RESEARCH ARTICLE OPEN ACCESS

An Efficient Blind Source Separation Based on Adaptive Wavelet Filter and SFA

Subi C , Ramya P2

1SUBI C. Author is currently pursuing M.E (Software Engineering) in Vins Christian College of Engineering.
2Ramya P M.E. Software Engineering, Asst prof in Vins Christian College of Engineering.
e-mail:subiprabamca@gmail.com,

Abstract:
Slow Feature Analysis (SFA) for vector-valued functions of several variables and apply it to the problem of blind source separation, in particular to image separation. It is generally necessary to use multivariate SFA instead of univariate SFA for separating multi-dimensional signals. For the linear case, an exact mathematical analysis is given, which shows in particular that the sources are perfectly separated by SFA if and only if they and their first-order derivatives are uncorrelated. A new construction of nonlinear locally adaptive wavelet filter banks by connecting the lifting scheme with the idea of image smoothing. The WAF consists of two parts. The first part is a wavelet transform that decomposes into seven frequency bands. The second part is an adaptive filter that uses the signal of the seventh lowest-frequency band among the wavelet transformed signals as primary input and a constant as reference input. To evaluate the performance of the WAF, two baselines wandering elimination filters are used a commercial standard filter with a cutoff frequency of 0.5 Hz and a general adaptive filter.

Index Terms—*Image separation, blind source separation, slow feature analysis, slow feature analysis, wavelet filtering.*

I. INTRODUCTION

Blind source separation is an important and exciting domain of research, with numerous potential applications in signal and image processing, telecommunication, speech recognition etc. this work, generalize the original univariate formulation of SFA, which is suitable for scalar valued sources in one variable, to a multivariate formulation, which is suitable for vector-valued sources in several variables.

This allows us to unmix several color images and not only, e.g., have several sounded sources An exact mathematical analysis is given that shows in particular that the sources are perfectly separated by SFA if and only if they and their first order derivatives are uncorrelated

For standard SFA, the output signals are uncorrelated. Thus if the original sources are correlated, it is not possible to achieve an accurate separation. When the sources are correlated, the following technique, decorrelation filtering (i) use a linear filter to decorrelate, in a statistical sense, the sources and their derivatives in the mixtures (ii) apply linear SFA to the filtered mixtures, obtaining an unmixing matrix (iii) apply the unmixing matrix just obtained to the original mixtures. If the filtered sources are perfectly separated by this unmixing matrix, so are the original sources. An appropriate decorrelation filter can be numerically obtained by solving a nonlinear optimization problem over a large set of images. Extensive numerical experiments demonstrate that decorrelation filtering reduces correlations between the original sources and their derivatives, leading to a significant improvement of SFA, in agreement with the theoretical analysis and predictions.

Decorrelation filtering can be applied to any linear separation method whose output signals are uncorrelated, for the case the original sources are correlated. One such method is ICA. While do not have the exact mathematical justification for this case, as with SFA, since decorrelation does not imply statistical independence, demonstrate experimentally that decorrelation filtering improves the separation quality of ICA significantly.1 Furthermore, find that decorrelation filtering increases the kurtosis of an image, which makes them more non-Gaussian, a crucial advantage for ICA. This, along with the decorrelation effect, helps speed up the running time for ICA, as demonstrated by experiments. One key challenge in blind source separation is to determine the number of original sources when it is unknown. When the number of mixtures is greater than or equal to the number of sources, this number, along with the original sources, can be determined by a simple regularization technique. Also discuss the more challenging scenario where the number of mixtures is less than the number of sources, and provide partial results.

A new construction of nonlinear locally adaptive wavelet filter banks by connecting the lifting scheme with the idea of image smoothing. The WAF consists of two parts. The first part is a wavelet transform that decomposes into seven frequency bands. The second part is an adaptive filter that uses the signal of the seventh lowest-frequency band among the wavelet transformed signals as primary input and a constant as reference input. To evaluate the performance of the WAF, two baselines wandering elimination filters are used a commercial standard filter with a cutoff frequency of 0.5 Hz and a general adaptive filter.

Related work: Many results available in the literature on the problem of image separation some algorithm utilizing ICA for image separation include: for separating lighting and reflections for separating astrophysical images for separating real-life images.

SFA method is differential decorrelation in which the mixing matrix is obtained by simultaneously diagonalizing two different differential correlation matrices which can be carried out by solving a generalized eigenvalue problem.The original sources can be dependent but their sub components in some frequency bands are mutually independent to estimate a filter to extract the independent sub-components and apply ICA to the filtered sources: the filter was estimated by minimizing the mutual between outputs

Decorrelation filtering can (i) give a theoretical analysis for an arbitrary number of sources (ii) give an empirical assessment of the method for upto 20 sources (iii) give a theoretical and empirical analysis for the case when the number of sources is not same as number of mixture (iv) provide another decorrelation filter of size 5*5 along with its empirical performance (v) Demonstrate experimentally that it is generally necessary to employ multivariate SFA to separate multi-dimensional signals(vi)provide a running time comparison between SFA, fastICA and filtering + fast ICA, along with an empirical analysis of the effect of decorrelation filtering on signal kurtosis which helps explain the significant speed up of Filtering + fastICA over fastICA alone (vii) provide an example of separation for astrophysical images, which are quite different from the images (viii) provide a non-technical overview of the method.

II. PROPOSED METHOD

In blind source separation, the input signal is assumed to be a mixture of some sources and the task is to recover the sources without any detailed knowledge about the sources or the mixing. Since nothing is known about the sources in detail, the separation can only be done on the basis of some general statistical properties.In SFA the assumption is that the sources are uncorrelated and have maximally different time scales, so that extracting the fastest and the slowest possible signals from a linear mixture of two sources should recover the sources. SFA is to assume that the sources are uncorrelated and have uncorrelated derivatives. While the assumption of uncorrelation seems obvious (statistical independence also implies uncorrelation), it is not generally valid. Images, for instance, tend to be brighter in the upper half than in the lower half, because light often comes from the top and the sky is brighter than the ground. In order to be still able to apply the above-mentioned techniques to correlated sources, apply a decorrelation operation on the data first, before doing the unmixing. Focus on images here and assume that the decorrelation operation takes the form of a linear spatial filter, i.e. a convolution of the image with a small kernel.

Assume you had two correlated images and a linear mixing matrix available. Then the normal procedure of mixing and unmixing would be to mix the images with the mixing matrix and then apply SFA to it to recover the images. This would not work, since the original images are correlated but the extracted images are uncorrelated by construction.

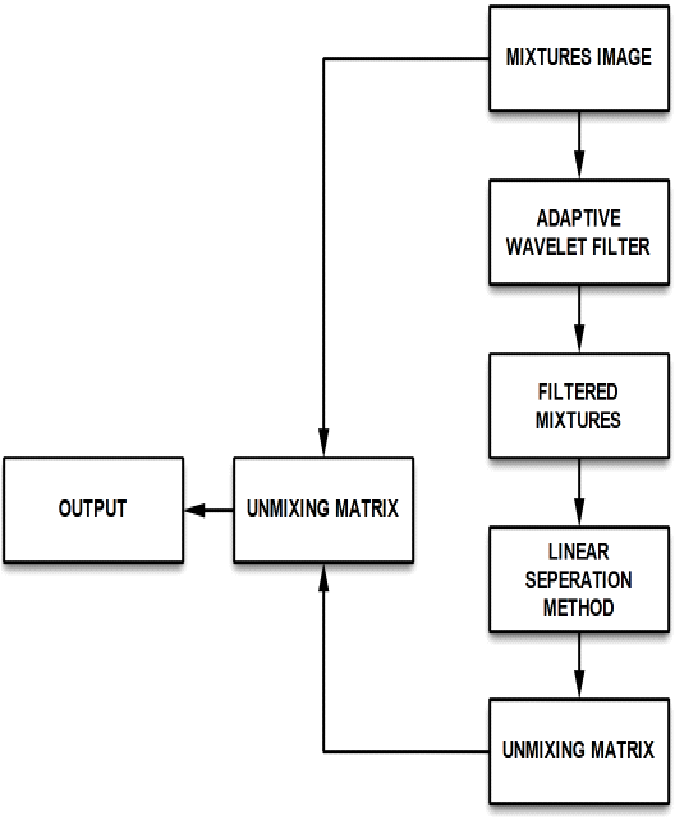

Fig1: Adaptive Wavelet Filtering for Blind Source Separation.

To fix that, you could apply the Adaptive wavelet filter to the images, then mix the filtered images and apply SFA to do the unmixing. That should yield a proper unmixing matrix that you could also apply to the mixtures of the original images. If you did not have the original images and the mixing matrix but only the mixed images and the mixed filtered images, you could proceed similarly: First determine the unmixing matrix on the mixture of the filtered images and then apply the unmixing matrix to the mixture of the original images to extract those.

Unmixing correlated images can thus be achieved as follows, if the mixing is linear:

1. Filter the mixed original images to obtain the mixed filtered images.
2. Apply the linear unmixing algorithm, e.g. SFA, to the mixed filtered images to estimate the unmixing matrix.
3. Apply the unmixing matrix to the mixed original images to extract the estimated original images.

A. Adaptive wavelet filter

It first partitions a time series into segments (or windows) of length 2n+1 points, where neighboring segments overlap by n+1 points. Thus, the time scale introduced by the algorithm is n+1 sample points. For each segment, fit a best polynomial of order K. Note that k=0 and correspond to piece-wise constant and linear fitting, respectively. Denote the fitted polynomial for the i^{th} and $(i+1)^{th}$ segments by $y^{(i)}(l1)y^{(i+i)}(l2)$,l1,l2=1,2n+1, respectively. Note the length of the last segment may be smaller than 2n+1 and define the fitting for the overlapped region is represented as given bellow.

$Y^{(c)}(l) = w_1 y^{(i)}(l + n) + w_2 y^{(i+1)}(l)$,l = 1,2,….,n + 1 …..1

In eq(1) the weights decrease linearly with the distance between the point and the center of the segment. Such a weighting ensures symmetry and effectively eliminates any jumps or discontinuities around the boundaries of neighboring segments. In fact, the scheme ensures that the fitting is smooth at the non- boundary points, and has at least the right- or left-derivative at the boundary points. Secondly apply the shrinkage function.

1) Wavelet transform of the observed data
2) Threshold the resulting wavelet coefficients
3) Inverse wavelet transforms to obtain an estimation of the signal.

(i) Optimal Wavelet Filter

Optimal wavelet Filter can be used to identify more repeated pattern very easily and also segment more different pixel from other pixel optimal filter use an Artificial BEE colony based wavelet filter algorithm that is used to separated more than two image accurately. Optimal wavelet filter is used to identify more texture images very perfectly. Advantages of this method are used to separate more than two images perfectly comparing to the previous method.

B. Linear separation

After applying adaptive wavelet filter to the images, then mix the filtered images and apply SFA to do the unmixing. Assume that the input is x = Ms, with sources s = s(t) = (s_1(t),...,s_N(t $))^T$ and an unknown invertible N × N matrix M. It measure the similarity between an extracted source y and the an original source s by their correlation. Assume that the sources both have zero mean and unit variance then,

$$\text{Corr}(y, s) = E(ys) = 1-\{E[(y-s)^2]\}/2 \quad \ldots\ldots (2)$$

In eq(2), the input is x = Ms, with sources s = s(t) = (s_1(t),...,s_N(t $))^T$ and an unknown invertible N × N matrix M. It measure the similarity between an extracted source y and the an original source s by their correlation

III. LINEAR MIXTURES THAN SOURCES REGULARIZATION

Consider the case where the number of distinct sources is N1 and the number of mixtures is

N2, with N2 > N1. Consider **x** as mixtures of N2 sources, only N1 of which are distinct, mixed by a random, invertible matrix M of size N2 × N2.

Fig2: Two linear mixtures of two images

Fig3: Filtering + SFA, correlations with original sources

IV. MULTIVARIATE VERSUS UNIVARIATE SFA

In general, it is necessary to employ multivariate SFA for multi-dimensional signals. The most crucial reason is that it is more robust numerically to use multi-dimensional masks to compute the derivatives of a multi-dimensional signal to apply univariate SFA represent a two-dimensional image as a one-dimensional vector by stacking together all of its columns followed by all of its rows. This essentially imitates multivariate SFA - a truly univariate version would vectorize for computing the x-derivative, for computing the y-derivative. Without filtering can achieve very good, but not perfect, separation using both univariate and multivariate SFA, with better performance by multivariate SFA. The difference is much more dramatic with filtering + SFA in this case filtering + univariate SFA is actually worse than univariate SFA alone, whereas filtering + multivariate SFA gives almost perfect separation. The reason is that, compared to the univariate case, the computation of derivatives is more robust using the masks H9,x and H9,y (Also obtained better results than univariate SFA by using similar masks of smaller sizes 3×3, 5×5, and 7×7 the worst results were obtained with univariate SFA when only the columns or the rows of the images were vectorized).

For multi-dimensional signals, the mathematical formulation of multivariate SFA is completely natural and more straightforward to implement (it is more cumbersome to vectorize signals of dimension higher than two). By utilizing multivariate SFA, one also has greater flexibility in experimenting with different derivative operators to choose one giving the best performance.

V. EXPERIMENTAL RESULTS

Flowers	0.7969	0.0417	1.9812
Texture	0.6685	0.0043	0.7298
Manmade	0.9772	0.051	1.75

Table 1 Average run time per pair of images

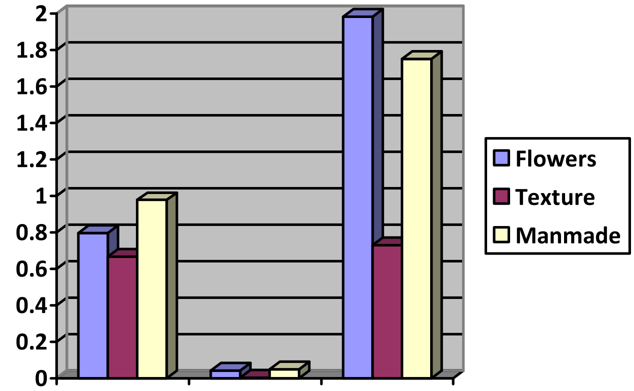

Fig 4 Average run time per pair of images

Sources	1.0000	12.883
Mixtures	0.9898	3.8789

Table 2 Highest correlation between Extracted sources

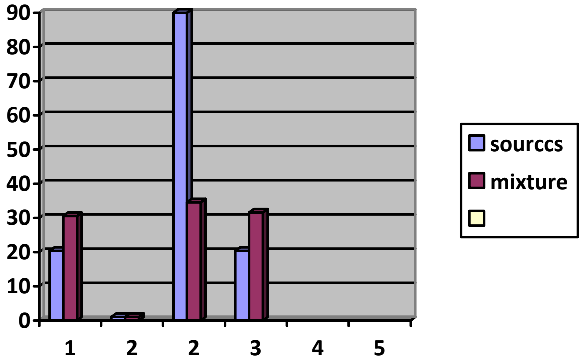

Fig 5 Highest correlation between Extracted sources

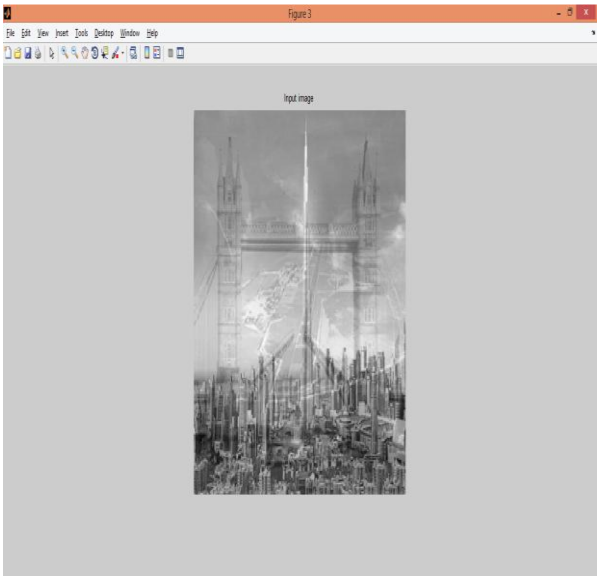

Fig 6: Fused Image (input image)

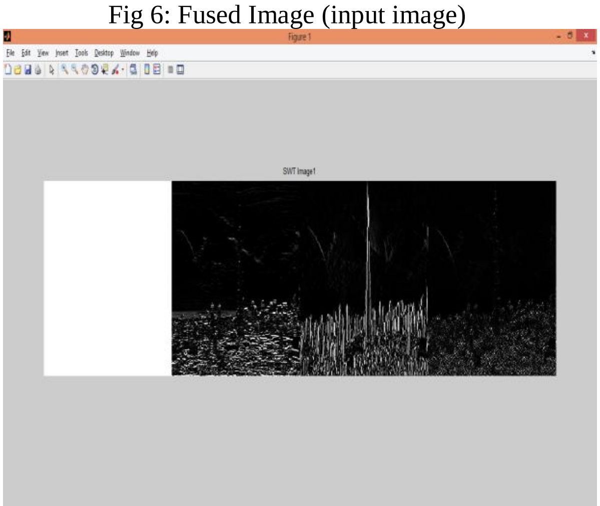

Fig 7: Stationary Wavelet Transform of image1

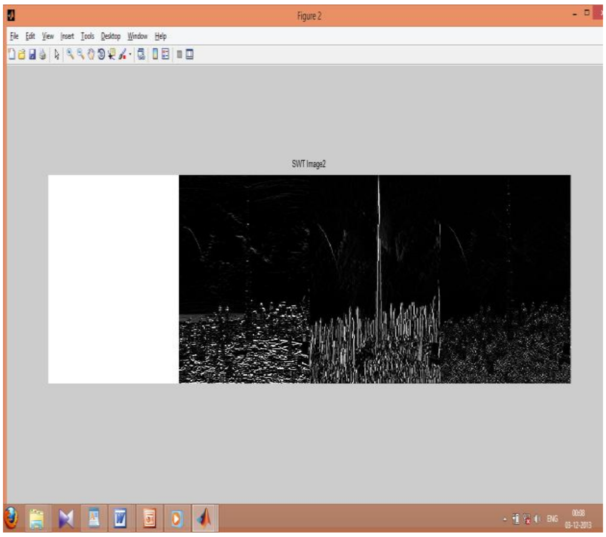

Fig 8: Stationary Wavelet Transform of image2

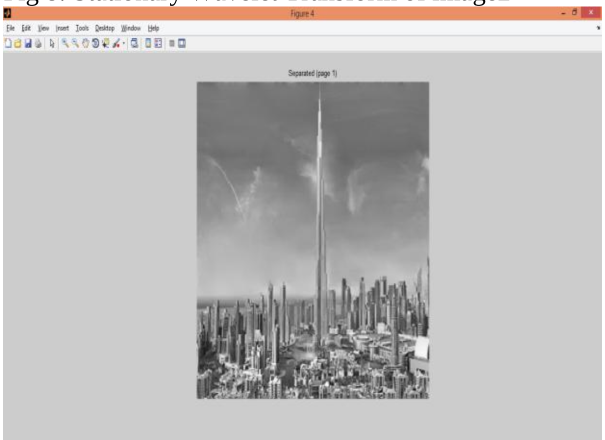

Fig 9: Separated image1

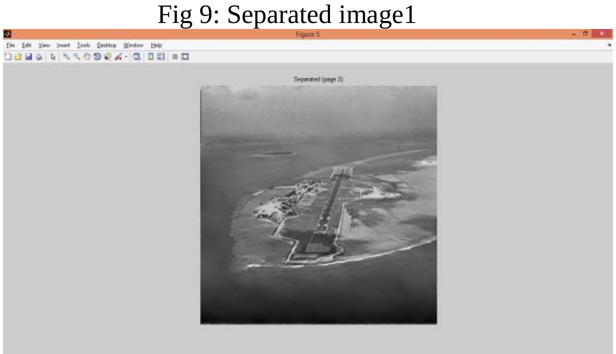

Fig 10: Separated image1

VI. CONCLUSION AND FUTURE WORK

Introduces the Slow Feature Analysis (SFA) method for vector-valued functions of several variables and apply it to the problem of blind source separation, in particular to image separation. It is generally necessary to use multivariate SFA instead of univariate SFA for separating multi-dimensional signals. And also introduce the Adaptive wavelet filter for blind source separation. There are number of problems are noted the wide literature survey the main objective of this one is to separate the image from the mixture image applied to the more texture image also produce high accuracy than conventional methods because it keeps also the edges in the image. The advantage of this method is simple to implement, fast to run, the correlations between the original sources and their derivatives are minimized. In my future enhancement, I have planned to improve the existing one because the existing method was not separating more than two images. In future I have planned separate more than two images.

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SUBI C Master of Computer Application in Annai Velankanni College and currently pursuing M.E(Software Engineering) in Vins Christian College of Engineering 2013, respectively.

RAMYA P M.E. Software Engineering Asst prof of Vins Christian College of Engineering.