PATTERN RECOGNITION USING CONTEXT-DEPENDENT MEMORY MODEL (CDMM) IN MULTIMODAL AUTHENTICATION SYSTEM

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ABSTRACT

Pattern recognition is one of the prime concepts in current technologies in both private and public sectors. The analysis and recognition of two or more patterns is a complex task due to several factors. The consideration of two or more patterns requires huge space for keeping the storage media as well as computational aspect. Vector logic gives very good strategy for recognition of patterns. This paper proposes pattern recognition in multimodal authentication system with the use of vector logic and makes the computation model hard and less error rate. Using PCA two to three biometric patterns will be fusion and then various key sizes will be extracted using LU factorization approach. The selected keys will be combined using vector logic, which introduces a memory model often called Context Dependent Memory Model (CDMM) as computational model in multimodal authentication system that gives very accurate and very effective outcome for authentication as well as verification. In the verification step, Mean Square Error (MSE) and Normalized Correlation (NC) as metrics to minimize the error rate for the proposed model and the performance analysis will be presented.

KEYWORDS

CDMM, Vector logic, Feature extraction, LU factorization, Biometric pattern, Mean Square Error (MSE) and Normalized Correlation (NC).

1. INTRODUCTION

The mathematical analysis of unique characteristics of human patterns such as face, fingerprint, palm, Iris, Vein and so on has been adopted worldwide on a large scale and used in different sectors, including Educational Institutions, banking, Airports, public and private organizations and also to facilitate the person identification cards (Smart User Cards) such as Aadhaar Cards, Driving License, Debit/Credit cards, etc. However, the successful use of biometric technologies in these areas does not imply ideal security systems.

In general, most of the pattern recognition agents are unimodal, i.e., they use only single biometric patterns to recognize whether the user is authorize or not, but even the best unimodals usually use iris, fingerprint and face patterns are far from perfect. They have many inherent problems with the use of unimodal technologies suffer from noisy sensor data, lack of individuality, non-universality, spoof attacks and error rates included in the use.

In the logical formalism, the combination of multiple patterns gets the best systems and overcomes some of the inherent problems of unimodal systems. The multimodal systems use two or more patterns as a combination either in fusion based or non-fusion based

authentication/verification from the same person in order to identify him/her. These models are expected to be more accurate and less problematic because of consideration of more independent pieces of evidence into account, prior to the decision.

The relentless advance in the accuracy of biometric pattern recognition technology, increase in the availability of digital media and mass availability of cheap computing power now provide unique opportunities to meet challenging budgets by drastically enhancing the operational efficiency of forensic investigators while even further enhancing public safety. Digital media can be bulk-ingested in an automated fashion to be processed to identify and extract potential actionable intelligence. Processing is continuous, consistent and predictable. Multiple identification technologies can be deployed and the most suitable algorithms integrated to meet evolving requirements.

In the development of human patterns based authentication system, the process can be done in two to three stages: In stage one, the selection of appropriate patterns of a human being with reasonably invariant and having different degradations is to be done and that can be processed for the extraction of features with different pattern sizes. Before extracting the features, the patterns can be fusion using some geometrical algorithms such as PCA, LDA, ICA and its variants. In the next stage, the features can be extracted using factorization methods to generate key components for the computational process. In the computational stage, the usage of vector logic to make the system as complex and produce effective and accurate outcome in the testing criteria based on decision strategy for the test sample by using threshold. In the decision strategy, the error rate will be computed for the training and testing computational patterns using either by Mean Square Error (MSE), Normalized Correlation (NC) or any other error models for pair of vectors. Finally, based on threshold criteria the system gets the acceptance of rejection of the person as a result.

In this paper, an intuitive strategy is considered from the vector logic as Context-Dependent Memory Model (CDMM). This model works with the concept Kronecker product in the vector logic, which makes the authentication systems very complex and less error rate and is very effective for verification. This paper presents the computational model in the multimodal authentication system using vector logic and will be discussed in section 1. The empirical study of this model and methodology approach of PCA and LU will be presented in section 3. Finally the derived computational model along with experimental results and analysis will be presented in section 5.

1.1. Vector Logic

Vector logic is a mathematical representation of matrix algebra [2] inspired from the models of image processing and recognition systems. In this formalism, the image data is represented as matrix models to compute the best features in terms of Eigen values and Eigen vectors as feature vectors. Vector logic is one of prime concept of vector algebra in the matrix calculus. In the algebraic formalism, the operations on vector logic can be done in numerous ways for a square matrices and rectangular matrices. In the theory of rectangular matrices, kronecker product is one of the prime products in the process of tensor products which compute in the region of image segmentation, de-noising, convolution filters, authentication security models and medical applications too.

In the process of image computation models, matrices and vectors have been used to represent the logical formalism of feature extraction and selection, sub spaces, sub regions, pattern filtering, pattern classification, compression, restoration, digitization, enhancement. The representation of pattern data in matrices extend to the complex domain; that actualizes the biometric authentication and verification as vectors that can be used to construct geometrical representation

of logical rules. The data elements could be represented as Monadic, Dyadic and so on. In the monadic data the data is a one-dimensional vector, whereas dyadic data is a two dimensional data matrix.

For the dyadic data in various biometric applications, both key dimensions of the data matrix simultaneously is often more desirable than traditional one-way decomposition. The prime key benefit of exploiting the duality between rows and columns to effectively deal with the high-dimensional and sparse data that are typical in many applications. The key idea is that the block structure in a two-dimensional dyadic data matrix A can be explored by its triple decomposition. The dyadic data matrix is factorized into three components: PA, Left Triangulation L_A and Right Triangulation R_A.

1.2. Kronecker Product as Context Dependent Memory Model (CDMM)

The kroneckerproduct [25] of two matrices denoted by $A \otimes B$ has been researched since the 19thcentury. Many properties and other decomposition techniques have been discover during this time and are a part of classical linear algebraic models and it has been applied in many classical applications and produces new theories. In the recent research the vector logic as tensor products are used in the fields of Signal and Image processing to eliminate noise, error rate and improves the accuracy and efficiency of the samples. One nice product is Kronecker product, which has several properties; some of the properties are [3, 4, 7]

$$(A \otimes B)(C \otimes D) = (AC \otimes BD) \tag{1}$$
$$(A \otimes B)^T = A^T \otimes B^T \tag{2}$$
$$(A \otimes B)^{-1} = A^{-1} \otimes B^{-1} \tag{3}$$

The kroneckerproduct can be applied to vectors (monadic) and matrices (dyadic). The representaion of kronecker product for a set of dyadic matrices is

$$D_\delta = V_m \otimes V_m \rightarrow V_m, D_\delta \varepsilon R^{Q \times Q^2} \tag{4}$$

Where $V_m \otimes V_m$ is the tensor product of V_m. The elements of this tensor product [7] are the Kernel products of the vectors belonging to $V_m : V_i \otimes V_j \varepsilon V_m \otimes V_m, \forall v_i, v_j \varepsilon V_m$ The product is essential in Vector Logic and also in the current application, and is defiend as follows. Given two matrices $A = [a_{ij}]_{mxn}$, $B = [b_{ij}]_{pxq}$ the Kronecker product $(A \otimes B)$ is given by $(A \otimes B) = [a_{ij}B]_{mp \times nq}$

$$A \otimes B = \begin{bmatrix} a_{11}B & a_{12}B \dots \dots \dots & a_{1n}B \\ a_{21}B & a_{22}B \dots \dots \dots & a_{2n}B \\ \vdots & \dots & \vdots \\ a_{m1}B & \dots \dots \dots & a_{mn}B \end{bmatrix}$$

Each $a_{ij}B$ is a block of size $p \times q$. $(A \otimes B)$ is of size $mp \times nq$.

Now-a-days, tensor algebra is playing a key role in the pattern analysis and recognition systems with the use of vector logic. The kronecker product can be used in the analysis of image patterns and numerous representations for segmentation, sub region analysis, de-noising, filtering and also

in biometric technologies. One advantage of kronecker product [4] is their compact representation and approximation reasoning.

2. RELATED WORK

In the computation of multimodal systems, user has to enroll two to three patterns through different sensors for registration as well as verification/authentication. Such patterns may be noise due to capturing of patterns or environment or sensing devices. Such noise may lead to more error prone.

Various kinds of multimodal systems have been discussed in [8-18] among them user authentication based on face and speech patterns, is one of the first multimodal biometric system [9]. Multimodal system using face and fingerprint features is then proposed [10] by taking two acoustic patterns from speech and three visual patterns. Clustering techniques have been used for the fusion of decisions from speech and face modalities are explored in [11]. Security can be improved by considering dynamic pattern like lip movement, a practical multimodal system by considering face, voice and lip movement is developed [12]. A frame work proposed by A. K. Jain et al, for multimodal biometric person authentication discussed in [8]. Details about desirable characteristics of a physiological and behavioral of human, different levels of fusion, security and privacy concerns are also discussed.

In order to consider the level of authentication, the extraction of features for different patterns is completely different and can be uniqueness. In the combination of such patterns, the computation modal and decision modal must produce accurate and less error rate and complexity should be high. For such kind of computation modals vector logic gives better outcome to minimize the error rate with good accuracy.

2. EMPIRICAL STUDY

We demonstrate the effectiveness of our biometric system using the two level multimodal authentication problems. We conduct a detail study of authentication system into three levels of fusion, for encoding and decoding of biometric patterns. At level one, the normalized person patterns fusion through PCA, at two using computational model the generated keys through LU factorization, and at level three the decision process can be computed. An overview of the computational process of the model is provided in Fig. 1 and Fig. 2 respectively. For empirical evaluation, we demonstrate the performance of authentication system on different bench mark data sets Yale and AT&T. We compare the obtained results with various recent distance metrics.

In this paper, we focus on the computational model often called Kronecker logic as associative model often called Context-Dependent Memory Model(CDMM) and also various pair wise vector distance can be considered for evaluating the chosen model to minimize the error rate and to increase the efficiency and accuracy of the person patterns and we present False Accepting Rate (FAR) and False Not Accepting Rate (FNAR) are summarized in Table. 1
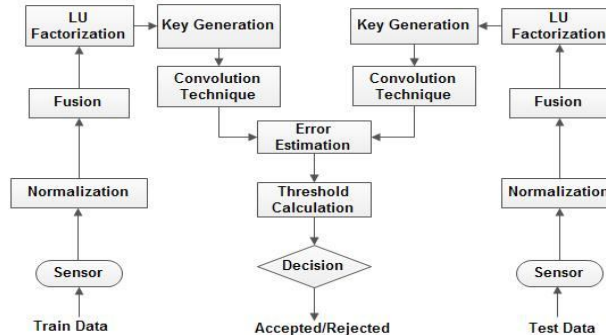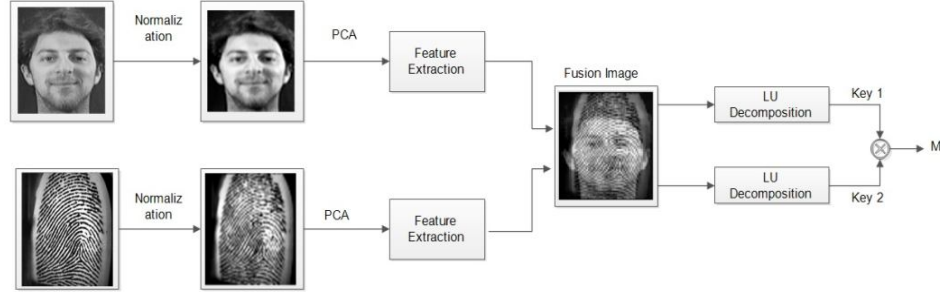
Figure 1: Frame work of the proposed model

Figure 2. Block Diagram of three level computation models

3.1 Context-Dependent Memory Model (CDMM)

Any linear system can be characterized by context dependency memory model [1,2]. If $\tau: H \to H$ is a linear system which maps the input signal $x(t)$ to the output $y(t)$, it is described by a function $H(t)$ such that

$$\tau(x(t)) = y(t) = x(t) \otimes h(t) = \int_{-\infty}^{\infty} h(\tau)x(t - \tau)d\tau \qquad (5)$$

The symbol represents the $\otimes$ Context dependency operation operation (also often called Kronecker Product). The theory generalizes the above system can be mapped into the characterization of nonlinear translation. If $\tau: H \to H$ is a non-linear system which maps the input signal $x(t)$ to the output $y(t)$, it is described by an infinite sequence of functions $h_n(t)$ indexed by n as

$$\tau(x(t)) = y(t) = \sum_{n=1}^{\infty} x(t) \otimes_n h(t) = \sum_{n=1}^{\infty} y_n(t) \qquad (6)$$

Where $\otimes_n$ represents the n_{th} order kernel operation in the vector logic and

$$y_n(t) = \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} h_n(\tau_n \dots, \tau_n)x(t - \tau_1) \dots x(t - \tau_n)d\tau_1 \qquad (7)$$

Here, $h_n(\tau_n \dots, \tau_n)$ are called as Taylor series exponential of the function. Note that (1) is a special case of (3) for n=1. Another intuitive way to think of series is to see it as the Taylor series expansion of the functional τ above. Switching to a discrete formulation, (3) can be written as

$$y_n(m) = \sum_{q_1=-\infty}^{\infty} \dots \sum_{q_n=-\infty}^{\infty} h_n(q_n \dots, q_n)x(m - q_1) \dots x(m - q_n) \qquad (8)$$

The infinite series in (4) does not lend itself well to practical implementations. Further, for a given application, only the first few terms may be able to give the desired approximation of the functional. Thus, we need a truncated form of Taylor series, which is denoted in this paper as

$$\tau(x(m)) = \sum_{n=1}^{p} y_n(m) = \sum_{n=1}^{p} x(m) \otimes_n h(m) \qquad (9)$$

Where p denotes the p_{th} order kernel logic. Note that $h(m)$ is a place holder for all different orders of kernels. The above equations can be defined for one-dimensional signals. All these

equations can be seamlessly generalized for two-dimensional image data, i.e. $I(x,y)$. The approach of this model can be mapped to 2-Dimage processing in the field of biometrics. Thus, this operation is an approximate operator that can be applied to image restoration and noise removal.

4. FUSION OF BIOMETRIC PATTERNS USING PCA

Image fusion process can be defined as the integration of information from a number of registered images without the introduction of distortion [19]. One of the goals of image fusion is to create a single enhanced image more suitable for the purpose of human visual perception, object detection and target recognition. This fusion of images obtained from different modalities is of great importance in applications such as medical imaging, remote sensing, Multimodal Biometrics and machine vision [20, 21].

In the process of image fusion, multi-sensor outputs can be combined to give a better quality image of the scene. Image fusion is generally divided into three categories; pixel level, feature level and decision level fusion [22, 23]. Pixel level fusion works directly on the pixels obtained at imaging sensor outputs while feature level fusion algorithms operate on features extracted from the source images. Decision level fusion uses the outputs of initial object detection and classification as inputs to the fusion algorithm to perform the data integration. From these three levels, the model considers feature level fusion patterns. The principle component analysis (PCA) is a mathematical way of determining the linear transformation of a sample of points in a N-dimensional space exhibiting the properties of the sample along the coordinate axes. It enables a decrease in the number of channels (or images) by reducing the inter-channel dependencies. This analysis is based on the computation of the covariance matrix and its diagonalization by finding corresponding Eigen values and eigenvectors. The first eigenvector (or principle component) is a linear combination of the initial images and usually contains more than 90% of the information contained in all the images. Two sets of data can then fused by concatenating all channels and performing a PCA transformation on all the channels to keep only the non-redundant information.

5. FEATURE EXTRACTION USING LU FACTORIZATION

There have been many research studies that perform decomposition based on Singular Value Decomposition (SVD) or eigenvector-based decomposition, each data vector into the singular vector space through the SVD, and then conducts the decomposition using traditional algorithms in the transformed space. Since, the computed singular vectors or eigen vectors do not correspond directly to individual ones, the decompositions from SVD- or eigenvector-based methods are difficult to interpret and to map to the final segments; as a result, traditional data segmentation methods must be applied in the transformed space. Another matrix decomposition formulation, LU factorization has been used for key extraction and generation from the fusion patterns. LU factorization has the intuitive interpretation for the result. However, it focuses on triangulation of the data matrix and does not take advantage of the duality between the rows and the columns of a matrix, where as SVD or other eigenvector decomposition methods focus on one dimensional data matrix, i.e. vector representation.

5.1 LU Factorization

The matrices can be factorized into various ways with the use vector logic [3,24], some of the factorization methods are LU, Cholesky, QR, Schur, SVD and Block matrix factorization and many more. Among these methods LU factorization is chosen since it works on Gaussian

transformations and generates triangular system with the complexity $O(m^3)$. The computation of LU factorization can be described for the matrices A and B of 3x3 matrices as:

$$A = (P_A^T L_A U_A) \otimes (P_B^T L_B U_B) = (P_A^T \otimes P_B^T)(L_A \otimes L_B)(U_A \otimes U_B) \quad (10)$$

6. COMPUTATION MODEL (CONVOLUTION KERNEL PRODUCT)

We describe a model where the input-output associations of a matrix are dependent on the context of multiplicative vector logic. In this context a remarkable operation that transforms the real matrix over the truly computing, into a triangular matrix. This transformation promoted by the context leads to the LU Decomposition of a matrix representation, which is a mathematical method in the field of Image Processing and signal processing.

The meaningful event in the representation is the activity of the large group of data patterns, naturally represented by high dimensional vectors or dyadic matrices. These representations are processed by associative memories (The association input-output pattern pairs) which store the information distributed and superposed over coefficients. In this paper, the associative memory is computed, the keys which are generated from the fusion patterns by using LU factorization,

$$key1 = LU(A) = (P_A^T L_A U_A) \quad (11)$$
$$key2 = LU(B) = (P_B^T L_B U_B) \quad (12)$$

Where A and B are fusion patterns of two pair biometric samples (face and finger print). The fusion is done by using PCA. The importance of this factorization is here to extract the best features by eliminating noise and lighting effect using Gaussian-distribution models. In the process of computation the CDMM uses the two keys from LU factorization and generates a memory representation $'M'$ over k, where k is the k_{th} order that uses Kronecker product as CDMM[5,6].

$$M^{(k)} = \sum \varrho_i (key1_i \otimes key2_i)^T \quad (13)$$

In general, $(A \otimes B)$ represents the Kronecker product.

$$M^{(k)} - \sum_k A_i [A_i \otimes \sum_{j(k)} B_j])^T \quad (14)$$

Where A is the one key pattern of one fusion set and B is another key pattern of the second fusion set, with i_{th} order kernel logic. In this expression an association can also be weighted by a scalar coefficient that represents frequency of the given association.

$$M(g \otimes W_{mxn}) = \sum_i < A_i, g > A_i (\sum_{j(i)} B_j^T) \quad (15)$$

Where, W is the weighted frequency of the association. In the linear combination we assume that the memory model has equal weights. Thus,

$$M(g \otimes W_{mxn}) = \sum_i < A_i, g > A_i (\sum j(i) B_j^T) = \sum A_i (\sum j(i) B_j^T) \quad (16)$$

Where, $g = \sum A_i$ and W is identity matrix. In this associative model, the memories are based on a matrix over a multiplicity of vector associations are superimposed. Another representation of the memory is,

$$M^{(k)} = \sum <A_i, A_k> g_i B_j^T \tag{17}$$

which is a structural representation of M for the context A_k. In this representation, the singular values of matrix $M^{(k)}$ correspond to the scalar product $<A_i, A_k>$. The potential flexibility of this model emerges from a compromise between the structured rigidity and selective capabilities of the information.

7. DECISION STRATEGY

In this paper, we considered two kinds of decision strategy approaches for verification/authentication or the recognition of chosen patterns with the use of CDMM at the training and tested levels M and M'. Mean Square Error (MSE) and Normalization Correlation (NC) are considered as two approaches for verification of the proposed model shown in figure(1).

7.1 Mean Square Error

The Mean Square Error (MSE) of an estimator $\hat{\theta}$ of a parameter θ is the function of θ defined by $E(\hat{\theta} - \theta)^2$ and it is denoted as $MSE_{\hat{\theta}}$. This is also called the risk function of an estimator, with $(\hat{\theta} - \theta)^2$ called the quadratic loss function. MSE measures the average squared difference between the estimator $\hat{\theta}$ and the parameter θ, a somewhat reasonable measure of performance for an estimator. MSE has at least two advantages over other distances:

   1. It is analytically tractable   2. It has the interpretation

7.2 Normalization Correlation

A popular approach of the pathway construction is based on the sample collection coefficient are mutual information measures to characterize the interaction between the two patterns via the computation task at the decision level. These measures of the interaction are computed from the computational task of observed patterns across various experimental conditions.

The present paper focuses on the correlation between test statistics associated with the memory signals produced by the trained and tested memory patterns from the effect of normalization procedures on these correlations.

Normalization is intended to mitigate the effect of the noise (error signal) i.e., inherent in the verification process. Normalization produces tend to reduce the variability of original data pattern.

$$EN_c = 1 - \frac{1}{d_{max}} \left(\frac{1}{N} \left(\Sigma_i |A(i) - B(i)(B(i)^1|^p) \right)^{\frac{1}{p}} \right) \tag{18}$$

Where A and B are two congruent patterns, d_{max} is the maximum possible distance between them.

8. EXPERIMENTAL RESULTS AND ANALYSIS

By considering benchmark Yale and AT&T, FERET data sets [27, 28] number of experiments made using the proposed framework with the computational task CDMM. The framework is divided into three levels of process. At stage one, using LU factorization the best features will be extracted as block matrix (dyadic matrix) from fusion patterns as keys. In stage two, the generated keys will be passed as inputs to the CDMM for computation to increase the complexity. In stage

three, this paper performs two kinds of decision strategy on pair wise data matrices from the patterns of the computational model for registration and verification. Mean square Error (MSE) and Normalized Correlation (NC) can be considered for verification of the biometric patterns through the framework. Based on the error rate of MSE and NC, the acceptance rate will be determined. From the observations of bench mark data sets for both similar and dissimilar patters of different poses using the proposed framework, the thresholds of MSE and NC bounded as 0.10, 0.25 respectively. In this paper, we are presenting three kinds of patterns with various key sizes $8x8, 16X16 ... 64X64$ The experimental results will be presented in the Table 1. Based on the analysis, the key size 8X8 using MSE and NC have failed for recognition since less number of features has been extracted. From the observations of MSE and NC thresholds the False Acceptance Rate (FAR) and False Non Acceptance Rate (FNAR) have been measured for the chosen key sizes of the patterns.

Key Size	Similar		Dissimilar		Dissimilar2	
	MSE	NC	MSE	NC	MSE	NC
8x8	0.16989	0.45022	0.13558	0.408484	0.142142	0.423452
16x16	0.18351	0.2212	0.06473	0.470359	0.066315	0.478301
24x24	0.14647	0.21929	0.08831	0.306719	0.089309	0.346723
32x32	0.13255	0.24038	0.09124	0.26171	0.081218	0.279634
40x40	0.14347	0.1513	0.07946	0.390177	0.073142	0.385437
48x48	0.10454	0.15067	0.0962	0.282631	0.091011	0.232712
56x56	0.11772	0.14998	0.08888	0.291341	0.081913	0.285432
64x64	0.12101	0.14921	0.0755	0.311495	0.067432	0.334527

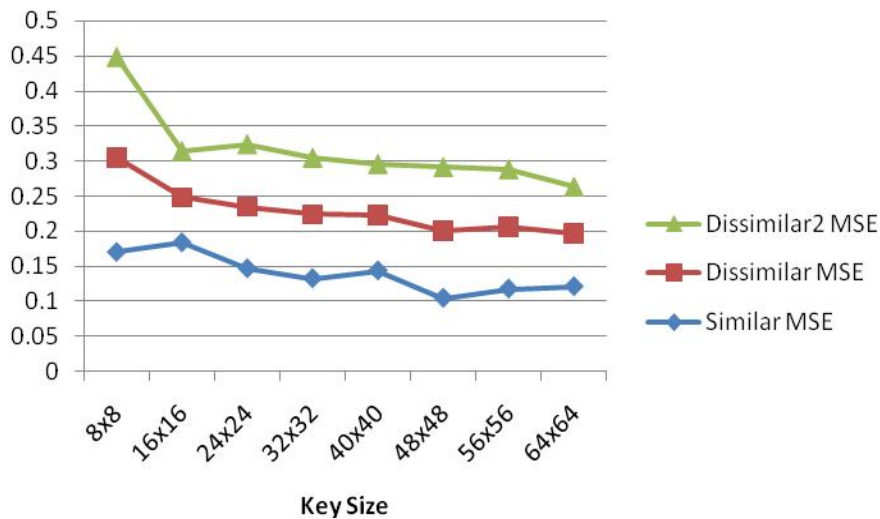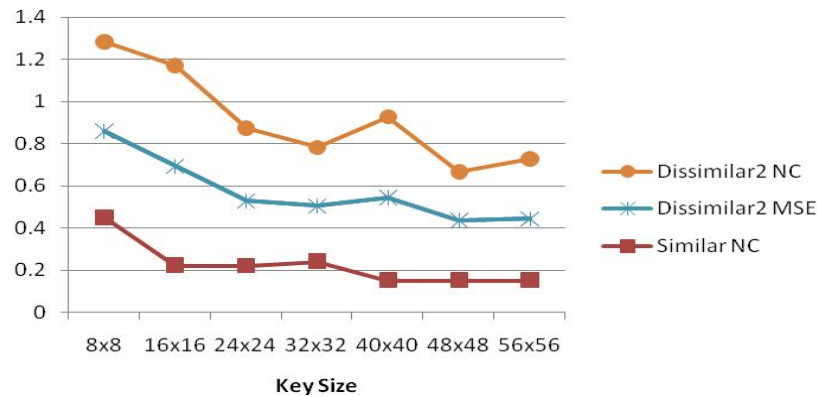Table 1. MeanSquareError

Figure 3. Mean Square Error

Figure 4. Normalized Correlation

9. CONCLUSION

The proposed model from the vector logic as CDMM takes place an instrumental role in many image restoration algorithms and removal of noisy with the use of LU factorization since Gaussian transformation eliminates noise. And also the CDMMwill be used in various forms like Approximate inverse pre-conditioners and Fast transformations such as Hartley transform, Fourier Transforms and Wavelet transforms for Image and Signal systems, and also it fits the problem of surface fitting with splines also can be used in stochastic network models. The complexity of the CDMM is $O(n^6)$, assume the two matrices are of $O(n^3)$. It is NP-hard. Using the proposed model of various samples, the key size 8X8 is failed due to less features from the fusion pattern for recognition/verification.

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