BLIND SIGNAL SEPARATION BY COMBINING TWO ICA ALGORITHMS: HOS-BASED EFICA AND TIME STRUCTURE-BASED WASOBI

Petr Tichavský[1], Zbyněk Koldovský[1], Eran Doron[2], Arie Yeredor[2] and Germán Gómez Herrero[3]

[1]Institute of Information Theory and Automation,
Pod vodárenskou věží 4, P.O.Box 18,182 08 Prague 8, Czech Republic
tichavsk@utia.cas.cz, zbynek.koldovsky@tul.cz

[2]School of Electrical Engineering, Tel-Aviv University P.O.Box 39040, Tel-Aviv 69978, Israel
Eran@amimon.com, arie@eng.tau.ac.il

[3] Institute of Signal Processing, Tampere University of Technology, P.O.Box 553, 33101 TUT, Finland
german.gomezherrero@tut.fi

ABSTRACT

The aim of this paper is to combine two recently derived powerful ICA algorithms to achieve high performance of blind source separation. The first algorithm, abbreviated as EFICA, is a sophisticated variant of a popular algorithm FastICA, and is based on minimizing a nonlinear HOS criterion. That means that the algorithm ignores the time structure of the separated signals. The second algorithm is WASOBI, it is a weight-adjusted variant of popular algorithm SOBI, which utilizes the time structure of sources for their separation and does not exploit non-Gaussianity of the sources. For both algorithms it is possible to estimate their separation ability and thus optimally choose the most appropriate separating algorithm. The proposed combination of these algorithms is tested on separating autoregressive signals that are driven by i.i.d. random sequences drawn from a general Gaussian distribution with parameter α, and on separating linear instantaneous mixture of speech signals.

1. INTRODUCTION

Blind Source Separation (BSS), which consists in recovering original signals from their mixtures when the mixing process is unknown, has been widely studied problem in last two decades. Independent Component Analysis (ICA), a statistical method for the signal separation, is also well-known issue in the community. Its aim is to transform the mixed random signals into mutually independent components as much as possible.

The squared instantaneous linear ICA model (the number of the mixed signals is the same like the number of the original ones) of given data is

$$\mathbf{x} \quad = \quad \mathbf{A}\mathbf{s} \tag{1}$$

where $\mathbf{s}$ represents a $d \times N$ data matrix, composed of d rows, so that each row denotes one independent component.

The goal of independent component analysis is to estimate the mixing matrix $\mathbf{A}$ or, equivalently, the demixing matrix $\mathbf{W} = \mathbf{A}^{-1}$ or, equivalently, the original source signals $\mathbf{s}$. Without any loss of generality we can assume that the independent components are centered (have sample mean equal to zero) and scale normalized so that their sample mean square is equal to 1. Since the separation can be done up to the original order and signs of $\mathbf{s}$ we assume, for simplicity, that it was recovered perfectly. In simulations we use the re-ordering method proposed in [14].

For an estimate of the de-mixing matrix $\widehat{\mathbf{W}}$ interference-to-signal ratio (ISR) matrix is defined by

$$\mathbf{ISR}_{k\ell} = \frac{\mathbf{G}_{k\ell}^2}{\mathbf{G}_{kk}^2}, \tag{2}$$

where $\mathbf{G} = \widehat{\mathbf{W}}\mathbf{A}$. Total ISR of the k-th estimated signal is k-th element of a vector $\mathbf{isr}$, where

$$\mathbf{isr}_k = \frac{\sum_{\ell=1,\ell\neq k}^{d} \mathbf{G}_{k\ell}^2}{\mathbf{G}_{kk}^2}. \tag{3}$$

At least three possible kinds of the separation criteria and corresponding algorithms have been proposed in the literature. The original signals are modeled 1) as non-Gaussian i.i.d. processes [1, 2, 3, 6], 2) weakly stationary (WS) random processes driven by Gaussian white noise [7, 10], and 3) sequences of independent Gaussian variables with time-varying variances [5]. The aim of this paper is to develop a method that takes into account the two former models [9, 18]. A straightforward generalization would be to model the signals as WS processes driven by arbitrarily distributed white noise. However, derivation of an efficient algorithm for such model is a very difficult task. Instead, we focus on a combination of two recently derived powerful ICA algorithms: EFICA [6] and WASOBI [10, 11, 17], that are, under several assumptions, asymptotically efficient within the frame of the model 1 and 2, respectively. This means that they attain corresponding Cramér-Rao bounds (CRLB) [12, 13] when the original signals $\mathbf{s}$ match the appropriate model, and the ulterior conditions are fulfilled.

In case of real data processing, the theoretical assumptions are *not* fulfilled for the most part. For instance, EEG data comprise both time and spatial structure, therefore, the contradictory models 1 and 2 can be both used for partial separation at least. It is believed that a suitable combination of the models may improve factuality of the separated components [18].

This work was supported by Ministry of Education, Youth and Sports of the Czech Republic through the project 1M0572.

2. EFICA

EFICA is one of ICA algorithms that are based on non-Gaussianity of the original signals. The underlying assumption is that each row $\mathbf{s}_k$, $k = 1, \ldots, d$ contains N independent realizations of a random variable ξ_k having a non-Gaussian distribution function $F_k(x) = P(\xi_k \leq x)$[1].

The algorithm EFICA is a sophisticately modified version of the popular algorithm FastICA [2]. We shall not present it here in details, only note that the algorithm utilizes adaptive choice of the contrast function. Let $g_k(\cdot)$ be the nonlinear function chosen for $k-$th signal, $k = 1, \ldots, d$ and let $g_k'(\cdot)$ be its derivative. Finally, let "E" stand for the expectation operator, which can be realized by the sample mean. Then the asymptotic ISR matrix has as elements

$$\mathbf{ISR}_{k\ell} = \frac{1}{N} \frac{\gamma_k(\gamma_\ell + \tau_\ell^2)}{\tau_\ell^2 \gamma_k + \tau_k^2(\gamma_\ell + \tau_\ell^2)} \qquad (4)$$

where

$$\begin{array}{rclcrcl} \gamma_k &=& \beta_k - \mu_k^2 & \quad & \mu_k &=& \mathrm{E}[\widehat{\mathbf{s}}_k g_k(\widehat{\mathbf{s}}_k)] \\ \tau_k &=& |\mu_k - \rho_k| & & \rho_k &=& \mathrm{E}[g_k'(\widehat{\mathbf{s}}_k)] \\ & & & & \beta_k &=& \mathrm{E}[g_k^2(\widehat{\mathbf{s}}_k)] \end{array}$$

In the best possible case, i.e., when g_k equals the score function ψ_k of the corresponding distribution F_k (if it exists) for all $k = 1, \ldots, d$, (4) is equal to the corresponding CRLB [13], which is

$$\mathrm{CRLB}_{k\ell} = \frac{1}{N} \frac{\kappa_\ell}{\kappa_k \kappa_\ell - 1}, \qquad (5)$$

where $\kappa_k = \mathrm{E}[\psi_k^2(\mathbf{s}_k)]$.

The theoretical ISR was shown to approximate the empirical ISR very well provided that the independent components are i.i.d., that means that they have no time structure. If the components are strongly time dependent, the theoretical ISR appears to be biased, in particular, overly optimistic. Nevertheless, in the proposed combination of EFICA with WASOBI, in cases where the time dependence is strong while the spatial structure is vanishing, WASOBI estimate will likely be used, and the inaccurate EFICA estimate is not needed et all.

3. WASOBI

WASOBI is one of ICA algorithms that utilize time structure of the independent components for their separation from the mixture and use only second-order statistics. Like SOBI and other second-order blind source separation methods, the computation proceeds via pre-selected number of time-shifted correlation matrices

$$\widehat{\mathbf{R}}_\mathbf{x}[\tau] = \frac{1}{N} \sum_{n=1}^{N} \mathbf{x}[n]\mathbf{x}^T[n+\tau] \qquad \tau = 0, \ldots, M-1 \quad (6)$$

(assuming $N + M - 1$ samples are available).
The observations' correlation matrices take the structure of

$$\mathbf{R}_\mathbf{x}[\tau] = \mathbf{A}\mathbf{R}_\mathbf{s}[\tau]\mathbf{A}^T \qquad \forall \tau \qquad (7)$$

[1]To be exact, at most one of the independent components is allowed to have Gaussian distribution

where due to the spatial independence of the sources, their correlation matrices $\mathbf{R}_\mathbf{s}[\tau] = \mathrm{diag}[R_1[\tau], R_2[\tau], \ldots, R_d[\tau]]^T$ are diagonal matrices and $R_k[\tau]$ is the auto-correlation of $s_k[n]$ at lag τ.

In WASOBI, the relation (7) is rewritten as

$$\mathrm{vec}\{\mathbf{R}_\mathbf{x}[\tau]\} = (\mathbf{A} \odot \mathbf{A})\boldsymbol{\lambda}_\tau \qquad (8)$$

where $\mathrm{vec}\{\cdot\}$ is the well known vec operator, $\odot$ denotes the Khatri-Rao product (a column-wise Kronecker product), and $\boldsymbol{\lambda}_\tau = \mathrm{diag}\{\mathbf{R}_\mathbf{s}[\tau]\}$. The computation proceeds by mean square fitting of the sample covariance matrices (6) by the structure (7) by means of the model parameters $\mathbf{A}$ and $\boldsymbol{\lambda}_0, \ldots, \boldsymbol{\lambda}_{M-1}$, using theoretically justified optimum weights. The optimum weights are estimated using a consistent initial estimate of the de-mixing matrix, provided e.g. by the SOBI algorithm.

The resultant asymptotic ISR matrix is equal to the corresponding CRLB. It can be shown that if all sources are AR of order $M-1$, then

$$\mathbf{ISR}_{k\ell} = \mathrm{CRLB}_{k\ell} = \frac{1}{N} \frac{\phi_{k\ell}}{1 - \phi_{k\ell}\phi_{\ell k}} \frac{\sigma_k^2 R_\ell[0]}{\sigma_\ell^2 R_k[0]} \qquad (9)$$

where σ_k^2 is the variance of the innovation sequence of the source,

$$\phi_{k\ell} = \frac{1}{\sigma_k^2} \sum_{i,j=0}^{M-1} a_{i\ell} a_{j\ell} R_k[i-j]$$

$\{a_{i\ell}\}_{i=0}^{M-1}$ are AR coefficients of the $\ell-$th source with $a_{0\ell} = 1$ for $k, \ell = 1, \ldots, d$.

It is worth to note that the optimal weights of WASOBI can still be found in the non-Gaussian case, by using estimates of higher order moments (up to fourth) of the sources - which may be computationally prohibitive, but still more convenient in the "efficient WASOBI" framework.

4. PROPOSED METHODS

The key advantage of the forementioned methods is their known theoretical performance which can be estimated via (4) and (9) using consistent estimates of the incorporated quantities, i.e., sample means and Yule-Walker or other AR coefficients estimates, respectively. This provides a very fast way how to evaluate relevance of the estimated components compared to the computationally demanding bootstrap methods [15]. A common drawback of both approaches is the fact that there is no theoretical background if the original signals do not fully agree with the assumed model (i.i.d. or Gaussian WS process), therefore (4) and (9) is valid for the given signal model only. Nevertheless, one can expect that the bias behavior is not much critical as shown in the simulation examples. Thanks to time-structure model used by WASOBI and its known performance (9) bootstrap surrogates of time-structured data are not required, which it is difficult to construct [15].

The next advantage is that both algorithms used (EFICA and WASOBI) are asymptotically efficient methods, indeed, for the given model of the original signals, therefore, good accuracy of their combination may be expected. This is in spite of the fact that if WASOBI is optimal, i.e. the model 2 holds, EFICA is totally useless and vice versa. Finally, note that the estimated ISR matrix via (4) or (9) is not symmetric, in general, compared to the Separability matrix proposed in [15] (see Figure 4).

A straightforward approach how to combine EFICA and WASOBI would be a simple decision-based method: to decide between signals estimated via EFICA and WASOBI by comparing (4) and (9). However, this gives satisfactory result only when all signals are well estimable by both algorithms and, thus, improves the accuracy of the estimates only. Here, we propose two alternative approaches intended for reliable and accurate independent components estimation.

4.1 Algorithm EFWS

The first method, called EFWS, proceeds in two main steps:

1. (a) Apply algorithm EFICA on the mixed data $\mathbf{x}$; let $\mathbf{s}^{EF}$ be the estimated source signals,
   (b) estimate the achieved ISR matrix $\mathbf{ISR}^{EF}$ via (4) and the corresponding vector $\mathbf{isr}^{EF}$, and
   (c) compute a *hypothetically* achieved ISR matrix by WASOBI $\mathbf{ISR}^{WA}$ of the estimated signals $\mathbf{s}^{EF}$ through (9) and the corresponding vector $\mathbf{isr}^{WA}$.
2. For each $k = 1, \ldots, d$ accept the estimated signal $\mathbf{s}_k^{EF}$ iff $\mathbf{isr}_k^{EF} > \mathbf{isr}_k^{WA}$. Let the accepted and the rejected signals be denoted by $\mathbf{u}$ and $\mathbf{v}$, respectively. Then, apply algorithm WASOBI either on
   (a) orthogonal complement of $\mathbf{u}$ in the subspace spanned by the rows of $\mathbf{x}$ (*orthogonal approach*) or
   (b) subspace of the rejected signals $\mathbf{v}$ (*non-orthogonal approach*).

The orthogonal complement can be found using the well known Gram-Schmidt process. Note that since both EFICA and WASOBI do not use the orthogonality constraint, the results obtained by the orthogonal and no-orthogonal approaches are different, in general.

4.2 Algorithm COMBI

The second method, abbreviated as COMBI, is more sophisticated method than EFWS at the expense of higher computational demand. It proceeds in following steps:

1. Let $\mathbf{z} = \mathbf{x}$
2. Apply both algorithms EFICA and WASOBI on $\mathbf{z}$; let the estimated source signals be $\mathbf{s}^{EF}$ and $\mathbf{s}^{WA}$, respectively. Similarly, the estimated ISR matrix are $\mathbf{ISR}^{EF}$ and $\mathbf{ISR}^{WA}$, and the corresponding vectors $\mathbf{isr}^{EF}$ and $\mathbf{isr}^{WA}$.
3. Let $E = \min_k \mathbf{isr}_k^{EF}$ and $W = \min_k \mathbf{isr}_k^{WA}$
4. If $E < W$,
   (a) accept those signals $\mathbf{s}^{EF}$ for which $\mathbf{isr}_k^{EF} < W$ and redefine $\mathbf{z}$ either as
      i. orthogonal complement of the selected signals $\mathbf{s}^{EF}$ in the subspace spanned by the rows of $\mathbf{z}$ (*orthogonal approach*) or
      ii. rejected signals of $\mathbf{s}^{EF}$ (*non-orthogonal approach*)

   else,
   (b) accept those signals $\mathbf{s}^{WA}$ for which $\mathbf{isr}_k^{WA} < E$ and redefine $\mathbf{z}$ either as
      i. orthogonal complement of the selected signals $\mathbf{s}^{WA}$ in the subspace spanned by the rows of the previous $\mathbf{z}$ (*orthogonal approach*) or
      ii. rejected signals of $\mathbf{s}^{WA}$ (*non-orthogonal approach*).
5. If there are more than one rejected signals, go to (2). Otherwise, if any, accept the rejected signal.

Both algorithms are proposed in two variants: the *orthogonal* and the *non-orthogonal* approach. They differ in the choice of the subspace of the to-be further improved signals. The non-orthogonal approach chooses the subspace of the rejected signals while the orthogonal one takes orthogonal complement of the accepted signals. The former assumes "good" estimate of the rejected subspace and may be more accurate since it relaxes the orthogonality constraint [4]. On the other hand, the latter approach should be used when reliability of the rejected signal subspace is questionable. We believe that the approach may be useful, e.g. in case of EEG data processing, which is the subject of further research. For the present, we use the non-orthogonal approach only.

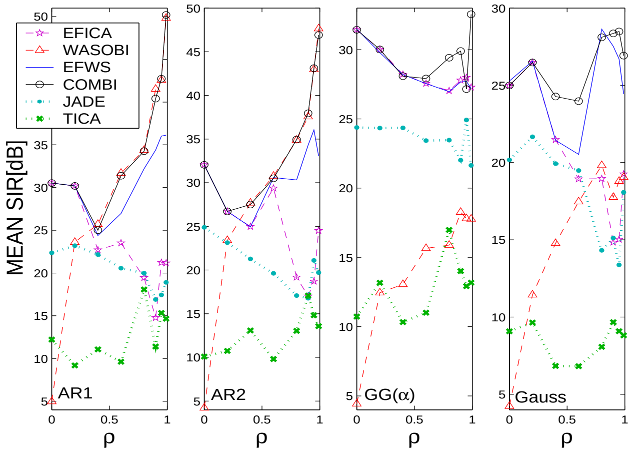

Figure 1: Average SIR achieved in separation of four signals AR1, AR2, GG(α), and Gauss for $\alpha = 1$ and $\rho \in [0, 1)$.

5. SIMULATIONS

An illustrative comparison with known ICA algorithms [1, 2, 3, 9, 10] has been conducted to demonstrate the facilities of the proposed methods. Four signals of length $N = 1000$ were mixed with a random matrix: two AR processes generated from white noise with generalized Gaussian distribution with parameter α (GG(α) - for definition see, e.g., Appendix B in [6]) with AR parameters $(1, \rho)$ (in the picture designated by AR1) and $(1, -\rho)$ (AR2), respectively, an i.i.d. process with GG(α) distribution (GG(α)), and a Gaussian white

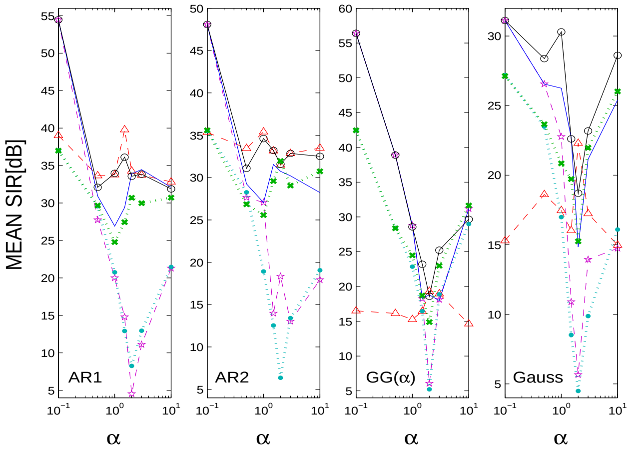

Figure 2: Average SIR achieved in separation for $\rho = 0.7$ and $\alpha \in [0.1, 10]$.

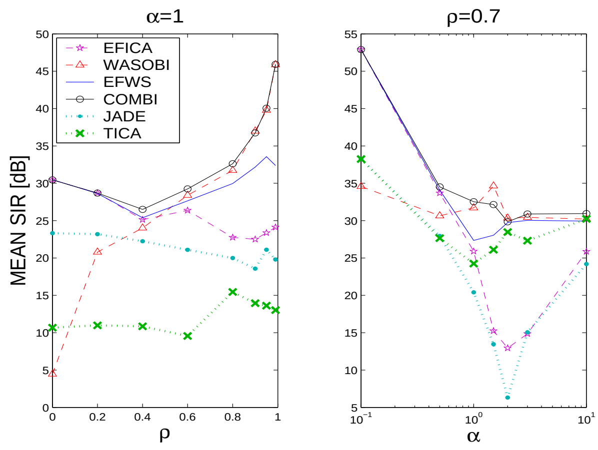

Figure 3: Sum of achieved SIRs of all signals for a fixed $\alpha = 1$ and a fixed $\rho = 0.7$, respectively.

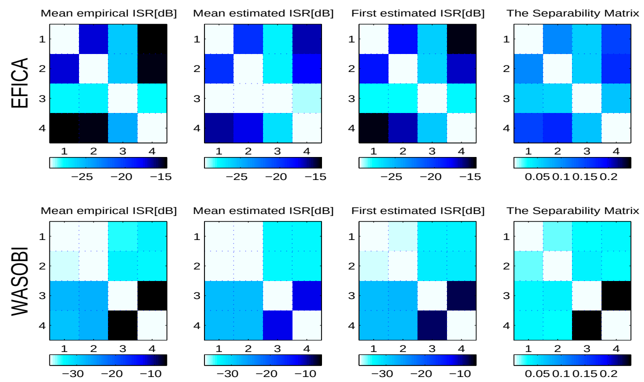

Figure 4: Mean empirical, average estimated and first estimated ISR matrix together with the Separability matrix [15] acquired when separating four signals: AR1, AR2, GG(α), and Gauss with $\alpha = 1$ and $\rho = 0.7$. Note that elements of the Separability matrix are defined in different units than those of the ISR matrix.

noise (Gauss). The experiment was repeated in 100 independent trials for each setup of parameters α and ρ taken from $\alpha \in [0.1, 10]$ and $\rho \in [0, 1)$. The mean achieved SIRs of the estimated signals are shown in figures 1 and 2, respectively, for a fixed $\alpha = 1$ and a fixed $\rho = 0.7$.

Note that for ρ "small" the signals have no time structure while the spatial structure grows with α being far from 2. Here, EFICA gains, but WASOBI lacks the time-information. By contrast, for $\rho \to 1$ the time structure of the two AR processes is significant while their spatial structure vanishes due to the Central Limit Theorem. In that cases, WASOBI outperforms EFICA. This is demonstrated in figure 3, where overall achieved SIR (of all signals together) from the experiments (fixed $\alpha = 1$ and fixed $\rho = 0.7$) is shown. As can be seen, both the proposed methods COMBI and EFWS benefit from partly contradictory advantages of the algorithms EFICA and WASOBI. Moreover, they are able to estimate the Gaussian i.i.d. signal, which has neither the temporal nor the spatial structure, thus, in case of WASOBI and EFICA, cannot be estimated unless all the other signals are estimable.

The performance of the ISR estimators (4) and (9) are presented in figure 4. The empirical ISR matrix achieved by EFICA and WASOBI when separating the four signals from the previous experiment (for $\alpha = 1$ and $\rho = 0.7$) is shown together with the average estimated one from 100 independent trials. An estimated ISR matrix in one (the first) trial is presented also to see the agreement with the mean empirical SIR and the averaged estimate from all trials. This points at good usability of the estimators. For comparison, the Separability matrix, introduced by Meinecke et al. in [15], computed by the bootstrap method proposed ibidem is included also. The average empirical ISR matrices achieved by the novel methods EFWS and COMBI in the same experiment are shown in figure 5.

To demonstrate the performance of the algorithm on real data, 10 speech signals of length $N = 5000$ were randomly selected from a database of isolated words[2] containing about 200 samples. After centering and normalization, the data were mixed with a random matrix, and consequently separated. Mean and median SIR obtained in 100 independent trials are summarized in Table 1.

The achieved accuracy of the novel methods is only slightly higher in this case. This is caused by the optimistic bias in ISR estimate (4) mainly. The order of AR modeling in WASOBI, consequently in (9), was chosen equal to 10. For illustration, a method making an ideal decision between EFICA and WASOBI estimates, i.e. a decision using empirical SIR of each estimated signal, would achieve mean SIR at 36.82 dB and median SIR at 31.78 dB. It should be noted that although nonparametric NPICA algorithm was very accurate, it has the drawback of being computationally much more intensive [6] than EFWS and COMBI, especially for high-dimensional datasets.

[2]http://noel.feld.cvut.cz/vyu/dzr/cislovky/OBRACENE_BYTY/

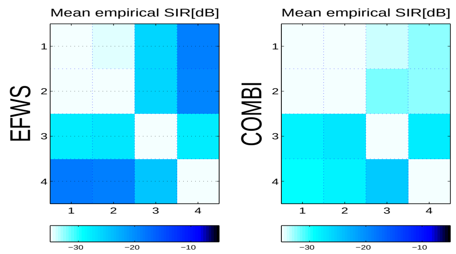

Figure 5: Average empirical ISR matrix achieved by the proposed algorithms EFWS and COMBI.

6. CONCLUSIONS

In this paper we have proposed novel ICA algorithms that effectively combine two powerful ICA methods EFICA and WASOBI, thus, allow separation of signals that are either i.i.d. non-Gaussian sequences or stationary Gaussian processes. Their wider applicability and superior accuracy were demonstrated by computer simulations by separation of stationary processes drawn from a general Gaussian distribution.

Table 1: Achieved mean and median SIR of 10 separated speech signals averaged over 100 independent trials.

Algorithm	MEAN [dB]	MEDIAN [dB]
EFICA	35.86	27.84
WASOBI	31.85	28.73
EFWS	35.86	27.88
COMBI	35.87	27.89
NPICA	35.80	30.40
FastICA	27.36	25.03
JADE	24.21	21.77
SOBI	23.95	20.67
ThinICA	23.98	21.43

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