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# **Recognition of Human-Face from Side-View using Progressive Switching Pattern and Soft-Computing Technique**

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# Abstract

Most of the research work done so far, only front – view of human-face images are used for the recognition of human-face. Side – view human-face images have been considered very less, to tackle such recognitions. In the present research work, front – view of human-face and side – view of human-face has been considered in two different aspects. The two aspects are *learning* and *understanding*. To support learning process, front – view of human-face images have been adopted and considerable amount of features have been extracted for the formation of vast corpus. To support understanding process, side – view of human-face images have been considered and a sufficient amount of features have been extracted. This understanding process has been carried out using progressive switching pattern and soft-computing technique. Recognizing human-face from side-view is a very knowledge intensive process, which must take into account sufficient amount of information's of it. The observable information's that have been extracted in the present work are categorized into four factors: *built, texture, complexion* and *hair*. Thorough discussions have been done in the present paper along with a proposed algorithm for the recognition of human-face from side-view. The algorithm has been tested and the results obtained so far, yields to 89% accuracy for true and positive recognition.

### Key words

Progressive switching pattern, soft-computing technique, unidirectional temporary associative memory, artificial neural network, fuzzy set theory, genetic algorithm

### **1. Introduction**

Since six decades research work through human-face are underway. From the literature, it has been observed that, the work has been carried out not only by researchers from engineering and technology field but also from the field of medical sciences. Automatic face recognition is one of the prime components for any biometrical study and it is gradually progressing since past sixty years. In the present paper, a thorough review report has been prepared and the issues for further research in this area have been investigated.

During past few decades many researches in face recognition have been dealing with the challenge of the great variability in head pose, lighting intensity and direction, facial expression and aging. A great deal of progress has been made by many researchers in improving the face recognition performance. Based on two-dimensional intensity images, a number of face recognition algorithms have been developed during the past few decades. Principal component analysis (PCA) is best for distribution of face images within the entire image space as suggested by Truk et al. [1]. These vectors define the subspace of face image and the subspace is called the face space. Kirby et al. [2] has developed idea for extensions of PCA, such as modular eigenspaces. Hu et al. [3] proposed to use one neutral frontal image to first create synthetic image under different poses and expression. A similar idea but a very new approach was proposed by Lee et al. [4]. They presented a combination of an edge model and colour region model for face recognition after the synthetic image using a 3D model. In the same year Michel Valstar et al.[5] has attempted to measure a large range of facial behaviour by recognizing facial action units (AU which means atomic facial signals) that produce expressions. The proposed system performs AU recognition using temporal templates as input data. Jolly D. Shah et al. [6] presents a multiple face detection method based on skin colour information and lines of leparability face model and recognition method based on principle component analysis and neural network. Face detection method YCbCr colour model and sigma control limits for variation in its colour components. In year 2007 Richa Singh[7] describe a face masaicing scheme that generates a composite face image during enrolment based on the evidence provided by frontal and semi-profile face image of an individual. In this scheme the side profile images are aligned with the frontal image using a hierarchical registration algorithm that exploits neighbourhood properties to determine the transformation relating the two images.

In the year 2008, Edward Kao et al. [8], shared through their work, that the process of automatically tracking people within video sequences in currently receiving a great deal of interest within the computer vision research community. In this work they contrasted the

performance of the popular mean-shift algorithms gradient descent based strategy with a more advanced swarm intelligence technique and they proposed a practical swarm optimization algorithm to replace the gradient descent search. They also combined the swarm based search strategy with a probabilistic data association filter state estimator to perform the track association and maintenance stages. In the same year Xiaozheng Zhang et al.[9] has presented a novel appearance based approach using frontal and side-view of face images to handle pose variation in face recognition, which has great potential in forensic and security application, involving police mugshot database. In the year 2011, Li Cheng et al. [10] examine the problem of segmentation foreground objects in live video when background subtraction as minimizing a penalized instantaneous risk function-yield a local online discriminative algorithms that can quickly adapt to temporal changes. In the same year, Hossian [11] has surveyed several important research work published in this area and proposed new technology to identify a person using multimodal physiology and behavioural biometrics. In the year 2013, Tilendra Shishir Sinha et al. [12], have further carried out the research through human-gait and human-face for the recognition of behavioural and physiological traits of the subject. They have adopted considerable and logical concepts of soft-computing techniques for the recognition of behavioural and physiological traits of the subject. From the above literature discussed so far it has been observed that very few researchers have adopted the soft-computing tools and its hybrid approaches, for the recognition of a human face from side-view (parallel to image plane). But it has been found that in the last six decades, research in automatic face recognition has been intensively carried out worldwide in the field of biometrical studies, and has been summarized by the following changes.

- From template-matching approach to knowledge-based approach
- From distance-based to likelihood-based methods
- From maximum likelihood to discriminative approach (genetic algorithm method)
- From no commercial biometrical applications to commercial biometrical applications

It has been also found from the literature that knowledge-based models are still playing a vital role in any biometrical research work. Still there is a scope for automatic face recognition, using innovative approach of soft-computing tools and its hybrid [13] approaches. Hybrid approach has been suggested by Sinha et al. [13], although the work has been carried out for speech processing. In the present work, soft-computing techniques like artificial neural network, fuzzy – set theory and genetic algorithms, have been adopted for the extraction of geometric features from the human-face image. Initially, the firing concepts of artificial neural network have been incorporated. As per the literature [14] and through experimental setup of the present work, it has

been found that, a neuron is fired when the output is more than its threshold value. A sigmoid threshold function has been utilized for the computation of geometrical features.

Geometrical features are defined as functions of one or more quality of objects that are capable to distinguish object from each other. Here human-face image feature vector has been considered with geometric parameters of moment, shape, switching and texture features. These parameters are reasonably robust to the varying conditions and are capable enough to describe the quality of subjects. The two basic feature extraction techniques are: first one is geometric approach and the second one is holistic approach, as suggested by J-H, Na and et al. [15]. Geometric approach, selects individual feature and characteristics of the human-face image based on geometrical relational parameters. Holistic approach, selects complete feature and characteristics of the human-face image based on the calculations done through principal component analysis, fishers linear discriminant analysis, independent component analysis, softcomputing techniques and forward-backward dynamic programming method. In the present, work both approaches have been applied. Both the approaches have been applied [16]-[17] because of some acceptable benefits to the research work with respect to fast recognition process. The main advantage of using such methods is the calculations over features with reduced dimensionality by projections and original data onto the basic vectors. During the initial start of switching of the frame of the human-face image considering side-view of the face of the subject, the neuron fires and hence the muscle activates. This has been analyzed further by considering frame by frame data of the human-face [18]. These frames of data have been fed as input for the computation of more additional parameters in steps: first the real-valued, second the neutral, third the normalized and finally the optimized and normalized parameter is computed.

The paper has been organized in the following manner -: section 2 proposes the mathematical formulations and analysis, section 3 describes the simulated results and discussions, section 4 gives the concluding remarks and further scope of the work. Finally the last section incorporates all the references been made for the completion of this work.

### **2.** Mathematical formulations and analysis

Consider 'Z' numbers of frames have been read. Each frame has been read as FRAME<sub>1</sub>, FRAME<sub>2</sub>, FRAME<sub>3</sub>, FRAME<sub>4</sub>, .....FRAME<sub>2-2</sub>, FRAME<sub>2-1</sub>, FRAME<sub>z</sub>. The whole process has been taken care with the following facts:-

- Read the frame with side-view of human-face image looking towards right direction
- Extract ear-nose-length parameter, P<sub>1L</sub>

- Similarly read the frame with side-view of human-face image looking towards left direction
- Similarly extract ear-nose-length parameter, P<sub>1R</sub>
- Compute average ear-nose-length parameter  $F_{1avg} = (P_{1L} + P_{1R}) / 2$

Where P<sub>1L</sub> signifies ear-nose-length of frame towards left direction

P<sub>1R</sub> signifies ear-nose-length of frame towards right direction and

F<sub>lavg</sub> signifies average ear-nose-length of frame with both directions.

Repeat the above process for the next frames. Hence it yields to the average ear-nose-length measures as real-valued parameter like

$$F_{2avg} = (P_{2L} + P_{2R}) / 2, F_{3avg} = (P_{3L} + P_{3R}) / 2, F_{4avg} = (P_{4L} + P_{4R}) / 2, F_{5avg} = (P_{5L} + P_{5R}) / 2, \dots, F_{(Z-1)avg} = (P_{(Z-1)L} + P_{(Z-1)R}) / 2, F_{Zavg} = (P_{ZL} + P_{ZR}) / 2$$
(1)

Further to compute the neutral parameter, consider the 'even' and 'odd' frames separately

Let ' $N_{odd}$ ' and ' $N_{even}$ ' be the number of odd and even frames respectively. Hence, the neutral parameter yields to,

$$F_{Oddavg} = (F_{1avg} + F_{3avg} + \dots + F_{(2Z-1)avg}) / N_{odd}$$
(2)

$$F_{\text{Evenavg}} = (F_{2\text{avg}} + F_{4\text{avg}} + \dots + F_{(2Z)\text{avg}}) / N_{\text{even}}$$
(3)

The normalized parameters for each frame have been further computed. The solution yields for 'odd' frames,

$$F_{Norm1} = \frac{F_{1avg} - F_{0i}}{F_{0dda1}} , \qquad F_{Norm3} = \frac{F_{5avg} - F_{0i}}{F_{0dda1}} , \qquad F_{Norm5} = \frac{F_{5avg} - F_{0i}}{F_{0dda1}} , \qquad (4)$$

$$F_{Norm(2Z-1)} = \frac{F_{(2Z-1)avg} - F_{0i}}{F_{0ddavg}}$$

Similarly for 'even' frames,

$$F_{Norm2} = \frac{F_{2avg} - F_{Evence}}{F_{Evenavg}}, \qquad F_{Norm4} = \frac{F_{4avg} - F_{Evence}}{F_{Evenavg}}, \qquad F_{Norm6} = \frac{F_{eavg} - F_{Evence}}{F_{Evenavg}}, \qquad (5)$$

$$F_{Norm2Z} = \frac{F_{(2Z)avg} - F_{Evence}}{F_{Evenavg}}$$

Further computing the average neutral and normalized parameters (NNP) for 'odd' and 'even' components, the solution yields to,

$$F_{\text{NormOddavg}} = (F_{\text{Norm1}} + F_{\text{Norm3}} + \dots + F_{\text{Norm(2Z-1)}}) / N_{\text{odd}}$$
(6)

$$F_{\text{NormEvenavg}} = (F_{\text{Norm2}} + F_{\text{Norm4}} + \dots + F_{\text{Norm(2Z)}}) / N_{\text{even}}$$
(7)

Next is to compute the average neutral and normalized parameter (NNP) for each frame of the dataset, the solution yields to,

$$F_{NNP1} = \frac{F_{Norm1} - F_{Norm0_i}}{F_{Norm0\,ddavg}}, \qquad F_{NNP3} = \frac{F_{Norm5} - F_{Norm0_i}}{F_{Norm0\,ddavg}}, \qquad F_{NNP5} = \frac{F_{Norm5} - F_{Norm0_i}}{F_{Norm0\,ddavg}}$$

$$F_{NNP(2Z-1)} = \frac{F_{Norm(2Z-1)} - F_{Norm0_i}}{F_{Norm0\,ddavg}}$$
(8)

••••

Similarly for 'even' frames,

$$F_{NNP2} = \frac{F_{Norm2} - F_{NormEvenc}}{F_{NormEvenavg}}, \quad F_{NNP4} = \frac{F_{Norm4} - F_{NormEvenc}}{F_{NormEvenavg}}, \quad F_{NNP6} = \frac{F_{savg} - F_{Evenc}}{F_{Evenavg}}, \dots \dots \dots \\ F_{NNP(2Z)} = \frac{F_{Norm(2Z)} - F_{NormEvenc}}{F_{NormEvenavg}}$$
(9)

In general the dimensions of the feature vectors are of higher dimensions. So for better results during recognition process the dimensions of these feature vectors have been reduced to lower dimensions, using forward-backward dynamic programming method. Mathematically, the illustration for this method has been done and the initial conditions that have been set are: first limit the search area and second searching using constraints for achieving dynamic characteristics.

Assume two distinguished human-face movement patterns, say  $x(t_i)$  and  $x(t_j)$  are defined, each with its own time base,  $t_i$  and  $t_j$ . Also assume that the beginning and end of the movement pattern are known, denoted as  $(t_{is}, t_{if})$  and  $(t_{js}, t_{jf})$  respectively. If both the patterns are sampled at the same rate, then both patterns begin at 't' sample i = j = 1, that occurs without any loss of generality. Thus, the mapping function,  $i = j \cdot (I / J)$ , is linearly related. The non-linear time warping functions has to be calculated with several assumptions. Let the warping function, w(k), be defined as a sequence of points:  $c(1), c(2), \ldots, c(k)$ , where c(k) = (I(k), j(k)) is the matching of the point i(k) on the first time-base and the point j(k) on the second time-base. The progressive switching patterns can be assumed as, first: horizontally left to right direction movement and horizontally right to left (45 degree to x-axis), second: diagonally left to right circular movement and diagonally right to left (45 degree to x-axis), third: diagonally right to left and diagonally left to right (135 degree to x-axis), fourth: vertically (parallel to y-axis), fifth: circularly clock-wise direction and circularly anti-clock-wise direction. Setting the initial conditions let the search window be restricted to the limit:  $|i - j.(I / J)| \le \gamma$ , where  $\gamma$  is some constant.

The warping, w(k), compares the appropriate parts of  $x(t_i)$  with that of  $x(t_j)$ . Setting the monotonic and continuity conditions on the warping function, it restricts to the relations between four consecutive warping points, c(k), c(k-1) c(k+1) and c(kk), where kk signifies +/- or -/+.

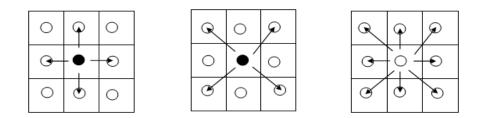


Fig 1. Boundary conditions for the neighbouring pixels

Thus from figure 1, there are eight ways to get to the point c(i,j), which has been given in equations (10), (11), (12) and (13), below,

$$\mathbf{c}(\mathbf{k}) = \mathbf{c}(\mathbf{i}, \mathbf{j}) \tag{10}$$

$$\mathbf{c}(\mathbf{k}-1) = \begin{cases} (i(k), j(k) - 1) \\ (i(k) - 1, j(k) - 1) \\ (i(k) - 1, j(k) \end{cases}$$
(11)

$$c(k+1) = \begin{cases} (i(k), j(k) + 1) \\ (i(k) + 1, j(k) + 1) \\ (i(k) + 1, j(k)) \end{cases}$$
(12)

$$c(kk) = \begin{cases} (i(k) - 1, j(k) + 1) \\ (i(k) + 1, j(k) - 1) \end{cases}$$
(13)

and the boundary condition or circular movements yields to,

$$\mathbf{c}(\mathbf{k}) = (\mathbf{I}, \mathbf{J}) \tag{14}$$

As per the boundary condition, matching of the beginning and end of the human-face movement pattern has been done using forward-backward dynamic programming method. Even to trace the optimal route through the human-face model for the best match of the pattern, this method has been applied. To formulize this, for the tracing of the best matching, the human-face movement patterns have been represented at each point, by their feature vectors,  $\beta_i(k)$  and  $\beta_j(k)$ , where  $\beta_i(k)$ denotes the feature vector of the human-face movement pattern  $x(t_i)$  and  $\beta_j(k)$  denotes the feature vector of the face movement pattern  $x(t_j)$ . On defining a distance measure between the two feature vector, it yields to,

$$d(c(k)) = d(i(k), j(k)) = |\beta_i(k) - \beta_j(k)|$$
(15)

Further warping function also called as membership function of each feature vector has been analyzed. So the parameters related to the corresponding performance index  $D(x(t_i),x(t_j))$  gets minimized. The performance index is the normalized average weighted distance, which has been related as,

$$D(x(t_{i}), x(t_{j})) = M_{w} \left[ \frac{\sum_{k=1}^{k} d(c(k))\rho(k)}{\sum_{k=1}^{k} \rho(k)} \right]$$
(16)

where  $\rho(k)$  are the weights, that yields to I + J, Thus equation (16) results to,

$$D(x(t_{i}), x(t_{j})) = \frac{1}{I+J} M_{w}^{in} \left[ \sum_{k=1}^{k} d(c(k)) \rho(k) \right]$$
(17)

On substituting the values of equations (10), (11), (12) and (13) in equation (17), each point in the search window has been attached with information for an optimal match upto its destination point (I, J). This way of searching is said to be forward technique of dynamic programming. After scanning has terminated, construction of an optimal match has been carried out by going backward from (I,J) to (0,0) or (1,1) point. This way of searching is said to be backward technique of dynamic programming. The combination of this two way of searching technique results to forward-backward dynamic programming searching method. For an optimal solution, minimum number of divergence values has been resulted, on searching. Thus to compute the divergence values for an optimal solution, let the probability of getting a feature vector,  $\beta$ , given that it belongs to some class  $w_i$ , yields,  $p(\beta/w_i)$ , similarly for the class  $w_j$ , yields  $p(\beta/w_j)$ . The sum of the average logarithmic ratio between the two conditional probabilities, results to information concerning the separability between the two classes. And it has been found that there is no loss to the concept. This gives the divergence values of the features. Thus the mathematical formulation yields,

$$D_{i,j} = (\mu_i - \mu_j) (\mu_i - \mu_j)^T \Sigma^{-1}$$
(18)

where  $\mu = \mu_i = \mu_j$  means the expectations and  $\Sigma$  mean the covariance.

From equation (18) divergence values have been calculated upto nineteen feature vectors. These divergence values have been categorized into basic metrics: *true positive (TP)*, *true negative* 

(TN), false positive (FP) and false negative (FN). These metric values have been made useful, by performing further analysis over them. In the present work, this has been done by analyzing five assessments: false positive rate (FPR), false negative rate (FNR), sensitivity (SV), specificity (SC) and accuracy (AC). The assessment, false positive rate (FPR), means the one in which segmentation of the object of interest of a test image results to an incomplete correct data. Mathematically, it yields to,

$$FPR = \frac{FP}{FP + TN} \tag{19}$$

The assessment, *false negative rate (FNR)*, means the one in which segmentation of the object of interest of a test image results to a complete incorrect data.

Mathematically, it yields to,

$$FNR = \frac{FN}{FN + TP}$$
(20)

The assessment, *sensitivity (SV)*, means the one in which positive values of the object of interest of test image are proportioned properly and are recognized with full capacity.

Mathematically, it yields to,

$$Sensitivity = \frac{Number of true positives}{Number of true positives + Number of false negatives} \times 100$$
(21)

The assessment, *specificity (SC)*, means the one in which negative values of the object of interest of test image are proportioned properly and are recognized with full capacity. Mathematical, it yields to,

$$Specificit y = \frac{Number of true negatives}{Number of true negatives + Number of false positives} \times 100$$
(22)

The assessment, *accuracy* (*AC*), means the one in which the measured and weighted values of the object of interest of test image are classified properly and results to linearity. Mathematically, it yields to,

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100$$
(23)

# 2.1 Solution methodology through proposed algorithm

The simulation and practical implementation of the present research work has been carried out through two proposed algorithms: (A) Front-view human-face analysis and (B) Side-view human-face analysis.

#### A. Front-view human-face analysis

- 1. Read the front-view of human-face image and hence convert into gray scale image
- 2. Perform filtering for the removal of noise from the image and select region of interest and also object of interest
- 3. Perform morphological image processing for thinning and thickening of the objects
- 4. Crop the image and extract features along with relevant parameters
- 5. Employ statistical methods of computing like cross-correlation and auto-correlation with deviation of neighboring pixels using 4-pair and 8-pair concepts of pixel pairing
- 6. Employ fuzzy-c means clustering method for the computation of normal behaviour pattern. Hence compute the mean of the clusters.
- 7. Plot the results and store the extracted parameters in the form of corpus as a trained data set

#### B. Side-view human-face analysis

- 1. Read the side-view of human-face image (test image) and hence convert into gray scale image
- 2. Initialize a progressive switching angle, say theta1 = zero
- 3. Perform filtering for the removal of noise from the image and select region of interest and also object of interest
- 4. Perform morphological image processing for thinning and thickening of the objects
- 5. Crop the image and extract features along with relevant parameters
- 6. Employ statistical methods of computing like cross-correlation and auto-correlation with deviation of neighboring pixels using 4-pair and 8-pair concepts of pixel pairing
- Employ fuzzy-c means clustering method for the computation of behavioural pattern. Hence compute the mean of the clusters.
- 8. Compute the distance measure of the extracted features of the test image and the parameters that are stored in the corpus (formed through trained image)
- 9. Compare the patterns for the best-fit using forward-backward dynamic programming of artificial neural network and validate the whole process using genetic algorithm. If the best-fit testing fails, then increment the progressive switching angle, theta1 by five

degree and repeat step 3. For fast processing the increment has been done by ten degree

- 10. Perform classification and characterization process using support vector machine and hence decision has been made for recognition
- 11. Compute the divergence values of metrics as formulated in equations (19), (20), (21), (22) and (23). Hence plot the results.

# 3. Simulated results and discussions

The present research work has been carried out by capturing the frontal part of human-face. The captured image has been divided into five regions of interest and is depicted in figure 2, below. The five region of interest (ROI) are: eye, nose, forehead, lips and chin regions. Manhattan distance measures have been done on these five regions like eye-to-nose distance, forehead width, eye-to-chin distance, nose-to-lips distance, nose-to-chin distance.

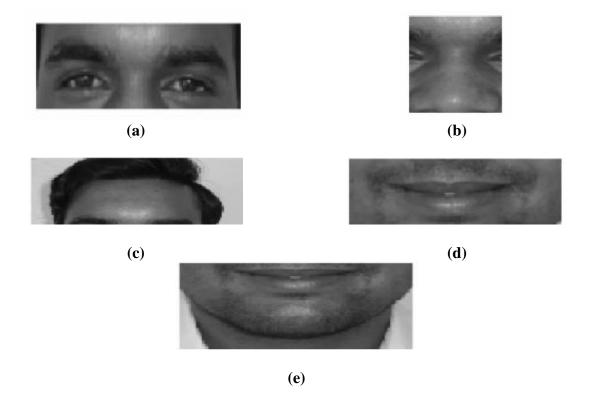


Fig 2. (a) ROI eye part (b) ROI nose part (c) ROI forehead part (d) ROI lips part (e) ROI chin part

These distances have been calculated and stored in a corpus. For the learning part of the whole system, each human-face image are analyzed and nineteen parameters are extracted and stored in the corpus along with the distances measured in pixels. Out of these nineteen parameters, few are playing an important role for the understanding part. The parameters that are considered for the recognition of human-face from side-view are: forehead width (FHW), eye-to-lips distance (ELD), eye-to-chin distance (ECD), lips-to-chin distance (LCD), eye-to-nose distance (END), no. of wrinkles (NOW), texture of the face (TOF) and normal-behaviour pattern (NBP). For the formation of corpus, the frontal part of the human-face has been considered. The blob diagram of the frontal part of the human-face has been shown in figure 2

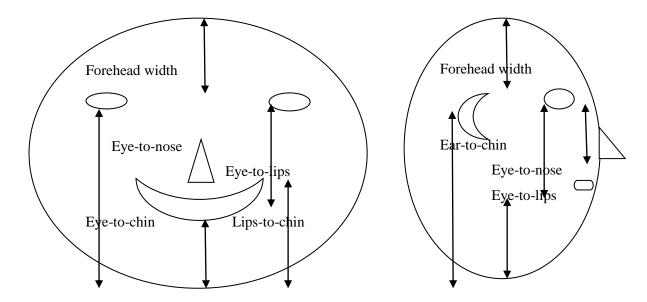


Fig 3. Blob diagram of the frontal and side-view part of the human-face showing the distance measures

From figure 3, an observation has been made for different distance measures. The distance measures along with number of wrinkles or edges, texture of the human-face and normal-behavioural pattern have been calculated and has been depicted in table 1.

Data Source	FHW	ELD	LCD	ECD	END	NOW	TOF	NBP
Img1	40.26	50.23	6.07	56.30	46.96	2.00	1.00	10.00
Img2	40.23	50.26	6.05	56.31	46.95	3.00	1.00	11.00
Img3	40.05	50.29	6.00	56.29	46.98	2.00	1.00	10.50
Img4	40.15	50.19	6.06	56.25	46.99	2.00	1.00	12.00

Table 1. Distance measures of parameters and other features of human-face of ten subjects

Img5	40.28	50.18	6.10	56.28	47.02	2.00	1.00	12.05
Img6	40.27	50.16	6.09	56.25	47.01	3.00	1.00	13.50
Img7	40.24	50.21	6.08	56.29	47.03	2.00	1.00	12.50
Img8	40.12	50.22	6.01	56.23	47.04	2.00	1.00	13.60
Img9	40.09	50.27	6.04	56.31	46.94	2.00	1.00	12.06
Img10	40.19	50.09	6.03	56.12	46.89	3.00	1.00	13.75

From table 1, it has been observed that, the number of wrinkles or edges (NOW) ranges in between 2 and 3. These values have been extracted for the subject whose age lies in between 35 to 50 of different gender. The method that have been applied in the present work, for the extraction of wrinkles or edges are the morphological components of digital image processing through canny and sobel property. Similarly, the values of the texture of the human-face has been calculated as unity. In the present work, texture has been calculated using statistical methods of computation through cross-correleation and auto-correlation. Also deviation of neighbouring pixels for texture analysis have been also done using 4-pair and 8-pair computations of neighbouring pixels. The final conclusion on the texture calculation has been done through forward-backward dynamic programming method of soft-computing technique. Further from table 1, it has been also observed that, normal-behavioural pattern (NBP) ranges from 10 to 15. These values have been extracted using fuzzy-c means clustering method with a mean value of the clusters for the normal behavioural pattern. The graphical representation of the parameters extracted from the frontal part of the human-face image has been shown in figure 4.

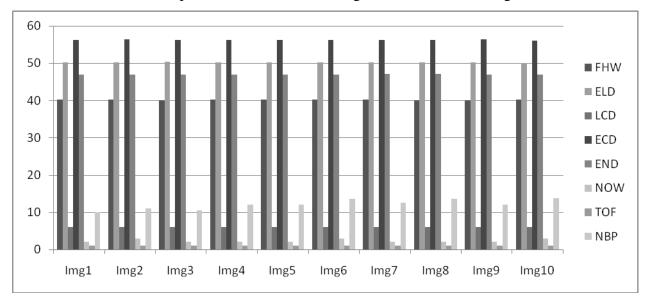


Fig 4. Graphical representation of the parameters extracted from the human-face image

For handling the second and main part of the present work, side-view of the human-face image has been considered as a test data sample for the recognition of human-face. Initiallly, a side-view of the human-face which is parallel to the x-axis with zero degree orientation has been fed as test data sample. Hence preprocessing techniques of digital image processing has been applied and result has been obtained. The techniques that have been applied are: loss-less compression, discrete wavelet transform for obtaining detail and coarser components of the switching pattern, statistical methods of computation for the computation of mean covariance of transformed vectors, prinicpal component analysis for the computation of eigen vectors and eigen values. The results obtained from the test image of the human-face with side-view has been shown in figure 5, figure 6 and figure 7, along with brief discussions and observations made through the present work.

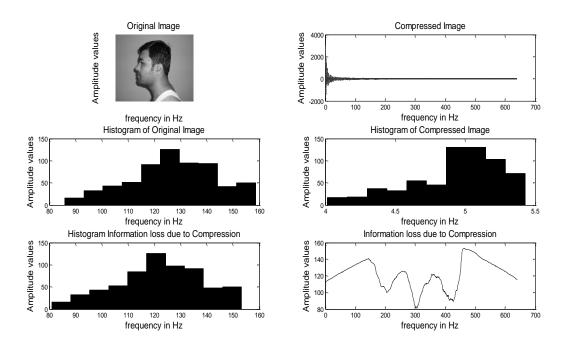


Fig 5. Loss-less compression of the test image captured from side-view of human-face

After performing loss-less compression on the test image, further calulcations like coarser and detail components of the switching pattern using discrete wavelet transform have been done and the results have been plotted as shown in figure 6.

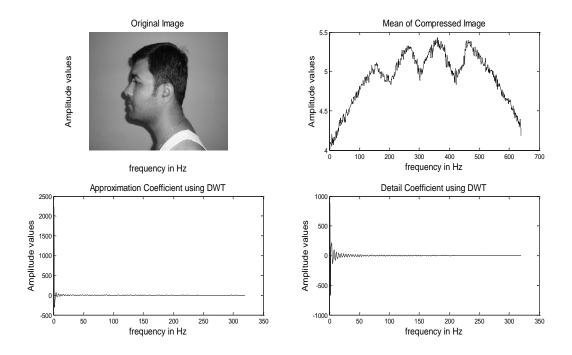


Fig 6. Discrete wavelet transform of the test image captured from side-view of human-face

From figure 6, it has been observed that, detail and coarser components have been calculated, which have been utilized for further calculation of odd and even components of the human-face image. In the present work, this has been achieved by employing lifting and inverse-lifting scheme of discrete wavelet transform. Further analysis has been carried out and more outcomes have been plotted in figure 7.

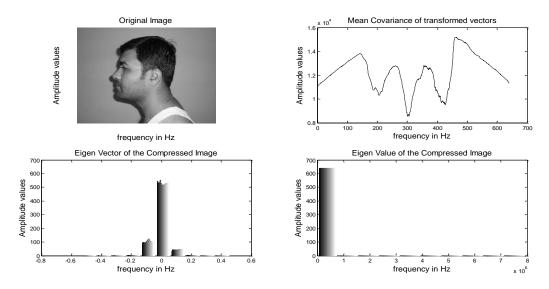


Fig 7. Principal component analysis of the test image captured from side-view of human-face From figure 7, it has been observed that transformed eigen vectors and its corresponding eigen value have been extracted for analysing the switching pattern. The switching angle has been

gradually increased. Initial analysis has been done on five degree progressive displacement. Later the same has been done with ten degrees increment. The comparison of the progressive switching patterns for odd multiples of frames of human-face image has been computed and shown in figure 8.

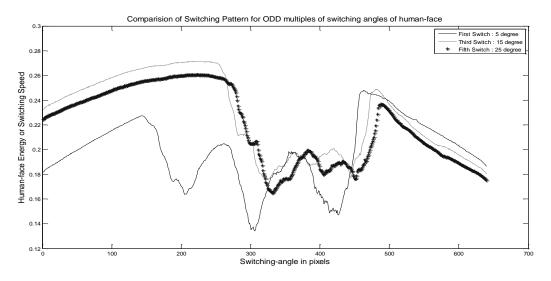


Fig 8. Comparison of switching pattern for odd frames of the test image

From figure 8, it has been observed that, for the first frame with five degree orientation, the extracted parameters have been matched. But the fitness test failed. Hence further analysis have been done for availing best fitness test, this has been achieved using progressive switching of the human-face with ten degree displacement. Finally, it has been found that most of the parameters are following the normal pattern of the trained data set stored in a corpus. Hence the best-fit measures have been done and further analysis for classification and recognition are performed using genetic algorithm of soft-computing technique. Further, the normal and cumulative distribution of progressive switching patterns of the test image has been shown in figure 9 and figure 10.

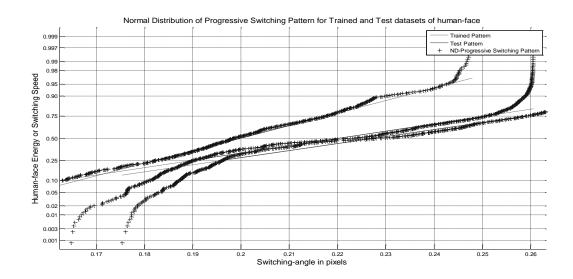


Fig 9. Normal distribution of progressive switching pattern for odd frames of the test image

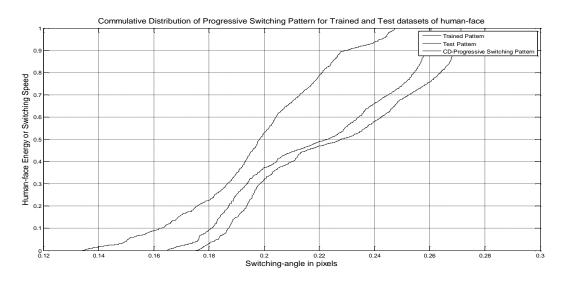


Fig 10. Cumulative distribution of progressive switching pattern for odd frames of the test image

The classification and characterization process of the progressive switching pattern of the test image of the human-face captured from side-view has been carried out using support vector machine of artificial neural network. The results have been found very remarkable and the plotting has been shown in figure 11.

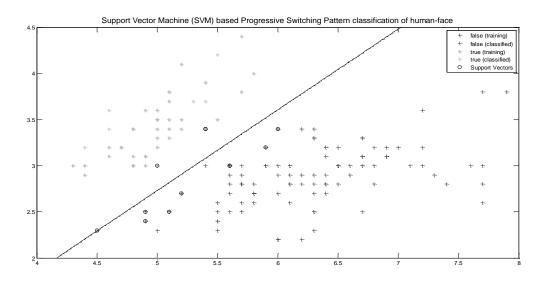


Fig 11. Classification of progressive switching pattern using support vector machine of artificial neural network of the test image of the human-face captured from side-view

The different divergence value of metrics for the test image captured from side-view of the human-face has been shown in table 2 and the plot has been shown in figure 12.

Data	FPR	FNR	Sensitivity	Specificity	Accuracy
Source			(in %)	(in %)	(in %)
Img1	5.9411	4.9112	95.0888	94.0589	94.1757
Img2	9.5504	30.0836	69.9164	90.4496	88.2385
Img3	9.4283	32.6887	67.3113	90.5717	87.9105
Img4	7.1306	11.9463	88.0537	92.8694	92.3386
Img5	9.9959	33.171	66.829	90.0041	91.5351
Img6	9.0173	37.9402	62.0598	90.9827	89.1475
Img7	8.5589	77.2401	22.7599	91.4411	85.2078
Img8	10.9437	78.8765	21.1235	89.0563	94.9759
Img9	13.2179	80.6998	19.3002	86.7821	95.3528
Img10	12.5232	79.2356	18.2003	88.4252	93.9536

Table 2. Divergence values of metrics for the human-face captured from side-view of ten subjects

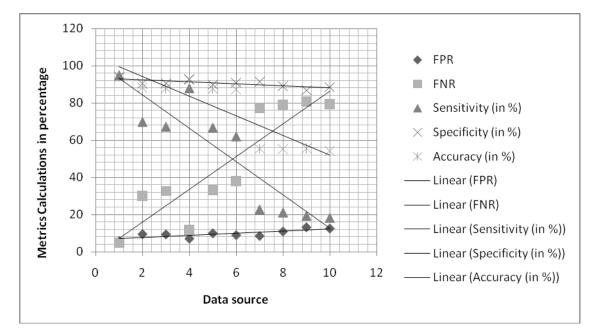


Fig 12. Graphical representation of divergence values of metrics of the test image of the humanface captured from side-view for ten different subjects

### 4. Conclusions and further scope of the work

In the present work, appropriate amount of results have been obtained and the analysis have been also done with acceptable value of recognition of human-face captured from side-view. Still there are scopes for carrying out the research work on the obtained results. The main possibility is the detection of behavioural pattern of the subject from side-view using fan-beam projection method. Another possibility is to increase the volume of the corpus for more and positive recognition rate thus increasing the efficiency achieved through the present research work. Further the algorithm proposed in the present paper for recognition of human-face from side-view has to be analyzed further with complexity under worst-case condition. To achieve such goals, high-end computing measures have to be carried out using advanced mathematical formulations and known algorithms from the literature. The performance measures with an optimal number of parameters required for the recognition of the human-face from side-view has to be also analyzed for the recognition of the human-face from side-view has to be also analyzed for the recognition of the human-face from side-view has to be also analyzed for the recognition of the human-face from side-view has to be also analyzed for the recognition of the human-face from side-view has to be also analyzed for the recognition of the human-face from side-view has to be also analyzed for the literature.

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