

Study of Noise Reduction about Economic time series data Based on ICA^{*}

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Abstract: This paper raised a new method about noise-reduction for 1D economic time series data based on ICA, making use of high rank statistical peculiarity of ICA, because of a large number of noises contained in economic series data. We expand 1D signal to many dims, drawing into invented noise components, and separate blind source. Compared to adapt-self filter, this method is excelenter. Authentic proof making effect clearly.

Key words: ICA ;economic time series data; noise reduction

I. INTRODUCTION

Adaptive filtering^[1] is about signal processing methods and techniques developed nearly 30 years, of which nonlinear adaptive filter has a good "self-regulation" and "tracking" capability, but it's less of practical application because of

complex calculations. The LMS algorithm, raised by Widrow and Hoff, Is widely used in practice, because of Small computation easy implementation, whos Basic iteration formula is

$$\begin{cases} e(t) = d(t) - X^T(t)W(t) \\ W(t+1) = W(t) + 2ue(t)X(t) \end{cases} \quad (1)$$

$W(t)$ is weight vector, $X(t)$ is input signal, $d(t)$ is output desired, $e(t)$ is error signal, u is Step factor.

Convergence speed and tracking speed are affected directly by u . Even The algorithms do not converge because of Inappropriate u , Shown in Figure1.

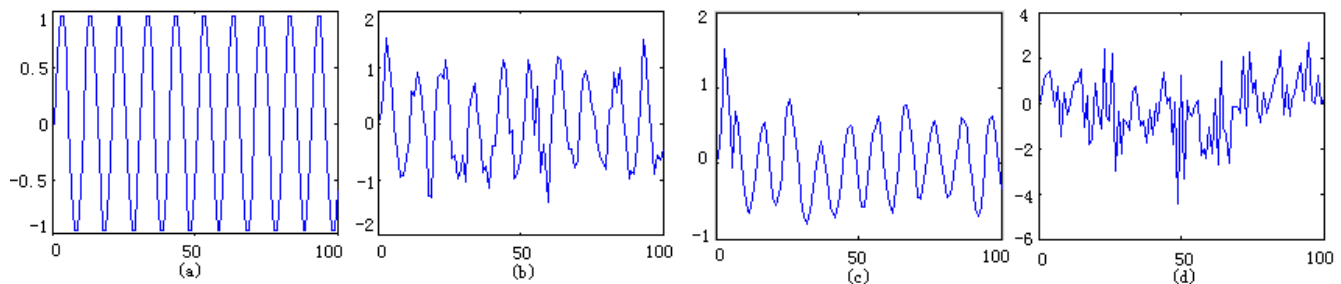


Figure1 the example of adaptive filter. (a) Real signal (output expected); (b) Signal with Gaussian white noise ;(c) $u=0.00001$, convergence ;(d) $u=0.3$, divergence.

In this paper, noise separation method based on independent component analysis is raised, because of this uncertainty adaptive filtering results, and do simulation and empirical analysis of the method.

II. NOISE REDUCTION TECHNOLOGY BASED ICA

The general model of ICA is

$$X(t) = AS(t) \quad (2)$$

Here, $X(t)$ is $m \times 1$ mixed vector, $S(t)$ is $n \times 1$ original signal column vector, A is $m \times n$ full rank mixing matrix. We find

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separation matrix W , S.T. $Y(t)=WX(t)$, under the assumption that the source component is statistical independence, to obtain the source signals estimated. Usually, signal observed is with a lot of noise signal when dealing with practical problems using ICA, so the model could expand

$$X(t) = AS(t) + N(t) \quad (3)$$

Here, $N(t)$ is $m \times 1$ noise vector.

Currently, many ICA algorithms more mature has been formed, of which JADE method is the more representative one, which albinos signal observed firstly, that

$$\begin{aligned} Z(t) &\stackrel{def}{=} WX(t) = W[AS(t) + N(t)] \\ &= US(t) + WN(t) \end{aligned} \quad (4)$$

In eq.(4), Estimating U depends high-order accumulation (fourth-order, generally).The define of matrix with fourth-order accumulation is

$$N = Q_z(M) \stackrel{def}{\Leftrightarrow} n_{ij} = \sum_{k,l=1}^n Cum(z_i, z_j^*, z_k^*, z_l^*) m_{lk}, 1 \leq i, j \leq n$$

When matrix A in eq. (3) degenerated into 1, output signal is one-dimensional observed signal with noise. Because ICA is one of multivariate statistical methods, whos handling objects

are multi-dimensional observation vectors. Appropriate virtual observation vectors must be involved in.

Considering the condition of p kinds of external noise, $N(t) = \sum_{i=1}^p a_i n_i(t)$, noisy observations could be expressed as

$X_1(t) = S(t) + N(t) = S(t) + \sum_{i=1}^p a_i n_i(t)$. If virtual observation vector is

$X_{virtual} = [x_2, x_3, \dots, x_{p+1}]^T = [n_1(t), n_2(t), \dots, n_p(t)]^T$, then EQ.(3)

could be written as

$$X = AS \Rightarrow X = \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_{M+1} \end{bmatrix} = \begin{bmatrix} s + \sum_{i=1}^p a_i n_i \\ n_1 \\ \dots \\ n_p \end{bmatrix} = \begin{bmatrix} 1 & a_1 & \dots & a_p \\ 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 \end{bmatrix} \begin{bmatrix} s \\ n_1 \\ \dots \\ n_p \end{bmatrix} = BS \quad (5)$$

EQ.(5) means that components in $n(t)$ are involved in X_i be addressed, and ICA can realize signal noise reduction and recover S , by identificating virtual full rank mixing matrix B . The process of noise reduction of one-dimensional observation signal is shown in Figure2.

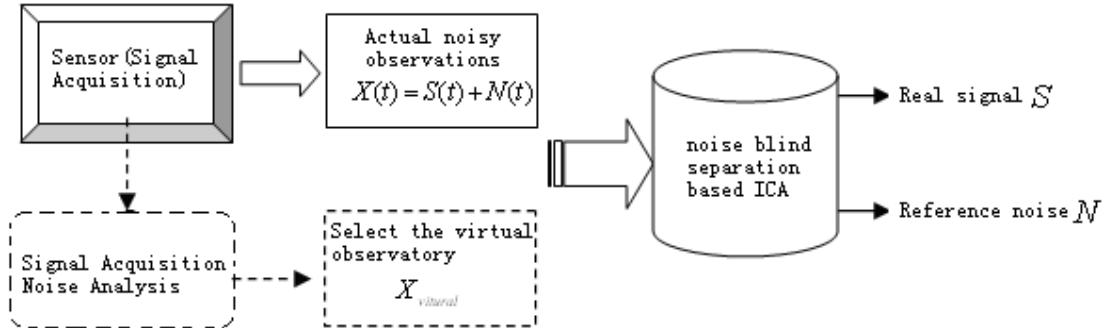


Figure2 the process of 1D signal noise reduction based on ICA

III. SIMULATION AND PRACTICE ANALYSIS

A. Simulation

We simulate for previous instances using the method proposed in section II. The result is shown in Figure3. Here, (a) is real signal isolated, (b) is noise isolated. From Figure3, we

can see that the effect of noise separation using ICA is better than adaptive filtering, and not affected by other factors.

B. Practice Analysis

This paper select historical data from the internet of China Securities Index (CSI HK 100 Index closed at all income, CSI

HK 100 Index Historical Quotes、Exchange Rate Information) as analysis object. The results shown in Figure4、5、6. From the results, we can see that data after noise reduction not only

remove the noise of time series data, but also maintain the overall trend with the original data.

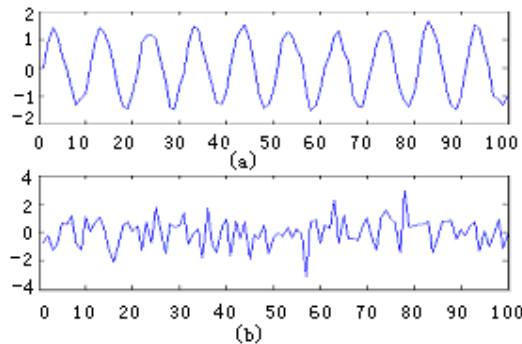


Figure3 noise-reduction based on ICA

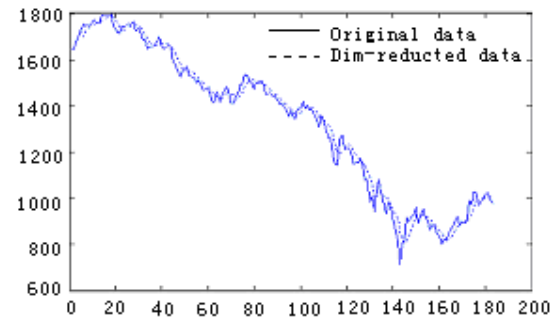


Figure4 the noise- reduction of the price of closing quotation

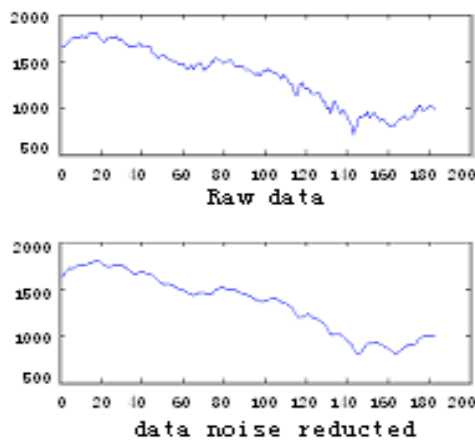


Figure5 the noise-reduction of historical prices

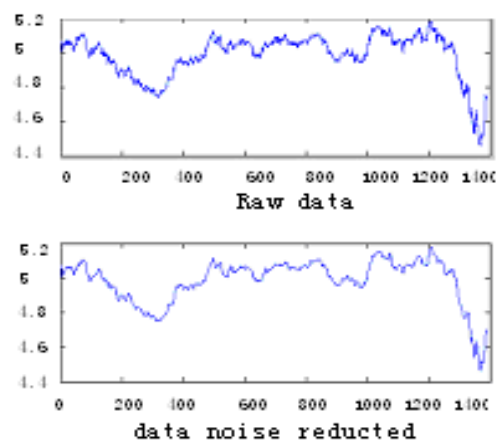


Figure6 the noise- reduction of exchange rate

IV. CONCLUSION

Compared with traditional adaptive filtering, the new method of noise reduction about economic time series data based on ICA, not only simple, but do not need to locate the features band of the signal to deal with, and does not require a large number of observation samples. At the same time, the results kept the trend of the signal characteristics change. On the other hand, what this article deals with is the additive noise, if it is multiplicative noise $X(t)=S(t)N(t)$, index transformation

$\lg(X(t))=\lg(S(t))+\lg(N(t))$ can be carried out first, of course, nonlinear ICA method can also be used to solve it.

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REFERENCES

- [1] Qi-Fa Zhang. Blind signal processing and application. Xi'an University of Electronic Science and Technology Press.2006
- [2] Xi-Wu Liu,Liu Hong,You-Ming Li. Independent component analysis and its testing application on seismic signal processing[J]. PROGRESS IN GEOPHYSICS.2003,1:90-96
- [3] Peng Cai,Shi-Jun Zhu. Noise elimination with independent component analysis[J] . PROGRESS IN EXPLORATION GEOPHYSICS.2007,1:30-35.
- [4] Le-Hao Fan,Xiao-Hui Qiu,Hai-Fei Si. The Technology of De-nosing Based on Independent Component Analysis[J]. JOURNAL OF JINLING INSTITUTE OF TECHNOLOGY .2006, 144-150.
- [5] J. Herault and C. Jutten.Space or time adaptive signal processing by Neural Network Models[J]. AIP Conf. Proc. 1986: 6-211.
- [6] P. Comen.Independent component analysis, a new concept.[J].Signal Processing, 1994, 36(3): 287-314.
- [7] A. J. Bell and T. J. Sejnowski.An information-maximization approach to blind separation and blind deconvolution[J].Neural Computation.1995,7(6): 1129-1159.
- [8] S. Amari, T. P. Chen and A. Cichocki.Stability analysis of learning algorithm for blind source separation.Neural Networks[J].1997,10(8):1345-1351.
- [9] T.W. Lee, M. Girolami and T. J. Sejnowski.Independent component analysis using an extended Infomax algorithm for mixed sub-Gaussian and super-Gaussian source[J] .Neural computation.1999,11(2):417-441.
- [10] A. Hyvarinen and E. Oja.A fast fixed-point algorithm for independent component analysis[J] .Neural Computation.1997,9(7):1483-1492.