

Progress Report

(July05-Dec05)

Project Title:

**Development of Independent Component Analysis
Based Blind Source Separation Algorithms for
Audio /Image Separation**



Principal Investigator

Prem K Kalra

**Department of Electrical Engineering,
Indian Institute of Technology, Kanpur
INDIA**

Objectives of the Project:

Aim of the project is to develop and compare various algorithms for blind source separation of audio and image separation. Following points summarize the objectives of this project:

- Study of existing methods for real-life separation problems.
- Comparison of different existing algorithms for separation of audio and image mixtures.
- Development of new ICA algorithms for Blind Source Separation of audio and image mixtures.

Tasks Accomplished:

- ? Image and audio data enhancement and separation modules have been developed in MATLAB.
- ? Following enhancement modules have been developed for fingerprints using:
 - Histogram equalization
 - 2-D Fast Fourier Transform
 - Binarization
- ? Following post-processing modules have been developed:
 - De-noising using Wiener filter.
 - De-noising using Median filter.
 - De-noising using Discrete Wavelet Transform.
- ? Following existing algorithms have been used for comparison purposes in order to seek the possibility of improvement in the performance of separation:
 - Gabor filter based segmentation algorithm
 - Linear and Nonlinear ICA Based on Mutual Information (MISEP)
 - Bell and Sejnowski ICA(BS ICA)
 - Equivariant Adaptive Separation via Independence(EASI)
 - Independent Component Analysis by Simultaneous Third- and Fourth-Order Cumulant Diagonalization (CuBICA)
 - Kernel Independent Component Analysis
 - Denoising Source Separation

Image and audio enhancement modules

GUI is made for image data enhancement. Images have been enhanced using following functions.

- ? Histogram equalization: It enhances the contrast of images by transforming the values in an intensity image, or the values in the color map of an indexed image, so that the histogram of the output image approximately matches a specified histogram. Histogram equalization defines a mapping of gray levels p into gray levels q such that the distribution of gray level q is uniform. This mapping stretches contrast (expands the range of gray levels) for gray levels near

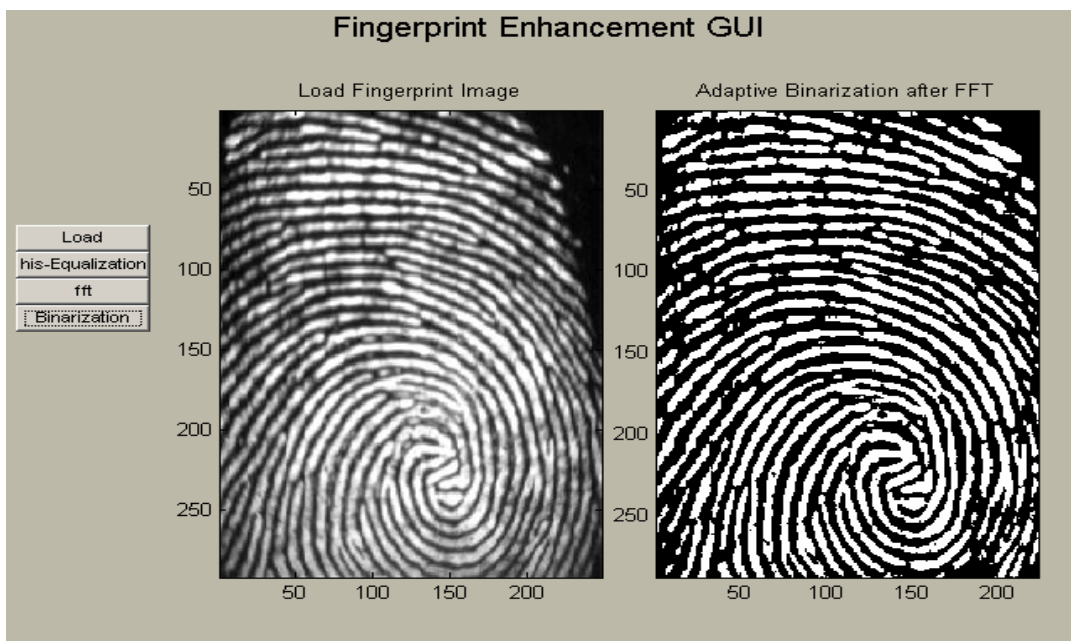
the histogram maxima. Since contrast is expanded for most of the image pixels, the transformation improves the detectability of many image features.

The probability density function of a pixel intensity level r_k is given by:

$$p_r(r_k) = \frac{n_k}{n}$$

where: $0 \leq r_k \leq 1$, $k = 0, 1, \dots, 255$, n_k is the number of pixels at intensity level r_k and n is the total number of pixels. The histogram is derived by plotting $p_r(r_k)$ against r_k . A new intensity s_k of level k is defined as:

$$s_k = \sum_{j=0}^k \frac{n_j}{n} = \sum_{j=0}^k p_r(r_j)$$



- ? Fast Fourier Transform: It is a mathematical procedure that transforms a function from the time domain to the frequency domain. It is used to increase the dynamic range of selected print features. The gray levels are stretched as a result, improving the visualization of the image.
- ? Binarization: The operation that converts a grayscale image into a binary image is known as binarization. We carried out the binarization process using an adaptive thresholding based on the local intensity mean. Adaptive thresholding typically takes a grayscale or colour image as input and, in the simplest implementation, outputs a binary image representing the segmentation. For each pixel in the image, a threshold has to be calculated. If the pixel value is below the threshold it is set to the background value, otherwise it assumes the foreground value.

An approach to find the local threshold (T) is to statistically examine the intensity values of the local neighbourhood of each pixel. The statistic which is most appropriate depends largely on the input image. Simple and fast functions include the mean and local intensity distribution,

$$T = \text{Local Mean}$$

Each pixel is assigned a new value (1 or 0) according to the intensity mean in a local neighborhood, as follows:

$$I_{new}(n_1, n_2) = \begin{cases} 1 & \text{if } I_{old}(n_1, n_2) \geq \text{Local Mean} \\ 0 & \text{otherwise} \end{cases}$$

Post Processing Modules

The signals that are achieved after the separation using any algorithm contain several types of noises. To denoise the signals thus achieved we have used Wiener filter, Median filter and Discrete Wavelet Transform.

- ? Wiener filter: Wiener filter performs a low-pass filtering of an intensity image that has been degraded by constant power additive noise. It uses a pixel-wise adaptive Wiener method based on statistics estimated from a local neighborhood of each pixel.



ORIGINAL IMAGE
(With white Gaussian Noise)



FILTERED IMAGE

- ? Median filter: Median filtering is similar to using an averaging filter, in that each output pixel is set to an average of the pixel values in the neighborhood of the corresponding input pixel. With median filtering, the value of an output pixel is determined by the median of the neighborhood pixels. The median is much less sensitive than the mean to extreme values (called outliers). Median filtering is

therefore better able to remove these outliers without reducing the sharpness of the image.



ORIGINAL IMAGE
(With Impulsive Noise)



FILTERED IMAGE

- ? For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance. Consider the human voice. If you remove the high-frequency components, the voice sounds different, but you can still tell what's being said. However, if you remove enough of the low-frequency components, you hear gibberish. In wavelet analysis, we often speak of approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components.

Existing Algorithms

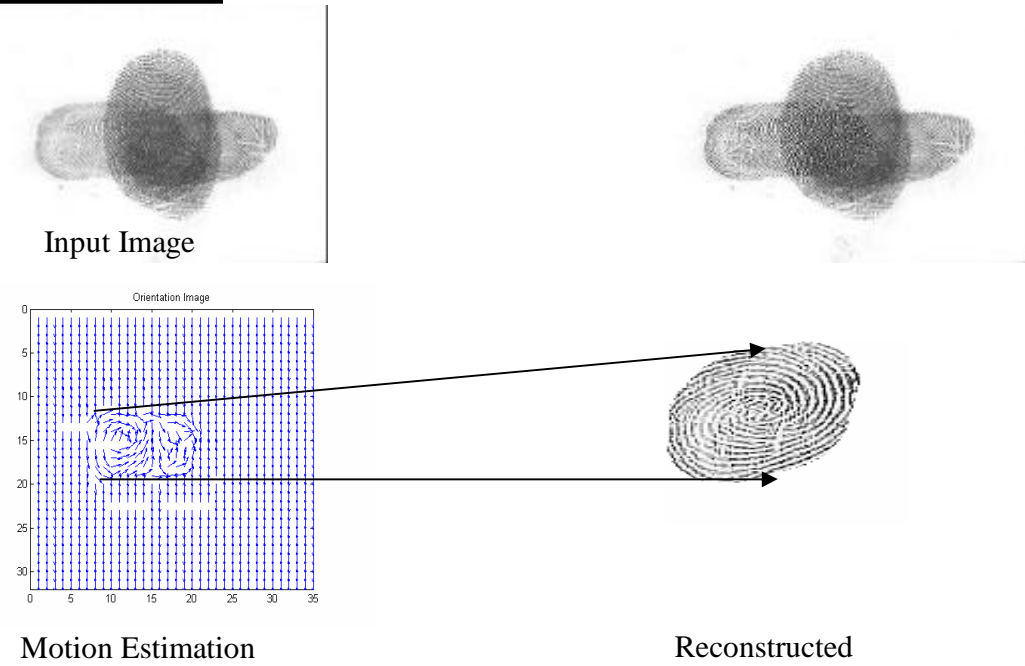
For Audio Separation:

Independent Component Analysis by Simultaneous Third- and Fourth-Order Cumulant Diagonalization (CuBICA), denoising source separation algorithm and Kernel ICA algorithms are tested for various real and artificially mixed data. It has been observed that the result for real life data is bit noisy but they are very well separated. These algorithms are very good for those cases where number of sensors is equal to the number of sources. They have been used for underdetermined case where one signal is extracted from the mixture but the estimation of other signals is yet to be done.

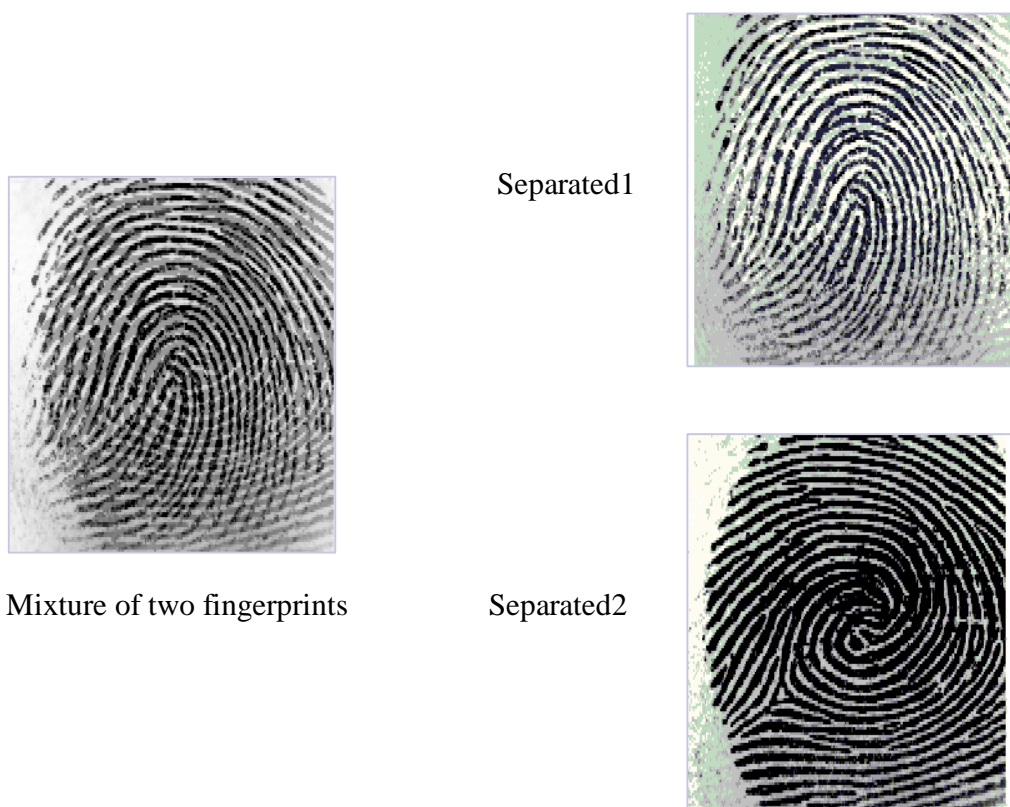
For Image Separation:

Gabor filter based segmentation algorithm, MISEP, EASI and Bell and Sejnoski ICA algorithms have been tested for fingerprint separation out of which MISEP is giving very fine results in case of a mixture of two fingerprints but for more than two it doesn't give very good results. All these algorithms are very good for artificial mixtures but for real time data there is a need of improvement. Some other algorithms are also there in process to be implemented on real life data.

Results of Gabor Filter:



Results of MISEP:



Results of EASI:



Mixture



Separated1



Separated2



Separated3

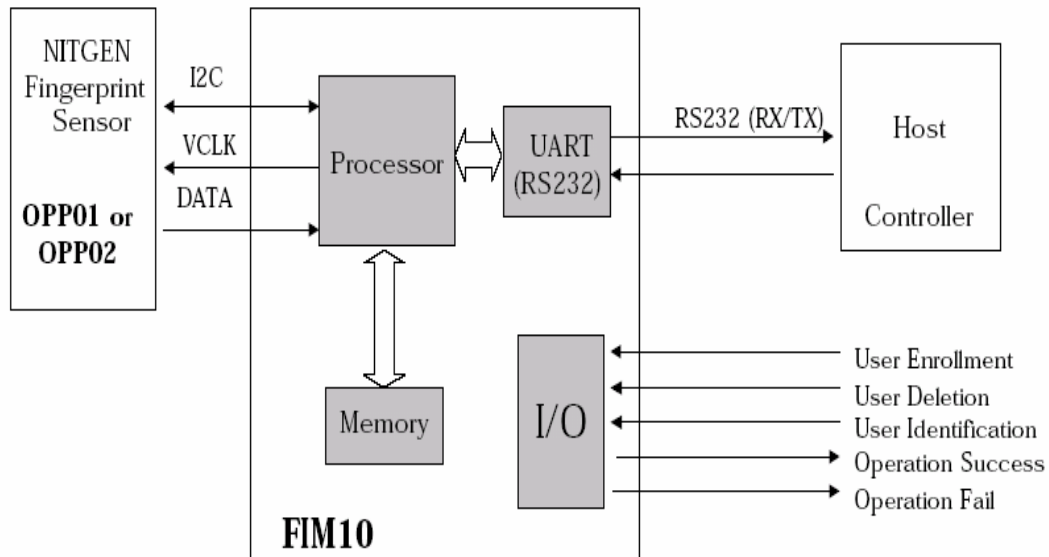
Hardware part:

Fingerprint Identification Module is an evolutionary standalone fingerprint recognition module consisted of optic sensor and processing board. It is much useful in scanning images of fingerprints.

About FDA01M:

The FDA01M (Stand-alone with built-in CPU) is independent fingerprint recognition module composed of an optical sensor and a processing board. It offers high recognition ratio, fast recognition speed by built-in CPU and remarkable algorithm. FM 01 boasts high identification rate and supports high speed 1: N identification and uploadability and downloadability of data, providing optimal condition for application to access control System. It provides high recognition ratio even to small-size, wet, dry, calloused fingerprint.

Block Diagram



RS-232C communication data consist of 8-bit data, no parity, 1-bit start-bit, and 1-bit stop-bit.

Common Description of Internal Processor Structure:

Processor FIM10 consists of the following internal blocks

- ? Nitgen fingerprint sensor.
- ? Serial port for communication.
- ? Memory

Specifications:

- ? Board Spec. ARM9, 8MB SDRAM, 1M flash
- ? Dimension 43 x 63 mm
- ? Optic Fingerprint Sensor OPP02MM1 LV, OPP02MM2 HV
- ? Supply Voltage LV 3.3V, HV 5.0 V
- ? Current Consumption 60 (idle) - 200 (Op.) mA
- ? Temperature range -20°C - +60°C
- ? Boot Up Time <0.4 sec
- ? External Interface RS232 (1 channel): 9600 - 115200[BP S]
- ? Method 1:1, 1:N, Password

- ? Authentication Time 1.2 [sec] (Capture + Extract + Match)

Features:

- ? Fast and Perfect Authentication through excellent Algorithm.
- ? Compact, lightweight and portable.
- ? High-performance, maintenance-free optical fingerprint scanner.
- ? Resistance to scratches, impact, vibration and electrostatic shock.
- ? Latent print image removal (does not accept prints left behind).
- ? Encryption of fingerprint templates.

Applications:

- ? Personal computer / workstation security.
- ? Network / enterprise security.
- ? E-commerce / e-business.
- ? Electronic transactions.
- ? Banking and financial systems.
- ? Medical information systems.
- ? Any password-based application.

Working:

When a user places their finger on NITGEN's fingerprint recognition device (FRD), for the first time, the fingerprint is scanned and a 3D fingerprint image is captured.

All fingerprints contain a number of unique physical characteristics called minutiae, which includes certain visible aspects of fingerprints such as ridges, ridge endings, and bifurcation of ridges. Most of the minutiae are found in the core points of fingerprints, and the core points themselves are found near the center of the fingerprint on the fleshy pad.

The user is enrolled, or registered, in the database after special minutiae based algorithm extract key minutiae points from the live image at the time of acquisition and converts the data into a unique mathematical template. This unique template is then encrypted and stored- it is important to note that no actual image of the fingerprint is stored, only the minutiae based template.

The next time a new fingerprint image for an individual is scanned by the FRD, another template is created and the two templates are compared to verify the users' identity.

In this manner all the stored templates are further utilized as the test data for the different algorithms of ICA applied over images.

Work Done So Far

- ? Image and audio data reading modules have been developed in MATLAB.
- ? Following pre-processing modules have been developed:
 - o Pre-whitening of the input data

- Principle component analysis
- Fourier Transformation and Directional Fourier Transformation with Improvements
- ? Following post-processing modules have been developed:
 - De-noising using Fast Fourier Transformation
 - De-noising using Wavelet Transformation
 - De-noising using Wiener filter.
 - De-noising using Median filter.
 - De-noising using Discrete Wavelet Transform.
- ? Following enhancement modules for fingerprints have been developed:
 - Histogram equalization of input data
 - 2-D Fast Fourier Transform of input data
 - Binarization of input data
- ? Following new algorithms for ICA have been developed implemented in MATLAB:
 - ICA using generalized mean neuron model
 - ICA using biologically motivated contrast function
 - ICA with lateral connections at output
- ? Following existing algorithms have been used for comparison purposes in order to seek the possibility of improvement in the performance of separation:
 - Bell and Sejnowski algorithm
 - FASTICA
 - JADE algorithm
 - Degenerate Unmixing Estimations Technique (DUET) algorithm
 - Gabor filter based segmentation algorithm
 - Linear and Nonlinear ICA Based on Mutual Information (MISEP)
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Plan of Work for Next Six Months

- ? Completion of purchase of Hardware.
- ? Improvements to algorithms of separation and cleaning for real life mixtures.
- ? Development of new neuron based ICA algorithms for separation of image/audio mixtures.
- ? In the real recording environment, signals picked-up by a microphone consist of direct-path signals as well as their delayed (reflected) and attenuated versions and noise signals. Therefore, the speech signal picked up by an M element linear microphone array is modeled as a linear convolutive mixture of R impinging source signals s_i .
Development of algorithms for convolutive mixtures.