

Blind Source Separation with Multi-Objective Optimization for Denoising

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Abstract—Blind Source Separation is an optimization method frequently used in statistical signal processing applications. There are many application areas such as ambient listening, denoising, signal detection, and so on. In this study, a new Strength Pareto Evolutionary Algorithm 2-based signal separation method is proposed, which combines Multi-Objective Optimization and Blind Source Separation algorithms. The proposed method has been tested for denoising, which is widely used in biomedical signal processing. That is, the Electrocardiogram (ECG) and White Gaussian Noise are mixed together with normally distributed random numbers and the original signals of the mixed signals are obtained again. To evaluate the performance of the proposed method and others (Multi-Objective Blind Source Separation and Independent Component Analysis), the Signal-to-Noise Ratio (SNR) of the ECG signal obtained from mixed signals has been measured. As a result of the simulation studies, it is seen that the performance of the proposed method is satisfactory.

Index Terms—Blind source separation; Denoising; Multi-objective optimization; Strength Pareto evolutionary algorithm 2; Optimization.

I. INTRODUCTION

Blind Source Separation (BSS) is a popular topic that is widely applied and has attracted great attention in the field of signal processing [1]. Denoising in medical electronics, signal detection in radar systems, and signal estimation in ambient listening are frequently used for BSS applications [2]. Technically, BSS can be defined as the estimation of the signals that make up this mixture from the mixture of signals without prior information [3]. Usually in BSS the source signals are estimated by optimization algorithms using an objective function. Optimization with a single-objective function (single-optimization) may not be sufficient for BSS in some application areas such as biomedical. Multi-Objective Optimization (MOO) methods are used to find a set of optimal solutions for such problems. MOO is a method that solves problems involving more than one objective function to be optimized simultaneously [4].

Since there is no information on the statistical properties of the signals and the mixing process in BSS, this process is explained by the Cocktail Party Problem (CPP) in the literature. Suppose that there are more than one person in a room and they are talking simultaneously. At the same time, imagine that there are many microphones in this room and the sounds of the people speaking are recorded. Estimate the original source signals from the sounds recorded by the microphone is defined as CPP [5]. For the solution of CPP, Independent Component Analysis (ICA), Joint Approximate Diagonalization of Eigenmatrices (JADE), and Non-negative Matrix Factorization (NMF) algorithms are the most frequently used methods [6]–[8]. Pelegrina, Attux, and Duarte [9] proposed a method to separate mixed signals with the MOO method. Studies have been carried out on the MOO-based ICA method for fMRI data analysis, as well as to remove the noise of the Electroencephalogram (EEG) signal in biomedical signal processing [10]–[12]. BSS is widely used in communications and audio source separation [3], [13]–[15]. BSS is also widely used in the separation of biomedical signals. These studies are mostly used to separate the electrocardiogram signals of the unborn child and the mother. However, in these studies, the single-optimization problem is applied. In some studies, the aim is to denoise biomedical signals such as ECG by means of single-optimization methods. In these studies, the use of single-optimization may be insufficient to separate biomedical signals with different statistical properties.

In this study, the Multi-Objective BSS (MO-BSS) method is examined, and a new method that increases the accuracy of the estimation in signal separation is proposed. In the proposed method, the signs are randomly mixed and the centralization and whitening process are applied. ECG and White Gaussian Noise signals randomly selected from the database have been used in the simulation study. In the proposed method, two different objective functions are determined and these objective functions are minimized by the Strength Pareto Evolutionary Algorithm 2 (SPEA2). In this direction, the aim is to develop an algorithm that separates mixed signals better than MO-BSS.

The remainder of this paper is organized as follows. In Section II, general information about BSS and MOO

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methods is given. The proposed MOO is explained in Section III. The simulation results are presented in Section IV, and some concluding remarks are made in Section V.

II. MATERIALS AND METHODS

A. Blind Source Separation

BSS is the separation of a set of source signals from a set of mixed signals without prior knowledge of the mixing process, which is a fundamental problem in the field of signal processing [16]. In the solution of the BSS problem, the separation process is performed on the basis of the statistical properties of the source signals. However, this requires some assumptions about the sources to be made. These assumptions are that the source signals are statistically independent and do not have a Gaussian distribution [17]. It is the statistical calculation of the independence ratios of the signals in the mixture and the separation of the signals in the mixture according to this calculation. The mathematical expression of the mixture of independent source signals in the BSS algorithms is expressed as follows

$$x(t) = As(t), \quad (1)$$

where $x(t)$, A , and $s(t)$ are the received signal vector, the mixing matrix, and the original sources, respectively. In the BSS algorithm, Z is considered as the inverse of A as the decomposition matrix. The estimate of $s(t)$, a random variable, is expressed by $y(t)$ and is expressed as follows

$$y(t) = Zx(t), \quad (2)$$

where $x(t)$, the matrix A , is tried to be estimated with a linear transformation. The independent components are tried to be found by multiplying $x(t)$ with the Z , which is the inverse of A . It is assumed that the signals found by the transformation result are independent from each other as much as possible [18], [19].

The decomposition matrix found in (2) includes the solution of a single-objective optimization problem, where the BSS problem is focused on a single solution and the set of resources has a single estimated solution. As shown in (3), the solution $J(W)$ is obtained with a single feature of the sources such as sparsity, non-Gaussian, etc.

$$\min_w J(W). \quad (3)$$

In practice, it may be necessary to have two or more guesses to make a decision. In this case, it may be more accurate to use MOO methods.

B. Multi-Objective Blind Source Separation Method

The MO-BSS method is used in BSS problems to find the optimal solution values of more than one desired objection. In MOO, there is no single best solution for all objections; instead, there are several solutions. Its mathematical representation is given in (4)

$$\min_w [f_1(W), f_2(W)], \quad (4)$$

where f_1 and f_2 are the objective functions [20]. It is often very difficult to find a single solution among cost functions that minimizes all of them. The solution to this is to find the set of non-dominant points in the minimization problem. The concept of Pareto optimality is used to solve this problem [9].

The Pareto method is used to distinguish possible solutions in a dominant/non-dominant way in optimization. In MOO, a solution is dominant if an objective function improves its values without affecting the other objective function (without reducing its performance). This phenomenon is called "Pareto optimality". If the solution of one objective function can be improved without reducing the other objective function, it is defined as a non-Pareto optimal solution [20], [21].

Evolutionary algorithms are generally used to obtain the Pareto optimal solution set. Although evolutionary algorithms do not guarantee optimality, it is a very popular method among multi-objective techniques. The Strength Pareto Evolutionary Algorithm (SPEA) has been introduced by Zitzler and Thiele [22]. Subsequently, the necessary updates were made by Zitzler, Laumanns, and Thiele [23] and used as SPEA2. Both can be given as examples of evolutionary-based MOO methods. Its enhanced version, known as SPEA2, will also be used in the signal separation techniques that will be presented in this study [9].

C. Strength Pareto Evolutionary Algorithm 2 (SPEA2)

The SPEA is a method developed to find or approximate the Pareto-optimal set for MOO problems [9]. The implementation of the SPEA2 method is explained in Algorithm 1 [24].

Algorithm 1. SPEA2 algorithm.

<p>Input: N (population size), \bar{N} (archive size), T (indicates maximum number of generations) Output: A (denotes non-dominated set) S.1: Initial population (P_0) and create empty archive ($\bar{P}_0 = \emptyset$). Set $t = 0$. S.2: Assign the fitness of the individuals in P_t and \bar{P}_t. S.3: Copy all non-dominated individuals into P_t and \bar{P}_t to \bar{P}_{t+1} keeping the size N. S.4: If $t \geq T$ or another stopping criterion is satisfied, then set A to the set of decision vectors in \bar{P}_{t+1}. Stop. S.5: Fill a mating pool using a binary tournament on \bar{P}_{t+1}. S.6: Apply recombination and mutation operators to the mating pool and set \bar{P}_{t+1} to the resulting population. Increment generation counter ($t = t + 1$) and go to S.2.</p>

SPEA uses an external archive containing previous non-dominant solutions, which is stored in the archive and updated after each iteration [23]. Archive members participate in the newly calculated population process. In the SPEA2 algorithm, a power $S(i)$ is calculated for each solution

$$S(i) = |\{j | j \in P_t + \bar{P}_t \wedge i \succ j\}|, \quad (5)$$

where $|\cdot|$, $+$, \succ represent the cardinality in the set, the

union of multiple sets, and the symbol of the Pareto domination relationship, respectively. P_i and \bar{P}_i represent population and empty archive. According to S , i^{th} the raw fitness value $R(i)$ calculated for the individual is given in (6)

$$R(i) = \sum_{j \in P_i + \bar{P}_i, j > i} S(j). \quad (6)$$

This fitness value is formed by the number of dominant and non-dominant solutions in a population. Therefore, it uses the archive truncation method to preserve boundary solutions and the nearest neighbor approach to preserve diversity [25]–[27].

D. Objective Functions

Two objective functions are used to separate the ECG signal from the White Gaussian Noise. The first objective for MOO is adapted to the minimization problem, and this optimization process is given in (7)

$$J_1(W) = -\sum_{i=1}^2 |E[W_i^T x(t)x(t-\tau)^T w_i]|, \quad (7)$$

where W_i^T represents the row i^{th} of W . It is determined based on a predefined delay τ of the calculation of $J_1(W)$. The ℓ_1 -norm minimization method is used as the second objective function. The purpose of SPEA2 is to take into account the sparseness of the resources

$$J_2(W) = \sum_{i=1}^2 \frac{\|W_i^T x(t)\|_1}{\|W_i^T x(t)\|_2}. \quad (8)$$

It is seen that the criteria used in MOO have different structures from each other. In addition, autocorrelation is used to take advantage of the temporal nature of the signals received. Therefore, the solution of the MOO problem is calculated as follows

$$\min_W \left[-\sum_{i=1}^2 |E[W_i^T x(t)x(t-\tau)^T w_i]|, \sum_{i=1}^2 \frac{\|W_i^T x(t)\|_1}{\|W_i^T x(t)\|_2} \right]. \quad (9)$$

With the MOO optimization method, the separation criteria are optimized simultaneously. As a result, values closer to the objective functions are obtained in each iteration. Taking into account Pareto in this optimization, the processing time may take a long time. Therefore, the processing time of MOO tends to be slower than that of single-objective methods [9].

III. PROPOSED METHOD

The MOO method has been applied to BSS methods, and success has been achieved. A number of studies have been carried out to increase the success rate in the analysis of biomedical signals for human health. Before the SPEA2 algorithm will be used for BSS, the signals have been mixed randomly and pre-processed for centralization and whitening. Thus, in addition to facilitating data processing,

it is aimed to reduce the data size and provide rapid convergence. The block diagram of this method is shown in Fig. 1.

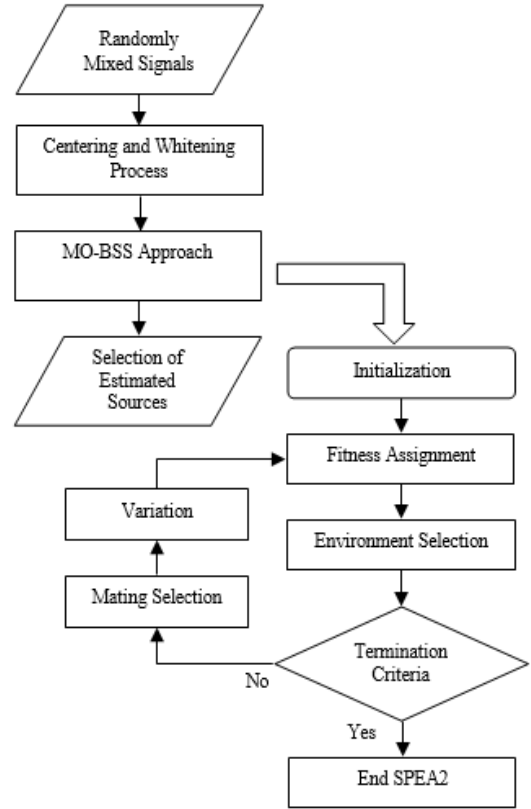


Fig. 1. Proposed block diagram [17].

The first pre-processing step that can be done is the centralization process. Centralization means that the mean value of the variable is set to zero. In other words, it is to subtract the average value of the measurement data from all the elements in the measurement data. This process simplifies the BSS algorithms. The mathematical expression of centralization is given by (10), where $E\{x\}$ is the expectation operator

$$x = x - E\{x\}. \quad (10)$$

Another important pre-processing step is the whitening of the signal. Some linear transformation must be performed so that the observation vector x is uncorrelated and has unit variance. Eigenvalue decomposition is used to perform the whitening transformation in a simple way. Thus, the mathematical expression of the decomposition of the covariance matrix of x is given by (11)

$$E\{xx^T\} = EDE^T, \quad (11)$$

where $E\{xx^T\}$ and E denote the covariance matrix of x and the orthogonal matrix of eigenvectors, respectively. D represents the diagonal matrix of its eigenvalues, namely $D = \text{diag}(d_1, \dots, d_n)$. The whitening process is represented by (12) and $D^{-\frac{1}{2}}$ corresponds to taking the square root of the diagonal eigenvalues

$$\tilde{x} = ED^{-\frac{1}{2}}E^T x, \quad (12)$$

where \tilde{x} represents the whitened observed signals. The effect of whitening on the mixing process is given below

$$\tilde{x} = ED^{-\frac{1}{2}}E^T As = \tilde{A}s. \quad (13)$$

As can be seen in (12), the matrix \tilde{A} (whitened mix matrix) after whitening has now become an orthogonal matrix. The next step is to apply the whitened signals to the MOO method. Size reduction in the parsing matrix with pre-processing will greatly improve the convergence speed and stability performance of the algorithm. Therefore, the success rate in BSS will increase significantly with MOO [28], [29].

IV. EXPERIMENTAL RESULTS

ECG and White Gaussian Noise signals are used to evaluate the performance of the proposed method. These signals are taken from the database source [30]. The proposed method has been applied to the MO-BSS and ICA algorithms by randomly mixed two different signals. To obtain the numerical values of the results, the algorithm has been run 100 times and the Signal-to-Noise Ratio (SNR) has been taken into account. The real experimental environment has been provided by randomly mixed the signals in each cycle.

As seen in Fig. 2, the original signals, randomly mixed signals, and suggested method results are shown in 1500 sample sizes.

The non-dominant solution set results are shown in Fig. 3 by applying two different objective functions to the SPEA2 algorithm. These results are the minimum solutions in the non-dominant set. Instead of finding a single solution, the Pareto-optimal set and the best solutions are shown in the graph. The user can estimate the source signal by choosing an appropriate solution from this non-dominant Pareto-optimal set. The graph is taken from a random loop of the algorithm.

Performance analyzes have been calculated using the SNR value shown in (14) to prove the accuracy of the signal separation process according to time-correlation and ℓ_1 -norm objective functions [31], where, $E_i\{\}$ represents the expected value, s_i represents the source signals, and n_i represents the noise signals

$$SNR \text{ dB} = 10 \log_{10} \left(\frac{E_i\{s_i^2\}}{E_i\{n_i^2\}} \right). \quad (14)$$

SNR for White Gaussian Noise have been measured for different values between 1000 sample length and 5000 sample length, and the results are given in both Fig. 4 and Table I. It is seen that the performance of the method we propose for White Gaussian Noise is more successful than the MO-BSS method.

Especially in the White Gaussian Noise, the proposed method has definitely proven to give better results than the

MO-BSS method. As can be seen in Fig. 4, it cannot be said that the sample lengths make a positive contribution to the separation performance. However, it should not be forgotten that increasing the sample length will increase the processing cost, and thus the separation time.

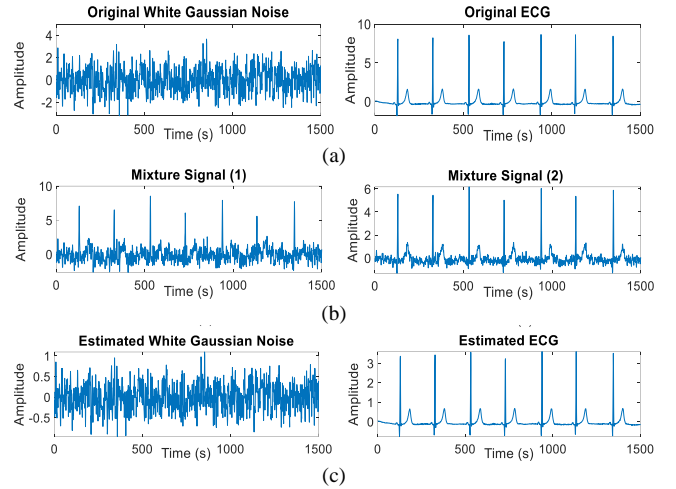


Fig. 2. (a) Original, (b) mixture, and (c) estimated source marks.

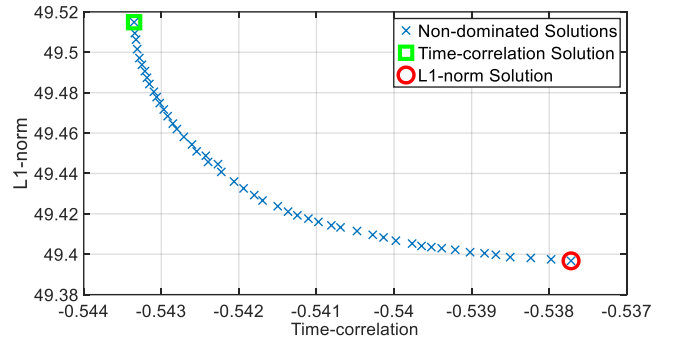


Fig. 3. As a result of the convergence of the SPEA2 algorithm, the non-dominant cluster.

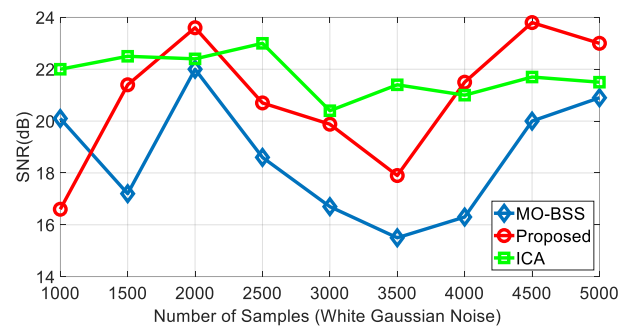


Fig. 4. SNRs for the noise signal.

TABLE I. SNR VERSUS SAMPLE LENGTH FOR WHITE GAUSSIAN NOISE.

Number of Samples	MO-BSS (SNR)	Proposed (SNR)	ICA (SNR)
1000	20.1	16.6	22
2000	22	23.6	22.4
3000	16.7	19.8	20.4
4000	16.3	21.5	21
5000	20.9	23	21.5

Due to the mixing matrix and the nature of the source signals used, the ICA method has been partially successful, especially in the estimation of the White Gaussian Noise. Figure 5 and Table II show that the performance of the proposed method gives better results when the sample size

increases in the ECG signal.

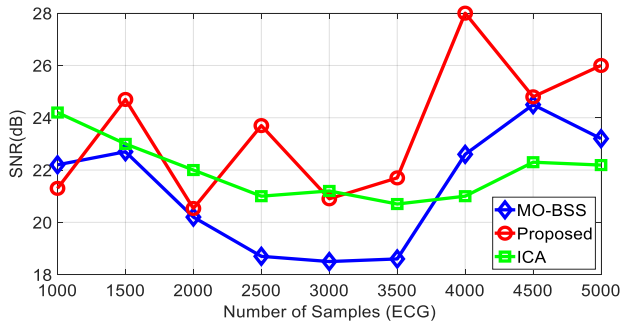


Fig. 5. SNRs for the ECG signal.

TABLE II. SNR VERSUS SAMPLE LENGTH FOR ECG.

Number of Samples	MO-BSS (SNR)	Proposed (SNR)	ICA (SNR)
1000	22.2	21.3	24.2
2000	20.2	20.5	22
3000	18.5	20.9	21.2
4000	22.6	28	21
5000	23.2	26	22.1

Figure 6 is given for the success of the White Gaussian Noise separation of the proposed method.

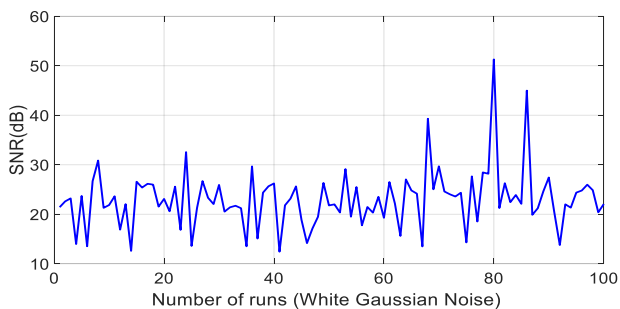


Fig. 6. SNRs for the White Gaussian Noise (100 runs for the proposed method).

It should be noted here that the methods used in the study for Monte Carlo analysis have been run 100 times, and the averages of the result values have been calculated. When looking the graph carefully, it is observed that the SNR is between 12 dB and 50 dB.

Figure 7 shows the SNR of the ECG signal for each Monte Carlo analysis cycle [32]. The main reason for these changes is the mixing matrix. As mentioned above, the mixing matrix is generated randomly. Furthermore, since the initial values are randomly assigned in the SPEA2 algorithm, these assigned variables should be expected to affect the detection performance. It has been observed in Fig. 7 that it varies between 15 dB and 50 dB, as in the previous figure.

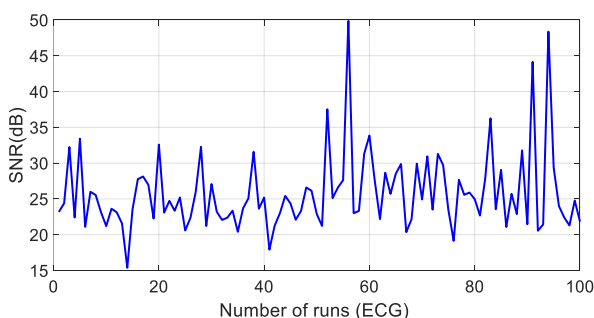


Fig. 7. SNRs for the ECG signal (100 runs for the proposed method).

TABLE III. OPERATION TIMES OF ALGORITHMS.

Number of Samples	MO-BSS (s)	Proposed (s)	ICA (s)
1000	5.83	5.75	1.8
2000	6.33	6.21	1.8
3000	6.92	6.9	2
4000	7.1	7.07	2.1
5000	7.44	7.38	2.2

In addition, it can be said that the proposed method decomposes ECG more successfully. Considering the signal separation performance of BSS algorithms, it can be said that almost all of them outperform other signals for White Gaussian Noise.

The operation times of MO-BSS, the proposed method, and the ICA method are given in Table III for different sample lengths. When the proposed method is compared in terms of MO-BSS operation times, it is seen that the proposed method is slightly advantageous. Since the operation time of the ICA method, which is the most frequently used with a single-objective function, does not use an evolutionary algorithm, the operation time is quite low.

V. CONCLUSIONS

Many BSS methods in the literature estimate source signals using a single-objective function. Especially in recent years, MOO algorithms are applied to BSS methods, which are frequently used in biomedical, communication, and security. Since no method is perfect in the separation of mixed signals, the existing methods have been developed and the best has been tried to be obtained.

In this study, we proposed applying pre-processing to the MOO method. With this study, it has been proven that we have increased the performance of our main objective, MO-BSS, at the same time, the usability has been proven by comparing the results with the single-objective ICA method, which gives successful results. The proposed method has been compared with the performances of MO-BSS and ICA. As a result of the simulation studies, the superiority of the proposed method over the traditional MO-BSS algorithm is confirmed. These comparison results have provided applicable results to users in the correct analysis of vital biomedical signals. In addition, the proposed method has low computational cost and high separation quality compared to MO-BSS.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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