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# A new blind source separation approach based on dynamical similarity and its application on epileptic seizure prediction

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ABSTRACT

Blind source separation is an important field of study in signal processing, in which the goal is to estimate source signals by having mixed observations. There are some conventional methods in this field that aim to estimate source signals by considering certain assumptions on sources. One of the most popular assumptions is the non-Gaussianity of sources which is the basis of many popular blind source separation methods. These methods may fail to estimate sources when the distribution of two or more sources is Gaussian. Hence, this study aims to introduce a new approach in blind source separation for nonlinear and chaotic signals by using a dynamical similarity measure and relaxing non-Gaussianity assumption. The proposed approach assumes there are dynamical stability in source signals and dynamical independence between them. The efficiency of the proposed approach is evaluated by synthetic simulation. Also, to evaluate the ability of the method in real-world applications and featuring its flexibility, the proposed approach is employed in epileptic seizure prediction by using EEG signals. The results show the potential and ability of the proposed method in nonlinear and chaotic signal processing.

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## 1. Introduction

Blind source separation (BSS) is an important problem in signal processing with applications across science and engineering. The ‘cocktail party problem’ is a classic example of the BSS problem where the goal is to recover the voices of individuals speaking simultaneously using recordings from ambient microphones placed throughout the room [1]. In the BSS problems, very little information about the underlying source signals is known and different methods attempt to solve the problem by considering some assumptions. One of the most common methods in the BSS is Independent Component Analysis (ICA) which uses statistical independence of the sources as a criterion for solving the unmixing problem. The ICA is used in many application domains [2,3], particularly in neuroimaging, in which the goal is to decompose electroencephalographic (EEG) data in temporally independent sources [4] and functional magnetic resonance imaging (fMRI) data into spatially independent brain networks [5]. Maximum-likelihood [6], minimization of the between-component mutual information [7] and neural network method (infomax [8,9]) are three of the most commonly used algorithms for ICA.

ICA meets the problem once Gaussian sources exist in the mixing procedure. The unmixing matrix loses uniqueness because of the rotational invariance of the Gaussian subspace; with only non-Gaussian sources uniqueness is preserved [10]. Therefore, once two or more Gaussian sources are present in the source signal mixture, ICA will result in spurious sparse sources because it can no longer separate those sources and ignores them. The main assumption of the ICA method is non-Gaussianity and mutually statistical independence of the sources. As a result, ICA is not able to unmix the Gaussian sources. On the other hand, in many cases, there is not any information about non-Gaussianity or mutually statistically independency of mixed sources. In this situation, the unmixing problem must be solved by considering other assumptions for sources. There are studies where methods were developed for blind or semi-blind source separation based on the different assumptions on the sources or the mixing process. Based on the assumptions and the approaches of the solutions, different techniques can be used to find the unmixing matrix including the derivative-based iterative methods [11–13] and searching algorithms [14–16]. In this study nonlinear and chaotic signals are considered as sources where there is not any assumption about Gaussianity. Certain assumptions are defined based on nonlinear

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dynamics of signals and an approach is introduced to define a cost function suitable for blind or semi-blind situations. Since the proposed cost function is not differentiable. Therefore, a metaheuristic search algorithm is used to find the best unmixing matrix which minimizes the cost function.

One of the most important challenges in nonlinear and chaotic signal analysis is how to consider the dynamics of signals. In this context, dynamics are related to the global behavior of the signal and its wholeness. The global behavior of signals may be taken into consideration with different concepts. For example, some dynamics quantifiers aim to quantify a specific dynamical behavior of signals or trajectory of signals in phase space like Lyapunov exponents, fractal dimensions (box counting dimension [17], correlation dimension [18], Higuchi dimension [19], etc) and entropies (approximate entropy (ApEn) [20] and Sample entropy (SampEn) [21]) that characterizes the rate of separation of infinitesimally close trajectories [22], space-filling capacity and the amount of regularity and the unpredictability, respectively. On the other hand, some methods aim to quantify dynamics without considering a specific behavior and they globally measure the similarity of dynamics of signals like fuzzified statistical behavior of local extrema (FSBLE) [23]. The FSBLE method is used as a dynamic similarity measure that quantifies dynamical similarity by using the information of amplitude and time of local extrema of signals. This study introduces a BSS method by considering the importance of dynamics in nonlinear and chaotic signals and employes some assumptions related to dynamics and dynamical similarity of signals.

It is important to evaluate a new proposed computational method in real-world and practical situations. In a practical situation, different aspects of the environment and system including external disturbances, modeling errors, and uncertainties can impact the performance and efficiency of the method. Different studies tried to cope with these problems and also handle the outliers to be efficiently applicable in real-world applications [24–28]. This study considered an electroencephalogram (EEG) based application, epileptic seizure prediction, to evaluate the proposed method in a real-world application. The EEG signal stems from a highly nonlinear and multidimensional system [29]. Thus, analysis of changing EEG dynamics are considered in many studies for detection or prediction of different states of the brain [30–36]. For epileptic patients, there are four main dynamical states: normal (far from seizure), pre-ictal (before seizure), ictal (seizure interval), and post-ictal (after seizure). There are many studies which aim to classify these states or predict seizure onset [37–39,41–43,40]. This study assumes that there is a dynamical source which causes or produces epileptic seizures. Based on this assumption, using the estimated source signal of epileptic seizures may help other available methods to increase the efficacy of the prediction systems.

The rest of this paper is organized as follows: Section 2 introduces the proposed method for the BBS problem and its assumptions. Section 3 presents the results for evaluating the method on synthetic data and its application on epileptic seizure prediction. Section 4 discusses the method limitations and finally Section 5 concludes the paper.

## 2. The method

The simplest model used in the BSS problem is a linear mixture of the sources $\mathbf{S}$ in the determined case (the number of sources $N_s$ is equal to the number of observations $N_o$) (Eq. (1)).

$$\mathbf{X} = \mathbf{A}\mathbf{S} \tag{1}$$

where $\mathbf{S}$ is mixed by the mixing matrix $\mathbf{A}$ (which is full rank) and observation matrix $\mathbf{X}$ is produced. $\mathbf{X}$ is $N_o \times N$ matrix, $\mathbf{A}$ is $N_o \times N_s$ matrix, $\mathbf{S}$ is $N_s \times N$ matrix and $N$ is the number of samples.

The goal is to estimate $\mathbf{S}$ as $\hat{\mathbf{S}}$ by having only the observation matrix. Thus, the unmixing matrix $\mathbf{B}$ must be found to obtain $\hat{\mathbf{S}}$ using Eq. (2).

$$\hat{\mathbf{S}} = \mathbf{B}\mathbf{X} \tag{2}$$

where unmixing matrix $\mathbf{B}$ is $N_s \times N_o$ and $\hat{\mathbf{S}}$ is an $N_s \times N$ matrix.

Some assumptions must be considered to obtain $\mathbf{B}$ matrix from observations. If the source signals are considered as chaotic or nonlinear with stable dynamics, the dynamics of the signals can be injected into the problem, to find the proper $\mathbf{B}$ matrix. here, two assumptions made to estimate $\mathbf{B}$ matrix are as follows:

(A) Each source signal has the highest dynamical similarity to itself.
(B) Each source signal has the lowest dynamical similarity to other source signals.

Assumption (A) refers to the dynamical stationarity of the source signals, which means the dynamical properties of the source signals are static over time. Assumption (B) refers to the dynamical independency of the source signals which is used to meet the most separability of the source signals.

The proposed approach for the BSS problem looks for the unmixing matrix $\mathbf{B}$ which produces the source signals that satisfy these two assumptions. First of all, the dynamical similarity must be quantified. This study uses the Fuzzified statistical behavior of local extrema (FSBLE) as a dynamical similarity measure which is described in Appendix A. FSBLE quantify dynamical similarity of two signals $s_1(t)$ and $s_2(t)$ as $Sim_{FSBLE}(s_1(t), s_2(t))$.

The solution in the proposed method in this study can be converted to an optimization problem which has two main factors as follows:

- Dynamical stationarity factor: Satisfaction of assumption (A) which is interpreted as maximizing *StaFac* function.
- Dynamical independency factor: Satisfaction of assumption (B) which is interpreted as maximizing *IndFac* function.

The dynamical stationarity factor aims to maximize the dynamical stationarity of each estimated source signal separately. To quantify dynamical stationarity, each estimated source signal is divided into $D$ segments where $D \geq 2$ and *StaFac* is calculated as Eq. (3).

$$StaFac = \frac{1}{N_s}\sum_{i=1}^{N_s}\{\frac{1}{D*(D-1)}\sum_{k=1}^{D}\sum_{l=1,l\neq k}^{D} Sim_{FSBLE}(\hat{S}_i^k, \hat{S}_i^l)\} \tag{3}$$

where $\hat{S}_i^k$ is the $k$th segment of the $i$th estimated source signal. The *StaFac* function calculates the average similarity of all pair segments of each signal across all estimated signal sources.

The dynamical independency factor aims to maximize independency of the estimated source signals. Maximization of the independency can be interpreted as minimizing dynamical similarity between each pair of source signals. Therefore, *IndFac* is defined to quantify the dynamical similarity between $D$ segments of all estimated source signals as Eq. (4).

$$IndFac = -\frac{1}{N_s*(N_s-1)}\sum_{i=1}^{N_s}\sum_{j=1,j\neq i}^{N_s}\left\{\frac{1}{D*(D-1)}\sum_{k=1}^{D}\sum_{l=1,l\neq k}^{D} Sim_{FSBLE}(\hat{S}_i^k, \hat{S}_j^l)\right\} \tag{4}$$

Eq. (4) proposes minus of the dynamical similarity of each subset of $D$ segments for two different estimated source signals.

Eq. (5) is used to combine the two factors as a cost function that must be minimized.

$$CostFcn = e^{-StaFac} * e^{-IndFac} \tag{5}$$

**Table 1**
Pseudo code for the proposed BSS method.

- Input: $N_o$ observation signals
- Input: Parameters of FSBLE ($n$ and $m$)
- Input: $D$
- Output: Estimated **B** matrix
- Output: $N_s$ source signals

start
1. Generate a population of **B** matrix randomly.
2. For each **B** in generated population:

Obtain estimated source signals from observation signals by using **B**.
Divide each source signal into $D$ segments.
Calculate *StaFac* and *IndFac* values.
Calculate *CostFcn*.

3. Find the best **B** matrix by considering *CostFcn* values.
4. If stop conditions are not achieved:

Generate a new population of **B** matrix according to the search algorithm.
Go to 2
else:
Return the best **B** matrix and related set of source signals as output.
end

By minimizing *CostFcn* both the stationarity and independency factors can be satisfied and the best source signals according to the assumptions can be estimated.

*CostFcn* is not differentiable because of the FSBLE basis. Hence, the present problem (minimizing the *CostFcn*) cannot be solved by a derivative-based iterative method which is the regular solution for many other BSS methods such as FastICA [44]. Therefore, meta-heuristic search algorithms like genetic algorithm [45] or imperialist competition algorithm [46] can be used to minimize the *CostFcn* function by searching over the elements of matrix **B**.

The proposed solution of the BSS problem is described in Table 1 as a pseudo code.

## 3. Method evaluation and results

Two approaches are considered to evaluate the proposed method. First, synthetic data are used as the source signals, and the ability of the method in estimating the sources is evaluated. In the second approach, EEG data as a real-world application are used to predict epileptic seizures and the proposed method tries to estimate the epileptic seizure source as a dynamical source in the fashion of a semi-blind source separation method.

### 3.1. Evaluation on synthetic data

The signals of three common nonlinear models as Lorenz, Mackey Glass, and Rossler are used in this section as the synthetic data. The $X$ signals of these systems in the parameter sets that cause chaos are considered as basic source signals. The basic source signals do not have Gaussian distribution. Therefore, common BSS methods like Fast-ICA can estimate basic source signals from a linear mixture of those. However, if the distribution of the basic source signals is transformed into Gaussian using histogram matching techniques, ICA-based BSS methods will not be able to estimate these Gaussian sources using their linear mixture.

Eqs. (6) to (8) are Lorenz [47], Rossler [48] and Mackey Glass [49] in a parameter set that causes chaos. Fig. 1a shows sample of basic source signals and histogram of their amplitudes which are approximation of their distributions.

$$\begin{aligned} \frac{dX}{dt} &= 16(X-Y) \\ \frac{dY}{dt} &= XZ + 45.92X - Y \\ \frac{dZ}{dt} &= XY - 4Z \end{aligned} \tag{6}$$

$$\begin{aligned} \frac{dX}{dt} &= -Y-Z \\ \frac{dY}{dt} &= X + 0.2Y \\ \frac{dZ}{dt} &= 0.4 + Z(X-5.7) \end{aligned} \tag{7}$$

$$X(i+1) = X(i) + \frac{0.2X(i-r)}{1+X(i-r)^{10}} - 0.1X(i) \tag{8}$$

The new sources are generated by matching the basic sources to a histogram of normal distribution using the histogram matching technique. Fig. 1b shows the transformed source signals. These transformed signals are considered as the sources and by using a randomly selected matrix **A** (Eq. (9)), observation signals are obtained (Fig. 2).

$$\mathbf{A} = \begin{bmatrix} 0.9106 & 0.8735 & 0.2118 \\ 0.0350 & 0.5249 & 0.3484 \\ 0.1741 & 0.3440 & 0.6669 \end{bmatrix} \tag{9}$$

It is obvious that the non-Gaussianity based methods such as fastICA will fail to estimate normalized sources. Nevertheless, Fig. 3 shows one example of estimated sources using these methods (JADE and fast-ICA).

In Fig. 3 results of estimating both basic and transformed sources from observations that are obtained using matrix **A** are shown. As it was expected, both methods are successful in estimating basic sources (non-Gaussian sources).

By using the proposed method, Fig. 4 presents the results of two runs of the method to estimate the transformed sources. Running the proposed method needs some initial parameters such as $D$ and the value of $m$, $n$, and $S$ in the FSBLE method. The value of these parameters can affect the result, which will be discussed in the next section. However, these parameters are practically set in this experiment as: $D=2$, $m=3$, $n=3$ $S=3$, and imperialist competition algorithm is used as the search algorithm. In the imperialist competition algorithm the practical number of populations, imperialist and maximum number of decades are set to 150, 30, and 150, respectively. Moreover, other parameters of the imperialist competition algorithm are initialized as the main paper suggested [46], including $\beta=2$, $\gamma=\pi/4$ and $\zeta=0.1$.

It can be seen in Fig. 4 that the proposed method is able to estimate these sources where common ICA-based methods are not. This is because of the independency of the method from the distribution of the source signals. To make a comparison between the performance of the proposed method and that of these ICA-based methods, the process of estimating the normalized sources is repeated 200 times and the root mean squared error (RMSE) of the estimated sources is considered as the comparison criterion. Fig. 5 shows the histogram of the estimated source RMSEs for each of the sources separately. In the proposed method, there is no order for the estimated sources. Therefore, the label of the source with the lowest RMSE is considered as the estimated source. In addition, RMSE is computed between z-score normalized signals.

Analysis of variance (ANOVA) is used to investigate if the results of the proposed method have a significantly lower error. For each of the source signals, the RMSE of the proposed method is compared to each of the fast ICA and JADE methods separately using ANOVA test. The test results show the proposed method estimated the sources with a significantly lower RMSE ($p$-value$<0.05$).

### 3.2. Application on epileptic seizure prediction

Prediction of epileptic seizures is considered as a real-world application of the proposed method for source estimation. This study

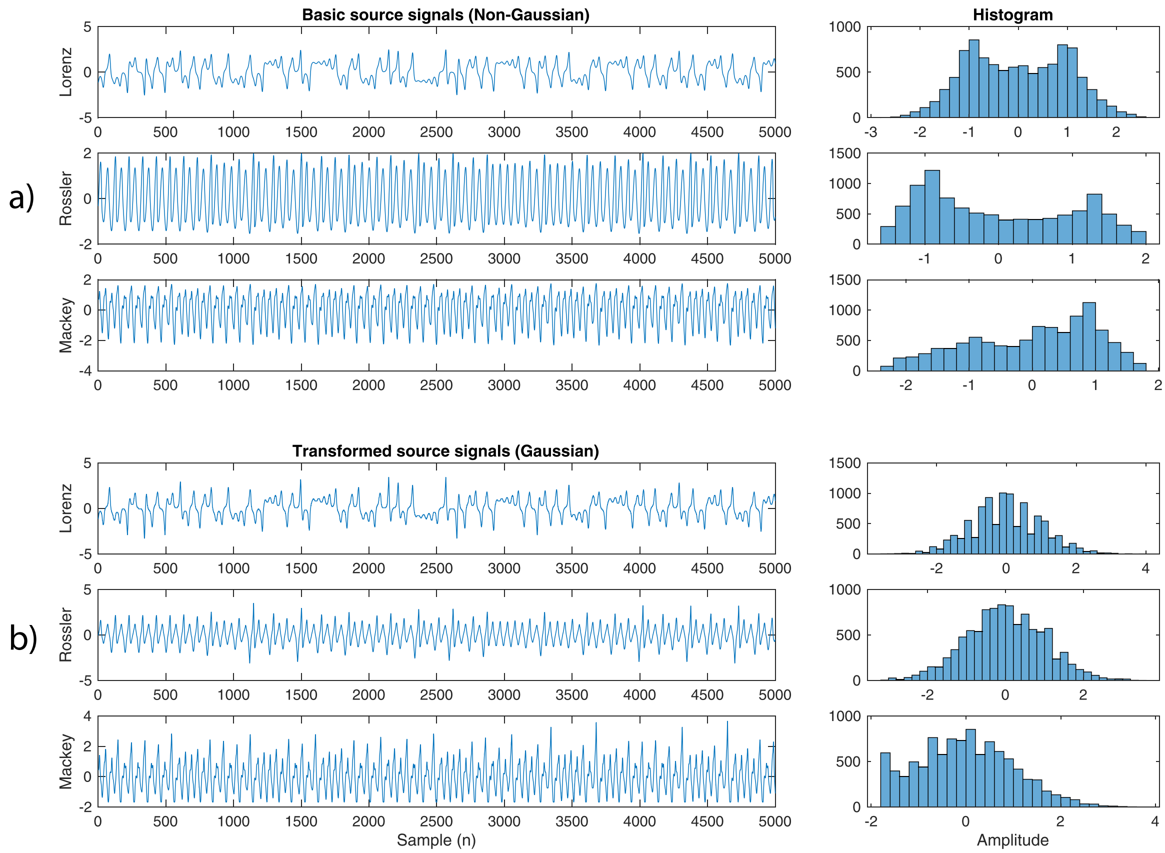


**Fig. 1.** The source signals and histogram of their amplitude values. a) Basic source signals obtain from Lorenz, Rossler, and Mackey Glass. b) The transformed source signals from a) to Gaussian distribution signals.

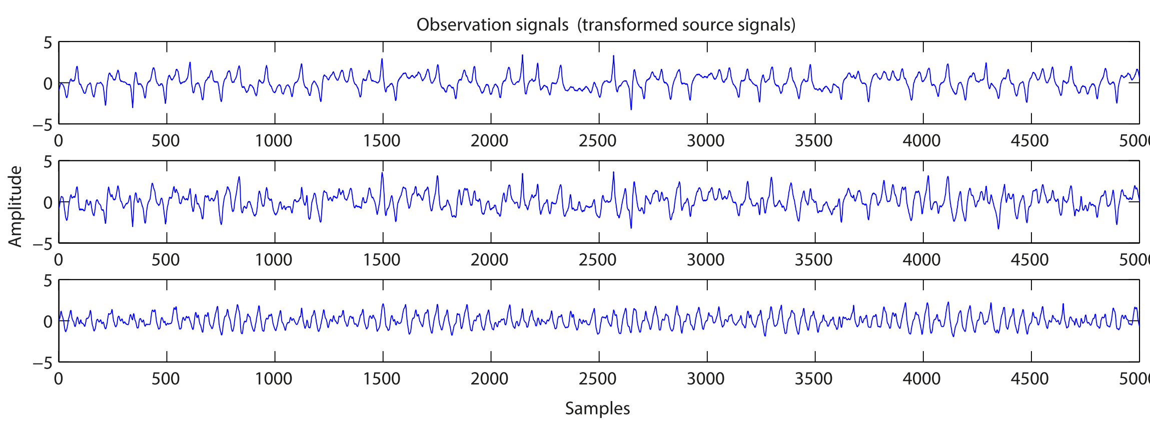


**Fig. 2.** A sample of observation signals obtained by multiplying the mixing matrix to transformed source signals.

assumes there is a dynamical source which causes seizure for each patient. Therefore, by having enough observation signals, this dynamical source can be found.

In this section, the proposed approach is used as a semi-blind source estimation method which uses some information about the observation signals to estimate a specific dynamical source. It is assumed that the dynamical source which causes seizures behaves differently in seizure onset from other times. With this consideration and having the number of $C$ observation signals which are a mixture of $C$ sources, the method assumptions will be turned as follows:

(A) Each of the $C-1$ source signals has the highest dynamical similarity to itself in normal and seizure onset.
(B) Each of the source signals has the lowest dynamical similarity to other source signals, far from seizure onset.
(C) The $C$th source signal has the highest dynamical similarity to itself, far from seizure onset.
(D) The $C$th source signal, far from seizure onset, has the lowest dynamical similarity to seizure onset.

These assumptions are made to separate a dynamical source which is inactive in far from seizure onset and is activated during seizure onset, in other words, the dynamic of this source is stationary until the seizure onset.

With these assumptions, a new cost function must be considered that covers these assumptions. Thus, new *IndFac* and *StaFac*

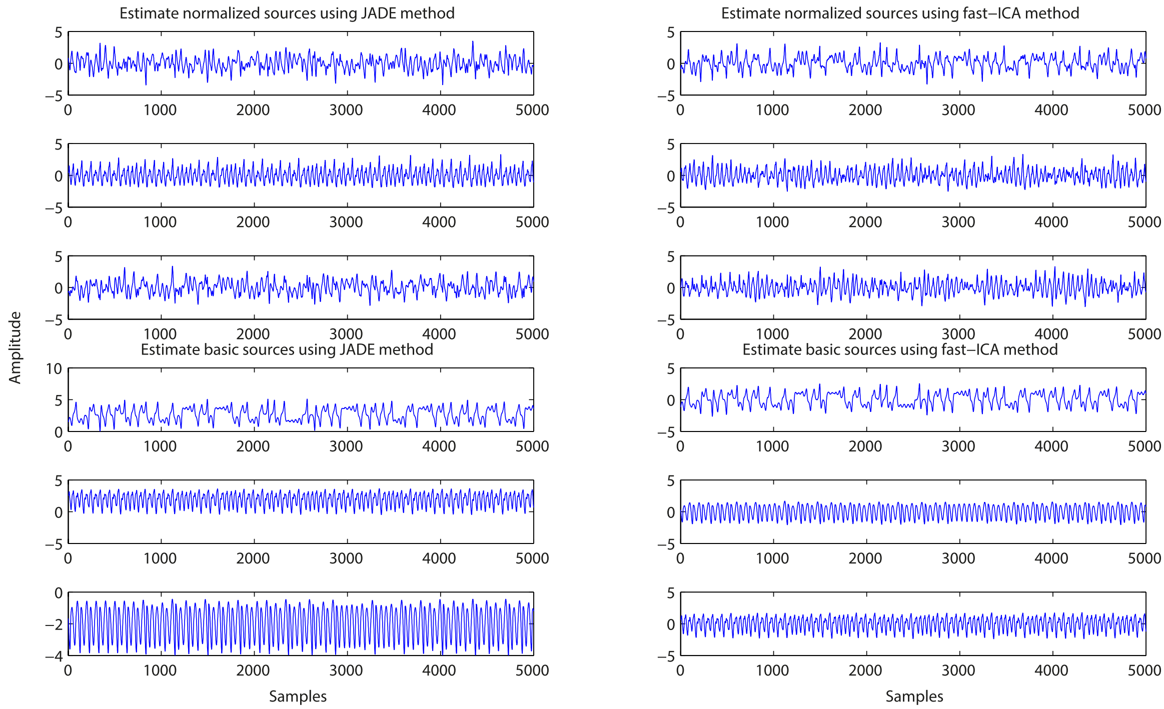


**Fig. 3.** Result of estimating basic and transformed source signals using JADE and fast ICA.

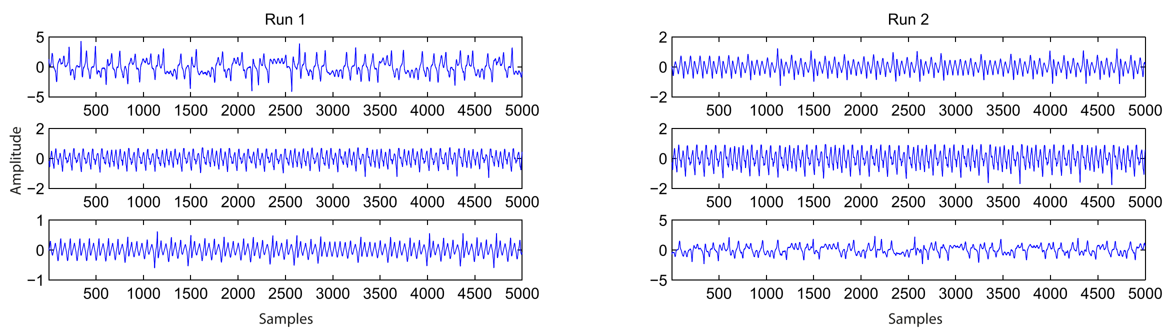


**Fig. 4.** Results of two runs of the proposed method to estimate transformed source signals.

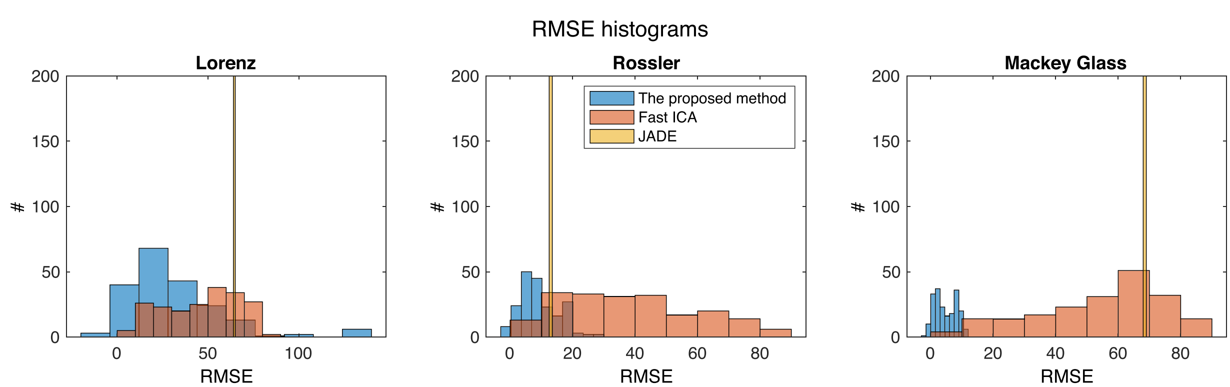


**Fig. 5.** Histogram of RMSE of the proposed method, fast-ICA, and JADE for the normalized estimated sources.

are redefined as Eqs. (10) and (11).

$$StaFac = \frac{1}{C-1}\sum_{i=1}^{C-1}\{\frac{1}{D*(D-1)}\sum_{k=1}^{D}\sum_{l=1,l\neq k}^{D} Sim_{FSBLE}(\hat{S}_i^k,\hat{S}_i^l)\} + \frac{1}{(D-1)(D-2)}\sum_{k=1}^{D-1}\sum_{l=1,l\neq k}^{D-1} Sim_{FSBLE}(\hat{S}_C^k,\hat{S}_C^l) \quad (10)$$

$$IndFac = -\frac{1}{C*(C)}\sum_{i=1}^{C}\sum_{j=1,j\neq i}^{C} \times \left\{\frac{1}{(D-1)*(D-2)}\sum_{k=1}^{D-1}\sum_{l=1,l\neq k}^{D-1} Sim_{FSBLE}(\hat{S}_i^k,\hat{S}_j^l)\right\}$$

$$-\frac{1}{D-1}\sum_{k=1}^{D-1} Sim_{FSBLE}(\hat{S}_C^k, \hat{S}_C^D) \tag{11}$$

The first part of Eq. (10) is related to the first assumption and the second part is related to the third assumption. Maximizing *StaFac* makes the first $C-1$ source signals to have the least changes in dynamic related to seizure over of all times. The second and fourth assumptions correspond to the first and second part of the *IndFac* equation respectively. Maximizing Eq. (11) makes all sources to be dynamically independent and also $C$th source has the highest dynamical changes depending on seizure onset.

In order to use this method according to the mentioned assumptions, first, we need $D$ segments of $C$ channel of EEG signals which $D-1$ segments come from the inter-ictal period and one segment comes from seizure onset. By minimizing the $CostFcn$, the $B$ matrix for each patient will be achieved. The $B$ matrix will be used to estimate the seizure-related source signal and this signal is used to predict epileptic seizures.

After finding the unmixing matrix for each of the patients, the epileptic seizure-related source can be estimated and the same approach as [50] is applied on the estimated epileptic-related source to predict epileptic seizures using the FSBLE method. Shortly, the FSBLE similarity between each 30 s window of the estimated epilepsy-related source signal and the same length of signal belonging to ten minutes before is calculated. Then, by using a threshold-based detection system, seizures are predicted.

Winterhalder et al. [51] proposed a framework for evaluating epileptic seizure prediction methods, which is used in this study. Based on this framework, two time margins need to be defined as seizure prediction horizons (SPH) and seizure occurrence period (SOP). SPH is defined as a time interval which starts when the prediction system forecasts an upcoming epileptic seizure by raising an alarm and it is expected there will not be any seizure during this time margin. SOP is defined as the period during which the seizure is supposed to occur. Therefore, a prediction alarm is a true positive (TP) if there will be no seizure after the alarm and during the SPH, and the seizure will occur inside the SOP. Any alarms in different situations would be false positive (FP) and the rate of FP in an hour is defined as the false positive rate (FPR). Based on these definitions and for an applicable prediction system in a real-world situation, SPH and SOP are two parameters that need to be set. Ideally, a small value of SOP and a large value of SPH is desirable which means the system can predict seizures very early, and also it can specify a narrow period for seizure occurrence. Also, when there is a tuning parameter such as the threshold in the proposed method, it is important to compare different systems by considering both rate of TP (sensitivity) and FPR. FPR-Sensitivity diagrams can be used to show the performance of a method. Also, for comparing sensitivities of different methods, it important to make the comparison in the same value of FPR.

#### *3.2.1. Dataset*

The Freiburg EEG database 2007 [52] is used in this study to evaluate the performance of the proposed method. This dataset contains invasive EEG recordings of 21 patients suffering from medically intractable focal epilepsy. The data were recorded at the Epilepsy Center of the University Hospital of Freiburg. The EEG data are available on 6 channels at a 256 Hz sampling rate.

For each of the patients, there are datasets named “ictal” and “interictal”, the former containing files with epileptic seizures and at least 54 min of pre-ictal data and the latter containing approximately 24 h of EEG-recordings without seizure activity. Therefore, in this study SOP+SPH is considered smaller than 54 min.

#### *3.2.2. Results*

The sensitivity of the prediction method is considered as the main measure of the performance. Therefore, the results should consider SPH, SOP, and FPR as parameters or variables. First, SPH and SOP are set to 600 and 1800 s respectively and Fig. 6 shows the diagram of FPR-Sensitivity based on different thresholds on the FSBLE similarity values.

The result which is presented in Fig. 6 is achieved by setting the $D$ value of 5 and in the FSBLE method $m$, $n$, and $S$ are practically considered as 3. Also, as the dataset contains 6 channels of EEG signals. In order to have the most number of achievable sources, $C$ is considered as 6. In this figure, the result is compared to periodic and random methods which aim to predict seizure periodically or randomly respectively [50].

To investigate the effect of SPH and SOP on the performance of the method, the sensitivity of the system is calculated at an approximately fixed FPR (FPR≈0.33) with different values of SPH and SOP. Fig. 7 shows the sensitivity of the proposed method in a fixed false positive rate and different SPH and SOP values.

As it is expected, increasing the SOP at a fixed SPH can only increase the sensitivity. However, there is not the same relationship between SPH and sensitivity in a fixed SPH. Table 2 reports the result of a number of studies which used the same approach to evaluate their results as a basis for a comparison with the proposed method. All of the Table 2 studies used the threshold technique to predict epileptic seizures and did not use any part of the dataset, especially the ictal recordings, to train a system or estimate any parameters. This paper only considered the studies for comparison which have used the same dataset and the same approach of evaluation and prediction. As we described in [50], there are at least two different approaches to design an epileptic seizure prediction system. In the first approach, interictal and ictal data of patients are used in system design to train a classifier. On the other hand, in the second approach, the decision is usually made by a threshold-based technique on a measure. Therefore, there is no need for ictal data and this approach is more suitable for real-world applications. This study considered some studies with the second approach for comparison.

The results in Table 2 show that the proposed method can achieve a competitive sensitivity at the same FPR, SPH, and SOP values. The higher sensitivity in the same FPR values means the method predicts more seizures than others with the same rate of false prediction. Also, the results are presented in SPH time of 600–1450 s, which means the patients have more than 20 min to be ready for the seizure and avoid dangerous situations. The proposed method has higher sensitivity in comparison to most of these studies in the same parameters and even in higher SPH and lower SOP.

## 4. Discussion

This paper aims to present a new approach for blind or semi-blind signal source separation based on the dynamics of signals using the FSBLE similarity index. Using FSBLE as the core of the proposed method needs initialization of some parameters such as $m$, $n$, and $S$. These parameters must be set by considering computation time and impact of those as it is described in [23]. Also, because of using FSBLE for dynamical similarity measurement, the proposed cost function is not differentiable. Therefore, it is necessary to find the minimum of the cost function by using a search algorithm. Using metaheuristic search algorithms can reduce computation time. In this study, the imperialist competition algorithm is chosen practically because of faster convergence. Although the method tries to reach the global minimum, it is possible that the search algorithm cannot find the minimum because of the limitation of such methods. Fig. 8 shows the cost function value based on

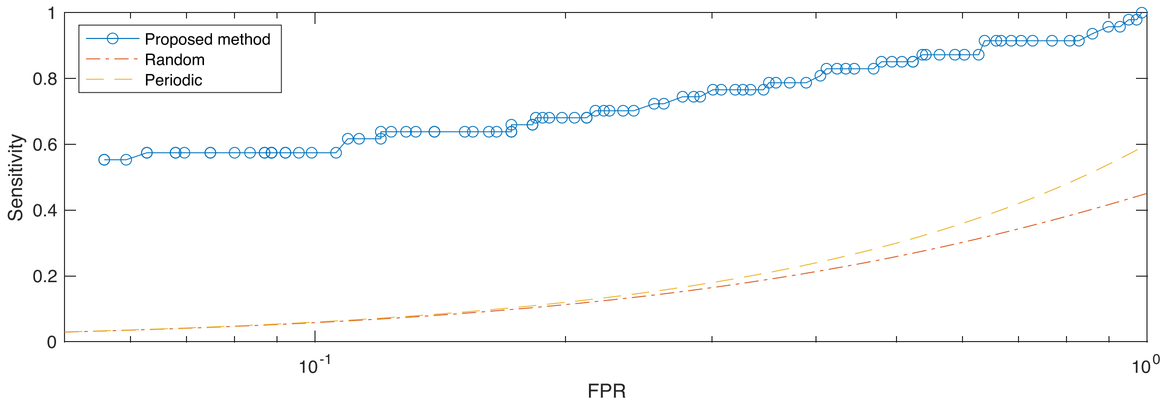


**Fig. 6.** FPR-Sensitivity diagram of the proposed method to predict epileptic seizure in comparison of random and periodic methods.

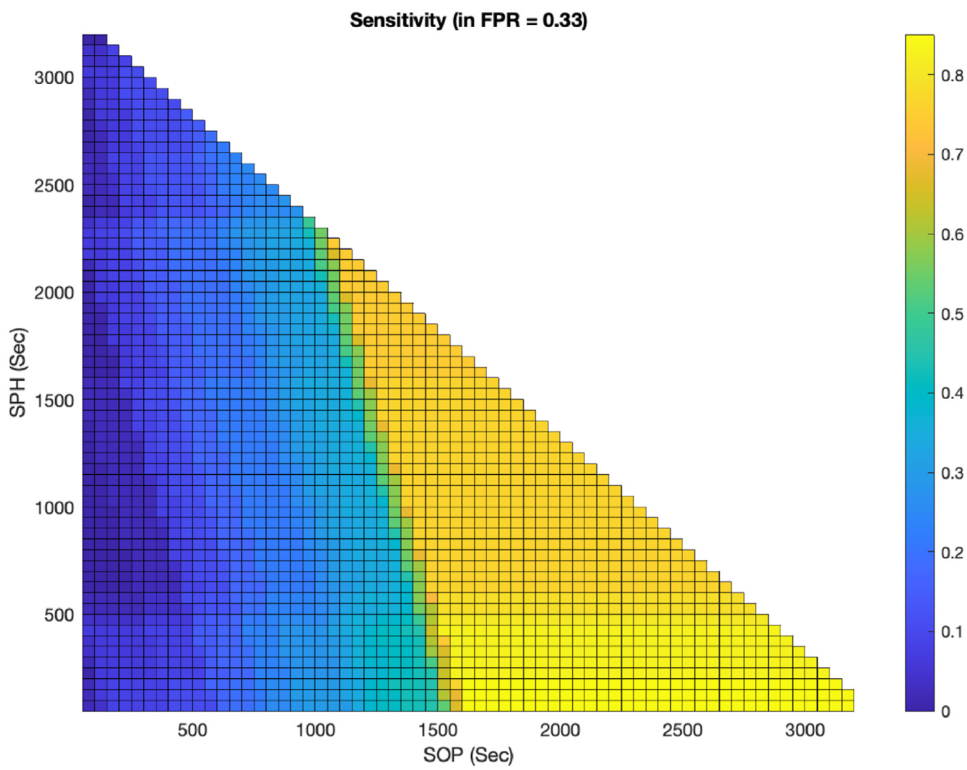


**Fig. 7.** Sensitivity of the proposed method in different SPH and SOP and FPR=0.33.

**Table 2**
Comparison of the results of studies with same evaluation approach.

| Method | SOP (Sec) | SPH (Sec) | FPR ($\frac{1}{hour}$) | Sensitivity (%) | Number of patient |
|---|---|---|---|---|---|
| SBLE [50] | 3060 | 180 | 0.33 | 63.75 | 21 |
| Lag Synchronization index [53] | 1800 | 600 | 0.3 | $\sim$ 75 | 21 |
| Dynamical Similarity Index [54] | 1800 | 5 | 0.33 | $\sim$ 57 | 21 |
| Effective Correlation Dimension [54] | 1800 | 5 | 0.33 | $\sim$ 39 | 21 |
| Phase synchronization [55] | 1800 | 600 | 0.33 | $\sim$ 80 | 10 |
| This study | 1450-1800 | 600-1450 | 0.33 | 76.60 | 21 |

two elements of unmixing matrix for observation signals in Fig. 2. plxrunonpara

The proposed cost function is designed practically to meet two main assumptions. Different cost functions can be defined based on assumptions, which should be defined based on the problem and the application. For example, in Section 3.2 the main assumptions and the cost function were adapted to the epileptic seizure prediction application to estimate a specific dynamical source. Also, the proposed method can be used as a semi-blind source separation by using existing information and changing the main assumptions.

The proposed method needs longer signals in comparison to some other methods such as ICA. In such methods, lengths of signals must be selected by considering stationarity of signal and large enough for reliable estimation [56]. However, the proposed method needs the consideration of dynamical stationarity between

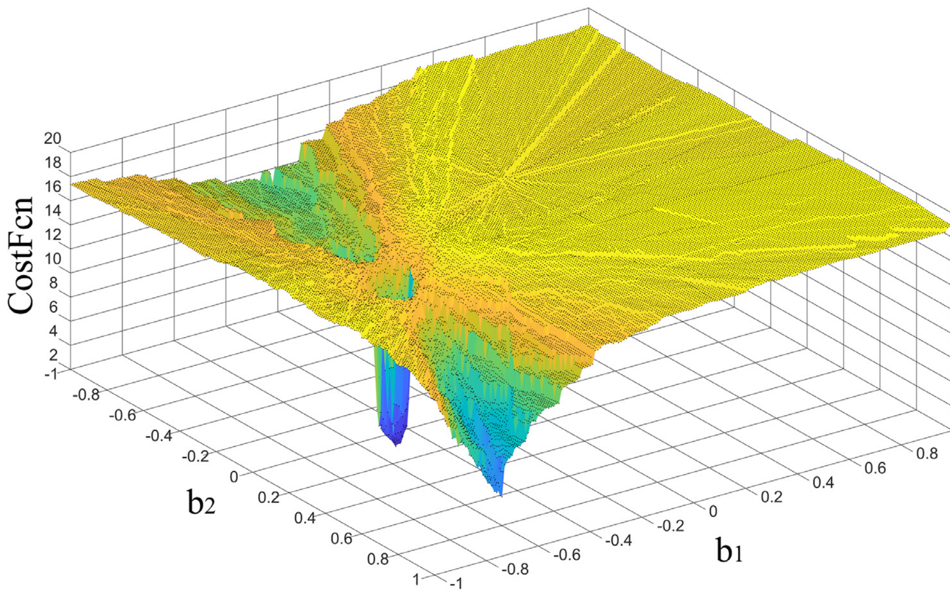


**Fig. 8.** The *CostFcn* values based on two elements of unmixing matrix.

each of the $D$ segments. Because of the undifferentiability limitation and using search algorithms, the proposed method works slower than the derivative-based iterative methods. For example, the computation time of 200 repeated estimates of the sources in Section 3.1 was $364 \pm 42$ s for the proposed method which is significantly higher than fast-ICA and JADE ($< 0.01$ s) on the same machine. The computation time and convergence of the method are directly related to the parameters of the selected search method, and the search method and its parameters should be chosen based on the application. On the other hand, the proposed method has the ability to estimate Gaussian source signals and also is flexible to be adapted with specific applications. In Section 3.2, the proposed method was used to find the seizure-related dynamical source by adapting the assumptions to the problem. This approach may also be useful to find other dynamical sources in other applications. For example, in the field of EEG signal processing, it can be used to estimate dynamical sources of a specific state of the brain such as sleep stages or emotions states.

## 5. Conclusion

This study proposes a new approach for blind source separation base on dynamical similarity. The proposed method can be used for nonlinear and chaotic source signals estimation. The method uses the FSBLE similarity measure to quantify dynamical stability and independency of estimated sources. Because of using FSBLE, it was necessary to search for the unmixing matrix and this study used the imperialist competition algorithm as a metaheuristic search algorithm. Unlike many other methods such as ICA-based methods, the proposed method, in its function field (nonlinear and chaotic signals), does not force any constraint to sources and their distribution. Also, if we consider the proposed approach without fixed assumptions, as it is used in Section 3.2, the approach has the flexibility to be adapted for more complex situations to estimate a specific source signal. The results show the ability and potential of the approach. In the real-world application of the epileptic seizure prediction, it was shown that by using the proposed approach we can be closer to an efficient system.

## Declaration of Competing Interest

None.

## CRediT authorship contribution statement

**Hamid Niknazar:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Ali Motie Nasrabadi:** Conceptualization, Resources, Supervision, Project administration, Funding acquisition. **Mohammad Bagher Shamsollahi:** Supervision.

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## Appendix A. Fuzzified statistical behavior of local extrema

The fuzzified statistical behavior of local extrema is a dynamical similarity measure which was developed for nonlinear signal analysis. The FSBLE method in [23] is described in detail. This method estimate dynamical similarity in five main steps as it is presented in Fig. A.9 as follows:

Step 1. In the first step, local extrema (LEs) of two signals are found. The amplitude and time difference of consecutive local extrema is used in the next steps.

Step 2. The possible value of the amplitude and time difference of consecutive LEs are divided into $m$ and $n$ intervals by using the histograms of their values. After calculating the histograms, the boundaries of the intervals are selected with the condition of making the same area of $m$ and $n$ segmented separately.

Step 3. The selected values of boundaries are used to define $m+1$ and $n+1$ membership functions on amplitude and time difference of consecutive local extrema values respectively. Hence, for each LE the $mfm$ matrix is constructed by using the value of membership into each membership function for amplitude and time difference using Eq. (A.1).

$$mfm_i = \begin{bmatrix} LEi_{A1,T1} & \dots & LEi_{A1,T(n+1)} \\ \vdots & \ddots & \vdots \\ LEi_{A(m+1),T1} & \dots & LEi_{A(m+1),T(n+1)} \end{bmatrix}$$

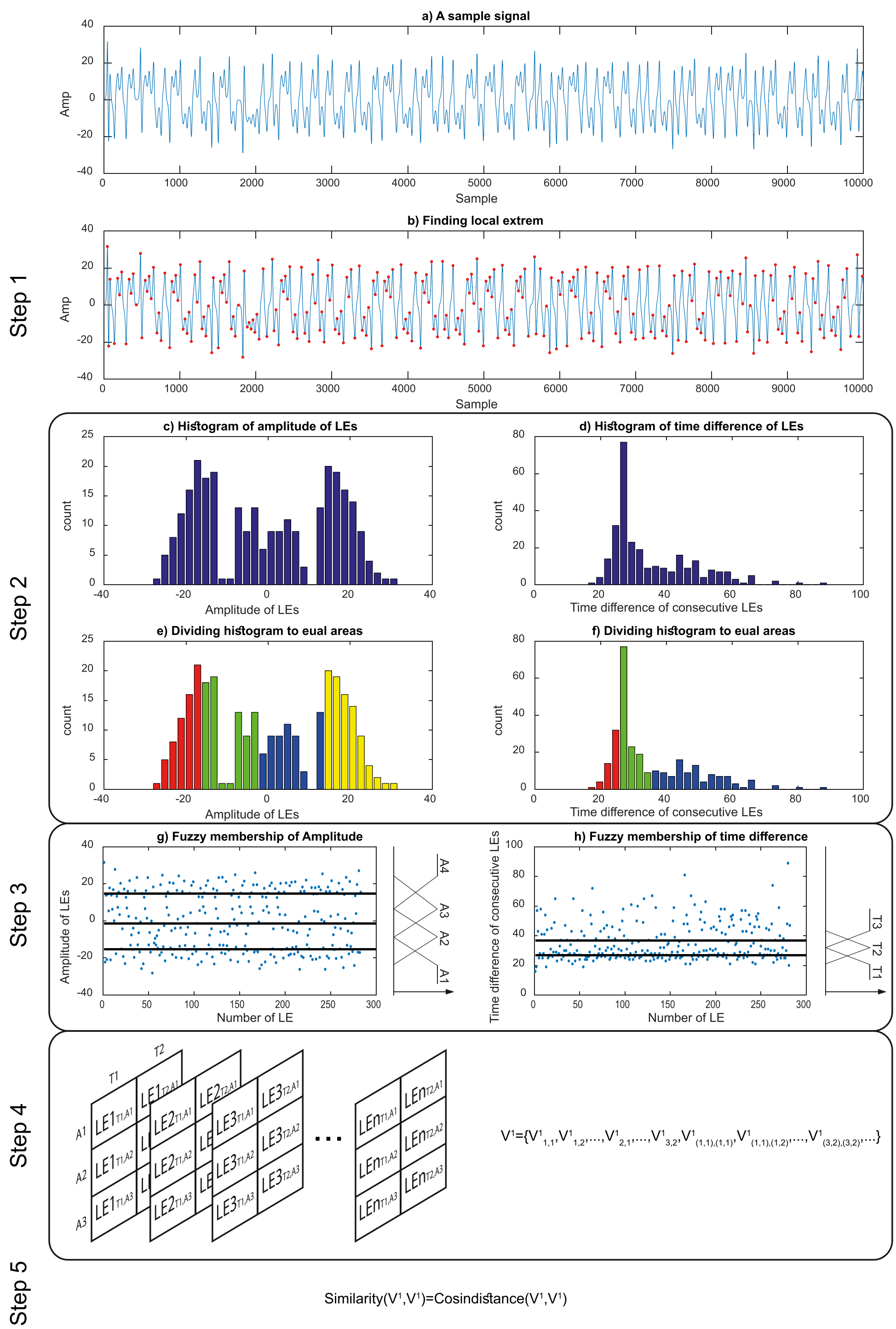


**Fig. A.9.** The five steps in FSBLE method to measure dynamical similarity between two signals [23].

$$, LEi_{Ao,Tp} = mf_{Ao}(Amp(LEi)) * mf_{Tp}(TD(LEi)) \quad (A.1)$$

where $LEi_{Ao,Tp}$ is the value of the membership of $i$th LE to $mf_{Ao}$ and $mf_{Tp}$ membership functions. $mf_{Ao}$ and $mf_{Tp}$ are $o$th and $p$th membership function of amplitude (Amp) and time difference (TD) respectively. Thus, each signal is transferred into a sequence of $mfm$ matrices.

Step 4. For a sequence with length of $s$ the number of $\sharp(s)$ (Eq. (A.2)) features ($V$) are extracted from the sequence of $mfm$ matrices using Eq. (A.3).

$$\sharp(s) = ((m+1).(n+1))^s \quad (A.2)$$

$$V_{(a1,b1)_1,\dots,(as,bs)_s} = \frac{1}{N-s}\Big[\sum_{i=1}^{N-s} mfm_i(a1,b1) * \dots * mfm_{i+s}(as,bs)\Big]^{\frac{1}{s}} \quad (A.3)$$

where $N$ is the length of the signal.

For each signal $V_S^{signal}$ is constructed by changing $s$ from one to $S$ (Eq. (A.4)).

$$V_S^{signal} = \Big\{V_{(1,1)}, \dots, V_{(m+1,n+1)}, V_{(1,1),(1,1)}, V_{(1,1),(1,2)}, \dots,$$

$$V_{(m+1,n+1),(m+1,n+1)}, \cdots \}\tag{A.4}$$

This vector has dynamics information of sequential local extrema and will be used in similarity measurement.

Step 5. As the final step, $V_S^{signal}$ of two signals are used to calculate dynamical similarity using cosine distance as Eq. (A.5).

$$Similarity(V_S^1, V_S^2) = \frac{\langle V_S^1, V_S^2 \rangle}{\|V_S^1\|.\|V_S^2\|}\tag{A.5}$$

where $\|V\|$is norm of $V$ and $\langle V_S^1, V_S^2 \rangle$ is inner product of $V_S^1$ and $V_S^2$.

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