Illumination Normalization for Fingerprint Recognition using Enhanced Multi-scale Low Rank + Sparse Decomposition with Artificial Neural Network

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Abstract
Image recognition are very sensitive to light conditions. In order to obtain the best possible performance it is desired to remove illumination variations from images. Low rank modeling are often used to model biometrical images as faces, fingers… etc. Low rank + sparse decomposition was recently proposed to capture uneven illumination as sparse errors and was shown to remove illumination variation while capturing the underlying fingers as the low rank component. Here, we propose modeling illumination changes for different fingerprint images as block-low rank, considering that illumination variations are spatially correlated in multiple scales. Initially we adopted an approach to learn a low-rank decomposition for image recognition and then we used Artificial Neural Network (ANN) model to regularize its index of resolvability. The adaptation of a multi-scale low rank modeling, as a matrix summation of block-wise low rank matrices, and increasing scales of block sizes, in addition to the novelty of using ANN in regularizing the index of resolvability, showed enhanced results that under an incoherence condition, the convex program recovers the multi-scale low rank components exactly, which represents the illumination normalization for fingerprint recognition. Experimental results demonstrated the effectiveness of the approach. It showed that the multi-scale low rank decomposition enhanced with ANN regularization the index could provide accurate intuitive decomposition and clearly enhanced results.

Index Terms
Multiscale Decomposition Modeling, Low Rank + sparse Decomposition Modeling, Illumination Variations, Fingerprint Recognition, Artificial Neural Network.

1. Introduction

In the current context, the computer security has become a research area of great importance, especially in reliable identification systems, where an efficient and robust design is a priority task. The identification of the individual has become essential to ensure the security of systems and organizations faced with this increasing stress, more biometric recognition methods have been proposed. Biometric recognition systems, used increasingly widely in both the private and public sectors, have many benefits for large variety of persons. However, the use of biometrics for identification or verification of an alleged identity also involves risks as to the respect for rights and fundamental freedoms. Fingerprint usually used by various parties to recognize the identity of persons [1].

The most problematic disturbance affect the performance of fingerprint recognition systems are large variations in pose and illumination. The variation between the images of different fingerprints in general, is smaller than the taken sample for the same finger in a variety of environments. Specifically, the changes induced by light could be greater than the differences between people, causing systems based on the comparison of images to classify erroneously the identity of the input image [2] [3] [4]. The differences between the images of a fingerprint in different lighting conditions are greater than the differences between the images of different fingers in the same lighting conditions. The finger verification system authenticates the claimed identity of a person and decides that the claimed identity is correct or not. In this case, it has a limited group of users and in most cases it can be forced or frontal pose request directions. But there are still many problems with the lighting condition. Here, we propose modeling illumination changes in different fingerprint images as block-low rank where illumination variations are spatially correlated in multiple scales. This multi-scale low rank decomposition project includes of both multi-scale modeling and low rank decomposition of matrix as shown in [5]. Adopting this approach, the novelty of this work consists of using ANN model in regularizing the index of resolvability, based on some assumptions, which will be explained in later sections. Hence, adding ANN model to multi-scale structure allows to obtain a more accurate signal representation and compact than conventional methods of low rank or sole multi-scale structure method, whenever the signal present multi-scale structures.

Besides this section, the second one will mention some related works and discuss their achievements, then the proposed methodology and contribution will be explained in details in the third section. The fourth section will explain the practical experiment and the obtained results. Last but not least, the fifth section will summarize and conclude the entire work

Manuscript received June 5, 2017
Manuscript revised June 20, 2017

2.Current Solutions

Low rank + sparse decomposition is a technique, which is used in several fields as imaging recognition, video surveillance..., etc. Fei Yang, [6] applied the low rank + sparse decomposition method using compressive sensing which that performs video reconstruction. This method is more robust than previous methods. Whereas, the reconstruction phase builds a new background model, which is continuously updated as new frames. This background of subtraction learned adaptively as the compressive measurements with low latency.

Different images pose difficulty and steep challenges to existing vision algorithms: illumination variation, partial occlusion, as well as poor or even no alignment makes the domain of transformation difficult to measure image similarity for recognition or classification.

On the other hand, Yigang Peng, [7] presented an image alignment method that can simultaneously align multiple images by exploiting the low-rank property of aligned images based on recent advances in efficient matrix rank minimization. This method is effective with extensive experiments on images taken under a wide range of real-world conditions and laboratory conditions of naturally images. This method provided solutions to the below issues:

- Solve a sequence of convex optimization problems, and hence, both tractable and scalable.
- Allow to simultaneously align dozens or even hundreds of images on a typical PC in matter of minutes.
- Act directly on the input images, and does not require any pre-filtering or feature extraction and matching.

As seen previously, our method incorporates multi-scale structure method in addition to low rank decomposition method. Zhou Wang, [8] demonstrate the effectiveness of a multi-scale structural similarity method which is a convenient way to incorporate image details at different resolutions. Since, it supplies more flexibility than the single-scale approached previously used in incorporating the variations of viewing conditions (e.g., display resolution and viewing distance). Kartic Subr, [9] also propose and adopt an effective feature of a multi-scale decomposition method with a new filter to the edge preserving of image decomposition. The sense of scale is equal to the size of the window.

Our work integrates the multi-scale structure and low rank decomposition with ANN model, which is detailed in the next section.

3. Methodology

This section, illustrates the techniques and equations used to achieve our objective. Moreover, it explains the adopted multi-scale structure proposed in [5], which we enhanced in this work.

A. Multi-scale low rank matrix modeling

Low rank matrix modeling shows a big adaptation in several areas with a wide variety of applications, such as biomedical imaging, face recognition [10] and collaborative filtering [11]. In particular, the data is a matrix Y, which is constructed from a multiple copies of similar data. $\{yi\}_{i=1}^{N}$ are observed as follows, which is often low rank:

$$Y=\begin{bmatrix} | & | & | \\ y1 & y2 & y3 \\ | & | & | \end{bmatrix} \quad (1)$$

While low rank modeling captures the notion of data similarity, any locality information that may be present in the data matrix will be completely ignored. Since the data are correlated in multiple scales models, it is clarity noticed that a multi-scale low rank modeling is the most suitable modeling. In order to formulate the multi-scale low rank model, it is supposed that the data matrix Y can be partitioned into different scales. Specifically, following the assumption of the approach proposed in [5], that a multi-scale partition $\{Pi\}_{i=1}^{L}$ of the indices of an M ×N matrix are given, where each block b in P_i is an order magnitude larger than the blocks in the previous scale P_{L-1}. Figure 1 provides an examples of a multi-scale partition with decimation along two dimensions.

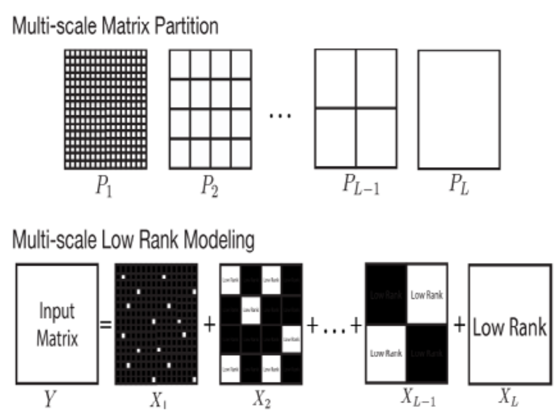

Fig. 1. Represent a multi-scale matrix partition and its associated multi-scale low rank modeling [5].

To convert easily between the data matrix and block matrices, then consider a block operator reshape $R_b(x)$, which extracts a block b of the full matrix X and reshapes the block in a m_i x n_i matrix (Figure 2).

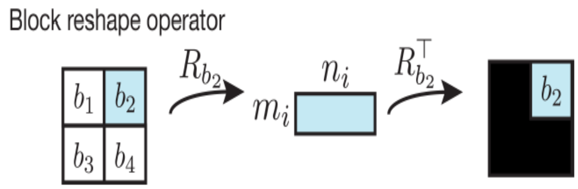

Fig. 2. Represent the block reshape operator R_b [5].

Given an $M \times N$ input matrix Y and its corresponding multi-scale partition and block reshape operators, the author in [5] propose a multi-scale low rank modeling that models the $M \times N$ input matrix Y as a sum of matrices $\sum_i^L$ Xi , in which each X_i is block-wise low rank with respect to its partition Pi . That is, considering the following model for Y:

Y= $\sum_{i=1}^{L} X_i$

$$X_i = \sum_{b \epsilon Pi} R_b^T (U_b\, S_b V_b^T) \qquad (2)$$

Where U_b, S_b, and V_b are matrices with sizes mi × rb, rb × rb and ni × rb respectively and form the rank-rb reduced SVD of $R_b(X_i)$. Note that when the rank of the block matrix $R_b(X_i)$ is zero, we have {U_b, S_b, V_b} as empty matrices, which do not contribute to Xi .

By constraining each block matrices to be of low rank, the multi-scale low rank modeling captures the notion that neighbors are more similar than global entries in the data matrix. In particular, the low rank + sparse modeling can be considered a low-scale modeling rank 2, in which the first scale has a block size of 1 × 1 and the second scale block size M × N. By adding additional scales between the sparse and low rank matrices, multi-scale low rank modeling can locally capture subordinated components that would otherwise require many coefficients to represent to the low rank + sparse.

The data matrix Y that fits our multi-scale low rank model, which represent the fingerprint images in different light conditions of the same person.

B. Proposed regularization of index method

In order to regularize the index of resolvability, we assume that the minimum description-length principle criterion motivated this complexity. When the parameter λ is set to equal one, and the distortion function d is set to be minus the log algorithm of likelihood. The uniform bounds of the statistical risk of estimators are motivated. Which allows us to use Artificial Neural Network model to assist in the regularization process of the large variety of parameters.

In order to use ANN to find the practical values of the selected regularization parameters $\{\lambda_i\}_{i=1}^{L}$ before the decomposition, the suggestions of Wright et al. [12] and Fogel et al. [13] were followed. Setting each λ_i parameter to be the Gaussian complexity of the norm $\| \cdot \|_i$.

$$\lambda_i \sim E\left[\|G\|_{(i)}^{*}\right] \qquad (3)$$

Which will be considered in our case as the objective of the ANN model.

C. Artificial neural network (ann) model

ANN is a methodology of artificial intelligence used to create numerical models that copy the structure of people neural framework. In ANN, the model is comprised of layers; input, hidden and output. Every layer comprises of number of neurons. Every one of these neurons is a logistic capacity that takes input sources and creates outputs as indicated by the capacity executed in the neuron. The quantity of neurons in the Input layer meets the quantity of elements used in the analysis. For instance, the quantity of input neurons in the input layer in our work is 13. The quantity of neurons in the hidden layer is a streamlining issue. At last, the quantity of neurons in the output layer relies on upon the quantity of required output values. In this work we have 16 neurons in the output layer, one concealed layer with ten hubs. Table 1 demonstrates the setup of our ANN in this work.

Table 1: Neural Network Model Configuration

Number of Nodes in Layer 1	13
Number of hidden Layers	1
Number of Nodes in hidden Layer	16
Iteration	1000
Number of Nodes in output layer	16
Number of Agents	16

The theory capacity $h(\theta)$ in ANN comprises of summations of elements of alternate layers. In this work the accompanying math models shows the used capacities. Table 2 demonstrates variable depictions.

$$g(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_{2+\cdots,} \qquad (4)$$

$$h(\theta)_i^l = \frac{1}{1+e^{-g(x)}} \qquad (5)$$

$$f_i = \sum_{i=1}^{m} h(\theta)_i \qquad (6)$$

$$f_{final} = \sum f_i \qquad (7)$$

Table 2: Model Parameters

x	Input neuron
h_θ	The hypothesis function
$h(\theta)$	The weight function
$g(x)$	The output function (Gaussian Function)
f	The summation of the weight functions

The full ANN model with the numbers of its components is shown in figure 3, below.

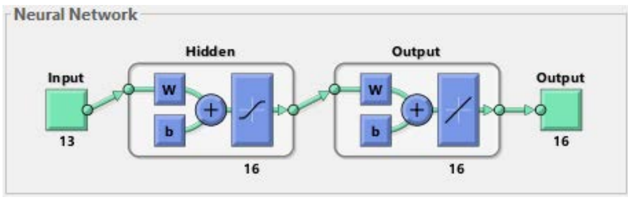

Fig 3: Artificial Neural Network Model

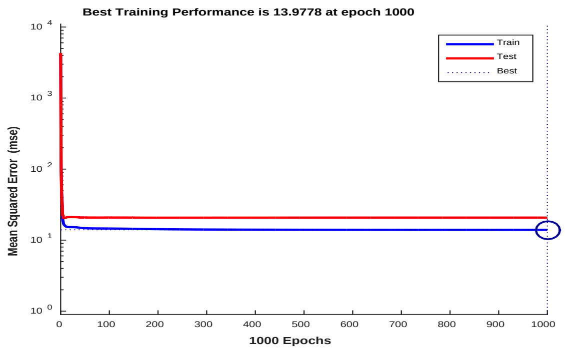

Fig 4: ANN Model Performance

After training the ANN model, using the above configuration, the training performance, was obtained and shown in the above figure. As it is clearly shown that the Mean Square Error (MSE) of the model approximately reached zero, at epoch 1000, where the performance is 13.9778.

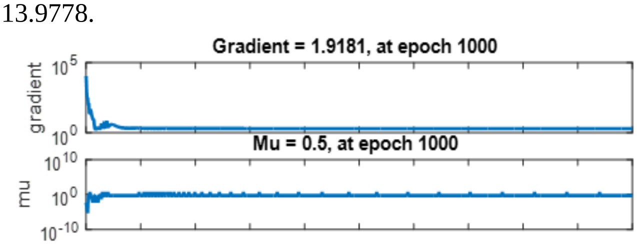

Fig 5: Training State

On the other hand, as shown in figure 5 above, the gradient of the model initially was just under 105, then it fallen dramatically to reach around 10. This figure fluctuated at the beginning, then it remained stable just below the value of 2, for the entire period.

The µ value for this model, started at around 10-5 then quickly raised to reach around 0.5, after some fluctuation, for the entire period.

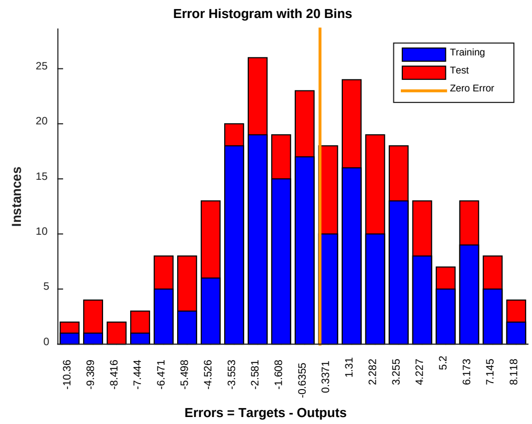

Fig 6: Error Histogram

Figure 5, shows the error histogram for the steps of training and testing of around 25 instances. It is clearly noticed that the majority of trials showed good error value, where most of the histogram bins are concentrated around 0.

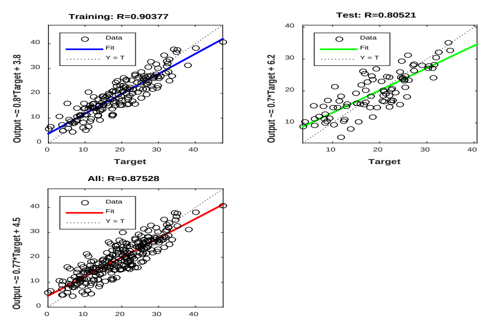

Fig 7: Training Regression

The regression of the training process of the ANN model is shown in the above figure, where it shows the target vs output fitness line for three regression values of R= 0.90377, R=0.80521 and R= 0.87528. Where the best fitness was shown for the first R value

I. PRACTICAL EXPERIMENT

In this work, we adopted the multi-scale low rank decomposition enhanced it using ANN model for regularizing the index of resolvability and applied the new proposed model on real datasets that are conventionally used in low rank modeling: illumination normalization for fingerprint images and regularization parameters λ_i were chosen exactly as $\sqrt{m_i} + \sqrt{n_i} + \sqrt{\log\left(\frac{MN}{\min\ (m_i, n_i)}\right)}$ for multi-scale low rank and min(m_i , n_i) for low rank + sparse decomposition. The implementation of this approach was simulated using MATLAB.

Fingerprint recognition algorithms are sensitive to illumination. In order to obtain the best possible performance for these algorithms, it is desired to remove illumination variations on the fingerprint images. Low rank + sparse decomposition enhanced with ANN model [14] was recently proposed to capture uneven illumination as sparse errors and was shown to remove illumination while capturing the underlying fingerprints as the low rank component. Here, we propose modeling illumination changes in different fingerprint images as block-low rank as the variations of illumination are correlated in multiple scales in spatial way. We considered fingerprint images from the FVC2004 fingerprint database [15]. For low rank + sparse decomposition, we found that the best separation result was obtained when each fingerprint image was normalized to the maximum value. For ANN enhanced multi-scale low rank decomposition, this work used the original unscaled image. Moreover, it decimated the space dimension only, based on the assumption the different illumination conditions were sorted in any order. (Figure 8) shows the input image.

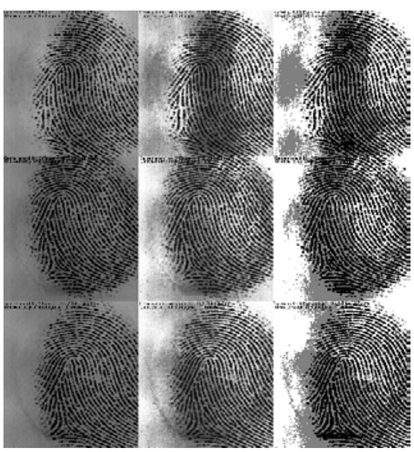

Fig 8. The input image.

These matrices are demonstrated in a compressed way, by decomposing the matrix into low rank blocks over several scales (Figure1). Using the proposed enhanced multi-scale with ANN approach, different scales of correlation in the used data matrix can be captured and more compressed representation can be provided, in comparison with conventional low rank approaches.

Fig 9. The resulting low rank matrix. (A: multi-scale approach. B: Proposed enhanced multi-scale with ANN approach)

When stacking each image frame as a column of the matrix, the resulting matrix is low rank with various block sizes. A small block size is more suitable to capture blood vessel dynamics; on the other hand, a large block size is able to capture background tissues accurately. Hence, a multi-scale low rank approach is desired to exploit all scales of correlations.

That is, each Xi is block low rank with a different block size, having a sparse matrix, represented by the smaller one and a low rank matrix, represented by the largest one. (Figure1). However, enhanced this approach using ANN, in order to provide accurate regularization of the index of resolvability and the parameters, allowed us to obtain clearly enhanced results in comparison with the original multi-scale approach, as shown in figure 5 above.

The proposed model of our work can be summarized in the flowchart below.

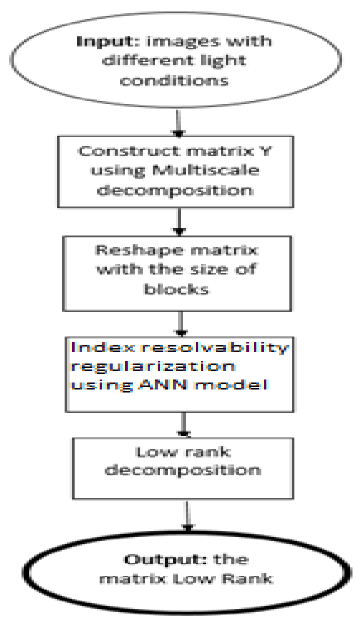

Fig.10. the flowchart of the entire application.

4. Conclusions

We have presented an enhanced multi-scale low rank matrix decomposition with ANN model method using a convex formulation and accurate index regularization, we can solve for the decomposition efficiently and exactly, given that the multi-scale signal segments are disjointed and its indices of resolvability are regularized accurately using the ANN model. Moreover, this provided empirical evidence that the proposed enhanced multi-scale low rank decomposition with ANN outperforms the original multi-scale approach on real datasets. Our experiments shows that the enhanced multi-scale low rank decomposition with ANN improves upon the low rank + sparse decomposition in fingerprint application. Otherwise, we believe that more improvement can be achieved if domain knowledge for all the applications is consolidated with the multi-scale low rank decomposition. Our contribution is to enhance the original Multi-scale decomposition with ANN to provide accurate regularization of the index of resolvability and apply it on fingerprint dataset, where different scales of occlusions are separated. First, we changed the illumination of images by applying histogram equalization and saved them as new images which represent the different scale of matrix (different illumination). Second, we are constructed the matrix Y over 9 time frames with image size (336*240). The resulting matrix is low rank with various block sizes. A small block size captures blood vessel dynamics in an enhanced way, while a large block size is more suitable in capturing background tissues. Hence, the proposed enhanced multi-scale low rank with ANN approach is desired to exploit all scales of correlations.

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