SEPARATION OF HINDI SOURCE SIGNAL IN BSS USING GDA-AGSO APPROACH

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Abstract- Blind Source Separation (BSS) is a measurable strategy for separating signals from unknown sources at various sensors. It is a dynamic research in the field of biomedical signal examination and speech investigation technique. For applying the inputsignal the noise is included. This is a fundamental issue in these days whether we need to distinguish a particular individual in the area of speech. To resolve this issue proposes a dynamic BSS approach based on the Adaptive Group Search Optimization (AGSO). In BSS the source signals are combined and isolated by utilizing kurtosis maximization function. The kurtosis of the signals is utilized as the principle execution and to find the optimalvalue. In that, the source signals are considered and Generalized Discriminant Analysis (GDA) to produce the mixingsignals to BSS with maximum kurtosis function. Besides, the kurtosis of the signals is utilized as the target execution and the AGSO is utilized to separate the signals. Examination were done with mixture of two speech sources utilizing two sensors, this proposed model demonstrate the better execution compared with existing algorithms.

Keywords- Blind Source Separation, Kurtosis maximization, Generalized Discriminant Analysis, Hindi Source signal.

I. INTRODUCTION

The fundamental thought of BSS to recognize the information source signals of the system from their mixer observed on sensors [1]. The recognizable proof of noise sources has dependably been a consistent learning of the leading noise sources with deference [2] to their commitments to the general noise levels gives significant data to noise control applications [3]. The BSS development has become a thought in its basic potential applications, for instance, sonar and radar signal preparing, remote correspondence, geophysical examination, biomedical signal handling, speech and image processing, and machine liability determination [4].

The fundamental goal is to distinguish singular signals (sources) from a concurrent recording (together called mixing) of numerous speakers [5]. In this signal partition issue, unknown individual signals and commitments in the subsequent mixtures are characterized as the sources and mixing matrix, separately [6]. The use of higher-order statistics isn't new to the source separation issue [7] a significant number of these techniques are associated with mechanized communication signals which naturally have a place with another quantifiable class than speech signals [8]. With sound uses of BSS, such as settling a cocktail party issue, signals are seen in a convoluted way with resonation [9]. Two methodologies are as of now used to assess modular parameters with signal capacities they are signal mixing and signal separation model [10]. In the main approach, the signal separation model is assessed from that the inputspeech signals are mixed and in the signal, separation show the mixed signals are isolated with Generalized Discriminant Analysis (GDA) technique [11]. The utilization of BSS strategies, which can perform signal partition, might be an elective approach with which to examine the separated signal [12].

Among the methodologies, the source signals can be either isolated concurrently or extricated one by one by optimizing for each a various signals for separating basis such as the kurtosis maximization function. [13] Either maximization or minimization the kurtosis function can give supportive information for signal expectation [14]. A few systems have been proposed in the literature for blind source separation that is basically characterized in view of optimization algorithm.
such as Adaptive Group Search Optimization (AGSO) algorithm for blind source separation [15]. This part portrays the signal expectation with in excess of one signal and kurtosis maximization is utilized to separate the signal at long last accomplishes the optimal value by utilizing GDA with AGSO techniques [17].

II. LITERATURE REVIEW

Ms. Meena Patil et al 2018 [18] had proposed kurtosis' parameter using propelled Hybrid Group Search Optimization (GSO) shows with GA. The fitness function is improved with the usage of kurtosis maximization model and scout honeybee arranges was upgraded with the use of LDA. Reenactments results show that proposed technique for using fitness function has arapid union, ease, and a superior signal to commotion extent for division assignments in light of GSO process. Examinations were finished with the moment mixture of two speech sources using two sensors, this model was to show the better execution estimations diverged from various systems.

Iván Gómez Araújo et al 2018 [19] had examined this strategy consolidates Blind Source Separation (BSS) strategies and transmissibility-based techniques. Here, BSS systems were utilized to improve source signals, and transmissibility based techniques were connected to appraise modular data from the recovered source signals. To accomplish this combination, another strategy to characterize a transmissibility work was anticipated. The recommended transmissibility work depended on the connection between the Power Spectral Density (PSD) of mixed signals and the PSD of signals from a single source. The numerical reactions of a truss structure with high amounts of added noise and firmly divided modes were prepared for utilizing the consolidated technique to assess its capacity to distinguish modular parameters in these conditions.

Bin Dong et al 2016 [20] had analyzed two new finding in this unique circumstance. Initial, an adequate condition was built up under which "virtual" sources returned by PCA correspond with genuine sources; it stipulates that the sources of intrigue ought to be disjointed as well as spatially orthogonal. A specific instance of this example was met by spatially disjoint sources – i.e. with non-covering bolster sets. Second, in light of this finding, a rule that implements both statistical and spatial orthogonality was broke down to indiscriminately isolate garbled sound sources which transmit from disjoint spaces. This measure can be effortlessly joined into acoustic imaging algorithms, for example, pillar framing or acoustical holography to distinguish sound sources of various causes.

Ivan et al 2018 [21] had exhibited a group of different criteria referred to as "referenced-based" has been as of late proposed for Blind Source Separation (BSS), which are basically the cross-insights or cross-cumulants between assessed outputs and reference signals. These contrast capacities have an engaging element in like manner: the corresponding optimization algorithms are quadratic regarding the searched parameters. Propelled by this reference-based plan, a comparable contrast work is built by acquainting the reference signals with negentropy, in light of which a novel fast fixed-point (FastICA) algorithm. The kurtosis-based Fast ICA algorithm was more robust contrasted with different methods.

Wei Zhao et al 2015 [22] had exhibited a group of different criteria referred to as "referenced-based" has been as of late proposed for Blind Source Separation (BSS), which are basically the cross-insights or cross-cumulants between assessed outputs and reference signals. These contrast capacities have an engaging element in like manner: the corresponding optimization algorithms are quadratic regarding the searched parameters. Propelled by this reference-based plan, a comparable contrast work is built by acquainting the reference signals with negentropy, in light of which a novel fast fixed-point (FastICA) algorithm. The kurtosis-based Fast ICA algorithm was more robust contrasted with different methods.
model of the system. The Independent Component Analysis (ICA), depending on the suspicion of the statistical independence of the removed sources, was utilized as an apparatus for each BSSF to extricate signals of the procedure under deliberation. It is likewise essential to take note of the high affectability of skewness in identifying faults with genuinely low amplitudes.

**III. PROBLEM IDENTIFICATION**

- High computational cost and the trouble of utilizing it for mixtures in excess of two sources with in excess of one signal [20].
- This issue is much more basic for Independent Component Analysis (ICA), which just a single mixed signal is assessed for a few signals.
- Single-point optimization technique which dependably has the drawback of moderate convergence speed, bad separate precision and effortlessly getting into the local optimization for BSS [18].
- FDICA (frequency domain ICA) and TDICA (time domain ICA) are joined with the target of accomplishing better proficiency that is conceivable. This algorithm has a steady conduct, however, the computational load is high [23]. To beat this issue, the BSS structure is utilized therefore to isolate the source's signal from the noisy signals.

**IV. PROPOSED METHODOLOGY**

Separation of speeches has an important theoretical significance in voice communications, the acoustic target recognition, and so on. The approach presents BSS model for maximizing the kurtosis parameter by utilizing optimization strategies. BSS plans to extricate original source signals from the mixed signals. The extraction of input signals from a mixed signal is a major approach in BSS handling applications. In signal partition, various streams of data are removed from original mixtures in BSS signals. At that point, the separated signals are to be recognized by the BSS algorithm utilizing the kurtosis maximization function. The unknown original source signals can be isolated and assessed utilizing just the observed signals which are given through imperceptible mixture by utilizing AGSO. These methodologies give ideal output value and maximize the kurtosis function contrasted with existing methods.

![Figure 1: proposed method](image)

**4.1 Blind Source Separation (BSS)**

BSS is an approach for evaluating source signals utilizing the information of mixed signals observed every data channel. In a few circumstances, it can recover every single individual source from the mixed signal, or at least to segregate a particular source. While actualizing BSS system for signal handling reason, it will increase the maximum quality of signals. It has remarkable potential in applications, for example, preparing for speech and image.

In the noise-free linear instant underdetermined case, the number of observations is smaller than the number of sources. The observation vector can be expressed as a linear transformation on the source vector as given by:

\[ X = A.S \]  

Where \( A \) is the mixing matrix (m*n), \( s \rightarrow \) source vector (n*1) components and \( X \) observation matrix-vector (m*1) components?
4.1.1 Gradient Discriminant Analysis (GDA) for BSS model
The GDA is a strategy for nonlinear characterization based on kernel function \( \phi \) which changes the first space \( S \) to another high-dimensional component space \( Z : \phi : S \rightarrow Z \): The within-class (or aggregate) scatter and between-class scatter matrix of the nonlinearly mapped information is [24]

\[
R^\phi = \sum_{c=1}^{C} K_c k_c^\phi (k_c^\phi)^T \quad \text{.......................... (2)}
\]

\[
P^\phi = \sum_{c=1}^{C} \sum_{x \in X_c} \varphi(x) \varphi(x)^T \quad \text{.......................... (3)}
\]

Where \( k_c^\phi \) is the mean of the class \( S \) and is the number of samples belonging to \( S_c \). The main aim of the GDA find such projection matrix \( V_{opt}^\phi \) that maximizes the ratio

\[
V_{opt}^\phi = \arg_{c \in C} \max \left( \frac{V_{opt}^\phi^T R^\phi V_{opt}^\phi}{V_{opt}^\phi^T P^\phi V_{opt}^\phi} \right) = v_1^\phi, \ldots, V_N^\phi \quad \text{.......................... (4)}
\]

Where

\[
v^\phi = \sum_{c=1}^{C} \sum_{i=1}^{K_c} \delta_{ci} \varphi(x_{ci}) \quad \text{.......................... (5)}
\]

The vectors \( V^\phi \) can be found at the solution of the generalized eigenvalue problem i.e.

\[
R^\phi V_i^\phi = \lambda_i P^\phi V_i^\phi \quad \text{where} \quad \delta_{ci} \text{ are some real weights and } x_{ci} \text{ is the } i^{th} \text{ sample of class } c. \text{ The solution is obtained by solving the equation (4). From the theory of reproducing kernels, any solution } v^\phi \in Z \text{ must lie in the span of all training samples in } Z ,
\]

\[
\lambda = \frac{\delta^T W D W \delta}{\delta^T W W \delta} \quad \text{.......................... (6)}
\]

Where \( \delta = \delta_c, c = 1, \ldots, C \) is a vector of weights with \( \delta_c = \delta_{ci}, i = 1, \ldots, K_c \). The kernel matrix \( W(K \times K) \) is composed of the dot products of nonlinearly mapped data,

\[
W = (w_{ci})_{i=1 \ldots K, j=1 \ldots K} \quad W_{ij} = (w(x_{ci}, x_{cj}))_{i=1 \ldots K, j=1 \ldots K} \quad \text{.......................... (7)}
\]

\[
D = (D_{ij})_{i=1 \ldots c} \quad \text{.......................... (8)}
\]

The matrix \( D(K \times K) \) is a block diagonal matrix such that represented in equation (8) where the \( c_{th} \) on the diagonal has all elements equal to \( \frac{1}{K_c} \). Solving the eigenvalue problem yields the coefficient vector \( \delta \) that defines the projection vectors \( v^\phi \in Z \). A projection of a testing vector \( x_{test} \) is computed as

\[
(V^\phi)^T \varphi(x_{test}) = \sum_{c=1}^{C} \sum_{i=1}^{K_c} \delta_{ci} W(x_{ci}, x_{test}) \quad \text{.......................... (9)}
\]

4.1.2 Optimization algorithm
A basic issue in blind speech separation is that of the combination of the utilized algorithms. The quantifiable criteria that are optimized by the algorithm often contain a few classes of stationary concentrations where the algorithms may plausibly join. The system is made out of three modules, to be particular signal mixing module, weight framework period module, and source detachment module. This Kurtosis advancement process accomplishes the optimal value by Adaptive Group Search Optimization (AGSO) algorithm.

4.1.3 Objective function
The fitness function is improved with the usage of kurtosis maximization process is upgraded with the use of conjugate gradient algorithm.
\[ \text{Kurt}(y) = \frac{E(p^4)}{[E(p^2)]^2} - 3 \quad \text{.......................... (10)} \]

Where \( p \) is considered as a source speech signal. The vast majority of the target capacities being utilized as a part of AGSO based BSS algorithms are produced with the likelihood that the output sources must be free from their linear mixtures. Consequently, we have obtained the fitness function.

### 4.4 Group Search Optimization

GSO is a novel optimization algorithm which depends upon searching performance and their group-living habitats. One significance of living respectively is that group searching allows aggregate individuals to increase patch finding rates as well as to reduce the variance of search success. The population of the GSO algorithm[18] is known as a group and every person in the populace is known as a member. All the while, a group comprises of three sorts of individuals:

- **Producer**: a member which utilizes its vision ability for searching food.
- **Scroungers**: scroungers are joiners, which follows the producing member.
- **Rangers**: Rangers play an important role in GSO searching and finding the procedure.

In AGSO, the animal searching behavior might be portrayed to discover assets, for example, nourishment, mates, or nestingsites and it maybe the most imperative sort of behavior in which an animal engages. One result of living respectively is that group searching permits group members to expand patch finding rates and in addition to lessening the variation of search achievement. This speculation generally in perspective of the Producer–Scrounger (PS) shows and the animals checking parts are utilized representatively to design an optimalsearching procedure for optimization issues.

#### 4.4.1 Updating the process

Based on the fitness evaluation update the new search measures in GSO strategy by using the producer, scrounger and ranger execution.

**Producer performance**

In the path of the functioning of the GSO technique, the action of the producer \( P_p \) at the \( i^{\text{th}} \) iteration is described below process. The producer will scan at zero degrees and then scan laterally by randomly sampling three points in the scanning field.

The producer performs the search operation at zero degree

\[ P_i = P_i^k + \mu_1 \max G_p^k(\phi^k) \quad \text{.............................. (11)} \]

Similarly, the search operation performs at right-hand side hypercube and left-hand side hypercube.

**Scrounger performance**

The group members are assigned as the scroungers will keep searching for opportunities by tracking the producer member. At the \( k^{\text{th}} \) iteration, the \( i^{\text{th}} \) scrounger members are modeled as random trackers of the producer. The mathematical model could be formulated as follow

\[ P_i^{k+1} = P_i^k + \mu_3(o(P_p^k - P_i^k)) \quad \text{............................. (12)} \]

Where \( P_i^k \) is the position of \( i^{\text{th}} \) scrounger at the \( k^{\text{th}} \) iteration? The \( \mu_3 \in R^{nth} \) is a uniform random number in the range of \((0, 1)\). Additionally, the operator \( o \) calculates the entrywise product of the two vectors and \( \mu_3 \) denotes a uniform random sequence lying in the interval of \((0, 1)\).

### 4.5 Adaptive Group Search Optimization (AGSO)

In the adaptive form of GSO, the velocity and position of the particles are updated in the ranger performance. In the existing technique the optimal value is not obtained, thus we consider the
AGSO algorithm for the proposed model. This will improve the kurtosis function in BSS; the updated equation for AGSO is given as follows

\[ U_{k}^{y+1} = c U_{k}^{y} + h_{1} * r_{1} * (S_{best_{k}} - S_{k}^{y}) + h_{2} * r_{2} * (G_{best_{k}} - S_{k}^{y}) \] .......................... (13)

\[ y_{k}^{y+1} = y_{k}^{y} + U_{k}^{y+1} \] .......................... (14)

\[ U_{k} \] is the particle velocity, \( S_{i} \) is the current particle, \( h_{1} \) and \( h_{2} \) are the learning factor, \( r_{1} \) and \( r_{2} \) are the random value within the [0, 1].

4.5.1 Optimal solution of the proposed approach

The fitness of the updated solution is predicted in the iteration. In ‘n’ number of iteration, the best solution obtained finally. The best solution is taken, if the process achieves ‘s’ number of iterations. Then all the signals can be separated out one by one through acurent separation with maximum kurtosis obtained from this optimization approach.

4.5.2 Pseudo code for the proposed method

\[ \text{Step 1: start} \]
\[ \text{Step 2: Initialize the population } p_{i} \]
\[ \text{Step 3: calculate fitness value } kurt(y) \]
\[ \text{Step 4: define producer of ranger based on the zero degree, right and left hand side of the hypercube.} \]
\[ \text{Step 6: scrounging performance} \]
\[ \text{Perform scrounging according to eqn 12.} \]
\[ \text{Step 7: ranger performance} \]
\[ \text{Perform ranger performance according to eqn 13 and 14.} \]
\[ \text{Step 3: calculate fitness of current number } kurt(y) \]
\[ \text{End for} \]
\[ \text{Step 8: set iter = iter + 1; } \]
\[ \text{Otherwise go to step 3.} \]
\[ \text{End while} \]

V. RESULT AND DISCUSSION

In the BSS, different Hindi speech signals were taken. The signals are mixed based on the BSS process using GDA with AGSO algorithm. The mixed signals are separated with the help of kurtosis maximization functions. Then various signals are compared and the accuracy chart is described in the below section.

| Table 1: Kurtosis value based on signals |
|-----------------------------------------|
| **Signals** | **Phases** | **Signals** | **Kurtosis value** |
| **Input signal** | **Separated signal** |
| Two signals | Phase 1 | Signal 1 | 12.38 | 12.20 |
| | mixture | 135.85 | 12.19 |
| | Noise 1 | 198.44 | 168.02 |
| | Phase 2 | Signal 2 | 11.38 | 11.25 |
| | Noise 1 | 198.44 | 11.10 |
| | Noise 2 | 110.22 | 98.81 |
Table 1 explains the different signals based on kurtosis value. In the BSS process, the two signals and three signals were analyzed. The algorithm can separate the mixed signal of at least two signals and separate the source signal from the mixtures. For each signal, the noise and mixtures are added. In the single signal, we prepared the signal as three phases, in stage 1 the kurtosis estimation of the input signal for signal 1 is 12.38 and the separated signal is 12.20, the mixture operation achieves input signal as 135.85 and the separated signal is 12.19. Similarly, at three signals we have to find the kurtosis value at their corresponding signals.

**Kurtosis analysis**

| Phase 1 | Signal 1 | 10.15 | 11.85  |
|---------|----------|-------|--------|
| Noise 1 | 198.49   | 110.22| 105.39 |
| Noise 2 | 70.69    | 11.10 | 11.10  |
| Mixture | 135.85   | 11.80 | 11.80  |

| Phase 2 | Signal 2 | 12.90 | 46.34 |
|---------|----------|-------|-------|
| mixture | 135.85   | 75.50 | 75.70 |
| Noise 3 | 110.22   | 16.95 | 16.95 |
| Noise 2 | 75.70    | 11.80 | 11.10 |
| mixture | 135.85   | 11.80 | 11.10 |

| Phase 3 | Signal 3 | 12.91 | 16.95 |
|---------|----------|-------|-------|
| mixture | 135.85   | 11.85 | 11.80 |
| Noise 2 | 110.22   | 16.95 | 16.95 |
| Noise 1 | 70.69    | 11.10 | 11.10 |
| Noise 1 | 198.49   | 110.22| 105.39|

The above chart represents the kurtosis maximization for two signals. To consider the BSS procedure, take the two signals it additionally separate the source signal from the mixture signals, the most extreme kurtosis achieves in the range as 12.20 for signal 1. The kurtosis maximization value for the input and separated signal for signal 2 is 11.38 and 11.25. Similarly, for signal 3 the input signal achieves kurtosis value is 12.71, the separated signal is 16.48.

**Figure 4: kurtosis analysis for proposed model**

**Figure 5: kurtosis analysis for proposed model**
The above graph represents the kurtosis maximization function for three signals. At signal1, the kurtosis attains input signal as 10.34, the separated signal is 45.38. From the simulation solutions of experimentation conclude that the BSS with GDA algorithm can separate the blind signals from the combined signals with the help of GDA-AGSO achieves the maximum kurtosis. The signal 2 achieves the 15.10 kurtosis value for the input signal in the BSS process and the separated signal is achieved kurtosis at 15.20.

**Performance analysis**

![Graph showing performance analysis](image)

**Figure 2: Two signal**

In figure 2 represents the performance analysis of two signals. The sensitivity of proposed model attains 100, the LDA-GSGA algorithm attains 80, and the ICA-GSO algorithm attains 72. In the specificity analysis, proposed algorithm GDA-AGSO attains 98, LDA-GSGA algorithm attains 45, and the ICA-GSO algorithm attains value as 70. Similarly, for accuracy, we have obtained the different values. Compared to this entire algorithm the proposed algorithm GDA-AGSO gives the better performance.

![Graph showing performance analysis](image)

**Figure 3: Three signal**

Figure 3 demonstrates the performance analysis of three signals. The performance metrics compared with three signal and the three algorithms. For the three algorithms, the proposed model GDA-AGSO gives the better performance. The sensitivity of LDA-GSGA range 78, the proposed algorithm achieves 100, ICA-GSO algorithm achieves 65. The optimal value is achieved by the kurtosis maximization algorithm. Similarly, for specificity and accuracy, our proposed algorithm gives the higher performance.

**VI. CONCLUSION**

This paper introduces a detailed study on the utilization of Hindi source signals for BSS. BSS is an attractive and capable technique equipped for separating the signal from their mixtures without a point by point learning of source signals and mixing forms. The procedure is considered for taking a few signals and it is mixed with the assistance of BSS process. This BSS representation for distinctive
mixture and separated the signals with maximum kurtosis is obtained. For the partition of the speech signal from the mixture signal, the most extraordinary kurtosis is refined with the assistance of GDA strategy. Moreover, to acquire the optimal value AGSO algorithm is performed. The precision 96% is acquired for our proposed technique. Further, theoretical endeavors of the enhanced BSS approaches with hybrid optimization will be created utilizing simple hardware and obtain maximum kurtosis value.

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