: Waveforms of two different sound using ICA.

In the first waveform of Figure 2 it shows the similarity of its pattern with the second waveform of figure 1 and the second waveform of figure 2 shows the same relationship with waveform 1st of figure 1. The third type of wavelength that we have left with the separated sound also does not make noise at all. Now compared to this when we visualize the ICA waveforms of figure 4.3 it is much easier to determine that the first form of wave 3 is exactly the same as the second.

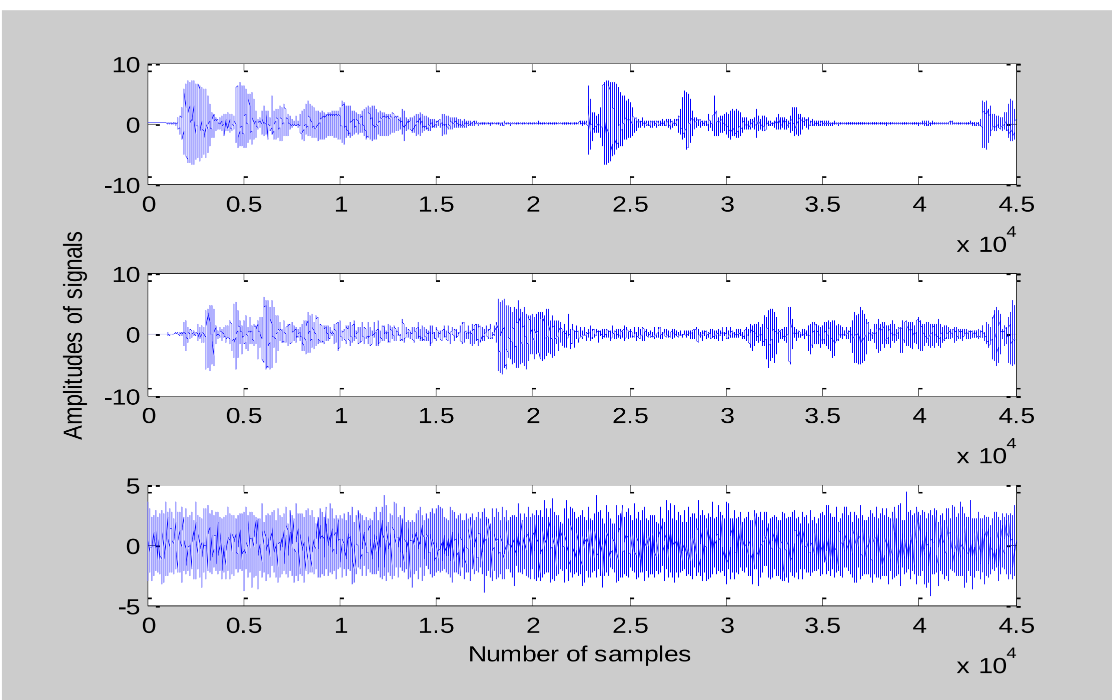

Figure 3: Two separated speech waveforms along with noise using the ICA.

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The sound of separate ICA speeches is similar to that of the WGN waveform. To confirm the above statement about Independent Vector Analysis (IVA) and the ICA division below is given some examples of separate expressions in which we used 3,4 and 5 expressions to combine and separate them using Independent Vector Analysis (IVA) Eigen value decomposition algorithm with fast ICA deflation nonlinearity.

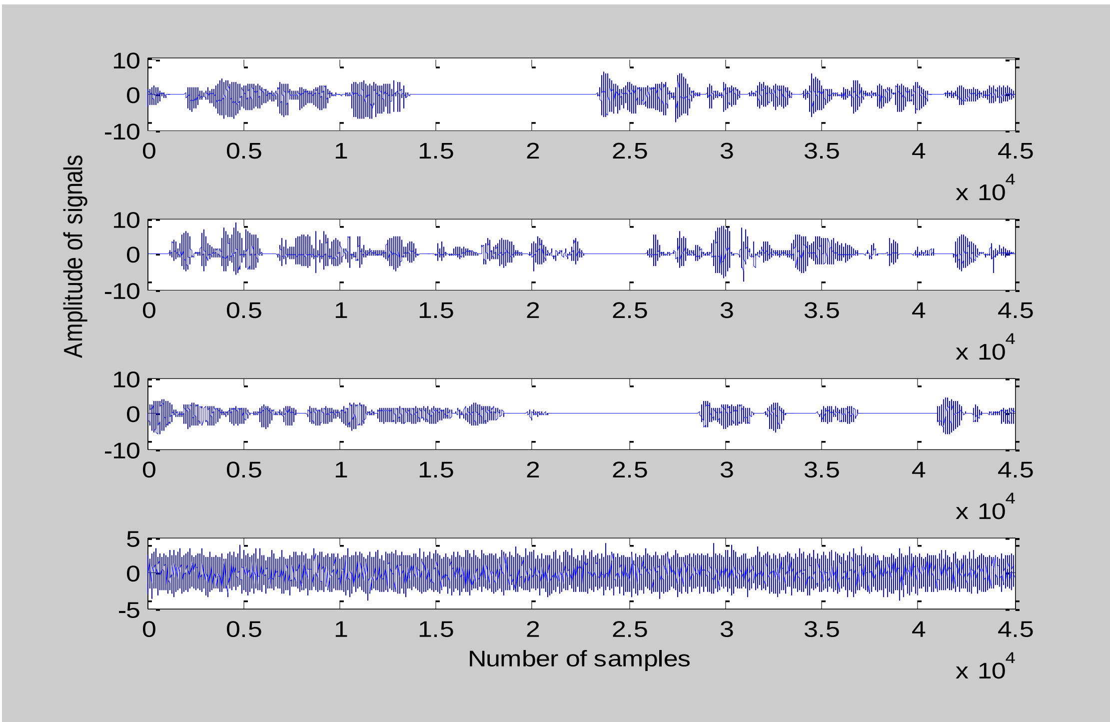

Figure 4: Waveform of three sound along with noise.

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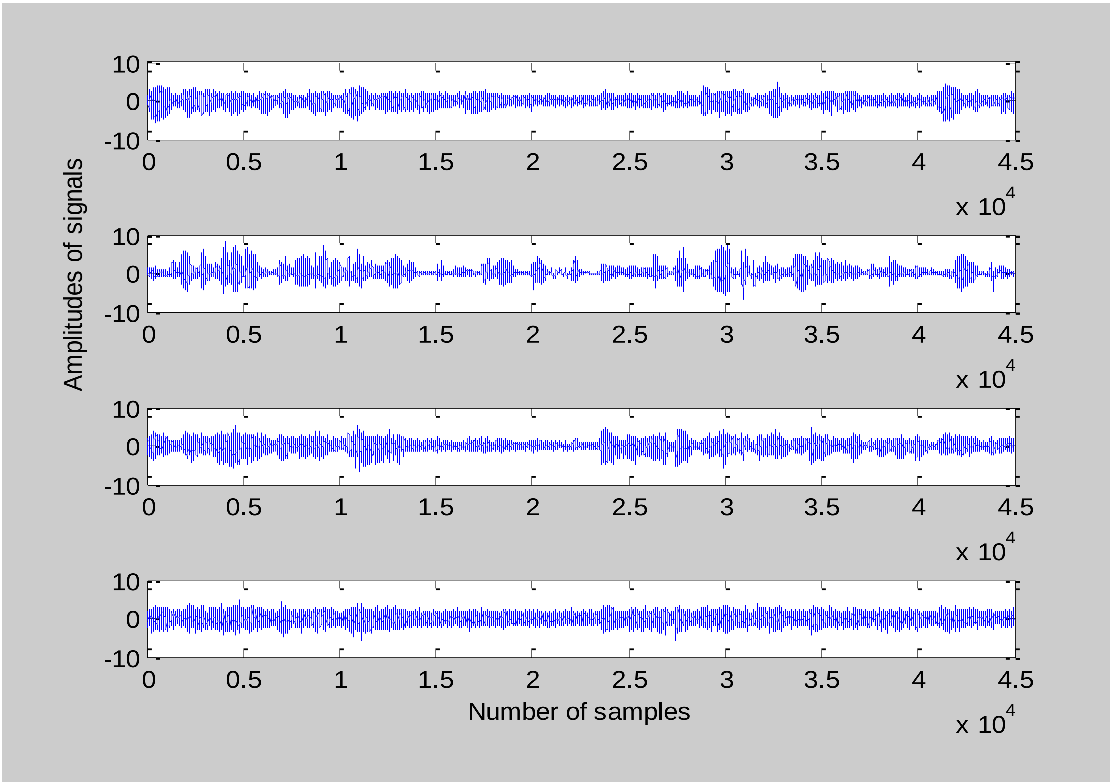

Figure 5: Separate speech of waveform using IVA.

So far we have presented and compared only the graphic results of this scenario, but the real difference always appears in the statistical data throughout the simulation environment. Visually we see the difference between Independent Vector Analysis (IVA) and ICA results to some extent but we cannot meet the minimum details of each algorithm because there is no standardized quality rating for each signal separately.

CONCLUSION

Vector Analysis (IVA) and Independent Component Analysis (ICA) with MATLAB have the potential to incorporate second-order dependencies by exchanging the axis of the data in the upper direction of the covariance. Distinguishing signals from a sound or non-sound component in its subdivisions is very difficult, even information is not available through the main sources or the mixed environment. Now a day with writing methods available that can help separate things from the organization. The methods used for this purpose include independent vector analysis (IVA) and independent material analysis (ICA) preferences in the literature. Independent vector analysis (IVA) is a method of distinguishing mixed mixed signals. IVA has expertise in controlling the permissive problem in blind domain classification (BSS) by using a circular dependence process on all frequency drums. ICA is a method used for classification of sources with multiple applications in literature, the ICA's main idea is that content in a mixed signal is statistically independent, or as independent as possible. Such an image appears to block important data formation in many applications, including feature extraction and signal separation. IVA is an effective tool for distinguishing a combination of signals from different sources into its components and the ICA is a multivariate signal calculation method for additional sub-components. An important goal of working with the ICA process is to consider statistical independence among the various resources available in this mix.

REFERENCES

[1] M. Arakeri, G. Reddy, A comparative performance evaluation of independent component analysis in medical image denoising, 2011. https://doi.org/10.1109/ICRTIT.2011.5972264.

[2] M. Anderson, G.-S. Fu, R. Phlypo, T. Adali, Independent Vector Analysis: Identification Conditions and Performance Bounds, Signal Process. IEEE Trans. 62 (2013). https://doi.org/10.1109/TSP.2014.2333554.

[3] Y. Du, D. Lin, Q. Yu, J. Sui, J. Chen, S. Rachakonda, T. Adali, V.D. Calhoun, Comparison of IVA and GIG-ICA in Brain Functional Network Estimation Using fMRI Data, Front. Neurosci. 11 (2017) 267. https://doi.org/10.3389/fnins.2017.00267.

[4] Z. Koldovsky, V. Kautsky, P. Tichavsky, J. Cmejla, J. Malek, Dynamic Independent Component/Vector Analysis: Time-Variant Linear Mixtures Separable by Time-Invariant Beamformers, IEEE Trans. Signal Process. 69 (2021) 2158–2173. https://doi.org/10.1109/TSP.2021.3068626.

[5] Y. Na, J. Yu, B. Chai, Independent vector analysis using subband and subspace nonlinearity, EURASIP J. Adv. Signal Process. 2013 (2013) 74. https://doi.org/10.1186/1687-6180-2013-74.

[6] J.-H. Lee, T.-W. Lee, F.A. Jolesz, S.-S. Yoo, Independent vector analysis (IVA): Multivariate approach for fMRI group study, Neuroimage. 40 (2008) 86–109.

[7] T. Adali, M.A.B.S. Akhonda, V.D. Calhoun, ICA and IVA for Data Fusion: An Overview and a New Approach Based on Disjoint Subspaces, IEEE Sensors Lett. 3 (2019) 7100404. https://doi.org/10.1109/LSENS.2018.2884775.

[8] S. Ma, V.D. Calhoun, R. Phlypo, T. Adalı, Dynamic changes of spatial functional network connectivity in healthy individuals and schizophrenia patients using independent vector analysis, Neuroimage. 90 (2014) 196–206. https://doi.org/https://doi.org/10.1016/j.neuroimage.2013.12.063.

[9] T. Adali, M. Anderson, G.-S. Fu, Diversity in Independent Component and Vector Analyses: Identifiability, algorithms, and applications in medical imaging, IEEE Signal Process. Mag. 31 (2014) 18–33. https://doi.org/10.1109/MSP.2014.2300511.

[10] X. Chen, H. Peng, F. Yu, K. Wang, Independent Vector Analysis Applied to Remove Muscle Artifacts in EEG Data, IEEE Trans. Instrum. Meas. 66 (2017) 1770–1779. https://doi.org/10.1109/TIM.2016.2608479.

