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The Algorithm Research of Blind Source Separation Based on Spatial Time-frequency Distribution for FSK Signal

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Abstract. Track circuit is an important guarantees of the railway security, a large number of non-stationary interference and noise induce from the electrified railway block in the process of the FSK signal transmission in the track circuit, seriously affect its testing accuracy and reliability. Aiming at the problem, this paper propose a algorithm of blind source separation (BSS) based on the spatial time-frequency distribution (STFD) and singular value decomposition(SVD). First using SVD on mixed signal to remove noise, then reassign spectrum and pre-white in STFD domain, improve the selection function of single autoterm in STFD matrix, the get unitary matrix by joint diagonal, last estimated out the mixed matrix. The algorithm is not limited with Gaussian source signal, so it has strong applicability. Computer simulation results indicate that the algorithm to effectively separate the non-stationary signals and improve its BSS performance in a low signal-to-noise (SNR) environment.

Introduction

Research on blind source separation from the last century, 80 years, J. Herault and C. Jutter both in the process of study on neural network is proposed. It refers to the lack of sources and channels, under the condition of prior knowledge, only by the observed mixed signal source signals. Blind source separation technique of "blind" feature so that it has a very wide scope, many local and foreign scholars has done extensive research on it, put forward many different algorithms are used for a variety of different fields. [4,5] Blind source separation technology will be applied to FSK Separation of signal interference, obtains good separation effect, but only for non-Gaussian and Nonstationary signal and signal to noise ratio has certain requirements. But in reality, the signal tends to be unstable, time-frequency analysis is one of the effective means to analyze the signal [6,7].

Response to these defects of method, this paper presents an improved algorithm of blind source separation based on spatial time-frequency distribution, first Mixed signals using singular value decomposition technology for noise reduction and In time and frequency domain signal white; and using an improved "source" selection criteria, extracted spatial time-frequency distribution in the matrix when the conditions are met, the last joint Diagonalization, are unitary matrices, and estimated mixing matrix.

Theoretical Framework

Basic Model for Blind Source Separation

Under normal circumstances, to deal with multidimensional signal can be represented as:

$$x(t) = y(t) + n(t) = As(t) + n(t) \tag{1}$$

in which: $x(t) = [x_1(t), x_2(t), \cdots, x_m(t)]^T$ is m number observe signal vector; $s(t) = [s_1(t), s_2(t), \cdots, s_n(t)]^T$ is n number non-stationary signal vector, and assumes that satisfy the conditions of zero mean and uncorrelated; $n(t)=[n_1(t),n_2(t),\cdots,n_m(t)]^T$ is independent of noise signals;

You can see from above, observation signal $x(t)$ is a linear combination of $s(t)$; A is $m\times n$ unknown full-rank matrix $(m\geq n)$.Additive noise $n(t)$ model is complex random process with zero mean and independent of the source signal.

$$E\left\{n(t+\tau/2)n^*(t-\tau/2\right\}=\delta(\tau)\sigma^2 I_m \tag{2}$$

in which, I_m is m dimensional identity matrix, $\delta(\tau)$ is Dirac δ function, σ^2 represents the unknown noise variance for all the observed signal is assumed to be the same.

Blind source separation is in the case of unknown matrix how to mix, mixing matrix A estimate of the $\hat{A}$. Once the $\hat{A}$ is known, the source signal can be estimated from the equation:

$$\hat{s}(t)\overset{def}{=}\hat{A}^{-1}x(t)\approx Cs(t)+\hat{A}^{-1}n(t) \tag{3}$$

In which, mark^{-1} pseudoinverse of the matrix, C the generalized elementary matrices. $\hat{s}(t)$ is the source signal restored. Due to the uncertainty of blind source separation, recovery and sorting of the signal may be different, but the signal frequency information feature to restore the most, this is the significance of blind source separation technology.

Spatial Time-frequency Distribution (SPTFD) and Single-source Frequency Selection

The discrete-time frequency distribution discrete form of Cohen Class signal $x(t)$ is :

$$D_{xx}(t,f)=\sum_{l=-\infty}^{\infty}\sum_{m=-\infty}^{\infty}\phi(m,l)x(t+m+l)\times x^*(t+m-l)e^{-j4\pi fl} \tag{4}$$

in which t and f represent the variables of time and frequency, $\phi(m,l)$ is time-frequency kernel, mark * represent the conjugate transpose.

The time-frequency distribution (cross-TFD) discrete form of the two signals $x_i(t)$ and $x_j(t)$ is:

$$D_{x_ix_j}(t,f)=\sum_{l=-\infty}^{\infty}\sum_{m=-\infty}^{\infty}\phi(m,l)x_i(t+m+l)\times x_j^{\ *}(t+m-l)e^{-j4\pi fl} \tag{5}$$

(4) and (5) to define the source signal and the signal STFD array as follows: $\left[D_{ss}(t,f)\right]_{ij}=D_{s_is_j}(t,f)$ $i,j=1,\ldots,n$,

$$\left[D_{xx}\left(t,f\right)\right]_{ij}=D_{x_ix_j}(t,f)\quad i,j=1,\ldots,m\text{, in which } D_{ss}(t,f)\in C^{N\times N}\text{, } D_{xx}(t,f)\in C^{M\times M} \tag{6}$$

In linear data model and do not take into account noise situations, STFD Matrix takes the simple form

$$D_{xx}(t,f)=AD_{ss}(t,f)A^H \tag{7}$$

The new coordinates are defined as follows:

$$\hat{t}(x;t,f)=\frac{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}sW_h(t-s,f-\xi)W_x(s,\xi)dsd\xi}{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}W_h(t-s,f-\xi)W_x(s,\xi)dsd\xi} \tag{8}$$

$$\hat{f}(x;t,v)=\frac{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\xi W_h(t-s,f-\xi)W_x(s,\xi)dsd\xi}{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}W_h(t-s,f-\xi)W_x(s,\xi)dsd\xi} \tag{9}$$

$$S_x^{(r)}(t',v';h)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}S_x(t,f;h)\delta(t'-\hat{t}(x;t,f))\delta(v'-\hat{f}(x;t,v))dtdv \tag{10}$$

$$\begin{aligned} trace\left(D_{xx}^{c}\left(t,f\right)\right) &= trace\left(UD_{ss}^{c}\left(t,f\right)U^{H}\right) \\ &= trace\left(D_{ss}^{c}\left(t,f\right)\right)\approx 0 \end{aligned} \tag{11}$$

in which $trace(\bullet)$ represent sign of matrix, ^{H} represent conjugate transpose of matrix.

The Algorithm of Blind Source Separation Based on Spatial Time-frequency Distribution

First, using the singular value decomposition technique m channel mixed signal noise, and in time and frequency domains, remove the correlation between signal and then obtain spatial time-frequency distribution of the data matrix, matrix time-frequency frequency when the selected parts, and finally the time-frequency joint diagonalization of the matrix, matrix is obtained, then estimated mixing matrix.

Specific steps are as follows:

（1） Taking into account the effects of aliasing noise, such as literature [8] in the singular value decomposition of mixed signals, after removing the smaller singular values, then inverse singular value decomposition, recover the signal.

（2） Eq.4, and eq.5 calculated signals STFD matrices, and eq.9 to rearrangements of the spectrum.

（3） Signal white, based on covariance matrix estimators in robustness in noisy environments than STFD matrices poor estimators, particularly when the signal is not stable. Therefore, this bleaching process using STFD matrices, replace the autocorrelation matrix. First time-frequency equalization, get $\tilde{D}_{xx}$, and calculate m number of the characteristic value $\lambda_1^{tf},\ldots,\lambda_m^{tf}$ of $\tilde{D}_{xx}$, According to the absolute values in descending order, as well as their corresponding eigenvectors。White noise under the assumption to estimate variance of white noise $h_1,\ldots,h_m$. The assumption of white noise environment to estimate variance of white noise $\hat{\sigma}^2$, $\hat{\sigma}^{tf}=\sqrt{\frac{1}{m-n}\sum_{i=n+1}^{m}\lambda_i^{tf}}$, it is the average of $m-n$ minimum eigenvalue of $\hat{R}_x$, n is the number of sources. Whiten signal is $z(t)=[z_1(1),\ldots,z_n(t)]=\hat{W}x(t)$。in which whiten matrix W is estimated as follow equation:

$$\hat{W}=[(\lambda_1^{tf}{}_1-\hat{\sigma}^{tf})^{-\frac{1}{2}}h_1,\ldots,(\lambda_n^{tf}-\hat{\sigma}^{tf})^{-\frac{1}{2}}h_n]^H,\ 1\le i\le n \tag{12}$$

（4） After seeking whiten spatial time-frequency distribution of matrix, The algorithm proposed this paper select M "single source point" $(t_i,f_i), i=1,2,\ldots$, and joint diagonalize the matrix M of time-frequency domain[9], get the unitary matrix U.

（5） Estimation of source signal is $\hat{s}(t)=UW_0X(t)$, mixed matrix A is $\hat{A}=W_0^{-1}U$.

Simulation Experiment

(1)The FSK signal with amplitude modulation signals are separated.

FSK signal carrier frequency $f_0=850Hz$, low frequency $f_d=26Hz$, frequency offset $\Delta f=55Hz$;FM jamming signal of frequency modulation signal $f_1=50Hz$,carrier frequency $f_2=300Hz$;sample frequency $f_s=4000Hz$, total sample 512 points.

Simulated signal based on type 1 calculate with amplitude modulation signals 2 group FSK mixed-signal, and mixed-matrix A can be freely selected, selected values are as follows:

$$A = \begin{bmatrix} 1 & 0.3 \\ 0.6 & 0.8 \end{bmatrix}$$

Observation signal added white noise, $SNR = 20dB$ .The observation signal time domain waveform, SPWVD time-frequency domain is shown in figure 1

You can see from figure 2, figure 3, based on SPWV of blind separation, completely recovery has source signal of time-frequency characteristics, to evaluation based on different of time-frequency distribution of non-smooth blind source separation algorithm of performance, respectively seeking take they estimated of source signal and original signal of time domain are square errors (RMSE) and similar coefficient , each species situation respectively implementation 100 times and get RMSE of mean values and standard deviations, as well as the similarity coefficients were values, as shown in table 1 below.

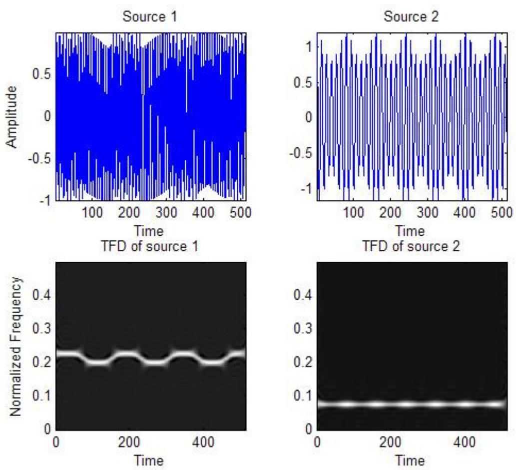

Figure 1. Source signals in time domain and its TFD.

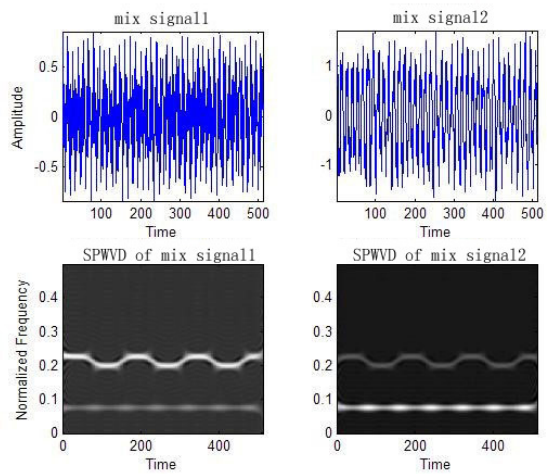

Figure 2. Observer signals in time domain and its TFD.

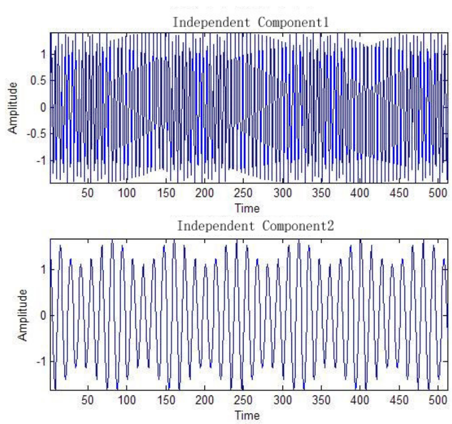

Figure 3. The waveform of separated signal based on SPWVD.

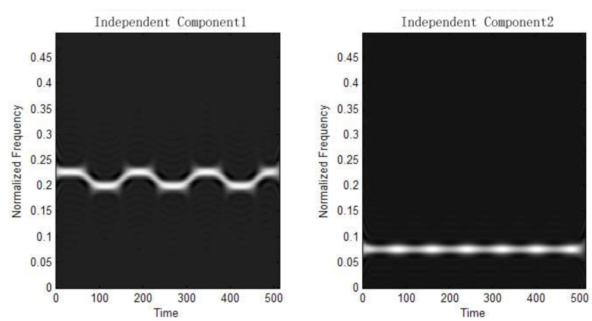

Figure 4. The TFD of separated signals based on SPWVD.

Table 1. The performance of BSS based on different STFD.

Time-Frequency Distribution	Source signal S1		Source signal S2	
	Estimated RMSE	Similarity Factor	Estimated RMSE	Similarity Factor
WVD	0.390±0.151	0.9377	1.690±0.047	0.9378
PWVD	0.3155±0.084	0.9503	1.712±0.023	0.9504
SPWVD	0.3158±0.071	0.9702	1.712±0.021	0.9705
PWVDR	0.3159±0.001	0.9601	1.712±2.709e-4	0.9606
SPWVDR	0.3159±0.001	0.9801	1.712±2.385e-4	0.9804

From table 1 it can be seen that WVD distribution algorithm for blind source separation of non-stationary, because there are serious cross, blind source separation and less effective than PWVD and SPWVD. After the time-frequency reassignment, STFD matrices to improve the time-frequency clustering, blind source separation performance improved further.

(2) FSK strength signals with amplitude modulation signals incorporated into white noise, based on SPWVD rearrange time-frequency distribution of different "single source" selection algorithm, source signal separation signal and correspond to the correlation coefficient with signal to noise ratio as Figure 5 shows. As can be seen by a new single self extracting ignorance of source separation separation performance than literature [9] algorithm and SAT algorithms have greatly improved.

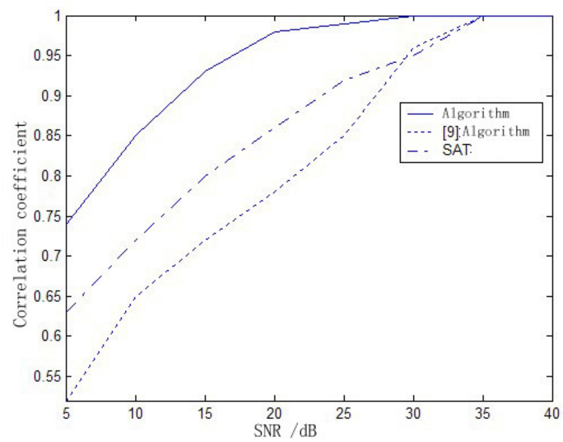

Figure 5. The correlation coefficient changing with different algorithm in SPWVD.

Conclusions

For FSK signal in non-stationary interference environments, parameters affected by the problem, using blind source separation algorithm of space time and frequency FSK signal amplitude modulation signal and separation of stochastic pulse interference signals. First time-frequency kernel-based on spatial time-frequency performance of blind source separation algorithms, theoretical analysis and computer simulation found that certain Snr, cross better suppress time-frequency distribution of blind source separation effect is ideal, by time-frequency reassignment time-frequency clustering to improve performance of blind source separation for further improvement. Then, under different signal to noise ratio is studied, using space-frequency isolation performance of blind source separation, shows that to a certain extent, the algorithm is insensitive white noise, and the use of time-frequency crossover inhibit good time-frequency distribution, has a better resistance to noise. Last documents [9] "single-source frequency" extraction and SAT algorithms compare the proposed algorithm in low SNR environments with better performance.

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