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FACE RECOGNITION BLOCK BASED STATICAL DCT AND TEXTURE

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ABSTRACT

In this study, a feature extraction methodology proposed for face recognition. The proposed methodology uses combined block DCT and texture feature. That is, the feature extraction used is combination of frequency and spatial domains. The frequency domain feature is statistical block based discrete cosine transformation of a small number of low frequency coefficients. The texture part of the feature vector used is based on co-occurrence matrix of the images higher frequencies. The classification vehicle used in the study is the micro-classifier network. The micro-classifier network is a deterministic four layers' neural network, the four layers are: input, micro-classifier, counter, and output. The network provides confidence factor, as well as proper generalization. Also, the network allows incremental learning, and more natural. The overall proposed face recognition methodology was tested using the standard ORL data set. The experimental results of the methodology showed comparable performance.

KEYWORDS: **Texture features; Classifier, Feature extraction; Image processing; Discrete Cosine transform; DCT;**

1. INTRODUCTION

Face recognition foundation fields are: neuroscience, computer vision, psychology, pattern recognition, digital image processing, and machine learning. Research efforts started decades back because of the intensive demands [1-12]. Security systems, targeting, tracking, robotics, human-computer-interfaces, digital cameras, games, entertainment, authentication, intelligence, satellite, reconnaissance, as well as image indexing applications use face detection and recognition. Acquired images recognition not a comparison process with recalled pre-stored known images. Face detection is a search process within an image for blocks, with possibly flexible scaling, contains face features, and possibly tracks them within a video feed. Recognition process includes: finding set of finding discriminating features, finding a proper training set, extracting and learning these features for discriminations. The learning process aims at finding discriminating metrics and/or boundaries on the feature elements. After learning, the induced metrics or boundaries are used to stamp the unknown face by its class ID or recalls its associated data. Face recognition difficulty comes from the variance in acquired image, for same person face, as a result of: scale, translation, illumination, poses, occlusion, clutters, orientation, expression, and imaging conditions. A good feature that reflects minimal changes in values for such minor changes rather focus on changes in basic object constructing features. Face recognition based system basically contains detection, feature extraction, learning, and classification.

Feature selection and extraction goal is finding a minimal subset of features from a set of large possible features that if used properly will lead to minimal recognition errors. The factors affecting feature selection include: dimensionality, in-class similarity, dissimilarity of inter-classes, ease of finding, computation complexity, and robustness to former mentioned challenges. Feature selection, as pivotal point, attracted the attention of the researchers in several domains [13-16]. The features used include [17-21]: Active Shape Models (ASM), Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA), Multi-dimensional Scaling (MDS), Self-organizing map (SOM), Gabor Wavelet Transforms (GWT), moments such as Legendre and Hue, and Discrete Cosine Transform (DCT). The deep learning feature finding focus on feature that sustains after successive filter applications and image reduction stages. The later feature finding coincide with the former mentioned good feature attributes.

Classifiers uses: similarity, probability or decision boundaries to establish metrics to use to infer unknown objects classes. Similarity metrics measure the closeness to the classes or the classes representatives such as nearest neighbor classifiers. The probability metric is in or out of class probability. Decision boundary metric, basically, position relative to the separating hyper-surfaces between the classes. The classify vehicles, roughly, could be set to two categories traditional, and neural networks. The traditional methods start from selected features and searches, using deterministic steps, normally non-iterative, methodology to infer structure or probabilistic metrics bases for the classifiers [2-9], [22]. The neural network approach starts with a preset state, say random initialization, and go on the learning process that iterates for a significant number of iterations to adapt itself to reasonable metrics [23-25].

Artificial Neural Networks, ANN, contains computing elements that are of relatively large number operates in parallel; the interconnections as well as the transfer functions coefficients of adaptable strength. Therefore, the networks contain also a significant number of adjustable parameters that enables the learning process [27]. The training process starts with a guess to these adjustable parameters to enable network operation. During training, hopefully, the interconnection strength and transfer function parameters are set to proper values that enables correct complex metrics to the network. Networks structure, normally, organized in layers from input to output. The layers between input and output are called hidden layers. The neurons are interconnected, unidirectional, bidirectional, or both. Neurons interconnections could exist of the same layer, to forward layer, backward one, or combinations. The network topology, transfer function, and learning method are the focal points in network design. The networks topologies include feed-forward and recurrent [26-28]. The transfer functions used in neural networks include: linear, tan, sigmoidal, Gaussian, and bi-radial. Networks learning could be supervising, unsupervised or reinforced. The structure could be deep or shallow. From the wildly used networks, multilayer perceptron, radial basis, Hopfield, Unsupervised Pre-Trained Networks (UPNs), Convolutional Neural Networks (CNNs), Recursive

Neural Networks and self-organizing maps. Neural networks application areas include: functions approximation, classification, control, robotics, forecasting, mapping, security alerts, marketing, classification, as well as recognition. There are many hardware realizations to networks [29]. Neural networks as a classifier, in general, takes the classification burden to a learning process however there are still basic questions about the proper structure, evolution, training data set selection, and the correct generalization ability [30-31].

In General, effective face recognition bases are (i) Invariant feature, or minimal variant, with respect to changes in: position, illumination, scaling, rotation, pose… etc. (ii) Classifying vehicle focus on in class similarities metrics and inter-classes discriminating metrics. Therefore, maps the feature vectors into their appropriate classes with minimal misclassification. (iii) Prober generalization abilities to unknown cases.

This study, proposes a combined feature vectors for face recognition methodology. The feature vector contains DCT block based statistical coefficients as well texture metrics. The DCT block based statistical part of the feature vector is extracted from low frequencies coefficients mean and standard deviation over the overall image blocks per-frequency. The texture part is extracted from the higher frequencies that is from the residuals of the former mentioned part. Each element in the vector is normalized to establish unified base and remove biases due change in lightening and other image acquisition conditions. The texture feature extraction uses co-occurrence matrix of the residuals of DCT vectors of the images. Therefor the feature vector used captures both low frequencies that carries the objects basic features and the texture attributes. The classification vehicle used is a binary classifier neural network, the micro-classifier network. The binary classifier network built on learning separating hyper-planes between pair of classes proposed in [24]. The classifier doesn't require rebuild of knowledge in incremental learning, offers acceptable generalization ability and deterministic in structure [32-34].

The remaining of this paper organized as following: Section two outlines the classifier neural network. Section three contains the proposed feature selection. Section four contains experimental study. Section five is the study conclusion.

2. CLASSIFY VEHICLE NETWORK

The proposed classification vehicle is the micro-based binary classifier network [32-34]. The network is composed of micro-classifiers. Each classifier learns during the training two classes separating hyperplanes. During the recognition it votes for a class of the two. i.e. it points to the position of the unknown image with respect to the two classes separating hyperplane [34], [32]. The votes per class is counted and the class of the unknown as well as the degree of confidence is computed. The network is of two hidden layers. The network offers some desired features as a neural network: the network architecture is deterministic once the problem is defined, enables incremental learning that is you do not have to retrain the entire network if there is a problem with a class or even a new class introduced. The performance of the network is comparable both in recognition and generalization ability. Also, the training is guaranteed convergence giving hyperplane separable sets. The network drawbacks are the number of micro classifiers are relatively high $n+(n-1)+(n-2)+....+2+1$ where n is the number of the classes and it does not learn nonlinear separating surfaces. The later issue could be covered by proper selection of feature set vectors or using higher moments [25]. Moreover, the generalization ability for linear separation is much better compared to nonlinear one's. Figure (1) shows network structure.

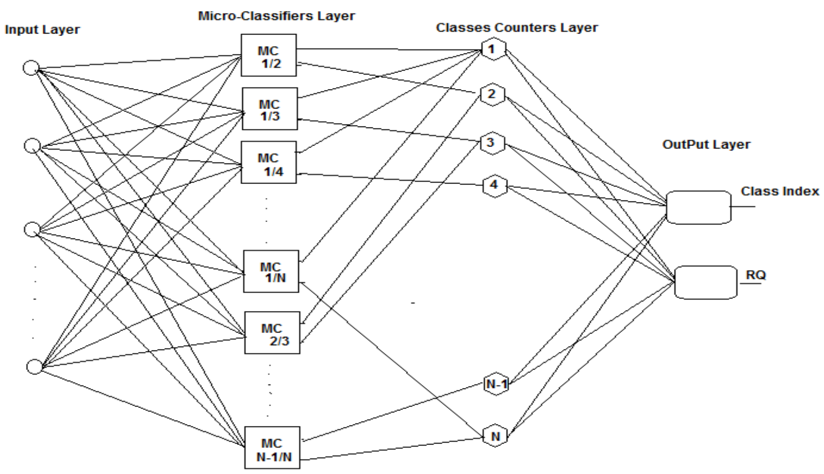


Figure (1) Classifier Network

Micro-Classifiers

The proposed classifier network built based on 'micro-classifier' as basic building block. The micro-classifiers training process could be summarized as following: -

Assuming the two finite sets $X, Y \subset R^l \quad l,\ finite,$

$$X = \{x_1, x_2, x_3, \ldots\ldots, x_M\} \qquad and$$
$$Y = \{y_1, y_2, y_3, \ldots\ldots, y_N\} \qquad x_i, y_i \in R^l$$

The search process is for $\varphi_x^*, \varphi_y^* \in R^l$ such that

$$\left\| x_i - \varphi_x^* \right\| < \left\| x_i - \varphi_y^* \right\| \qquad and$$
$$\left\| y_i - \varphi_y^* \right\| < \left\| y_i - \varphi_x^* \right\| \qquad \forall x_i \in X, y_i \in Y,$$

The learning algorithm is based on the study in [24]. The algorithm searches for weighting to the training set vectors to induce representative's proper separating hyper-plane between the two sets. The algorithm used in that study is proven to converge to the separating hyper-plane if exist and case of 2nd order separable sets the algorithm existence around a local minimum dominates others. The experimental study shows that the convergence in case of linear separable sets does not require large number of iterations even in dense sets and the probability of being in minimal state after few numbers of iterations greater than others for non-linear case. The algorithm evolves to representatives say φ_x^*, φ_y^* then:-

The hyper plane divides the range of points either X or Y. The classifier for unknown vector Z considered X side if $(Z - 0.5(\varphi_x^* + \varphi_y^*)) \bullet (\varphi_x^* - 0.5(\varphi_x^* + \varphi_y^*)) >= 0$ otherwise considered Y side. The micro-classifiers increment the counters of the potential classes from their perspectives. The micro-classifiers act in parallel on its inputs. The second layer acts on the class's counters $clsc_i$ the vector assumed to be of class $n \quad iff\ clsc_n > clsc_i \quad \forall i \neq n \quad and \quad RQ = ((clsc_n + 1)/m) > T$ where m is classes count, $T \in [0.5, 1]$ is the recognition threshold, and RQ is the recognition quality.

3. PROPOSED FEATURE EXTRACTION

Feature extraction is a key stone building block in computer vision systems. Features could be global, local, or both. Features could be extracted from raw images directly or from successive reduction and after filters application as in deep learning. Features bases could be edges, texture, and statistical. Features could be extracted from spatial, and/or frequency domains.

DCT used effectively within the most famous encoding schemes for both image and video encoding, JPEG, and MPEG. The use comes from the fact that DCT low frequencies significantly contribute to images visual appearance and contain objected focal structure elements of natural images. Therefore, using such coefficients as a base in classifiers is legitimate. Figure (2) shows original face against a recalled with 1% lowest percent of coefficients. From the figure the overall shape of the face, position of the eyes, head shape, as well part of: ear and nose are there in the recovered image. DCT lower frequencies coefficients as features contains two major problems: do not carry on texture information, and sensitive to changes in brightness and object position. Such problems are vital to the recognition process.

The features used in this study are both DCT low frequencies and texture information [35]. The DCT features are used block based, quantized, and statistical to avoid the former mentioned drawbacks. The texture features are taken from the higher frequencies that is the residual from the DCT used block based, normalized, and statically based.

Figure (2) a recalled picture from 1% of the holistic 2-D DCT

Discrete Cosine Features

Photoreceptors of current technology enabled devices to have signals than that is received by human retinal. However, today human's biological systems in both memory and recognition supersedes the electrical or optical human made system for the same purposes. So, biological received signals as projectors are more compact and further conclusive compared to man-made keeping and recognition. Consequently, thinking for other forms or transformations is natural. The transformations are also needed to conclude the high redundancies into more abstracted forms of representations. Generally, human vision, and machine processing benefit from the details of an image to some saturation point after which undesired effects happens. From the widely used transformations: Fourier, Discrete Cosine transformation (DCT), Karhunen-Loeve transform (KLT), Legendre moments, Hue moments, and others.

The discrete cosine transformation is widely used as mean for image abstraction as well as feature extraction. The DCT used as holistic, in which transformation applied to the entire image, and block based to overcome the computation complexity of the transform [36] The use of the transform in image processing included both single (based on raw and column scans) and two dimensional transform. The outcome of the 2-D transformation is a real matrix of the same dimension of the original one. The DCT has an inverse that could be used to retrieve the original image from the transformation frequency domain matrix. To make it more clear for a block based, which is used here in: -

Let us assume that an image matrix an image matrix $f(x, y)$ of dimensions $n*N, m*M$ where NxM the block size used consequently the DCT of that block will be:-

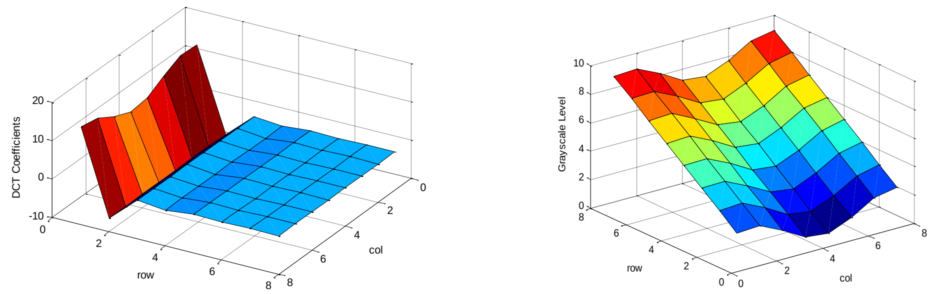
$$C(u,v) = \alpha(u)\alpha(v)\sum_{y=0}^{M-1}\sum_{x=0}^{N-1} f(x,y)\cos(\frac{(2x+1)\pi u}{2N}) \quad \cos(\frac{(2y+1)\pi v}{2M})$$

where

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}} & u = 0 \\ \sqrt{\frac{2}{N}} & u \neq 0 \end{cases}$$

And, the inverse transformation is: -

$$f(x,y) = \sum_{v=0}^{M-1}\sum_{u=0}^{N-1} \alpha(u)\alpha(v)C(u,v)\cos(\frac{(2x+1)\pi u}{2N}) \quad \cos(\frac{(2y+1)\pi v}{2M}) \quad (01)$$



(a) (b)

Figure (3): (a) DCT for an image block and (b) is the original image block

For a block based DCT, That is applied to $n*m$ blocks of the image matrix. Figure (3) shows an image block in special and DCT transformed. From the figure, one can easily see that most of the power is within the lower frequencies. Out of the $N*M$ coefficients an l_{dc} coefficients selected in zigzag form similar to that of JPEG encoding, figure (4). For the former image matrix that makes matrix of dimension ($n*m$) by l_{dc} The coefficients are quantized using uniform quantization into l_q then normalized to the unit magnitude. From the processed matrix blocks per frequency coefficient the mean and standard deviation computed and considered as features. The makes DCT feature vector of length $l_{dc}*2$.

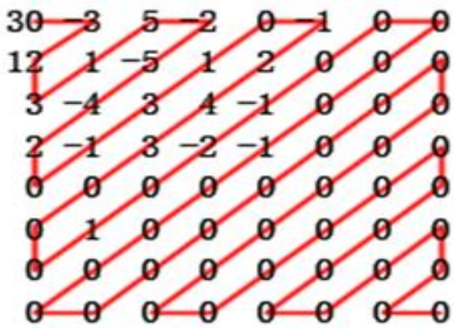


Figure (4) Zigzag sequence for DCT feature vector

Texture Features

The texture features used in the study extracted from the residual image matrix. That is the $C(u,v)$ coefficients selected from the zigzag process of set zero and the inverse DCT equation (01) applied per image block and the residual whole image reconstructed containing higher frequencies. The constructed image is what we call the residual image. On this residual image matrix, Gray-Level Co-Occurrence Matrix (GLCM) is computed based using eight neighbors. Figure (5) is an example of GLCM matrix. Out of GLCM matrix the Contrast, Correlation, Energy, and Homogeneity per neighbor class is computed. The extracted values are normalized per type. The total number of texture features are 8*4, eight neighbors with four former mentioned features.

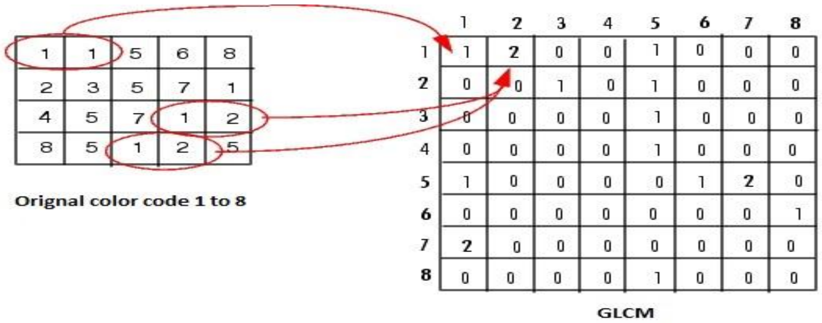


Figure (5) GLCM matrix formation for a single neighbor

4. TESTING AND RESULTS

The source images used in the testing process is the standard ORL database [37]. The most commonly used subset of the ORL database is the famous 40 subjects. Each subject has 10 images in different poses/orientations. These images are gray scaled 0 to 255. Samples from the dataset are in figure (6).

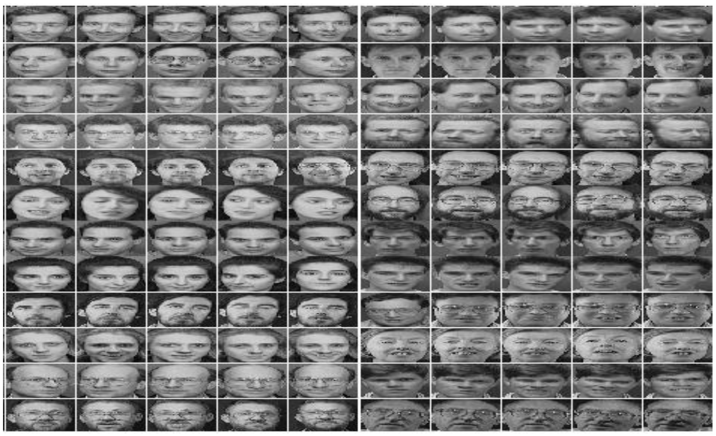


Figure (6) Samples of the standard testing dataset.

Experiment 1

In this experiment, we focus on the study of the effect of block length on the performance. So, the block length, l varied from the smallest block size which is 2 to 24 which makes the smallest of n, m being two. The l_{dc} and l_q set to four. The texture subset is fully used. The result of the experiment is in figure (7).

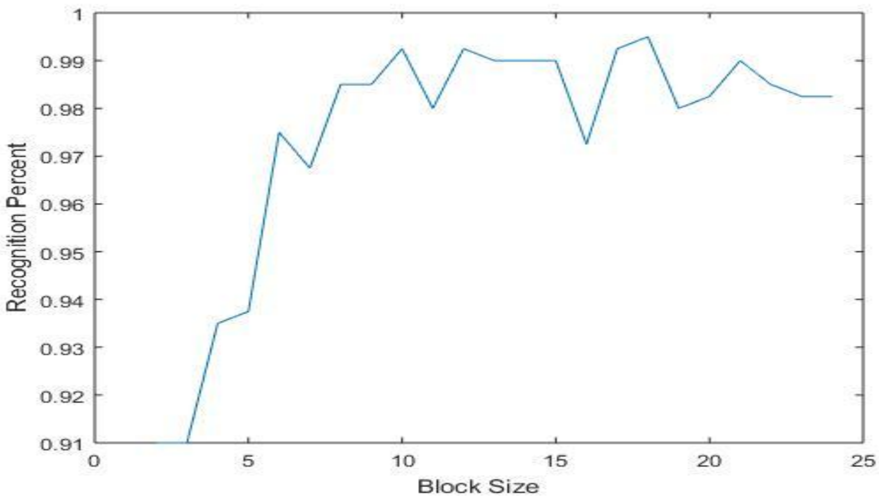


Figure (7) l_{dc} , l_q =4 and block from 2 to 24

From figure (7), the recognition percent overall is very well with block length increases the recognition increases after some length some sort of saturation occurs. That comes from the fact that very smaller blocks are not information inclusive. On the other sized significantly large block sizes lead to smaller total number of blocks which makes the statistics lose its validity. Apparently, the size related to the size of the image building significant sub-objects.

Experiment 2: -

This experiment focus on the study of the effect number of quantization levels on the performance. So, the quantization length , l_q

varied from 4 to 20. The l_{dc} kept on 4 and block length l set to 10 . The texture subset is fully used. The result of the experiment is in figure (8).

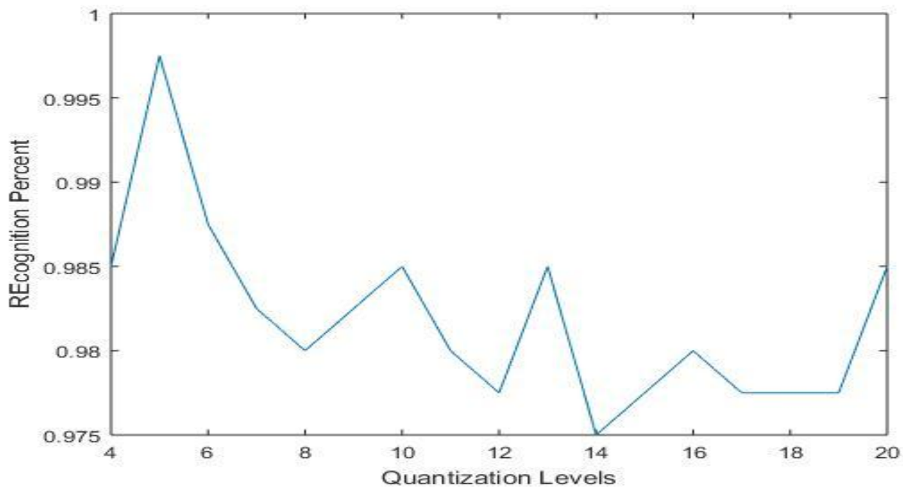


Figure (8) l_{dc} , l_q =4 and block from 2 to 24

Quantization levels aims at making feature less sensitive to minor changes. Figure (8) shows, in general, there are some quantization levels more tending to be towards the low numbers performs better than previous and followers. The reason is with very low quantization differentiability decrease and on the other hand overfitting occurs.

Experiment 3: -

This experiment focus on the study of the effect length of DCT length used length, l_{dc} . So, it varied from 2 to 10 and, the block length, l set 10 and quantization levels set, l_q , to 5. The texture subset is fully used. The result of the experiment is in figure (9).

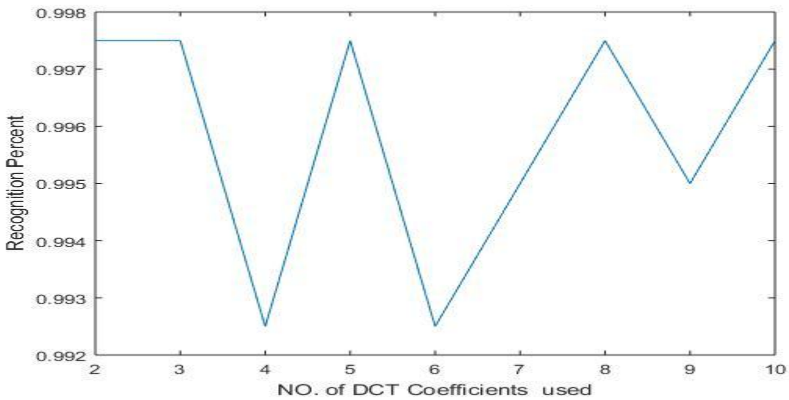


Figure (9) l_{dc} , l_q =4 and block from 2 to 24

From figure (9) the recognition percent is relatively high starting from the two coefficients. However, the performance oscillating at low numbers and more stable as the length increases.

Experiment 4,5: -

These are conclusive to the performance change as the feature parameter's change. Figure (10) shows percent surface as number of quantization levels and DCT length change. Figure (11) show percent surface as block length and DCT length change.

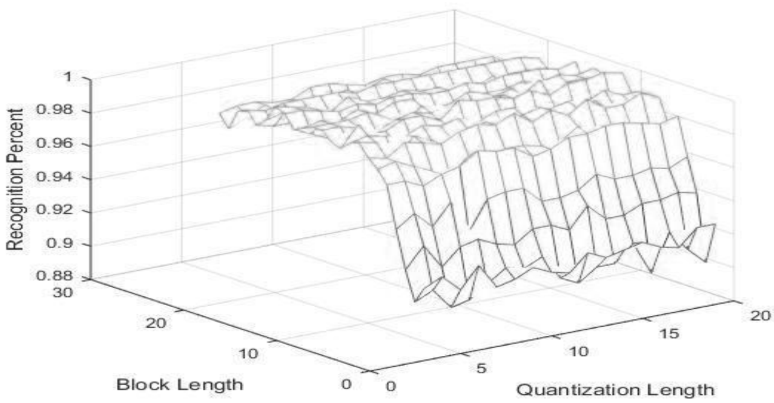


Figure (10) l_{dc} is kept at five, block length and quantization levels varied

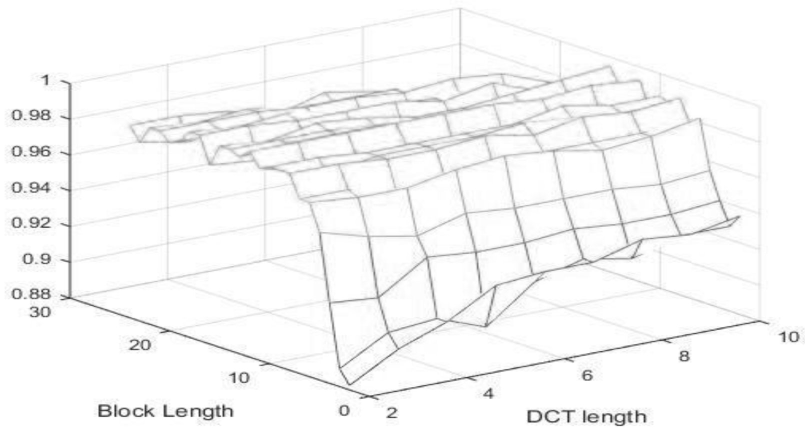


Figure (11) l_q is kept at four, block length and DCT length varied

There are a lot of bench marks on ORL database which includes: [38] of correct recognition reports percent's from 85.42% to 93.75 using PCA and NPCA, [39] reported similar to former results on PCA and LDA recognition percent's from 88.1% to 95.98% on ORL database. Neural networks were used with Eigen-faces in [40] using perceptron neural networks case of testing on the entire 400 images 360 was correct identified with 50 Eigen-faces and 15 hidden layer neurons.

The proposed recognition methodology is simple compared to that of deep networks and choices are deterministic. Also, the training is more straight forward [32-34]. Moreover, the architecture allows incremental learning and partial retraining when needed. There is some insignificant change in performance occurs if the choices of features are around the right for the sub-objects constituting image object under the recognition. The overall recognition percent if choices are made around the right will be comparable to others.

5. CONCLUSION

In this paper, proposed feature extraction methodology for face recognition studied. The proposed feature extraction was used together with the micro-classifier network. The proposed overall face recognition methodology applied to the ORL data set varying the feature extraction parameters. The parameters under the study was number of DC coefficients, the block size, and the quantization levels used.

The study shows overall comparable results and it points to the fact that there is a margent of right selection per parameter in which the network performance will retains well performance. The block length is to be large enough to contain significant constituting sub-object but not large to lose the statistical value. The number of DC coefficients showed be large enough to contain significant discriminating information and it will reach some saturation. After saturation, there will be either insignificant classification or even negative effect. The quantization levels for small number, it loses the decrementing value and large number leads to overfitting performance. So, in general, these parameters values related to the overall image size and the what we could call local features sizes. It could be easily inferred in this approach, if the object under recognition is relatively small compared to background blocks that makes statistical values as well as the texture metrics biased towards background which is a serious recognition problem. This problem could be avoided if background blocks ignored. In our, dataset the objects were significantly large compared to background and therefor the effect of the background blocks is limited.

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A survey on Sentimental Analysis algorithms and techniques

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Abstract-*Social web has been the lead of data in recent years. The data on social web simulates the customer reviews, comments, and opinions of people about products, opinion, events, etc. The automatic mining technique that is used to gather and analyze text and classify it into positive, negative and neutral is called Sentimental analysis using Natural language processing. The main objective of this paper is to give explain insights on SA algorithms and techniques.*

Index Terms-*Sentimental Analysis (SA), Natural language processing, Opinion Mining*