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IMAGE FEATURE ENCODING USING LOWNERIZATION TENSOR

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ABSTRACT

In recent days, technology plays a major role in real-time applications of current usage and at the same time security is one of the critical task in order to utilize and access data as well applications/tools. In this scenario, vulnerability is the most important factor for any real-time application. There is a need to minimize the vulnerability of any application up to date. In majority applications, traditional human traits like Face and fingerprint can be treated as one of the prime data to provide security, through these patterns with conventional methods of access is major risk to deal. A multimodal authentication method has been proposed by these two human traits for authentication by applying a two level of process for the analysis, encoding and Decoding, 1) to preprocess the images and then extract the features using Non-Negative Matrix Factorization (NNMF) and 2) to encode and decode the extracted features using Tensor based Lownerization method. The major contribution of this method is to minimize the vulnerability of traits/patterns which extracted the features by applying NNMF method. The extent of the proposed method has been validated with the results that are obtained in two ways. In one way, after extracting the features fusion can be applied. In another way fusion is not applied. Here the two distinct metrics viz., Euclidean Distance and Mean Square Error are used. When compared to the existing papers the proposed encoding and decoding method gives better security. Mean Square Error Distance gives better results when comparing to the Euclidean Distance.
Keywords: *Multimodal Authentication, Preprocessing, Tensors, Lownerization Tensor, IF Encoding*

1. INTRODUCTION

Nowadays, everyone and everywhere have access to the internet. Data collection has become a simple task. As a result, database maintenance is fairly prevalent everywhere. When all of these databases are combined, the number of dimensions and database size will both grow. The first fundamental stage in any recognition method is feature selection and approximation. When the dimensions are large, feature extraction is challenging and computing complexity is significant. Approximation approaches [1-5] are particularly useful for picking the best features and extracting them. After extracting the features, we have to store these features for authentication purpose. This authentication will act as a security for any application. Sometimes facial emotions are also very much helpful for recognition [23]

The security of any personal information or data is paramount. Biometric [6] is an authentication method that has mostly supplanted passwords and pin codes in recent years. Face, Fingerprint, and Palm are only a few of the qualities that are employed for authentication. Unimodal biometric systems were built for recognition and authentication in the past. Recognition is not done perfectly if the trait that is utilized for authentication is damaged. The Unimodal biometric system has to contend with problems like unacceptable error attacks, spoof attacks, restricted degrees of freedom, intra – class variations and noisy data. To overcome these problems by using Multimodal authentication [7,8] can be utilized for recognition and authentication that is integrate the evidence by multiple sources of information. The concept of multimodal biometrics is gaining traction as a way to create authentication systems that are trustworthy, accurate, and robust. Sensor level, feature level, match-score level, rank level, and decision level information fusion can all be done in multimodal biometrics fusion [9].

A biometric system basically functions as a pattern recognition system that collects biometric information from a person, extracts a set of features from the data, and compares those features to a database of template sets.

A biometric system may function as an identity system or a verification system, depending on the application context. In an identification system, a person is identified by matching their features to a database of template images. Whereas in verification system, the person being verified must affirm their identification. This template is then compared to the person's biometric traits. Templates can be designed with fusion or without fusion of extracted image features. Some of them are using fusion based authentication and some of them are non-fusion based authentication. But the accuracy is depending upon different factors.

In this paper, a better image encoding technique was proposed called the Lownerization tensor technique, so that extracted image features can be stored securely for authorization of the image. This paper can be organized as follows in further sections. Section 2 provides Literature survey. Different types of tensor techniques are described in Section 3. Section 4 represents use of Lownerization tensor technique and Section 5 represents the experimental results and comparisons are demonstrated. The paper was concluded in Section 6.

2. LITERATURE SURVEY

Feature encoding is a key element in the pipeline of image rendering. These days, the codebook approach i.e., the representation is based on the descriptors extracted locally and coded based on codebook, is used for the representation of the images. However, codebook memory costs increase rapidly depending on the dimension of local functionality. Shinomiya et al. [10] introduced a compact codebook-based functional coding technique by using fuzzy clustering in two approaches. To modify fuzzy clustering to properly compute high dimensional vectors such as local features is the first approach. The second approach is to update the codebook for each image and use KL divergence to embed the differences in the image functionality.

Xihui Lin et al. [11] presented the optimization and expansion of Non-negative Matrix Factorization (NMF), which is utilized to solve non-negative matrix issues. To use a masking strategy on the NMF decomposition during iterating algorithms in order to keep particular structures or patterns in one or both of the output matrices, which can be created based on prior information and desirable attributes to generate a more meaningful decomposition.

Muja Marius et al. [12] developed scalable Nearest Neighbor Algorithms for High Dimensional Data to solve the difficulty of finding nearest neighbor matches to high dimensional vectors that represent the training data in computer vision machine learning algorithms. The proposed approach and the kd-tree are the most efficient algorithms for matching high-dimensional features. By scanning various hierarchical clustering trees, the suggested approach for matching binary features. The optimal nearest neighbor method and its parameters are determined by the properties of the data set, and they explain an automated setup procedure for determining the best algorithm for searching a certain data set. It is not possible to scale to enormous data sets in a single machine's memory. Any of the algorithms can be utilized with a distributed nearest neighbor matching framework that was proposed.

Lionel Moisan et al. [14] proposed a probabilistic criterion for evaluating the meaningfulness of a rigid set as a function of both the number of pairings of points (n) and the correctness of the matches. The projection of n physical points onto two viewpoints (stereovision) is generally limited to $n \geq 8$. In order to compensate for the restricted accuracy of the matches, more than 8 point matches are desirable when there is a rigid motion between two images.

3D laser scanning is a novel technique for quickly creating a 3D picture representation of an object by collecting spatial position of points and obtaining 3D coordinates of the target surface. In the fields of photogrammetry and computer vision, obtaining a D model from objects is a difficult task. Xingchangetal. [15] Proposed 3D modeling of spatial objects performed using spatial data acquired via a 3D laser scanner on the ground, and how to reconstruct a 3D scene model using laser range images. This approach described a collection of algorithms for 3D reconstruction, that is, the implementation of image segmentation and area registration based on planar features. After retrieving the image area, the image was segmented to extract the features of the plane and registered to recognize the initial configuration between the sensor's coordinate systems from the two views. Finally, create a triangular mesh to create a 3D surface model. The results of this method are accurate and robust.

2.1 Research gap:

Many existing image encoding techniques focus on achieving high compression ratios while maintaining acceptable image quality. However,

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there is a gap in developing methods that can strike a better balance between compression efficiency and preserving perceptual quality, particularly for high-resolution images. Further, with increasing concerns about privacy, there's a gap in research on image encoding techniques that can protect sensitive information while still maintaining efficient compression and usability. These challenges of image analysis and processing can be addressed by Image feature encoding using tensor low-rank approximation (tensor Lownerization). This technique aims to capture essential features of images while reducing the dimensionality of the data. Here are some reasons for the need of image feature encoding using tensor Lownerization:

High-Dimensional Data: Images are high-dimensional data, often represented as matrices or tensors. The sheer volume of pixels or elements in an image can lead to computational and storage challenges [24]. Tensor Lownerization helps in reducing this dimensionality by approximating the original image tensor with a lower-rank decomposition.

Dimensionality Reduction: Traditional image representations, such as pixel values, might not capture the intrinsic features of images efficiently [26]. Tensor Lownerization offers a way to reduce the complexity of an image while preserving important features, enabling more efficient processing and analysis.

Noise and Irrelevant Information: Images can be noisy or contain irrelevant information [25]. Tensor Lownerization can help in denoising images by focusing on the most significant features and suppressing noise.

Feature Extraction: In image analysis, it's often important to extract meaningful features that represent the content of an image [27]. Tensor Lownerization can be used to extract these features and encode them in a more compact form, which can be used for tasks such as image classification, object recognition, and scene understanding.

Efficient Storage and Transmission: In applications where storage and transmission resources are limited [28], using tensor Lownerization to encode images can help reduce the amount of data that needs to be stored or transmitted while still maintaining the ability to reconstruct important features.

Multi-Modal Data Fusion: Images can have multiple modalities (e.g., color channels, depth information, infrared data) [29]. Tensor Lownerization can be applied to fuse these modalities effectively and capture the combined information in a compact representation.

Semantic Understanding: In tasks like image captioning or generating textual descriptions from images, tensor Lownerization can help in capturing the semantic content of the image while removing irrelevant visual details.

Visual Data Compression: Tensor Lownerization offers a way to compress images while maintaining a certain level of quality. This is particularly useful in scenarios where bandwidth or storage is limited, such as in remote sensing, satellite imagery, or IoT devices.

Efficient Learning: In machine learning models that involve images as inputs, tensor Lownerization can reduce the complexity of the input data, leading to faster training and inference times while still retaining the essence of the images.

Interpretable Representations: The lower-dimensional representations obtained through tensor Lownerization might be more interpretable than raw pixel values, allowing researchers and practitioners to gain insights into the underlying image features more easily.

2.2 Context of the problem:

In summary, image feature encoding using tensor Lownerization serves as a powerful tool to reduce the complexity of image data while retaining essential information. It offers benefits in terms of computation, storage, noise reduction, and feature extraction, making it valuable in a variety of image analysis and processing applications.

Consequently, in this paper, a better image encoding technique was proposed called the Lownerization tensor technique, so that extracted image features can be stored securely for authorization of the image.

3. TENSORS

The process of transforming or mapping lower-order data into higher-order data is known as tensorization. A matrix, a third-order tensor, or a higher-order tensor, for instance, can be produced by tensorizing low-order data that is in the form of

a vector. The so-called "low-order" data could also, for instance, be a matrix or third-order tensor. Tensorization can happen along one or more modes in the latter scenario.
As shown in the example, a vector C can be transf ormed into a matrix L or a tensor L of any order K .. The following Figure 1 shows the conversion of vector to tensor.

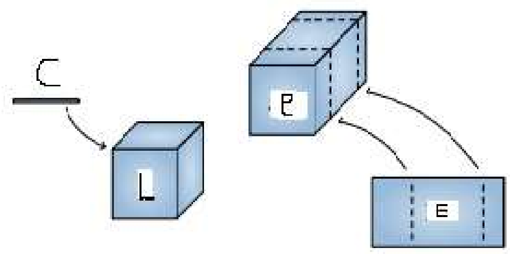

Figure 1 : 3rd-order tensorization of a vector C to a tensor L (left), and 2nd-order tensorization of a matrix e to a tensor E (right).

The conversion or transferring in the cases above was a rearrange, however other mappings can also be taken into account. A range of mappings and associated tensorization methods are available through Tensorlab.

There are different types of tensorization and detensorization techniques are there

1. A Hankel matrix/tensor mapping is used in hankelization. The Tensorlab commands hankelize and dehankelize correspond.
2. A Löwner matrix/tensor mapping is used i n Löwnerization. The commands loewneri ze and deloewnerize in Tensorlab are equi valent.
3. Reshaping and folding are used during seg mentation.
   Segments may overlap in a more sophistic ated variation. The segmentize and deseg mentize commands in Tensorlab are equiv alent.
4. Similar to segmentation, decimation also employs a reshaping/folding mapping, but it does so from the perspective of subsampling. Decimate and dedecimate are the corresponding Tensorlab commands.

Tensor Rank
If a tensor $A\epsilon \boldsymbol{Z}^{I_1 x I_2 x \ldots x I_N}$ can be written as the outer product of N vectors, it is said to be rank-one. A separate mode is corresponding to each vector.

$$A = a^{(1)} o a^{(2)} o \ldots . o a^{(n)}$$

The rank of the tensor is represented by rank(A)[22] and it can be expressed as the least number of rank-one tensors need to sum to the specified tensor A. It can be represented as

$$rank(A) = argmin\left\{Z\epsilon N: A = \sum_{i=1}^{Z} a_i^{(1)} a_i^{(2)} \ldots a_i^{(N)}\right\}$$

Tensor Vectorization
The higher order tensor $A\epsilon \boldsymbol{Z}^{I_1 x I_2 x \ldots x I_N}$ is converted into a vector B by mapping each element to the vector's element with index. It can be written as

$$index = 1 + \sum_{n=1}^{N} (i_n - 1) \prod_{m=1}^{n-1} I_m$$

Let us consider an example, Let a tensor A

$$A_{..1} = \begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix}, A_{..2} = \begin{bmatrix} 5 & 7 \\ 6 & 8 \end{bmatrix}$$

The following result is produced by vectorization

$$Vec(A) = [1 \quad 2 \quad 3 \quad 4 \quad 5 \quad 6 \quad 7 \quad 8]^T$$

Tensor Multiplication:
There are different tensor multiplication methods are there
1. Inner Product: Let us consider the two sensors A, B with the same order and same size, $A, B \in \boldsymbol{Z}^{I_1 x I_2 x \ldots x I_N}$ I . The inner product of two sensors A, B is denoted as [22]

$$w = \langle A, B \rangle = \langle vec(A), vec(B) \rangle = \sum_{i=1}^{I1} \sum_{i=1}^{I2} \ldots \sum_{i=1}^{IN} a_{i1i2\ldots iN} b_{i1i2\ldots iN}$$

2. Outer Product: The outer product of two tensors A and B is denoted by $C = AoB$, where $A\epsilon \boldsymbol{Z}^{I_1 x I_2 x \ldots x I_N}$ **and** $B\epsilon \boldsymbol{Z}^{J_1 x J_2 x \ldots x J_K}$ **the new tensor C is defined as** $C\epsilon \boldsymbol{Z}^{I_1 x I_2 x \ldots x I_N x J_{1x} J_2 x \ldots x J_k}$

4. PROPOSED LOWNERIZATION TENSOR TECHNIQUE

4.1Preprocessing and Feature Extraction

Preprocessing involves removing unnecessary elements and enhancing contrast to

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make them more visible. Filtering can be divided into two categories. In image processing, there are two types: linear and nonlinear. Image processing is used in a variety of fields, including remote sensing, medical imaging, textiles, and material research. In this paper Image preprocessing done with the mean (average) or median filter is one of the strategies. The mean filter replaces each pixel's value with the average of all pixel values in a small area (often a N by N window, where N = 3, 5, 7, and so on). Each pixel's value is replaced with the median value obtained in a local neighborhood in the median filter. Figure 3 shows the overall structure of the proposed work.

Once preprocessing is over, the next step is feature extraction.The extraction of characteristics is critical for this identification. When there are numerous attributes and the attributes are vague or have poor predictability, NMF is helpful. NMF can create significant patterns, subjects, or themes by combining attributes. The original attribute collection is linearly combined into each feature produced by NMF. Each feature has a set of coefficients that represent the relative importance of each attribute to the feature as a whole. Each numerical attribute and each unique value of each categorical attribute has a unique coefficient. All of the coefficients are positive.

NMF divides a matrix A into two matrices with lesser ranks and non-negative entries [16].

$$X \approx AB where X \in R^{n\times m} A \in R^{n\times k} B \in R^{k\times m} \quad (1)$$

Here the matrix X rows represents the features, matrix X columns represents the samples. A can be perceived as a feature mapping depending on the context. Samples are compactly represented in Column H. NMF can be expressed mathematically as

$$\min_{A\geq 0, B\geq 0} L(X, AB) + J_A(A) + J_B(B) \quad (2)$$

The loss function can be defined as L(a,b) which is frequently selected as square error $\frac{1}{2}(a-b)^2$ or KL divergence distance as $a\log\left(\frac{a}{b}\right) - a + b$.

Sadly, factorizations of non-negative matrices are typically far more challenging to compute than factorizations.

There are three primary challenges:

1. The size of M that is required to obtain a "excellent" representation is unknown. When using conventional factorization.
2. Non-convex optimization problems typically have a large number of local minima.
3. The best rank M approximation may not be directly related to the best rank M+1 approximation because NMF is not incremental.

The following figure 2 [21] shows the the NMF, Vector Quantization (VQ) and PCA part based comprehensive representation of faces.

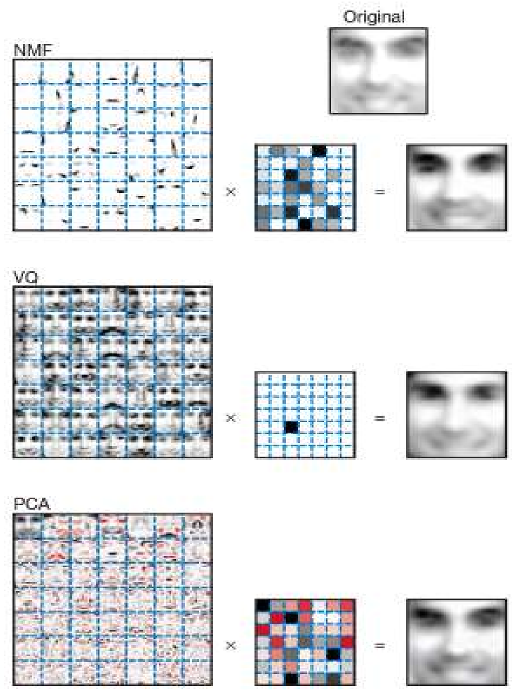

Figure 2. The following figure shows the NMF, Vector Quantization (VQ) and PCA part based comprehensive representation of faces.

After extracting the features from the face and finger fusion can be applied and the results can be stored in the memory. Algorithm can be run in two ways. One is on fusion image and other is non fusion images. Fusion can be done with Principle Component Anaysis(PCA).

4.2 Feature Encoding using Lownerization Tensor method.

Once features are extracted, they are stored in a smart card for authentication purposes. In the literature, there are many algorithms proposed by different types of authors. If these features are stored directly in the smart card, there is a chance for vulnerability. Hence, these features are encoded and stored in the smartcard, and at the time of verification, these features are decoded and used for authentication.

In this paper, a new tensor method called Lownerization [17] is used for encoding and decoding. The method is illustrated in figure 3.

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When computing the inner product, norm, and MTKRPROD[13,14,15], the multi-linear structure can be used instead of constructing the entire tensor. This is the main advantage of the Lownerization matrix.

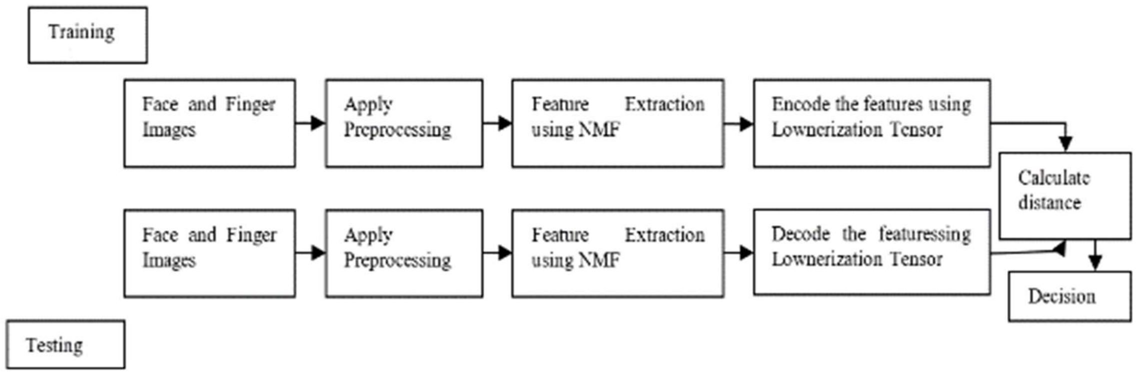

Figure 3. Block Diagram Of Proposed Lownerization Tensor Technique.

Let $A \in C^N$ be a vector and it have the evaluation points $p \in C^N$. Let's divide [1, 2,...,N] into two vectors $m \in C^P$ *and* $n \in C^Q$ *with* $N = P + Q$. Let us consider an interleaved partitioning (m=[1,3,..]and n=[2,4,…]) or black partitioning (m=[1,2,…P] and n= [P+1,…N]) can be used. Now the Lowner matrix $Z \in C^{P\times Q}$ is defined as follows

$$(\boldsymbol{Z})_{\boldsymbol{p},\boldsymbol{q}} = \frac{\boldsymbol{f}_{\boldsymbol{m}(\boldsymbol{p})}-\boldsymbol{f}_{\boldsymbol{n}(\boldsymbol{q})}}{\boldsymbol{v}_{\boldsymbol{m}(\boldsymbol{p})}-\boldsymbol{v}_{\boldsymbol{n}(\boldsymbol{q})}}, \forall \boldsymbol{p} \in \{1,2,..P\}, \forall \boldsymbol{q} \in \{1,2,..Q\} \quad (3)$$

For example consider a vector A=[10,11,12,13] and evaluation point B=[5,6,7,8] . The lowner matrix using interleaved partitioning is given by

$$K = \begin{bmatrix} \frac{11-10}{6-5} & \frac{10-13}{5-8} \\ \frac{12-11}{7-6} & \frac{12-13}{7-8} \end{bmatrix}$$

4.3 Distance Metric: These distance metrics are used to calculate the similarity between data points of training and testing**.** In this paper Mean Square Error (MSE) distance is used to calculate the distance between training and testing images. Let M and N are two images, and each image contains K pixels and $m_j$and n_j represents the j^{th}pixel in image M and N then the MSE of two images M and N can be defined as

$$\text{MSE(M,N)}=\frac{1}{K}\sum_{i=1}^{k}(m_i - n_i)^2 \quad (4)$$

If two points are in a straight line, then calculate the distance between these two points with the help of the Euclidean distance

Let M=(g,h) and N=(o,i) then calculate the Eucidean distance between these two points M and N as

$$distance(M,N) = \sqrt{(o-g)^2 + (i-h)^2}$$

5. RESULTS AND DISCUSSION

In this paper the results can be obtained in two methods. In the first method as a first step in the training, image preprocessing can be applied to the face and finger by using the mean filter technique. After that, features can be extracted using Non Negative Matrix factorization. Once features can be extracted fusion can be applied. Now this fusion can be encoded with the Lownerization Tensor technique. Now these features can be stored in a smart card. In the authentication process, for the testing images first we need to perform the de-Lownerization technique and then follow the same steps in the order as mentioned above. At the end, calculate the difference between training and testing images with the help of the distance metric using Mean Square Error. Now define the threshold value based on the error obtained by running different types of testing and training images. Finally, compare the obtained distance with the threshold value and make a decision whether the person is authorized or not.

In the second method after extracting the features fusion cannot be applied. Euclidean distance can be used as a distance metric for calculating the similarity between training and testing images.

The results of experiments can be obtained using conventional databases [18, 19, 20]. All of these tests may be carried out in a Windows 10 environment with 6GB of RAM, an i3 Intel processor, and a 500GB hard disc.

Table 1 and Fig 4 shows the method 1 results. Here features can be extracted from face and finger using NMF and these features can be fusioned and, Lownerization tensor is used as Encoding

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technique and Mean Square distance can be used as a distance metric. For this model threshold T can be defined as 6.40. This method can be compared with PESN Krishna Prasad et.al [16] , it gives better results for the key size 16x16 also. Existing method fails for the key sizes 8x8 and 16x16.

Table 1: *Proposed Feature Extraction Using NMF, Fusion Applied For The Extracted Features And Lownerization Tensor Is Used As Encoding Technique And Mean Square Distance As A Distance Metric*

S.No	Key Size	MSE	
		Similar	Dissimilar
1	8x8	4.350015	4.607736
2	16x16	6.402805	4.328069
3	24x24	11.648962	4.18441
4	32x32	21.367552	5.527439
5	40x40	20.331642	5.633834
6	48x48	73.444716	4.098385
7	56x56	32.247267	4.046477
8	64x64	43.27675	5.306438

Fig. 4 shows the graphical view of Proposed Feature Extraction using NMF, Fusion applied for the extracted features and Lownerization tensor is used as Encoding technique and Mean Square distance (MSD) as a distance metric.

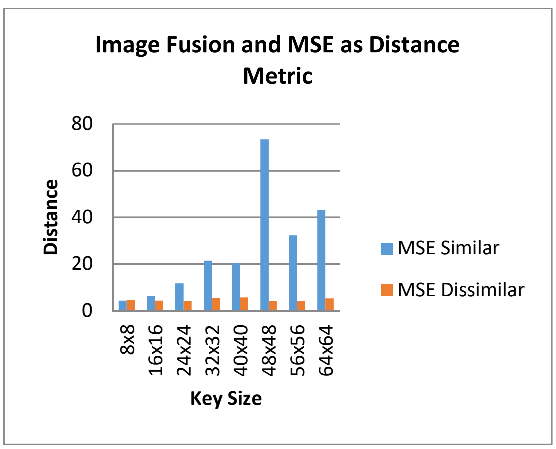

Fig. 4 Proposed Feature Extraction Using NMF, Fusion Applied, Encoding Technique And MSD.

Table 2 and Fig 5 shows the method 1 results. Here features can be extracted from face and finger using NMF and these features cannot be fusioned and , Lownerization tensor is used as Encoding technique and Mean Square distance can be used as a distance metric. For this model threshold T can be defined as 12.80. This method can be compared with PESN Krishna Prasad et.al [16] , it gives better results for the key size 16x16 also. Existing method fails for the key sizes 8x8 and 16x16.

Table 2: *Proposed Feature Extraction Using NMF, Fusion Not Applied For The Extracted Features And Lownerization Tensor Is Used As Encoding Technique And Mean Square Distance As A Distance Metric*

S.No	Key Size	MSE	
		Similar	Dissimilar
1	8x8	8.720012	7.125487
2	16x16	12.801275	7.325584
3	24x24	22.584458	8.125454
4	32x32	42.254885	9.925471
5	40x40	40.125154	9.658423
6	48x48	140.25141	8.128798
7	56x56	65.245845	8.257814
8	64x64	76.125484	10.25144

Fig. 5 shows the graphical view of Proposed Feature Extraction using NMF, Fusion not applied for the extracted features and Lownerization tensor is used as Encoding technique and Mean Square distance (MSD) as a distance metric

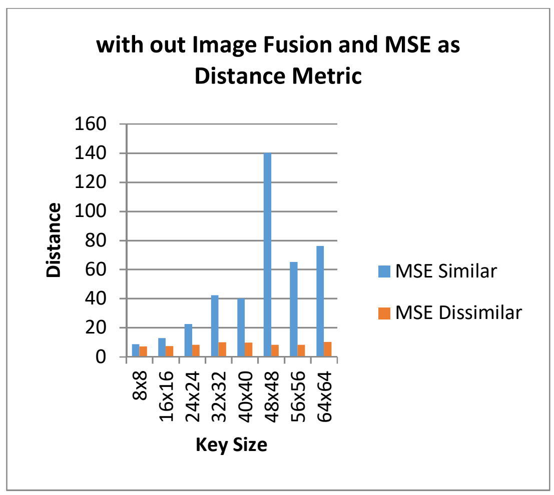

Fig. 5 Proposed Feature Extraction Using NMF, No Fusion, Encoding Technique And MSD.

Table 3 and Fig 6 shows the method 2 results. Here features can be extracted from face and finger using NMF and these features can be fusioned and , Lownerization tensor is used as Encoding technique and Euclidean distance can be used as a

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distance metric. For this model threshold T can be defined as 62.7. This method can be compared with PESN Krishna Prasad et.al [16] both fails for 8x8 and 16x16 key sizes.

Table 3: *Proposed Feature Extraction using NMF, Fusion applied for the extracted features and Lownerization tensor is used as Encoding technique and Eucidean distance as a distance metric*

S.No	Key Size	Euclidean Distance	
		Similar	Dissimilar
1	8x8	57.934	41.3504
2	16x16	43.1072	38.835
3	24x24	87.8838	52.9884
4	32x32	79.53	54.7434
5	40x40	86.0814	47.6754
6	48x48	62.7	57.7224
7	56x56	82.6302	53.3286
8	64x64	81.6078	45.3018

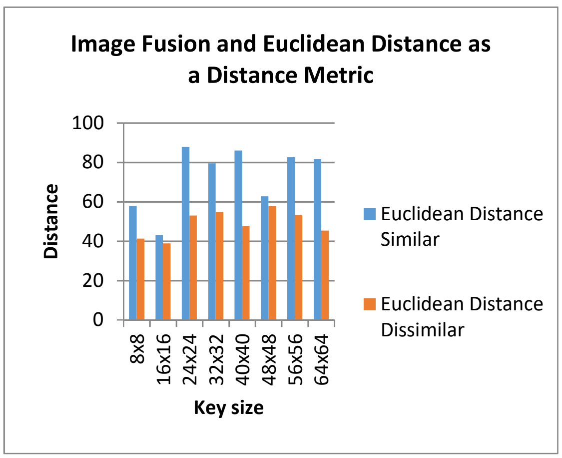

Fig. 6 Proposed Feature Extraction using NMF, Fusion, Encoding and Euclidean distance.

Fig. 6 shows the graphical view of graphical view of Proposed Feature Extraction using NMF, Fusion is applied for the extracted features and Lownerization tensor is used as Encoding technique and Euclidean distance as a distance metric

Fig. 6 shows the graphical view of Proposed Feature Extraction using NMF, Fusion is not applied for the extracted features and Lownerization tensor is used as Encoding technique and Euclidean distance as a distance metric

When comparing these two different methods with the existing [16] method 1produces the better

Table 4 and figure 5 show method 2 results. Here features can be extracted from face and finger using NMF and these features cannot be fusioned and , Lownerization tensor is used as Encoding technique and Euclidean distance can be used as a distance metric. For this model threshold T can be defined as 117.17. This method can be compared with PESN Krishna Prasad et.al [16] both fails for 8x8 and 16x16 key sizes

Table 4: *Proposed Feature Extraction using NMF, Fusion not applied for the extracted features and Lownerization tensor is used as Encoding technique and Euclidean distance as a distance metric*

S.No	Key Size	Euclidean Distance	
		Similar	Dissimilar
1	8x8	135.912	108.4672
2	16x16	146.8096	51.78
3	24x24	117.1784	70.6512
4	32x32	126.04	72.9912
5	40x40	114.7752	63.5672
6	48x48	183.6	76.9632
7	56x56	194.1736	71.1048
8	64x64	196.8104	60.4024

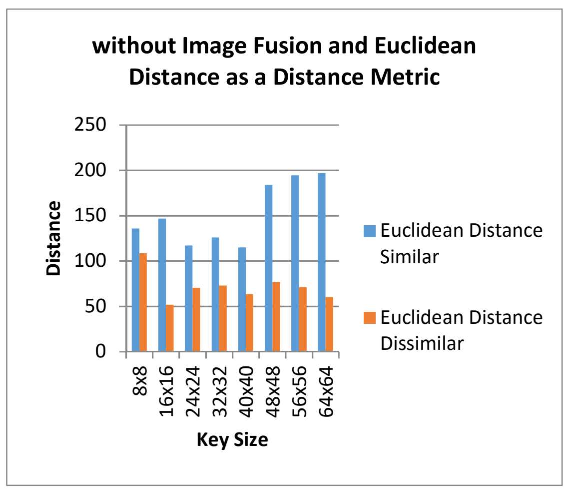

Fig. 6 Proposed Feature Extraction using NMF, No Fusion, Encoding and Euclidean distance

results. Whereas method 2 does not work for the key sizes of 8x8 and 16x16. Also the distance metric Mean Square Error gives better results when comparing the Euclidean Distance

6. CONCLUSION

In this paper, the author contributed a two level framework for extracting the features from human traits/patterns such as face and fingerprints by applying NNMF and encoded and decoded using Tensor based Lowernerization. In method 1 after extracting the features from the training images these feature are fusioned and distance metric MSE is used to calculate the distance between training and testing images. Next time after extracting the features from the training images these feature are not fusioned and distance metric MSE is used to calculate the distance between training and testing images. This method works from 16x16 keysize.

In method 2 after extracting the features from the training images these feature are fusioned and distance metric Euclidean distance is used to calculate the distance between training and testing images. Next time after extracting the features from the training images these feature are not fusioned and distance metric Euclidean Distance is used to calculate the distance between training and testing images. This method works from 24x24 keysize. When comparing these results with PESN Krishna Prasad et.al method 1 gives better results.

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