

FPGA Implementation of ICA for mixed signal using Frog Leap Optimization Algorithm

Hari Krishna Moorthy¹, Manukumar G. C²

^{1,2}School of Engineering & Technology, Jain University, Bangalore – 562112, India

Abstract: Speech verification is a bio-metric system which performs the computing task of validating a user identity using the characteristics feature extracted from their speech samples. The independent component analysis (ICA) is one of the major trending technologies to differentiate signals from their mixed quantity. ICA is one of the technique to extract a signal from a compound signal. The fundamental approach of ICA is to find a suitable representation of multivariate data. The representation is often sought as a linear transformation of the original data. Linear transformation methods include principal component analysis (PCA), factor analysis, and projection pursuit. Independent component analysis (ICA) is a recently developed method in which the goal is to find a linear representation of non-Gaussian data so that the components are statistically independent. This kind of analysis captures the essential structure of the data in many applications including feature extraction and signal separation. The use of evolutionary computation based optimization such as Frog Leap Optimization Algorithms are stochastic search methods that mimics the identity of natural biological evolution with additional operations of crossover and feedback resolves the permutation ambiguity to a large extent.

Keywords: ICA, PCA, Frog leap optimization, Linear Transformation

1. Introduction

Independent component analysis (ICA) is one of the most widely used BSS techniques for revealing hidden factors that underlie sets of random variables, measurements, or signals [1]. ICA is essentially a method for extracting individual signals from mixtures. The major amount of data resides in the physical assumptions that the different physical processes generate unrelated signals. The simple and generic nature of this assumption allows ICA to be successfully applied in diverse range of research fields.

ICA methods do not find a global solution since it may get stuck with local variables. In addition to the problem of getting trapped in local variables, these algorithms have the uncertainty like scaling and permutation [2]. The performance of all available algorithms depends on a contrast functions that is the function of statistical independence. Evolutionary computation techniques such as Genetic Algorithms and Shuffled Frog Leap Optimization Algorithm are designed to minimize the problems faced in case of ICA [3][4].

An evolutionary optimization algorithm that mimics the social behavior of natural biological objects/species is an exciting development in optimization area. The Shuffled Frog Leap optimization Algorithm is method that mimics the mimetic evolution of a group of frogs when seeking for the location that has maximum amount of food [5]. The usage of optimization algorithm enables to find global optimal solution. ICA algorithms are mostly applied in signal and image processing field, which usually entails large volumes data that are transferred in and out of the VLSI designs [6].

2. Theoretical foundations of ICA

Consider a random observed vector $X=[X_1, X_2, \dots, X_m]^T$

whose m elements are mixtures of m independent elements of a random vector $S=[S_1, S_2, \dots, S_m]^T$ given by

$$X=AS$$

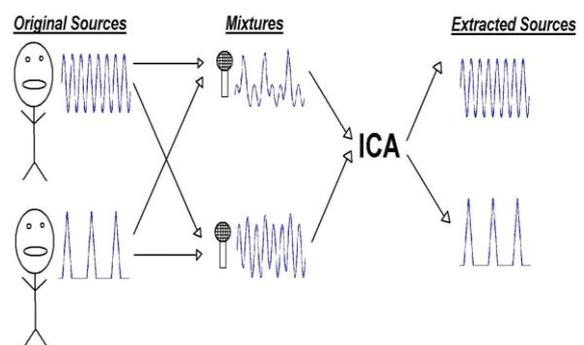


Figure 1: Extracted original signal using ICA

Where A represents an $m \times m$ mixing matrix. The goal of ICA is to find the unmixing matrix W (i.e. the inverse of A) that will give Y , the best possible approximations of S .

$$Y=WX \cong S$$

In order to use ICA five assumptions must be met. First, there must be a statistical independence between each of the sources S_i . Second, the mixing matrix must be square, full rank and the mixtures must be linearly independent from one another. Third, the stochasticity model S must be noise free. Fourth, the data are centred, pre-processed and whitened. Fifth, the source signal must not have a Gaussian probability density function (pdf) except for one single source that can be Gaussian.

3. Statistical Independence

Let $(X_1, X_2 \dots X_m)$ be random variables with pdf $F(X_1, X_2 \dots X_m)$, then the variables x_i are mutually independent if $F(X_1, X_2 \dots X_m) = F_1(X_1) F_2(X_2) \dots F_m(X_m)$ that is, if the pdf of the x_i , is equal to the multiplication of each marginal pdf of the x_i . Statistical independence is a

relation that can be expressed in the form of uncorrelatedness between two variables [6]. For a randomly centred variable the uncorrelatedness is expressed by the following equation.

$$E[X_i X_j] = E[X_i] \cdot E[X_j] \text{ for } i \neq j.$$

where $E[.]$ is the expectation.

There are several ways to increase independence and each of them involves the use of different algorithms. There are two main families of ICA algorithm which include minimization of mutual information and maximization of non-gaussianity.

3.1 Minimization of Mutual Information

Mutual Information is defined for a pair of random variables as:

$$I(X; Y) = H(X) - H(X|Y)$$

where $H(X|Y)$ is the conditional entropy and $H(X)$ is the entropy of X . Conditional entropy is given by

$$H(X|Y) = H(X, Y) - H(Y)$$

where $H(X, Y)$ is the joint entropy of X & Y . Entropy can be defined by Shannon as:

$$H(X) = -\sum_X P(X) \log P(X).$$

$$H(Y) = -\sum_Y P(Y) \log P(Y).$$

$$H(X, Y) = -\sum_{X,Y} P(X,Y) \log P(X,Y).$$

Entropy can be seen as a measure of uncertainty. The lower the value the more information we have about a given system. Hence mutual information can be seen as the reduction of uncertainty regarding variable X after the observation of Y . After some manipulation of the entropy equation the unmixing matrix W can be computed as

- 1) Initialize $W(0)$.
- 2) $W(t+1) = W(t) + \eta(t) (I - f(Y)Y^T) W(t)$.
- 3) If not converged, go back to step 2.

where $\eta(t)$ is the step size, $f(Y)$ is non linear function, I is the identity matrix. In case of super-Gaussian distribution $f(Y)$ is given by $f(Y) = \text{Tanh}(Y)$ and for sub-Gaussian distribution $f(Y) = Y - \text{Tanh}(Y)$.

3.2 Maximization of non- Gaussianity

Independent components can be estimated by focussing on non -Gaussianity. It can be assumed that each underlying source is not normally distributed and one way to extract the components is by forcing each of them to be as far from the normal distribution as possible. Negentropy can be used to estimate non-Gaussianity. Negentropy is a measure of distance from normality defined by:

$$N(X) = H(X_{\text{Gaussian}}) - H(X).$$

where X is a random vector known to be non- Gaussian, $H(X)$ is the entropy and $H(X_{\text{Gaussian}})$ is the entropy of a Gaussian random vector whose covariance matrix is equal to that of X .

The unmixing matrix can be computed by the Fast ICA algorithm:

- 1) Initialize W_i .
- 2) $W_i^+ = E(\Phi^1(W_i^T X)) W_i - E(X \Phi(W_i^T X))$
- 3) $W_i = W_i^+ / \|W_i^+\|$
- 4) $W_i^+ = W_i - \sum_{j=1}^{i-1} W_j W_j^T W_i$

- 5) If not converged, go back to step 2. Else go back to step 1 with $i=i+1$ until all components are extracted.

where W_i is a column vector of the unmixing matrix W , W_i^+ is a temporary variable used to calculate W_i . $\Phi^1(\cdot)$ is the derivative of $\Phi(\cdot)$ and $E(\cdot)$ is the expected value. once the given W_i has converged the next one (W_{i+1}) must be made orthogonal to it in order for the new components to be different from it.

4. ICA Architecture

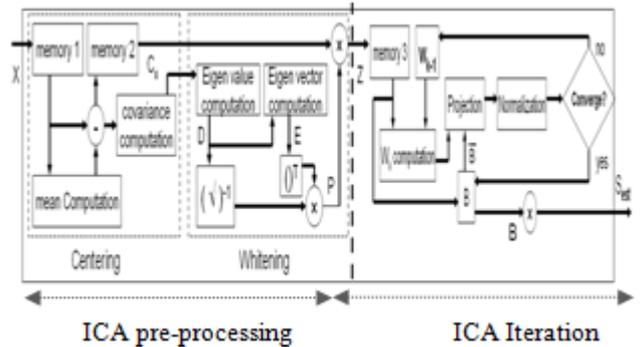


Figure 2: ICA Architecture

Before applying ICA algorithm it is necessary to perform pre-processing followed by ICA iteration. The first step in pre-processing is called Centring. It consists of subtracting mean from each of its observed mixture. The second step is called Whitening. It consists of linearly transforming the centred observed mixture to obtain new vectors which are called White [7]. The components of the whitened vector are uncorrelated and their variance equal to unity. This means that the covariance matrix of the whitened data is equal to identity matrix. One way to perform whitening is using Eigen Value Decomposition (EVD) method.

The direct implementation of the complete ICA Architecture requires complex arithmetic operations like division, square root and multiplication which are costly in terms of silicon area and power dissipation. To design an area and power efficient ICA architecture it is necessary to use architectural symmetry to reduce number of arithmetic operations wherever possible.

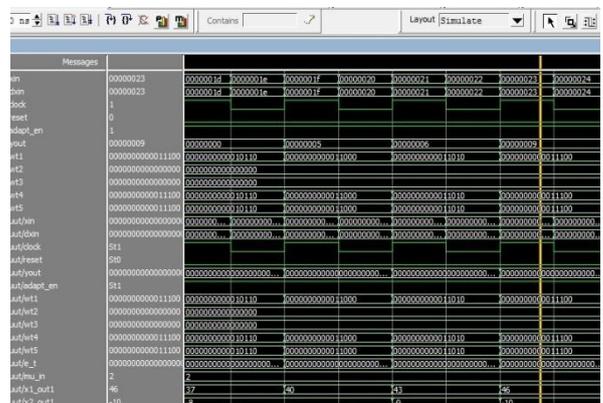


Figure 3: Weight vector output of ICA

5. Shuffled Frog Leap Algorithm

The Shuffled Frog Leap algorithm is a memetic meta-heuristic that is designed to seek a global optimal solution by performing a heuristic search. It is based on the evolution of memes carried by individuals and a global exchange of information among the population. The SFL algorithm involves a population of possible solutions defined by a set of frogs that is partitioned into subsets referred to as memeplexes. Within each memeplexes the individual frogs hold ideas that can be influenced by the ideas of other frogs and evolve through a process of memetic evolution. After a number of memetic evolution steps, ideas are passed among memeplexes in a shuffling process. The local search and the shuffling continue until convergence criteria are satisfied.

An initial population of 'P' frogs are created randomly. For S-dimensional problems, each frog *i* is represented by S variables as $X_i = (x_{i1}, x_{i2}, \dots, x_{is})$. The frogs sort in descending order according to their fitness. Then the entire population is divided into *m* memeplexes, each containing *n* frogs. Within each memeplexes, the frog with the best and the worst fitness are identified as X_b and X_w respectively. The frog with the global fitness is identified as X_g . Then the evolution process is applied to improve only the frog with the worst fitness in each cycle.

Change in frog position (D_i) = rand (.). ($X_b - X_w$).

New position X_w = Current position $X_w + D_i$

$$(D_{max} \geq D_i \geq D_{min})$$

where rand (.) is a random number between 0 and 1 and D_{max} is the maximum change in frog's position. If this produces a better frog it replaces the worst frog. If no improvement becomes possible in the latter case then a new solution is randomly generated to replace the worst frog with another frog having any arbitrary fitness. The calculations will continue for specific numbers of evolutionary iterations within each memeplexes

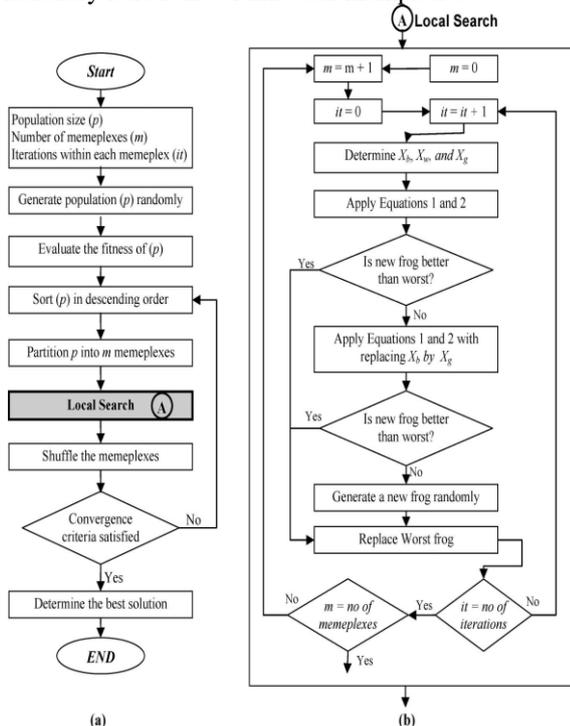


Figure 4: Flowchart of the Shuffled Frog Leap Algorithm

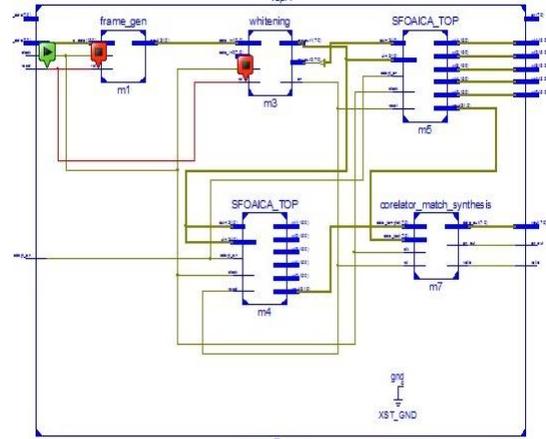


Figure 5: Top level RTL view of ICA Block

6. Results and Discussion

The concept of ICA can be used in various fields such as speech, image and Biomedical applications. By using advanced technologies such as VLSI the complexity parameters such as processing speed, power and the number of memory units can be drastically reduced. Various numbers of algorithms such as has been proposed based on ICA but by using the Frog Leap Algorithm we can optimize the complexity parameters to a greater extent. The simulations are done using Xilinx 14.7 and the tested using Spartan3A kit. The output weight vectors of the ICA and the RTL view are shown in Fig 3 and Fig 5 respectively.

7. Conclusion

ICA is a very general-purpose statistical technique in which observed random data are linearly transformed into components that are maximally independent from each other, and simultaneously have interesting distributions. ICA can be formulated as the estimation of a latent variable model. The intuitive notion of maximum nongaussianity can be used to derive different objective functions whose optimization enables the estimation of the ICA model. Alternatively, one may use more classical notions like maximum likelihood estimation or minimization of mutual information to estimate. A computationally very efficient method performing the actual estimation is given by the Frog Leap Optimization Algorithm. Applications of ICA can be found in many different areas such as audio processing, biomedical signal processing, image processing, telecommunications, and econometrics.

References

- [1] H. Du, H. Qi and X. Wang, "Comparative Study of VLSI Solutions to Independent Component Analysis", IEEE Trans. Industrial Electronics, vol.54, no. 1, February, 2007.
- [2] Hyvärinen and E. Oja, "A fast fixed-point algorithm for independent component analysis," NeuralComput., vol. 9, no. 7, pp. 1483-1492, Oct. 1997.
- [3] Xia Li, Jianping Luo, "An improved shuffled frog leaping algorithm with external optimisation for continuous optimization", 2010 Elsevier.

- [4] Special issue: Swarm intelligence and its applications
2012 Published by Elsevier Inc.
- [5] K. K. Shyu, M. H. Lee, Y. T. Wu and P. L. Lee,
“Implementation of Pipelined FastICA on FPGA for
Real-Time Blind Source Separation”, IEEE Trans.
Neural Networks, vol. 19, no. 6, pp. 958-970,
June,2008.
- [6] Hyvarinen, “Fast and Robust Fixed-Point Algorithms
for Independent Component Analysis”, IEEE Trans.
Neural Networks, vol. 10, no. 3, May, 1999.
- [7] S.Mishra and C.N.Bhende, “Bacterial
ForagingTechnique-Based Optimized Active Power
Filter for Load Compensation”, IEEE Trans. Power
Del. vol.22, no.1, pp.457-465, Jan.2007.
- [8] Y.Tan and J.Wang, “Nonlinear Blind SourceSeparation
Using Higher Order Statistics and a Genetic
Algorithm”, IEEE Trans. On Evolutionary
Computation, vol.5, No.6, pp.600-611, Dec. 2001.
- [9] T-W. Lee, M. Girolami, and T.J.
Sejnowski,“Independent ComponentAnalysis using an
Extended Infomax Algorithm for Mixed Sub-Gaussian
and Super-Gaussian Sources,” Neural
Computation,Vol.11,pp. 417-441, 1999.
- [10] Xia Li, Jianping Luo,” An improved shuffled frog
leaping algorithm with external optimisation for
continuous optimization”, 2010 Elsevier.
- [11] A. Papoulis. Probability, Random Variables, and
Stochastic Processes. McGraw-Hill, 3rd edition,1991.
- [12] A.J. Bell and T.J. Sejnowski. An information-
maximization approach to blind separation and blind
deconvolution. Neural Computation, 7:1129–1159,
1995.
- [13] N. Delfosse and P. Loubaton. Adaptive blind
separation of independent sources: a deflation
approach. Signal Processing, 45:59–83, 1995.
- [14] M.C. Jones and R. Sibson. What is projection pursuit ?
J. of the Royal Statistical Society, Ser. A,150:1–36,
1987.
- [15] R. Vigário, J. Särelä, and E. Oja. Independent
component analysis in wave decomposition of
auditoryevoked fields. In Proc. Int. Conf. on Artificial
Neural Networks (ICANN’98), pages 287–292,
Skövde,vSweden, 1998.