ISSN No:-2456-2165

Recognition and Extraction of Required Signals Of Interest in Audio Signals

Pavan Kumar[1], Shreya K Shetty[2], Prajwal Diwakar[3], Swasthik Narayan Bhat[4], Dony D'souza[5]
Senior Assistant Professor[5]
Electronics & Communication Engineering
MITE Moodabidri, India

Abstract:- Without knowing all of the mixing matrix and source signal properties, blind source separation is a process of differentiating sources of signals mixed with time, location, and frequency. This algorithm is widely chosen since it not only has a fast convergence time but also performs well in separation. Blind Source Separation (BSS) is a method of isolating sources from a combination without first determining which sources are present. To accomplish the above objective, several methods have been offered, one of which is ICA (independent component analysis). Duet presupposes that signals are non-overlapping in the temporal domain, while independent component analysis asserts that signals are linearly separable. In the event of blind source separation, ICA is used. They are quite similar to the older traditional fast fixed- point (FastICA) methods based on kurtosis, but they differ in that they are more efficient in terms of processing performance than the corresponding latter ones, which is especially noticeable when the number of samples is large. The Cocktail Party Problem degrades the quality of discourse in this situation. Cocktail party issues are defined as a mix of several sources of speech signals picked up by a microphone. ICA, which has the ability to split many voice signals into individual ones, can be used to solve the aforesaid problem. Gradient and FastICA algorithms are used to apply the principle of negentropy by maximizing non- Gaussianity approaches in ICA. The MATLAB results show that Fast ICA has a faster execution time than gradient with the small number of iterations. Independent component analysis was used to estimate source signals using mutual information minimization. Maximizing non-Gaussianity improves performance in certain cases. The use of kurtosis and negentropy are two strategies for maximizing non-Gaussianity. Because kurtosis is the most vulnerable to outliers and is a computationally resilient process, negentropy is more dependable. For syntactic verification of mechanical and structural systems, the two routine BSS solutions are ICA and SOBI. The traditional FastICA methods are still the most widely used tools for estimating independent components. FastICA functions can be used in a variety of computer languages, including MATLAB.

Keywords:- *Blind Source Seperation, FastICA Algorithm, PCA Algorithm, Second Order Blind Identification, Negentropy, Kurtosis.*

I. INTRODUCTION

Identifying the modal parameters, like those of frequency, damping, and modal shape, are some of the most noteworthy aspects in structural dynamic analysis. BSS methodology has gained favour in modal identification because it is simple, converges faster, nonparametric, and involves no existing experience of the dynamic system. Traditional BSS procedures like ICA and SOBI, as well as their modified counterparts, are mainly utilized for fundamental research and theorem analysis,according to early literature. As interest in the study rose, it became evident that typical BSS procedures had some shortcomings. The total count of sensors must not be less than that of the sources, notably, the problem of the generated BSS, which is a key speculation that ensures efficient implementation of traditional BSS systems. However, due to a variety of practical constraints, such as cost and accessibility, the installation of several sensors may not be possible. Furthermore, in most circumstances, the need of appropriate sensors is too stringent to meet without prior knowledge of active modals. As a result, implementing unfalsifiable BSS strategies for structural dynamic analysis which can manage several sources as well as using minimal number of sensors is crucial. Due to numerous constraints, BSS has recently been a hot issue. Many innovative methods for audio extraction have recently been used and applied. The Independent Component Analysis, Principle Component Analysis, Independent Vector Analysis, Binary Masking method, and others have all produced accurate results. These methods were chosen for our project and implemented.

II. LITERATURE REVIEW

According to Ref. [1],in order to produce a relevant indicator, the three BSS algorithms were compared using three types of synthetic signals. We discovered that Maximum Kurtosis ICA performed poorly in all circumstances and should be avoided in future research; A FastICA idea relying on HOS offered a greater evaluation of primary sources than SOBI centred on SOS, even though the PDF of mixed signals revealed no significant differences. FastICA, on the other hand, performed better in the other scenarios we looked at. BSS, on the other hand, is commonly employed in EEG signal processing presently. Biomedical signals, on the other hand, provide a problem because it is not always easy to establish a reality that be used to assess the BSS decomposition's reliability. A review of concurrent intracranial registers such as Electrocorticography (ECoG), as per the observations, could serve in monitoring the effectiveness of the BSS systems examined.

In Ref.[4], it was revealed that using a second-order analytical concept similar to that used in BSS, we may discern Modal Factors. On a set of extended and pre-treated data, modal interactions and mode shapes should be assessed by using SOBI. To extract frequency and damping from modal responses, simple single degree of freedom techniques can be utilised. This methodology is used to provide a novel class of non-parametric output-only modal identification algorithms, as well as instances of its application. The proposed methodology for modal identification is proved to be a novel and dependable method. For the given situation, the modal parameter quality of the method is found to be comparable to that of state-of-the-art parametric approaches.

According to Ref.[5], the current work uses two BSS approaches, ICA and SOBI, to do a modal investigation that simply looks at the output. The concept of virtual source is utilised and contributed to the implementation of these BSS approaches. Numerical and experimental samples are provided to demonstrate the proposed Modal Analysis approach.

According to Ref. [7], in the domain of signal processing, BSS methodologies have lately attracted much interest.ICA and SOBI are two common BSS techniques for modal detection of mechanical and structural systems. Per the available information from disparate experts, ICA functions properly for systems with quite minimal degrees of structural damping, such as damping proportions of the range of 1% critical. SOBI-based solutions are evidenced to be far more exceptional to ICA methods for precise structural applications with significant amounts of damping. When non- stationary sources, particularly the ones seen during earthquakes and other intermittent excitations, are present, traditional SOBI techniques suffer. This work presents an innovative SOBI-based strategy called the Modified Cross- Correlation approach to tackle these issues. The feasibility of phrasing the dilemma of structural system detection as a BSS problem is also raised. The conclusions of the simulations for simulated wind and observed earthquake excitations are shown as intrinsic frequencies, mode patterns, and damping fractions. The suggested model excels the current ICA and SOBI methods in terms of detection. Exploratory and sizeable structural simulation data are used to showcase the convenience of the recently suggested methodology for structural recognition challenges.

According to Ref.[11], the main concept is to examine the frequency range choices in the frequency continuum and determine the most susceptible frequency channel that will most likely transport the most substantial fault information. A defect frequently distinguishes its naturally connected frequency band from others. If this band is correctly identified, the defect monitoring approach won't immediately compromise between several unassociated frequency channels. The Data Cleaning phase in this work is concerned with locating, deleting, and reinstating defective or omitted content, whilst Smoothing was used to erase unwelcoming cluttering and data with a lot of volatility. The frequency bandwidth/frequency resolution determines the spectral negentropy. By partitioning finely and continuously, systemic negentropy can be assessed for frequency granularity approaches.; By cascading and indicating all of the channel negentropies in a single graphic, the Infogram, which is a pictorial illustration of negentropies, can be generated. The pictorial illustration formerly specified as infogram canbe used to generate its SE. The infogram's peak corresponds to the frequency region where the recurrent transients occur.

The kurtosis and its reciprocal are offered as objective metrics of the clipping degree of Musical signals in Ref. [13]. The factual and subjective quality estimates of clipped Music signals were matched using matching maps. These maps can be used to calibrate the objective speech quality metrics stated before. The potential to considerably simplify and speed up calculations is related to the lack of the requirement for preliminary estimation. When compared to competing measures, the proposed measures have a significant advantage in terms of the PDF of the examined signal.

It was discovered in Ref. [15] that the Negentropy can be thought of as a No Gaussian Negentropy for practical reasons. It's critical to keep in mind that the Negentropy of the signals acquired with the help of the sensors should be as high as feasible, ensuring that the vector's constituents are as independent as possible. Although there are many different types of ICA procedures, the FastICA method was used in this application because it is based on the database's Covariance and Negentropy, and it searches for information that is identical to each other, grouping them together, and implying that this data belongs to the same signal. InfoMax is considered as the alternative way. Principally, InfoMax was based on the mathematical concept of "Optimal Transference Information" through Artificial Neural Networks (ANNs) and other related system processes published by Linsker in 1987, implying that this technique for editing content had been designed by other sorts of procedures preceding ICA. InfoMax is based on increasing the entropy of an ANN's output.

III. PROPOSED METHODOLOGY

This project includes the both Signal Mixing and Separation processes. As demonstrated in fig.1, the Source Signals are received initially. S_1, S_2 and S_3 are the three Independent Source Audio Signals. These signals will be mixed to obtain the Mixed Signals.X_1, X_2 and X_3 are the Outputs obtained after mixing the Independent Source Signals. They are dependent signals, i.e. dependent to each other. These mixed signals will be separated using algorithms such as FastICA algorithm, Binary Masking Algorithm, Independent Vector Algorithm (IVA) and Principal Component Analysis Algorithm. With this algorithm, De-mixing of the mixed signals X_1, X_2 and X_3 will be taken place. On the process of this algorithm, Mutually Independent signals like Y_1, Y_2 and Y_3 will be obtained. These signals are the Output signals for our Input signals. If these signals, on comparison with the input signals, shows no Error or Noise, the process is said to be Successful and it implies the Low Signal to Noise Ratio in the Algorithm.

ICA is an empirical concept that allows us to represent a multidimensional arbitrary vector as a linear fusion of as many non-Gaussian arbitrary factors as we select. ICA is a non-Gaussian aspect assessment procedure that is reminiscent to principal component analysis. Data analysis, source disjunction, and feature extraction are all applications of ICA. Projection pursuit is an exploratory data analysis technique that emphasises visualisation. It is based on the discovery of low-dimensional multivariate projections with strongly non- Gaussian distributions. ICA and projection pursuit are technically extremely similar. The FastICA algorithm is an operationally productive method of ICA that is used for approximation. It employs a fixed-point iteration approach that has been proven to be effective in independent tests. This procedure is 10-100 times quicker than conventional gradient descent algorithms when speaking about ICA. Another benefit of the FastICA algorithm is that it can also be used for projection pursuit, making it a general-purpose data analysis approach that can be utilised for both exploratory and estimate of independent components (or sources).

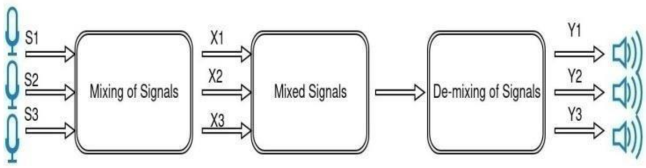

Fig. 1: Block Diagram of the proposed Methodology

PCA is a procedure that determines the major constituents and uses them to modify the data's foundation, while the first few constituents are being used frequently and the remaining ones usually omitted. PCA is utilised in investigative data assessment and simulation design. It's commonly used for dimensionality decrement, which entails mapping each data value against only the first few major constituents to produce lower-dimensional output with the minimal level of dispersion.

Negentropy is a non-Gaussian metric that defines how much the things are in order . It's considered to be the opposite of Entropy. An arbitrary variable's entropy is an indicator of the event's ambiguity. The highest entropy is achieved by a distribution with the most potential randomness.

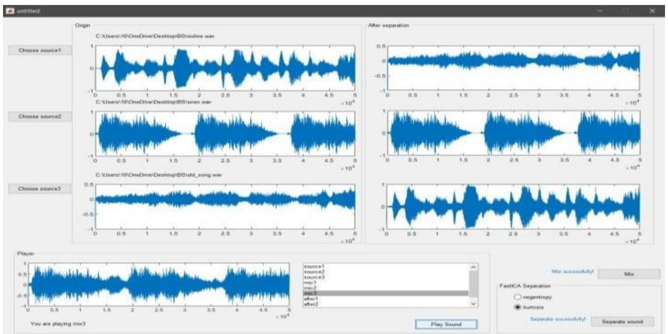

Fig. 2: Input Audio Signals

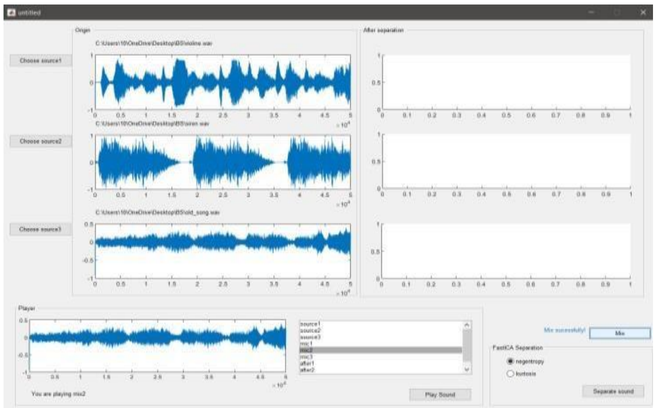

Fig. 3: Output Audio Signals

Among all arbitrary parameters with identical dispersion, the Gaussian parameters have the greatest Entropy. Entropy can be used as a criterion of non-Gaussianity due to this core trend. The entropy of "spiky" PDFs or those focused around certain values is low. The aim is to find a generally non- negative metric of non-Gaussianity that is also zero for a Gaussian variable. The so-called Negentropy is one such measure.

The Negentropy has two significant attributes: (1) it is never negative and is 0 only if and only if y has a normal pdf, and (2) it is robust to differentiable sequential operations. Its main disadvantage is that it is quantitatively demanding. As a result,we must approximate the Negentropy.

Kurtosis (K) is a descriptive statistic that indicates the degree to which a data distribution is peaked. The degree to which data values are concentrated around the mean in a data distribution is called Peakness. Datasets with a high kurtosis feature a prominent peak near the mean that rapidly declines, as well as weighty tails. Data with low kurtosis generally have a horizontal top symmetric about the mean rather than just a towering peak. Because they may have varying degrees of peakedness, data distributions with the same means, standard deviations, and degrees of skewness might have distinct kurtosis.

Higher K values indicate peaked distributions, whereas lower K values indicate flatter distributions. However, in practise, we frequently deduct 3 from the estimated K values to obtain positive or negative K values with regard to 3. This is because the K value for a normal curve commonly approaches 3 and comparisons are frequently conducted with normal curves in mind. A positive kurtosis in any examples suggests a distribution with more data values concentrated around the mean than a normal distribution. A negative kurtosis, on the other hand, suggests a more dispersed distribution than a normal distribution.

ISSN No:-2456-2165

IV. CONCLUSIONS

The Negentropy-based FastICA Algorithm collected back three different types of Sound Sources, and per the simulation findings. When analyzing the extracted signals with the source signals, however, there is an overturned effect, and the audio source's serial number, which must be mentioned in the software, is also changed. Secondly, the BSS capacity needs to be investigated further if noise is blended with Mixed signals, notably in the case of Underwater Reverberation. Also, the accuracy of the Mutually Independent Signals, which are the Output Signals after De-Mixing, has to be improved, which is something we'd like to work on in the future.

REFERENCES

[1.] C. J. Ortiz-Echeverri, P. Karla Daniela, B. G. Galindo-Burgos and J. Rodríguez-Reséndiz, "Blind source separation problem algorithms for audio and biomedical signals," 2018 XIV International Engineering Congress (CONIIN),

[2.] 2018, pp. 1-7, doi: 10.1109/CONIIN.2018.8489812..

[3.] C. Uhl, M. Kern, M. Warmuth and B. Seifert, "Subspace Detection and Blind Source Separation of Multivariate Signals by Dynamical Component Analysis (DyCA)," in IEEE Open Journal of Signal Processing, vol. 1, pp. 230-241, 2020, doi: 10.1109/OJSP.2020.3038369.

[4.] W. Zhou and D. Chelidze, "Blind source separation based vibration mode identification," Mechanical Systems and Signal Processing, vol. 21, no. 8, pp. 3072–3087, 2007.

[5.] S. I. McNiell and D. C. Zimmerman, "A framework for blind modal identification using joint approximate diagonalization," Mechanical Systems and Signal Processing, vol. 22, no. 7, pp. 1526–1548, 2008.

[6.] F. Poncelet, G. Kerschen, J.-C. Golinval, and D. Verhelst, "Output- only modal analysis using blind source separation techniques," Mechanical Systems and Signal Processing, vol. 21, no. 6, pp. 2335– 2358, 2007."PDCA12-70 data sheet," Opto Speed SA, Mezzovico, Switzerland.

[7.] P. Bofill and M. Zibulevsky, "Underdetermined blind source separation using sparse representations," Signal Processing, vol. 81, no. 11, pp. 2353–2362, 2001.

[8.] B. Hazra, A. J. Roffel, S. Narasimhan, and M. D. Pandey, "Modified cross-correlation method for the blind identification of structures,"

[9.] J. Antoni and S. Braun, "Special issue: blind source separation," Mechanical Systems and Signal Processing, vol. 19, no. 6, pp. 1163– 1165, 2005.

[10.] M. Pal, R. Roy, J. Basu and M. S. Bepari, "Blind source separation: A review and analysis," 2013 International Conference Oriental COCOSDA held jointly with 2013 Conference on Asian Spoken

[11.] Language Research and Evaluation (O-COCOSDA/CASLRE), 2013,pp. 1-5, doi: 10.1109/ICSDA.2013.6709849.

[12.] H. A. Al-Barhan, S. M. Elyass, T. R. Saeed, G. M. Hatem and H.

[13.] T. Ziboon, "Blind Source Separation Based on random mixing coefficient," 2020 3rd International Conference on Engineering Technology and its Applications (IICETA), 2020, pp. 164-168, doi:10.1109/IICETA50496.2020.9318954.

[14.] Moise Avoci Ugwiri, Marco Carratú, Vincenzo Paciello, Consolatina Liguori, "Benefits of enhanced techniques combining negentropy, spectral correlation and kurtogram for bearing fault diagnosis, measurement", Volume 185, 2021, 110013,ISSN 0263-2241.

[15.] S. Ghavami and B. Abolhassani, "Blind Detection of DS-SS Signals over Fading Channels Using Negentropy or Kurtosis without any prior Knowledge," 2007 IEEE International Symposium on Signal Processing and Information Technology, 2007, pp. 329-333, doi: 10.1109/ISSPIT.2007.4458160.

[16.] A. Prodeus, I. Kotvytskyi and A. Grebin, "Using Kurtosis for Objective Assessment of the Musical Signals Clipping Degree," 2019 IEEE International Scientific-Practical Conference Problems of Infocommunications, Science and Technology (PIC S&T), 2019, pp. 655-659,doi: 10.1109/PICST47496.2019.9061420.

[17.] Ronghui Zheng, Guoping Chen, Huaihai Chen, "Power spectrum and kurtosis separation method for multi-shaker non-Gaussian random vibration control", Mechanical Systems and Signal Processing, Volume 162, 2022, 108015, ISSN 0888-3270.

[18.] E. S. Juan, I. Soto, G. Salinas and P. Adamse, "Separation of VLC signals using FastIca and InfoMax," 2017 First South American Colloquium on Visible Light Communications (SACVLC), 2017, pp.1-6, doi: 10.1109/SACVLC.2017.8267612.