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A Novel Blind Audio Source Separation Utilizing Adaptive Swarm Intelligence and Combined Negentropy-Cross Correlation Optimization

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Abstract: This paper presents a novel computational framework for blind audio source separation (BASS) that enhances existing Independent Component Analysis (ICA) with an adaptive swarm intelligence algorithm (ASIA) in over-determined scenario to find an optimal de-mixing matrix that could efficiently separate mixed signals. The proposed ASIA methodology addresses the challenges of optimal parameter determination in stochastic optimization process of swarm intelligence approach for an estimation of the precise unmixing matrix. In order to ensure the separated signals are as independent as possible in BASS task, a complex and non-convex optimization problem is formulated where the unmixing matrix is customized to minimize mutual information and maximize the non-Gaussianity of the signals. To solve our optimization problem the study introduces a weighted combination of negentropy and cross-correlation in the fitness function of the proposed ASIA. Additionally, it incorporates an adaptive inertia weight and velocity clamping mechanism into the traditional swarm optimization technique to addresses the challenges associated with parameter determination in stochastic optimization techniques. This unique approach of proposed framework ensures maximum statistical independence of the separated signals from the unknown mixed signals. Overall analysis of experimental outcome demonstrate that the proposed framework exhibits superior blind separation of mixed audio signals, showcasing enhanced computational efficiency and de-mixing accuracy compared to conventional baseline approaches

Keywords: Audio Signal, Mixed Signal, Blind Source Separation, Independent Component Analysis, Swarm optimization

1. INTRODUCTION

Blind Audio Source Separation (BASS) is a powerful technique that is used to extract individual audio sources from a mixture of sounds [1]. It is widely used in many auditory signal processing applications such as speech enhancement, music processing and Bioacoustics. However, separating audio signals from a mixture without knowing the source signals or mixing process poses significant challenges [2]. This means that BASS algorithms must be able to handle the inherent complexity and non-stationarity of audio signals, each with its unique temporal signatures and frequent reverberations [3]. Additionally, the blind nature of the separation task makes it inherently prone to inaccuracies, requiring careful design of BASS algorithms. Independent Component Analysis (ICA) has been a traditional method for Blind Audio Source Separation (BASS) due to its effectiveness in separating statistically independent sources [4]. However, ICA's performance is often dependent on the optimal selection of various parameters and the underlying assumption that the sources are non-Gaussian and mutually independent [5]. These limitations can hinder separation accuracy and computational efficiency. ICA-based source separation methods often get trapped in local optima and are not very robust against non-linear mixtures. Additionally, existing ICA-based methods often face slow convergence issues and lack precision in estimating the mixing matrix, affecting the accuracy of source separation [6]. Therefore, the prime aim of this paper is to introduce a novel computational framework that can significantly enhances the application of conventional ICA methodology for BASS by integrating an adaptive swarm intelligence algorithm (ASIA). The proposed ASIA methodology is precisely designed to address the common pitfalls associated with optimal parameter determination in standard particle swarm optimization (PSO) algorithm and as well as to ensure reliable unmixing matrix estimation using classical ICA. The proposed ASIA employs an adaptive inertia weight and a velocity clamping parameter to fine-tune the optimization process with higher precision. To further strengthen the performance of the BASS task

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in the proposed framework, we introduce a weighted combination of negentropy and cross-correlation in the fitness function of the ASIA. This unique combination serves as a key-enabler in devising an effective objective function for solving optimization problem of maximizing the statistical independence of the separated signals. The proposed objective function is derived in such a way that strategically operates the unmixing matrix to minimize mutual information while concurrently maximizing the non-Gaussianity of the signals. The incorporation of the cross-correlation is ensuring minimal similarity between the separated signals, thereby significantly enhancing the robustness and efficacy of the proposed BASS framework using ASIA driven ICA. The core contribution of this paper is highlighted as follows:

• ASIA-ICA Integration: Integration of ASIA with conventional ICA for BASS, addressing common pitfalls in parameter determination in standard PSO algorithms.

• Enhanced Optimization: Introduction of adaptive inertia weight and velocity clamping parameters in ASIA, enhancing the optimization process compared to traditional PSO algorithms, leading to more reliable unmixing matrix estimation in classical ICA.

• Weighted Fitness Function: Proposes a weighted combination of negentropy and cross-correlation in the ASIA's fitness function, enhancing the objective function for maximizing the statistical independence of separated signals during BASS.

The rest of the manuscript is organized as follows: Section II briefly review some related work in BASS context through signal processing and metaheuristic algorithms. In Section III, the proposed ASIA scheme is discussed in details. Then the obtained results are presented in Section IV and finally Section V concludes the paper with core findings and future research direction.

2. RELATED WORK

Numerous research studies have been done in the literature to address BASS problem. The existing studies includes methods such as time-frequency-masking [7], computational auditory scene analysis (CASA) [8], beamforming [9], independent component analysis (ICA) [10], and principal component analysis (PCA) [11]. Each of these methods have their own limitations and may not perform optimally in all situations. In addition, many new techniques have been introduced in audio BSS research, including non-negative matrix factorization (NMF) [12], sparse component analysis [13], dictionary learning [14], and the application of neural networks [15]. However, these methods are very sensitive to noise, an unavoidable aspect in many practical applications. Among the numerous existing methods, ICA has been widely recognized for its effectiveness in solving BASS problems. ICA aims to represent a set of mixed signals as a linear combination of statistically independent components [16], [17]. However, in complex audio environments, ICA based methods often get stuck in local optima, affecting the accuracy of the source separation [18]. The work by Kitamura [19] introduces a computational scheme integrating Independent Vector Analysis (IVA) and single-channel NMF to separate the mixed auditory signal into discrete components in the context of determined BSS problem. However, this approach may fail to converge to an optimal solution when introduced to complex speaker mixing problems. Leplat et al. [20], introduced an approach that combines NMF with β-divergences to measure the discrepancy between the mixed signal and its reconstruction. To encourage a compact representation in the dictionary matrix, a penalty term is employed, promoting basis vectors with reduced volume. The work carried out by Mogami et al. [21] addresses blind multichannel mixed audio separation. The proposed approach combines ICA with deep learning to estimate the unknown mixing matrix and update the time-frequency structures of each source. However, the dependency on pre-trained models limits flexibility and generalizability the approach and also this work lacks a discussion on computational complexity associated with the proposed scheme.

Eldin and Youssif [22] presented a hybrid scheme that combines hidden Markov model (HMM) and CASA to solve cochannel speech BSS. The HMM is applied as a preprocessing method to improve pitch tracking, pitch enrichment, and pitch grouping. Subsequently, CASA is utilized for speech separation. However, HMM is sensitive to initial conditions and assumes stationary statistical properties of the input signals. Therefore, it may lead to slow convergence issues. To improve convergence rate and obtained sub-optimal solution, Khalfa et al. [23], [24] suggested a PSO with high-level exploration mechanism that incorporates additional operators namely crossover an application of genetic algorithms (GA) and a bee colony optimization (BCO) method, to update particle velocity and position. The approach demonstrates robustness in BSS based on experimental results. However, the utilization of these additional operators, significantly increases algorithm complexity and increase algorithm response time. The work carried out by Zi et al. [25] have studied performance of the several swarm-based optimization scheme to solve BASS problem. There are also many research works carried out in similar direction by applying metaheuristic such as Xia et al. [26], used butterfly optimization algorithm, Lee, and yang [27] used gravitational PSO. Abbas and Salman [28] suggested PSO driven ICA with the objective of optimizing the mutual information function for speech source separation. The PSO method implemented in this work is Quantum PSO which is very sensitive to initial parameters setup such as quantum gates and quantum rotations, which itself is time consuming empirical analysis.

The study of Ansari et al. [29] presents a comprehensive survey of BSS techniques with a focus on artificial intelligence frameworks. It explores the necessity and applications of BSS and highlights significant research gaps and future directions. Brendel et al. [30] explored convolutive

BSS, emphasizing the relevance of ICA and its variants in environments with overlapping acoustic sources. Fras et al. [31] proposes an advanced method for optimizing source separation and dereverberation in automatic speech recognition using delayed subsource non-negative matrix factorization and a statistical estimator. It addresses the challenges of overlapping speech and room reverberation, demonstrating significant improvements in word error rate and signal-to-distortion ratio. Yang et al. [32] introduces a new blind source separation algorithm for dealing with reverberation in the cocktail party problem. It details the development of a unique cost function and the use of Newton gradient descent for optimizing the demixing matrix. The research work conducted by Salvio et al. [33] discusses the impact of noise on workplace productivity and well-being, presenting a dual clustering approach to sound source separation using machine and deep learning techniques. The study utilizes long-term sound data, applying Gaussian mixture models and semi-supervised deep clustering to effectively differentiate between traffic and speech noises, highlighting the practical application and validation of these techniques in real-world settings.

The study by Ansari et al. [34] presents an extensive literature survey on BSS in signal processing applications like audio signal recovery. It delves into the significance and applications of BSS, examining traditional and AI-based frameworks. The review highlights existing methods and identifies crucial research gaps, suggesting potential avenues for further investigation to enhance the efficacy and efficiency of BSS systems. The work carried out by Gu et al. [35] explores the impact of source sparsity on the performance of the IVA algorithm for BSS. Through mathematical analysis and experimental validation, it demonstrates how frame-level W-disjoint orthogonality correlates with the algorithm's performance, asserting that IVA can achieve optimal separation under specific sparsity conditions, thus providing insights for enhancing BSS strategies. Lan et al. [36] introduces improvements to the Wave-U-Net model for vocal and accompaniment separation using an attention module and a spatial pyramid pooling layer. These enhancements aim to bridge semantic gaps and expand the receptive field, respectively. Comparative tests on the Musdb18 dataset show significant performance gains over existing models, evidenced by improved SDR, SIR, and SAR metrics. Gu et al. [37] proposes a new algorithmic framework, Minimum Variance Independent Component Analysis, which optimizes the computation of demixing filters using weighted covariance matrices based on the maximum signal-to-interference ratio (SIR) criterion. Supported by deep neural networks, MVICA surpasses conventional BSS methods and beamforming techniques in several performance metrics, including SIR, speech intelligibility, and perceptual quality, as confirmed by extensive experimental testing.

Despite many significant research efforts in the field of audio BSS, there remains a significant gap between the theoretical capabilities of the above discussed methods and their practical performance in real-world. This is because of the following reasons:

- The ill-posed nature of the BASS: In the BASS task there are infinitely many possible solutions to the problem, given a mixed signal. This means that it is difficult to find a unique solution that is also accurate.

- The complexity of audio signals: Audio signals are complex and non-stationary, which makes it difficult to design algorithms that can effectively separate them.

- The presence of noise: In real-world applications, the mixed signal is often corrupted by noise and interference. This makes it even more difficult to separate the source signals.

The existing statistical techniques and metaheuristic optimization methods are versatile and can be applied to a wide range of problems. However, when used to solve the BASS problem, their effectiveness often diminished due to the need for significant modifications to handle the complexities of audio signals.

A critical aspect of this challenge is accurately estimating the true mixing matrix, which is of significant practical importance in BASS. To address these limitations, we propose a comprehensive and flexible system and methodology explicitly customized to address the complexities of BSS in audio environments. Our approach is precisely designed to provide a reliable customized solution for BSS, with a particular focus on addressing the intricacies presented by complex audio environments.

3. METHODOLOGY

In this section, the study first details on the theoretical basis for the proposed ASIA algorithm and then discusses the implementation procedures to address BASS problem effectively.

A. *Mathematical Model*

Consider n source signals represented by S(t) $\in[s_1, s_2, s_3, , s_n]$ where s_i refers to the i^{th} source signal. If each signal in S(t) is statistically independent of each other, then the mixing model is described as follows:

$$X(t) = AS(t) + N(t) \tag{1}$$

Where, X(t) $\in$ $[x_1(t), x_2(t), x_3(t), , x_n(t)]^T$ is a vector of observed mixed signals at time t, T is transpose operator, A is mixing-matrix of size n×n, and N(t) is a vector representing the noise at time t, such that: N(t) $\in$ $[n_1(t), n_2(t), n_3(t), , n_n(t)]^T$. Thus, from Equ (1) it is clear that the observed mixed signal X(t) is a linear combination of the signal S(t) and noise N(t). Therefore, the prime aim in the BASS task is to separate signal X(t) and reconstruct or recover the S(t), without knowing the actual mixing matrix A. The unmixing model in BASS task can be described as follows:

$$Y(t) = WxX(t) \tag{2}$$

Where, $Y(t) \in [y_1(t), y_2(t), y_3(t), , y_n(t)]^T$ is an output vector consisting of recovered and separated signals $y_i(t)$ which should be similar to the original source signal S(t), W is the mixing matrix, which is an approximated form of actual mixing matrix A. However, in the real-world, estimating W precisely is quite challenging task as A is unknown. Figure 1 presents the depiction of the above discussed mixing and de-mixing model in the context of BASS

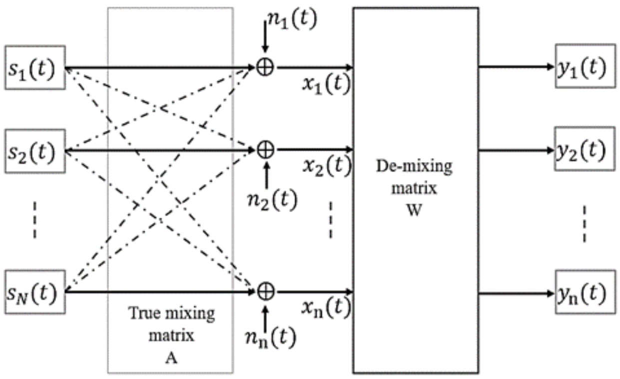

Figure 1. Schematic illustration of the BASS process

Figure 1 illustrates the BASS process as described by the above mathematical model. It depicts how multiple source signals $s_i(t)$ are combined and mixed with noise $n_i(t)$ through the true mixing matrix A to produce the observed mixed signals $x_i(t)$. The unmixing (or de-mixing) matrix W is then used to estimate the inverse of A and recover the original source signal as $y_i(t)$ from the mixed signals. However, the task of recovering the original signals basically depends on accurately estimating the unmixing matrix. But, in real-world scenarios, this the exact composition of true mixing matrix is often unknown, making the estimation process inherently complex. Factors such as the presence of noise, the assumption of linearity in mixing, and the potential correlation between source signals add layers of difficulty to this estimation. Therefore, the next sub-section discusses the application of ICA in the context of BASS and also explore the potential issues associated with ICA based solutions.

B. *ICA-based BASS Solution*

ICA is one of the popular statistical methods for separating mixed signals into their individual components. It assumes that the mixed signals are statistically independent, and are non-Gaussian, meaning that they have no correlations or shared statistical properties. ICA algorithm employs two common statistical measures, namely negentropy (NE) and mutual information (MI), for the quantification of non-Gaussianity and statistical independence in the separated signal Y(t). The non-Gaussianity is a vital attribute of ICA for the isolation of mixed signals into distinct components, while MI assesses the degree of mutual dependence between the separated signals. The process involves maximizing NE and minimizing MI to enhance the non-Gaussian characteristics and statistical dependence of the signal, thereby facilitating the separation procedure. Considering the BASS example discussed in Figure 1, the algorithm 1 describes the procedure of ICA to recover independent source signals Y(t).

The algorithm-1 takes mixed audio signals X(t) and number of iterations T as its input and takes mixed audio signals Y(t). It begins with preprocessing operations namely data centering and whitening. Data centering eliminates first-order statistics from X(t) and whitening ensures the data has unit variance. Next, an unmixing matrix W of size N×N is initialized randomly due to the blind nature of the problem. The algorithm then estimates the separated signals $Y_E(t)$, computes NE i.e., $J(y_i)$ for each signal in $Y_E(t)$, where, $H(y_i^G)$ is the entropy of a Gaussian random variable with the same covariance as the separated signal y_i and $H(y_i)$ is the entropy of the separated signal y_i. It then updates the values in W, and normalizes the columns of W.

Algorithm 1 ICA based recovery of separated signals

Input: X(t) (mixed audio signals), T (number of iteration)
Output: Y(t) (separated audio signals)
Start
1. Preprocessing
Center and whiten the mixed signals X(t)
2. Initialize random unmixing matrix: W of size N×N
3. For each ICA iteration i = 1: T, do
4. Estimate the separated signals: $Y_E(t) = WX(t)$
5. Compute NE (J) for each separated signal to measure non-Gaussianity: $J(y_i) = H(y_i^G) - H(y_i)$
6. Update the unmixing matrix: $W = arg[max_W \sum_i J(y_i)]$
7. Normalize the column of W
8. Check convergence
9. Compute the MI between the separated signals: $MI(Y_E(t)) = \sum_i H(y_i) - H(Y_E(t))$
10. Check: the maximum number of iterations is reached and convergence criteria are met
If yes
go to step 11
Otherwise,
go back to step 4.
11. Return the separated signals:$Y(t) = Y_E(t)$
End

The algorithm checks for convergence by computing the MI between the separated signals and checking if the maximum number of iterations has been reached. The quality of the estimated separated signals Y(t) is ensured by checking the convergence criteria, which include computing MI between separated signals and checking if the maximum number of iterations and convergence criteria have been met. The sub-sequent section discusses the challenges in applying ICA for BASS.

C. Challenges with ICA in BASS

The prime objective of ICA is to find the unmixing that minimizes mutual information (MI), thereby maximizing independence and enhancing the non-Gaussianity of the separated signals. This objective can be mathematically represented as an optimization problem:

Optimization problem 1: Maximize the sum of NE (J) for the i-th separated signal, such that:

$$\max_{w} \sum_{i=1}^{N} J(y_i(t)) \tag{3}$$

In the Equ (3) $J(y_i(t)) = H(y_i^G(t)) - H(y_i(t))$, and $H(y_i^G(t))$ is the entropy of a Gaussian random variable with the same covariance as $y_i(t)$ and $H(y_i(t))$, is the entropy of $y_i(t)$.

Optimization problem 2: Minimize the MI between the separated signals, such that:

$$\min_{w} MI(Y(t)) \tag{4}$$

where, $MI(Y(t) = \sum_{i=1}^{N} H(y_i(t)) - H(Y(t))$is the mutual information between the separated signals which measures their statistical dependence. The solution to this optimization problem will give the optimal unmixing matrix that separates the mixed signals into their independent components. However, achieving solution to these optimization problems to find an optimal unmixing matrix is not without its challenges, especially due to the following reasons.

- Blind nature of solution: ICA is a powerful technique for BASS, but it is often difficult to find an optimal unmixing matrix. This is because the problem is blind (lack of access to ground truth source signals). The accuracy of the unmixing matrix significantly affects the quality of the recovered signals.

- Sensitivity to Initialization: As shown in the Algorithm-1, the unmixing matrix is initialized randomly, which can affect the solution that the algorithm converges to, in complex search space with multiple local optima.

- Getting Stuck in Local Optima: The search space for ICA is complex with multiple local optima. If the algorithm converges to a local optimum, the separated signals may still exhibit mixtures of the original sources, compromising the independence of the separated signals.

- Parameter Selection: The performance of ICA can be sensitive to the choice of algorithm parameters such as the number of components and learning rate.

- Assumption of Non-Gaussianity: ICA relies on the non-Gaussian nature of the source signals. If the signals are Gaussian or close to Gaussian, the separation might be inaccurate.

D. Need for Optimization in ICA

The challenges faced in ICA, primarily the problem of local optima, highlight the need for robust optimization techniques. Optimization is vital in ICA for BASS as it helps navigate the complex landscape to find the global optimum to estimate optimal unmixing matrix, that yields independent components that align with the true underlying sources. Considering Equ (3) and (4), the optimization problem can be re-formulated as follows:

$$\left\{ maximize_W \sum_{i=1}^{N} \mathcal{J}(y_i(t)) \qquad subjected\ to:\ MI(Y(t)) \leq \epsilon \right. \tag{5}$$

Where, ϵ is a small threshold value.The problem arises when this optimization landscape is highly $non-convex$ with many local optima.

In an ideal situation, the optimization landscape is subjected to a single global maximum that corresponds to the true underlying sources. However, in practice, the optimization landscape or solution space have multiple local maxima and minima, making it difficult for the optimization algorithm to find the global maximum. Therefore, the problem of ICA getting stuck in local optima can be understood in terms of the solution space that ICA is trying to navigate. Mathematically, a local optimum refers to a point W_local such that there exists $\epsilon > 0$ where:

$$O(W_{local}) \geq O(W), \forall W \in B(W_{local}) \tag{6}$$

But there exists some global optimum W_{global} such that:

$$O(W_{global}) > O(W_{local}) \tag{7}$$

Where, O= $\sum_{i=1}^{N} J(y_i)$,B(W_{local}) is the ball of radius ϵ centered at W_{local}. This means that W_{local} is a local maximum within a small neighborhood, but not necessarily the global maximum. When the algorithm gets stuck at W_local, it fails to find the true optimal solution W_{global} (optimal unmixing matrix) that maximizes the non-Gaussianity of the separated signals. This means that the separated signals $Y = W_{local}$ X may not represent the true underlying sources, thus affecting the performance of ICA in blind source separation.

E. PSO as an Optimization Technique

PSO is a meta-heuristic optimization algorithm based on the intelligence of swarms that have ability to explore the search space effectively and avoid getting stuck in local optima. PSO achieves this by maintaining a population of swarm of particles $P_{i}{}_{i=1}^{N}$, traverse the search space with each particle's position representing a candidate solution. Each particle moves through the search space based on its own experience and the experience of neighboring particles, allowing for a balance between exploration and exploitation. The movement of each particle is guided by its personal best-known position, $pbest_i$, and the global best-known position gbest among all particles in the swarm. PSO utilizes a fitness function that evaluate how good a solution is. Here, the objective function captures the essence of the optimization problems in Equ (3) and (4) as follows:

$$f(W) \leftarrow \max_{W} = (\sum_{i=1}^{N} J(y_i(t)) - \lambda MI(Y(t))) \tag{8}$$

Where, λ is a weight parameter that balances the two objectives of maximizing non-Gaussianity J and minimizing MI. The fitness function f(W) then becomes evaluating the quality of each candidate solution, i.e., the value of W that maximizes this objective function. Then the optimal unmixing matrix, W_{global}, corresponds to the global best position in the swarm, such that:

$$W_{global} = arg \max_{W} f(W) \tag{9}$$

The iterative process of PSO facilitates a balance between exploration and exploitation in the search space, converging towards W_{global} by leveraging the collective intelligence of the swarm. The rationale behind considering PSO algorithm for optimization is that it is simple to implement and often converges to the optimum solution faster than other optimization algorithms. However, PSO is not without its own shortcomings, with a significant drawback being the risk of particles overshooting the global optimum. In addition to addressing these challenges, it is also crucial to consider the limitations that arise from relying exclusively on NE and MI as objective functions in the optimization process. While NE and MI are vital for ensuring that the separated signals are non-Gaussian and independent, respectively, they do not necessarily guarantee that these signals are accurate representations of the original sources. This discrepancy can lead to a false positive scenario, where the algorithm might incorrectly suggest successful source separation, despite the separated signals lacking meaningful correlation with the original signals. Therefore, the proposed algorithm ASIA considers incorporating mechanism of adaptive inertia weight and velocity clamping in the PSO algorithm.

F. Proposed ASIA Algorithm For BASS

In order to mitigate the challenges associated with ICA and PSO in BASS, this research study proposes ASIA that integrates adaptive swarm intelligence and combined negentropy cross-correlation (NECC) optimization approach. As discussed, earlier negentropy is a measure of non-Gaussianity of separated signal Y(t), while cross-correlation (CC) measures the similarity between two signal sets as a function of the time-lag applied to one of them, providing insights into how closely related two sequences are. Therefore, incorporating CC helps to validate that the separated signals are true representations of the original sources. If the cross-correlation between separated signals and original mixed signals is low, it indicates that the separated signals accurately represent the original sources without any mixing. The computation of CC to ensures better separation quality is given as follows:

$$C(Y,X) = 1/N \sum_{i=1}^{N} \sum_{j=1}^{N} |corr(y_i(t), x_j(t)) \tag{10}$$

Where, $corr(y_i(t), x_j(t)$ is the CC between i-th component of separated signal Y(t) and j-th component of original mixed signals X(t), and N denotes the number of components in the signals. The motivation behind introducing the NECC technique is the need to achieve a more precise and reliable separation of audio signals. Since maximization of NE in ICA, ensures the statistical independence of source components, but only depending on NE can sometimes be insufficient for ensuring the accuracy of separation, especially when source signals share similar statistical properties or when the mixing environment introduces complex noise patterns. To complement NE's strengths and address its limitations, CC analysis is incorporated. By minimizing the CC between the separated signals and the original mixed signals, it can be ensured that the separated components are true and distinct representations of the original sources, thereby enhancing the quality of separation. This dual approach not only maximizes statistical independence through negentropy but also validates the separation accuracy through CC, presenting a precise optimization framework. It is to be noted that the concept of combined NECC is proposed as a novel fitness function within an ASIA framework for BASS. The fitness function is formulated to optimize the unmixing matrix W by simultaneously maximizing negentropy and minimizing cross-correlation.

1) Proposed Fitness Function: The fitness function of proposed ASIA algorithm is a weighted combination of (NE), (MI), and CC to find the optimal unmixing matrix W that maximizes the objective function, thereby ensuring that the separated signals are as independent, non-Gaussian, and accurate representations of the original sources as possible. Therefore, using Equ (10), the fitness function is updated as follows:

$$f(W) \rightarrow \max_{W} = (\sum_{i=1}^{N} J(y_i) - \chi - \psi) \tag{11}$$

Where, χ is ${}_1MI(Y)$, ψ is $\lambda_2 C(Y,X)$ and λ_1 and λ_2 are the regularization parameters that control the trade-off between maximizing the non-Gaussianity, minimizing the MI, and minimizing the CC.

2) Adaption to PSO: The performance of PSO depends on the number of particles, and the number of iterations, with the potential for variations in particle velocities to result in overshooting the global optimum and lacks a convergence guarantee to W_{global}. The proposed ASIA addresses this by incorporating adaptive inertia weight and a velocity clamping parameters to fine-tune the optimization process of swarm intelligence with higher precision, thereby ensuring a balanced exploration-exploitation trade-off. The adaptive inertia weight w, is dynamically adjusted during

the optimization process to balance global and local search abilities, calculated as follows:

$$w(t) = w_{max} - (\frac{w_{max} - w_{min}}{iter_{max}})iter_{current} \tag{12}$$

Where, w_{max} and w_{min} are the maximum and minimum bounds for the inertia weight, respectively. The velocity clamping is used to restrict the particle's velocity within a predefined range to prevent overshooting. The updated velocity is calculated as follows:

$$v_i^{'} = min(max(v_i - v_{clamp}), v_{clamp}) \tag{13}$$

Where, v_i is the original velocity and $v_i^{'}$ is the clamped velocity of particle i and v_{clamp} is a velocity clamping parameter.

The implementation procedure of the proposed ASIA method is described in the algorithm-2 which combines the principles of adaptive swarm intelligence with a unique fitness function, aiming to optimize the separation of audio signals through an adaptive, iterative process.

The process begins with the initialization of key parameters (Step 1), which include the maximum and minimum inertia weights (w_{max}, w_{min}), regularization parameters (λ_1, λ_2), the velocity clamping parameter (v_{clamp}), learning rates (c_1, c_2), and the initial unmixing matrix (W). These parameters are very important as it guides the optimization process and ensure a better trade-off between exploration and exploitation process to determine optimal fitness of potential solutions. The next step is executed towards initialization of a swarm of particles (Step 2), where each swarm represents a potential solution for determining the unmixing matrix. Initially these particles are randomly assigned with positions and velocities for the exploration of the solution space. In the next step the fitness of each particle is then evaluated (Step 3) using a composite fitness function f(W), which integrates the negentropy mutual information and cross-correlation between the separated and original mixed signals. This fitness function encapsulates the dual objective of maximizing statistical independence and ensuring reliability to the original signals. The next of the algorithm initializes both personal and global best positions (Step 4) to track the most potential solutions found by individual particles and the swarm, respectively. This process performs crucial operation in the search process towards obtaining increasingly optimal solutions. The algorithm then initializes an optimization loop (Step 5), where the swarm iteratively updates the particles' velocities and positions based on their fitness evaluations, personal bests, and the global best solution found so far. This process continues till a stopping criterion such as a maximum number of iterations is met. The dynamic adjustment of inertia weight and velocity clamping within this search process fine-tunes the exploration process, preventing premature convergence and ensuring a thorough exploration of the solution space. After successful execution of Step 5, the algorithm computes an optimal unmixing matrix W_{global} (Step 6), corresponding

Algorithm 2 ASIA for recovery of separated signals

INPUT: Mixed audio signals (X), Maximum iterations ($iter_{max}$), Number of particles (N)
Output: Separated audio signal (Y)
Start
1. Initialization of Parameters
w_{max} (maximum inertia weight) , w_{min} (minimum inertia weight), λ_1 and λ_2 (regularization parameters), v_{clamp} (velocity clamping parameter), c_1 and c_2 (learning rates), W (random unmixing matrix) w_{max} (maximum inertia weight), w_{min} (minimum inertia weight), λ_1 and λ_2 (regularization parameters), v_{clamp} (velocity clamping parameter), c_1 and c_2 (learning rates), W (random unmixing matrix)
2. Initialization of Swarm
Initialize a swarm of N particles $P_{i_{i=1}}^N$ with random positions and velocities.
3. Evaluate Fitness
For each particle, evaluate its fitness using f(W): $f(W) = \sum_{i=1}^{N}[J(y_i) - \lambda_1 MI(Y)] - \lambda_2 C(Y, X)$ Where $Y = WxX$

4. Initialize Best Positions:
Initialize personal best positions $[pbest]_i$ for each particle
Initialize global best positions gbest
5. Optimization loop
for iter = 1 to $[iter]_{max}$ **do**
for each particle i= 1 to N: **do**
Update the inertia weight w(t) using Equ (12)
Update particle velocity:
$v_i(t+1) = w(t)v_i(t) + c_1\alpha + c_2\beta$
where, $\alpha = rand()([\text{pbest}]_i - [pos]_i)$
$\beta = rand()(gbest - [\text{pos}]_i)$
Clamp velocity v_i:
$v_i(t+1) = min(max(v_i(t+1) - v_{clamp},, v_{clamp}))$
Update particle position pos:
$[pos_i](t+1) = [pos]_i(t) + v_i(t+1)$
Evaluate new fitness f(W) updated position
Update $[pbest]_i$ if new fitness is better.
Update gbest if new fitness is better than current
If stopping criteria are met, break the loop
End of for
6. Optimal Unmixing Matrix
The optimal unmixing matrix W_{global} is the position corresponding to gbest
7.Separate Audio signals using y $Y = W_{global}X$
8.Return Output: separated audio signals Y
End

to the global best solution. This matrix is then used to separate the audio signals (Step 7), producing the estimated separated signals Y from the mixed inputs X. Finally, the algorithm returns the separated audio signals Y as output (Step 8), which represents the separated and recovered original source signals from their mixed form.

4. RESULT AND DISCUSSION

The design and development of the proposed ASIA model is done using python programming language executed on Anaconda distribution installed on windows 10 machine. This presents the outcomes for the experimental analysis carried with different test cases of mixed auditory signals. The study considers male and female voice signal from SiSEC-08, dev2 dataset. The performance assessment is conducted in terms of both visual analysis and numerical outcome analysis. For numerical analysis, the study considers three statistical parameters namely SIR (Signal-to-Interference Ratio), SAR (Signal-to-Artifacts Ratio) and SDR (Signal-to-Distortion Ratio). **S**IR: This metric quantifies the level of the desired signal in relation to the interference caused by other signals, computed as follows:

$$SIR = 10log_{10}(\frac{P_{desired}}{P_I}) \tag{14}$$

Where, $P_{desired}$ is the power of desired signal, and P_I is the power of the interference from other signals.

SAR: This metric assesses the quality of the separated signal by measuring the ratio of the desired signal to the artifacts introduced during the separation process.

$$SAR = 10log_{10}(\frac{P_{desired}}{P_A}) \tag{15}$$

Where, P_A is the power of the artifacts introduced during the separation process

SDR: This metric provides a comprehensive evaluation by measuring the ratio of the desired signal to the distorted signal post-separation.

$$SDR = 10log_{10}(\frac{P_{desired}}{P_{distortion}}) \tag{16}$$

Where, P_D is the power of the distorted signal post-separation.

A. Test Case 1: Three male speaker

In this test case, a mixed signal was created using three male speech signals. The proposed ASIA algorithm was then applied to separate the mixed signal, and its performance was compared with the Fast-ICA algorithm, ICA-PSO and the NMF method. Fast-ICA is a computational method used to separate a multivariate signal into additive, independent non-Gaussian signals. NMF is a group of algorithms in multivariate analysis and linear algebra, where a matrix V is factorized into two matrices W and H, with the property that all three matrices have no negative elements. Table 1 illustrates the comparative analysis of the SDR for three male audio mixed signals.

TABLE I. SDR ANALYSIS FOR 3 MALE AUDIO MIXED SIGNAL

Methods/Signals	S1	S2	S3
Fast-ICA	34.75	36.16	30.98
NMF	-19.8	-25.18	-3.55
ICA-PSO	40.5	37.2	35.5
ASIA(PROPOSED)	47.86	38.19	43.02

TABLE II. SIR ANALYSIS FOR 3 MALE MIXED SPEECH SIGNALS

Methods/Signals	S1	S2	S3
Fast-ICA	34.78	36.16	30.99
NMF	9.28	3.4	-12.46
ICA-PSO	45	40	39
ASIA(PROPOSED)	49	39	45

The results demonstrate that the proposed ASIA algorithm outperformed both Fast-ICA and NMF across all the three signals. The SDR scores of the proposed method for S1, S2, and S3 were 47.86, 38.19, and 43.02, respectively. These scores are notably higher compared to Fast-ICA and significantly surpass the negative scores achieved by NMF.

The lower scores of NMF indicate a considerable amount of distortion in the separated signals. This substantial difference in performance is attributed to the augmented capabilities of the ASIA algorithm. By integrating adaptive swarm intelligence and combined negentropy cross-correlation (CC) optimization approach, ASIA ensures not only the non-Gaussianity and independence of the separated signals but also verifies that the separated signals are true representations of the original sources.

The above-mentioned Table II illustrates the comparative analysis of the SIR for three male audio mixed signals. SIR scores demonstrate the effectiveness of ASIA in minimizing interference, outperforming Fast-ICA and significantly outpacing NMF.

The above-mentioned Table III illustrates the comparative analysis of the SAR for three male audio mixed signals. The SAR scores confirm that ASIA minimizes artifacts in the separated signals, with the highest scores across all signals. In contrast, NMF yielded substantially lower scores, implying significant artifacts in the separated signals.

TABLE III. SAR ANALYSIS FOR 3 MALE MIXED SPEECH SIGNALS

Methods/Signals	S1	S2	S3
Fast-ICA	46.56	69.56	65.36
NMF	-19.31	-23.54	-21
ICA-PSO	70	75	72
ASIA(PROPOSED)	66.77	94.09	83.27

TABLE IV. SDR ANALYSIS FOR 3 FEMALE AUDIO MIXED SIGNAL

methods/Signals	S1	S2	S3
Fast-ICA	30.15	35.23	26.46
NMF	4.49	6.35	8.48
ICA-PSO	38	42	31
ASIA(PROPOSED)	45.25	55.32	34.62

TABLE V. SIR ANALYSIS FOR 3 FEMALE MIXED SPEECH SIGNALS

methods/Signals	S1	S2	S3
Fast-ICA	31.61	35.95	26.1
NMF	5.21	7.39	10.16
ICA-PSO	40	45	32
ASIA(PROPOSED)	42.26	55.5	34.63

B. *Test Case 2: Three female speaker*

In test case 2, we evaluated the performance of our proposed ASIA algorithm on a mixed signal composed of three female speech signals. We analyzed the results using the SDR, SIR, and SAR metrics, with the outcomes presented in the following tables.

The results in Table IV demonstrate that the proposed method significantly outperformed both Fast-ICA and NMF in terms of SDR scores, indicating its superior ability to reduce signal distortion.

As shown in Table V, the proposed method exhibited superior interference minimization capabilities, achieving higher SIR scores compared to Fast-ICA and significantly outperforming NMF. Table VI further validates the efficacy of our method, with the proposed ASIA algorithm achieving the highest SAR scores, indicating minimal artifacts in the separated signals. The overall analysis confirms the superiority of the proposed ASIA method in consistently extracting and preserving the quality of female speech signals, effectively.

C. *Test Case 3: Single female and male speaker*

This section presents a detailed analysis of test case 3, where the mixed signal was composed of a single female and a single male speaker. The outcome analysis shown in Table VII, the proposed algorithm distinctly outshines both Fast-ICA and NMF with regards to the SDR metric, thereby affirming its superiority in separating speech signals with minimal distortion.

TABLE VI. SAR ANALYSIS FOR 3 FEMALE MIXED SPEECH SIGNALS

methods/Signals	S1	S2	S3
Fast-ICA	53.54	59.71	55.53
NMF	13.78	13.79	13.8
ICA-PSO	63	68	60
ASIA(PROPOSED)	68.87	69.23	65.42

TABLE VII. ANALYSIS OF SDR FOR SINGLE MALE AND FEMALE SPEAKER

methods/Signals	S1	S2
Fast-ICA	20.15	25.23
NMF	6.86	10.34
ICA-PSO	30	35
ASIA(PROPOSED)	33.54	42.32

TABLE VIII. ANALYSIS OF SIR FOR SINGLE MALE AND FEMALE SPEAKER

methods/Signals	S1	S2
Fast-ICA	21.01	27.55
NMF	8.11	12.36
ICA-PSO	32	40
ASIA(PROPOSED)	33.95	47.74

As illustrated in Table VIII, the proposed algorithm demonstrates impressive results in terms of SIR, with scores of 33.95 and 47.74 for S1 and S2, respectively.

As evident in Table IX, the proposed method surpasses in the SAR metric with 43.98 and 49.79 for S1 and S2, respectively. This indicates a lower presence of artifacts in the separated signals obtained through the proposed algorithm.

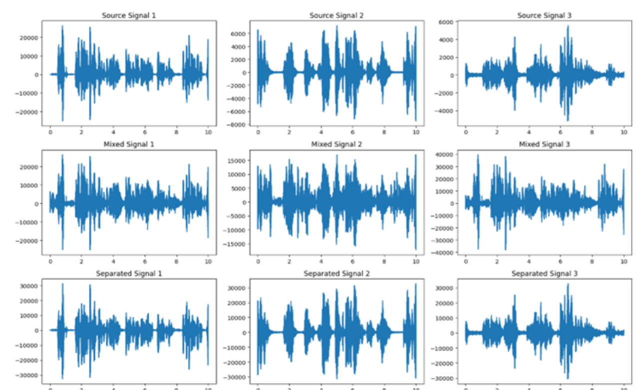

Figure 2. Visual analysis for 3 male voice signal

The extensive evaluation across three different test cases demonstrates the robustness and exceptional performance of the proposed ASIA for BASS task. The above-mentioned graphical representations in Figure 2, 3 and 4 depicts the progression of distinct voice signals: from their original

TABLE IX. SAR ANALYSIS FOR SINGLE MALE AND FEMALE SPEAKER

methods/Signals	S1	S2
Fast-ICA	29.56	23.49
NMF	18.25	19.06
ICA-PSO	42	47
ASIA(PROPOSED)	43.98	49.79

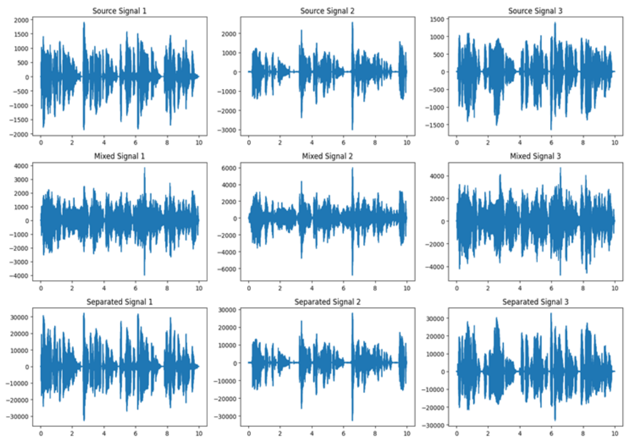

Figure 3. Qualitative analysis of test case-2: 3 female voice signals

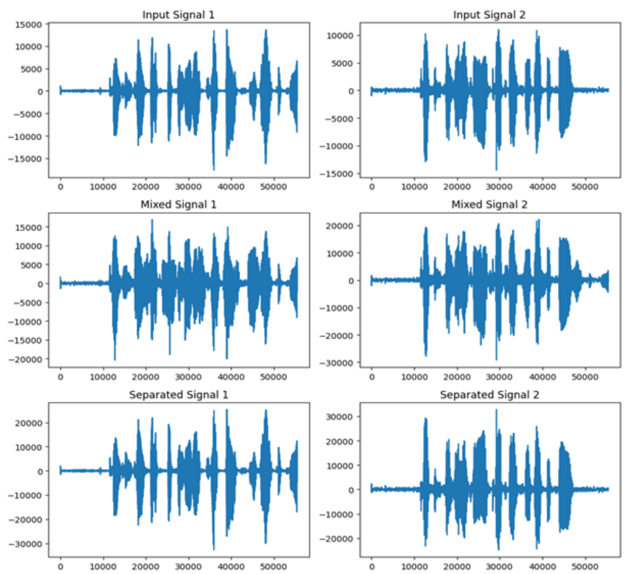

Figure 4. Qualitative analysis of test case-3: 1 female and 1 male

source states, through a mixed phase, and ultimately to their separated states after being processed through an audio separation algorithm. Overall performance analysis exhibits that the proposed ASIA scheme consistently outperformed traditional methods such as Fast-ICA, ICA-PSO, and NMF in terms of Signal-to-Distortion Ratio (SDR), which directly translates to clearer and more distinct audio outputs. The application of ASIA has also shown a significant improvement in minimizing interference, as reflected in the SIR. The higher SIR values with ASIA indicate that it is more effective at isolating the desired signal from other competing signals, thereby reducing confusion, and enhancing the clarity of the output. Moreover, higher SAR scores suggest that ASIA not only separates signals effectively but it also provides output with minimal distortion and fewer artifacts, which is crucial for maintaining the natural quality of the audio. The visual outcomes demonstrated in form of qualitative analysis of input and output waveform signals validates the effectiveness with consistency of ASIA's performance across varied test cases ranging from multiple speakers of the same gender to a mixed-gender scenario, highlights its robustness and adaptability.

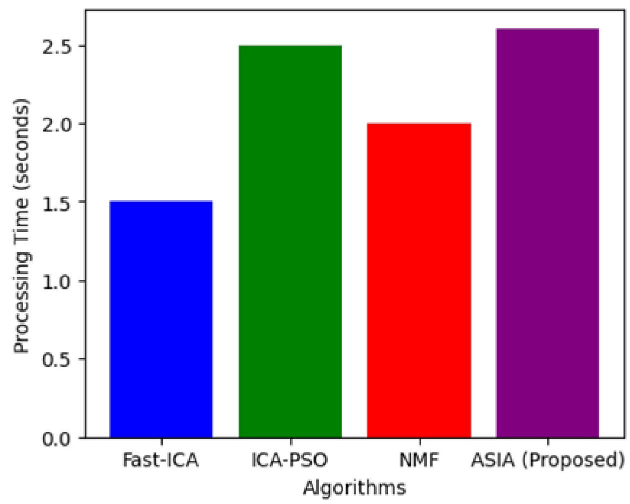

Figure 5. Analysis of the processing time

The above Figure 5 illustrates the comparative processing times of four different algorithms used for BASS. The algorithms compared are Fast-ICA, ICA-PSO, Fast-ICA, ICA-PSO, NMF, and the proposed ASIA method. Based from the graph trend Fast-ICA has the shortest processing time, taking just 1.5 seconds. This is expected as Fast-ICA is known for its computational efficiency due to its simpler, less iterative approach to Independent Component Analysis. ICA-PSO shows a longer processing time of 2.5 seconds. The increased time can be attributed to the hybrid nature of this algorithm, which combines the ICA method with Particle Swarm Optimization, adding to the computational load, while NMF is represented with a processing time of 2.0 seconds, which is quicker than ICA-PSO but slower than Fast-ICA. NMF's time reflects its own iterative process of factorizing matrices, which, while complex, appears to be less so than the hybrid ICA-PSO approach in this instance. On the other hand, the proposed ASIA is the most time-consuming, with a processing time of 2.8 seconds. This suggests that the advanced integrations and optimizations within ASIA, aimed at enhancing the quality of audio separation, come with a trade-off in terms of computational time with slight variation.

5. CONCLUSION

This research presented a novel approach named ASIA to solve BASS problem in an overdetermined scenario. This approach integrates adaptive PSO and ICA with a unique fitness function based on combined negentropy and cross-correlation. The key innovation of ASIA is the incorporation of adaptive inertia weight and velocity clamping into PSO to enhance parameter optimization in stochastic processes.

Additionally, ICA is employed to maximize the statistical independence of the separated signals by optimizing an unmixing matrix that minimizes mutual information and maximizes non-Gaussianity. Experimental results demonstrated that ASIA outperforms traditional methods in separating mixed audio signals. However, it is currently limited to overdetermined scenarios. Future work will focus on the enhancing proposed algorithm to solve underdetermined BSS problem using more optimized approach.

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