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Full Length Research paper

Optimized mask selection for person identification and camera distance measurement based on interocular distance

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This paper presents a multi-resolution masks based pattern matching method for person identification. The system is commenced with the construction of multi-resolution mask cluster pyramid, where the mask size is chosen depending on the distance between two eyes, computed from the detected face. Experimental results show the effectiveness of the system with significantly higher precision, recall rates and matching probability comparing with conventional single resolution mask based person identification systems. This paper also presents a novel person to camera distance measuring system based on eye-distance. The distance between centers of two eyes (interocular distance) is used for measuring the person to camera distance. The variation in eye-distance (in pixels) with the changes in camera to person distance (in inches) is used to formulate the distance measuring system. Experimental results show the effectiveness of the distance measurement system with an average accuracy of 94.11%.

Key words: Single resolution mask, multi-resolution masks, person to camera distance, person identification.

INTRODUCTION

Many algorithms have been proposed for person identification (Valentin, 1994; Chellappa, 1995; Zhao, 2002), creating a new industry (Hansen, 2005). Scientists working with these systems know that some persons are harder to recognize than are others. Consequently, research on person identification remain in the center of attention to the researchers because of its' versatile application. These researches are diversified in two methods (Brunelli, 1983), geometric feature-based methods and template-based ones. The basic method of template matching uses a convolution mask (template), tailored to a specific feature of the search image, which we want to detect. Other sophisticated methods involve extensive pre-processing and transformation of the extracted grey-level intensity values. Turk and Pentland (Turk, 1991) used principal component analysis (PCA), to pre-process the gray-levels of the image. The other implementation of template matching method is using a deformable mask (Yuille, 1992; Black, 2007). Instead of using several fixed size masks, a deformable mask is used and there by changed the size of the mask hoping to detect a face in an image. Hasanuzzaman et al. (2005) proposed a system that first detects the face and identifies the user to learn skin-color information of the person (Hasanuzzaman, 2005; Hasanuzzaman, 2007). It uses face templates pyramid with different resolutions and orientations where two eyes on the upper part of the probable face are located to make sure of the presence of the face (Bhuiyan, 2004).

For measuring object to camera distance, two widely used approaches are: contact and non-contact approaches (Chen, 2007). In contact-based approach, various methods can be used, such as ultrasonic distance measurement (Carullo, 1996; Carullo, 2001), laser reflection methods (Osugi, 1999; Shin, 2000). These two methods use the theory of reflection. If the

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reflection surface is not uniform, the measuring system generally performs poorly or not at all. On the other hand, image-based measuring systems based on pattern recognition or image analysis techniques (Kanade, 1995; Tanaka, 1998) generally demand huge amount of storage capacity and high-speed processors. The proposed distance measurement method in this paper is quite different from other existing image processing based person to camera distance measuring techniques which requires additional CCD cameras (Sid-Ahmed, 1990; Liguori, 2001), laser projectors, etc. during the measurements. The distance between two eyes (in pixels) of a person in an image reduces as the person moves away from the camera and vice versa. This property is used to measure the person to camera distance based on a certain eye-distance in real time.

To overcome the problems and difficulties encountered by the existing person identification techniques caused by mainly huge computational necessity, an eye-distance based mask selection for person identification method is presented in this paper. Based on an established relationship between the eye-distance and face size (both in pixels), the mask dimension is selected for further processing by computing the minimum distance qualifier (Manhattan Distance). The proposed method in this paper is quite different from other existing template matching based person identification systems which uses single resolution mask. This method improves the mask selection procedure thus saving computational cost significantly by simply discarding masks of unnecessary dimensions at the very beginning.

The partial work of this paper has been presented in MUE, 09 (Rahman, 2009a, b). Thus the complete work is presented in this paper.

PROPOSED SYSTEM

Eye distance measurement

This system forms an image pyramid of the input images and uses a template matching approach for face and eye detection (Chen, 2007). An image pyramid is a set of copies of the original image at different scales, thus representing a set of different resolutions. To locate the face a mask is moved pixel-wise over each image in the pyramid, and at each position the image section under the mask is passed to a function that assesses the similarity of the image section to a face. If the similarity value is high enough (with respect to some threshold), the presence of a face at that position is assumed. From that position, the position and size of the face in the original image is generated. This eye detection is identical to face detection system which forms an image pyramid of the detected face images and uses a template matching approach for eye detection. The Euclidian distance between two eyes is computed using the following:

$$d_{ep} = \sqrt{(E_{LX} - E_{RX})^2 + (E_{LY} - E_{RY})^2} \tag{1}$$

Where (E_{LX} , E_{LY}) and (E_{RX} , E_{RY}) are the coordinates of the left and right eyes respectively and d_{ep} is the distance between two eyes in terms of pixels.

Formulation of person to camera distance measurement equation

After a comprehensive study conducted over 35 people of both sexes and from different height ranges, it is found that a relation exists between eye distance (in pixels) and person to camera distance (in inches). A sample square of eye distance versus person to camera distance graph of several persons is presented in Figure 1. From the figure it is noticeable that the square of eye distance versus person to camera distance graph is significantly identical thus it can be generalized for persons of different physical identities. Table 1 presents collected measured data of three persons on different predefined camera to person distances (in inches).

Equations (2) and (3) are formulated after a thorough study of the nature of Eye Distance^2 versus Person to Camera Distance graphs of 35 people, which simulates the graphs in real-time.

$$d_{ep}{}^2 = \frac{MAX_{ed}}{(1 + \frac{d_c - Mid_G}{Mid_G})(\sqrt{d_c - MIN_{ed}} - 1)} \tag{2}$$

$$d_c{}' = d_c \pm V\,(2 - \frac{d_{ep}}{MAX_{ed}}) \tag{3}$$

where d_{ep} is the distance between two eyes, MAX_{ed} is the maximum eye distance point, MIN_{ed} is the minimum camera distance point, Mid_G is the mid point of square of eye distance Vs person to camera distance graph , d_c is the primary camera to person distance (with error), $d_c{}'$ is the corrected camera to person distance and V is the correction weight. Positions of MAX_{ed} , MIN_{ed} , Mid_G points are shown in Figure 2. These values are generalized considering the data collected of 35 people.

Before measuring the person to camera distance, the person is trained with different predefined distances from the camera starting from 7 inches and increased up-to 31

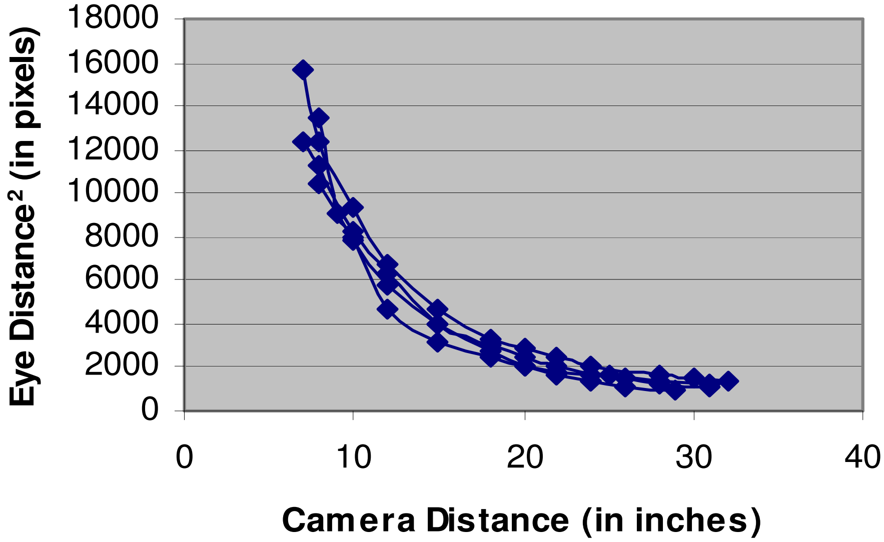

Figure 1. Sample relation between eye-distance and person to camera distance.

Table 1. Sample measured data.

Square of eye distance (in pixels)			Person to camera distance (in inches)
Person 1 (Abir)	**Person 2 (Wahid)**	**Person 3 (Robin)**	
1228	1150	1225	31
1350	1329	1370	28
1580	1450	1685	25
1900	1959	2034	22
2226	2145	2501	20
2720	2890	3000	18
4000	3986	4005	15
5800	6120	6277	12
7800	7980	8200	10
10400	10350	11211	8
14500	13500	12400	7

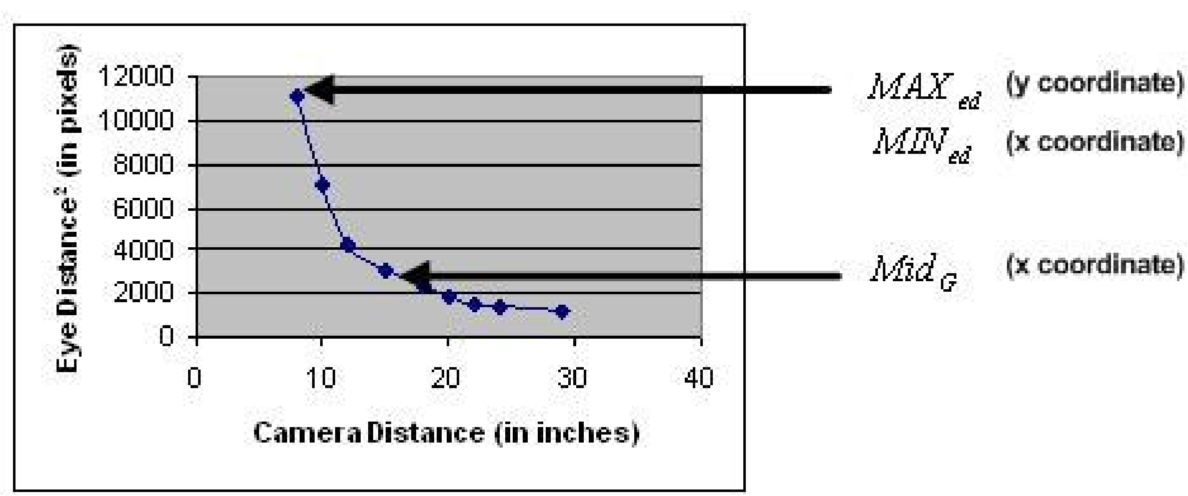

Figure 2. Relation between eye distance and object to camera distance.

Table 2. Intrinsic parameter table.

MAX_{ed} Range	MIN_{ed} Value	Mid_G Value	Value of V	Sign
MAX_{ed} >16000	8	23	8	+
13000< MAX_{ed} <=16000	8	20	6	+
11000< MAX_{ed} <=13000	8	18	4	+
9500< MAX_{ed} <=11000	8	15	0	N/A
MAX_{ed} <=9500	7	15	4	-

Table 3. Relation between eye distance, face size and height.

No. of persons	Height range	Actual camera to object distance (in inches)	Average eye distance (in pixels)	Average face dimension
5	5' 8" and over	32	34.33	58 × 58
		30	36.07	65 × 65
		28	38.19	68 × 68
		24	43.32	78 × 78
		22	47.09	85 × 85
		20	50.38	90 × 90
		18	55.31	100 × 100
		15	65.11	115 × 115
		12	80.46	145 × 145
		10	93.43	168 × 168
		8	107.90	190 × 190
		7	129.29	213 × 213

inches. During the training session corresponding person to camera distances (in inches) and eye distances are mapped and the MAX_{ed} value of that person (when the person is in the highest distance from the camera) is set by the system. It is also found that there are generally 5 categories of MAX_{ed} values ranging from 16000 - 9500 in which the persons tested have been categorized.

Depending on the MAX_{ed} value, the other parameters of (2) and (3) are set according to Table 2. Figure 3 shows the different square of eye distance versus person to camera distance graphs depending on different MAX_{ed} value. The values of Table 3 are set after analyzing the characteristics of square of eye distance versus person to camera distance graphs of Figure 3.

Person to camera distance measurement

Person to camera distance measurement is accomplished by calculating the eye distance and then mapping the corresponding person to camera distance from the generalized (2) and (3) with the values of the parameters from Table 2 after identifying the person along with corresponding MAX_{ed} value of that person. If the person is not identified then the default parameters values are chosen. Figure 4 shows the complete architecture of the proposed distance measuring system. The person to camera distance measurement algorithm is described bellow:

Step 1: Detect the center of the two eyes and find the Euclidian distance between them (Hasanuzzaman, 2007).

Step 2: If the person is identified then retrieve the MAX_{ed} value of that person from the database.

Step 3: Set the values of MIN_{ed}, Mid_G, V from Table 2 according to MAX_{ed}, where MAX_{ed} is the maximum eye distance point, MIN_{ed} is the minimum camera distance point, Mid_G is the mid point of Eye Distance^2-

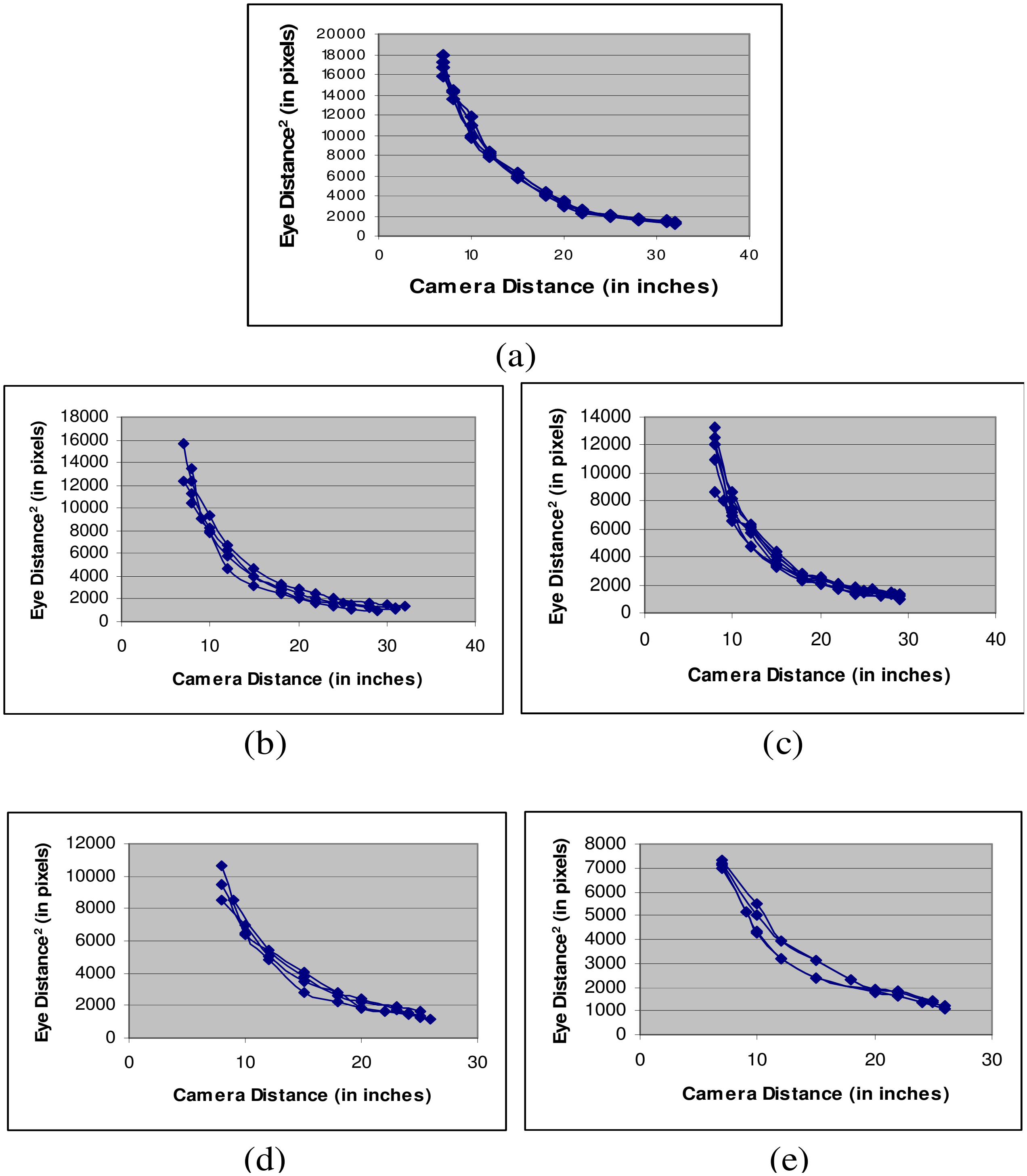

Figure 3. Square of eye distance versus person to camera distance graph (a) where MAX_{ed} >16000 (b) for 13000< MAX_{ed} <=16000, (c) for 11000< MAX_{ed} <=13000, (d) for 9500< MAX_{ed} <=11000 and (e) MAX_{ed} <=950.

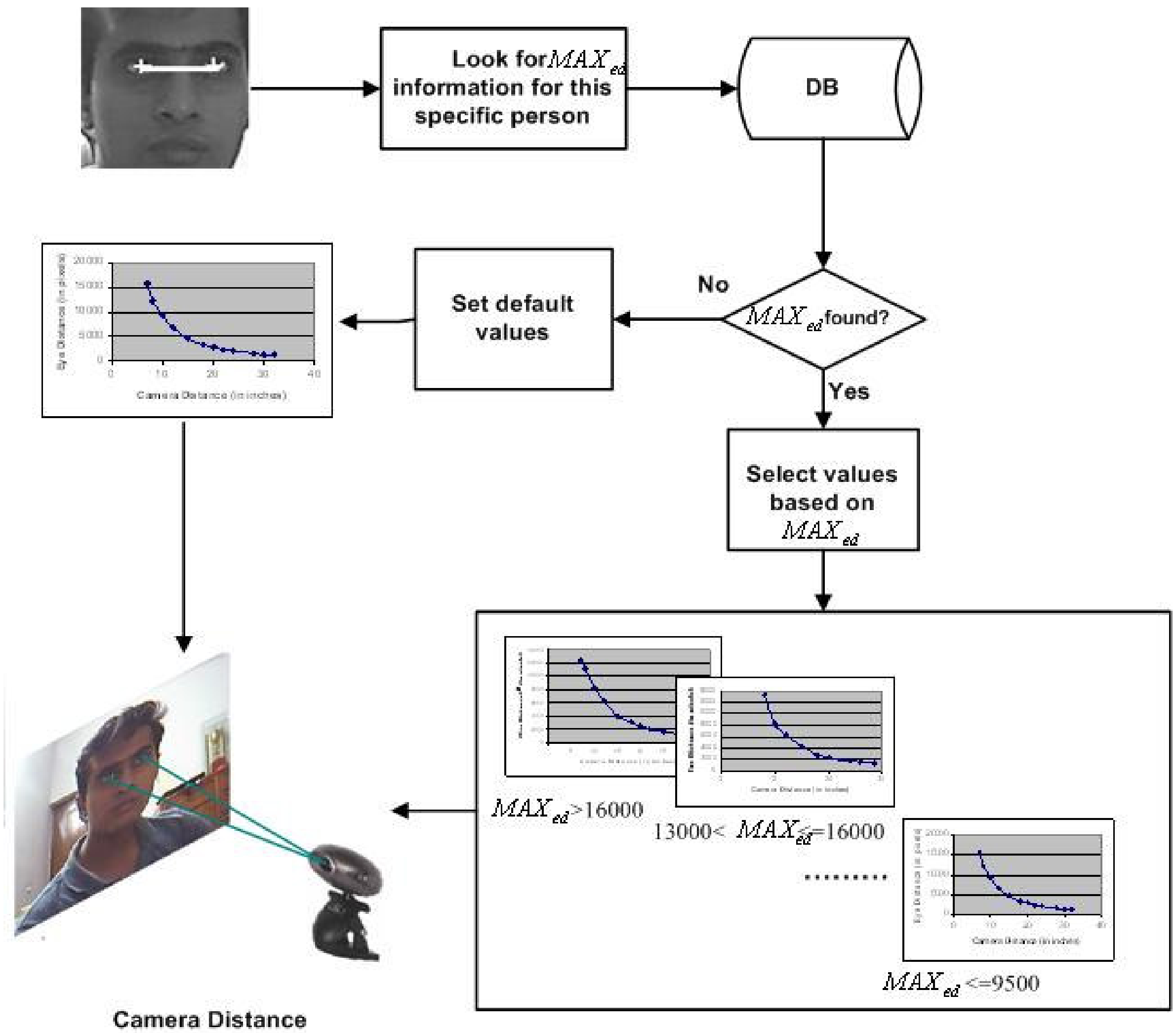

Figure 4. Person to camera distance measurement system architecture.

Camera Distance graph and V is the correction weight.

Step 4: Calculate primary camera to person distance, d_c from the (4)

$$d_c^{\,2}\,(d_c - MIN_{ed} - 1) = \left(\frac{MAX_{ed} \times MID_G}{d_{ep}^{\,2}}\right)^2 \qquad (4)$$

Where d_{ep} is the distance between two eyes.

Step 5: Make correction to the camera to person distance by the following equation:

$$d_c' = d_c \pm V\left(2 - \frac{d_{ep}}{MAX_{ed}}\right)$$ Where d_c is the primary camera to person distance (with error), d_c' is the corrected person to camera distance and V is the correction weight and return d_c'.

Step 6: If the person is not identified, set the default value as MAX_{ed} = 11000 and goto Step 2.

Normalization and training

After face is detected, the face area is normalized before passing to the face recognition and person identification module as shown in Figure 5. Detected face is converted to grayscale using (5) and scaled to nearest dimension using (6) and saved as a gray bmp Image;

$$Gr_i = \frac{R_i + G_i + B_i}{3}, i = 1, 2, 3, \ldots\ldots, M \times N \qquad (5)$$

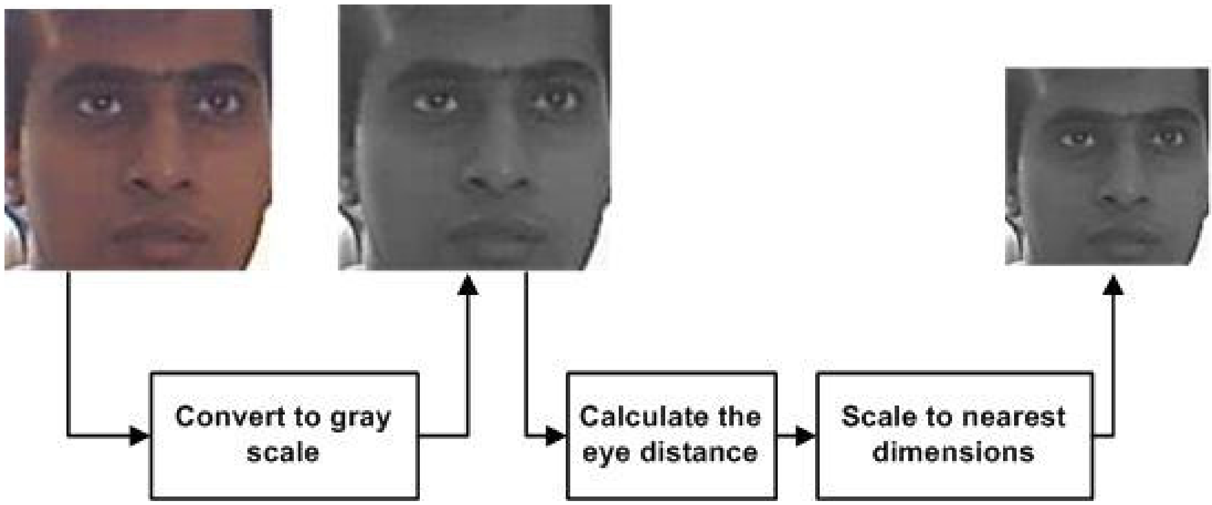

Figure 5. Normalization method.

Where, Gr_i is the gray level value of i^{th} pixel of the gray image. R_i, G_i, *and* B_i corresponds to red, green and blue components of the i^{th} pixel in the color image. Suppose $M \times N$ is the initial image dimension, it is scaled to $M' \times N'$ dimension. The scaling is done as follows. Suppose, we have a segment of square $P[(x^l, y^l) - (x^h, y^h)]$ we sample it to dimension $Q[(0,0) - (M' \times N')]$ using following expression,

$$Q(x^q, y^q) = P(x^l + \frac{(x^k - x^l)}{M' \times N'} x^q, y^l + \frac{(y^k - y^l)}{M' \times N'} y^q) \quad (6)$$

The training module is invoked when a new face is encountered. The person must be trained before he/she can be identified in future encounter. This module takes face samples and creates a face cluster for a new person, P_i. The face cluster is normalized and rescaled to different dimensions (50 × 50, 60 × 60, 70 × 70, 80 × 80, 90 × 90 and 100 × 100) and inserts in the training database.

Relation between eye distance and face size

After a comprehensive study over twenty four persons, it is found that both eye distance and face dimension are largely interdependent. Table 3 shows the relation of person height, eye distance and face dimension. Figure 6 shows the relation between eye distance and face size for the persons with different height ranges. From the collected data it is noticeable that relation between eye distance and face dimension is linear regardless of height of a person. It is also found that, the average face dimension is approximately 1.8 times of average eye distances.

Person identification

In the person identification system, multi-resolution masks are used to make the system robust against face size. The Person Identification module of the system has a training face database containing K images (I_t) with different resolutions. The person identification system takes input test image, I_{ts} one by one generated from face detection and normalizes to nearest mask size depending on the eye distance. The mask size is selected for matching with the previously saved templates with different dimensions by the following (7),

$$M' \times N' = M_s \times d_{ep} \quad (7)$$

where, $M' \times N'$ is the mask size, M_s is mask factor which is determined empirically to 1.8, as found in Subsection C and d_{ep} is the eye distance in pixels. Figure 7 shows the relation between M_s and d_{ep}.

The system generates Boolean decision regarding whether the input image(s) are recognized or not. The eye-distance based mask selection process is shown in Figure 8. This person identification method is described using following steps.

Step 1: Calculate the eye distance, d_{ep}

Step 2: Set the value of Mask Size Factor, $M_s =$

Step 3: Normalize and set the dimension of the face size,

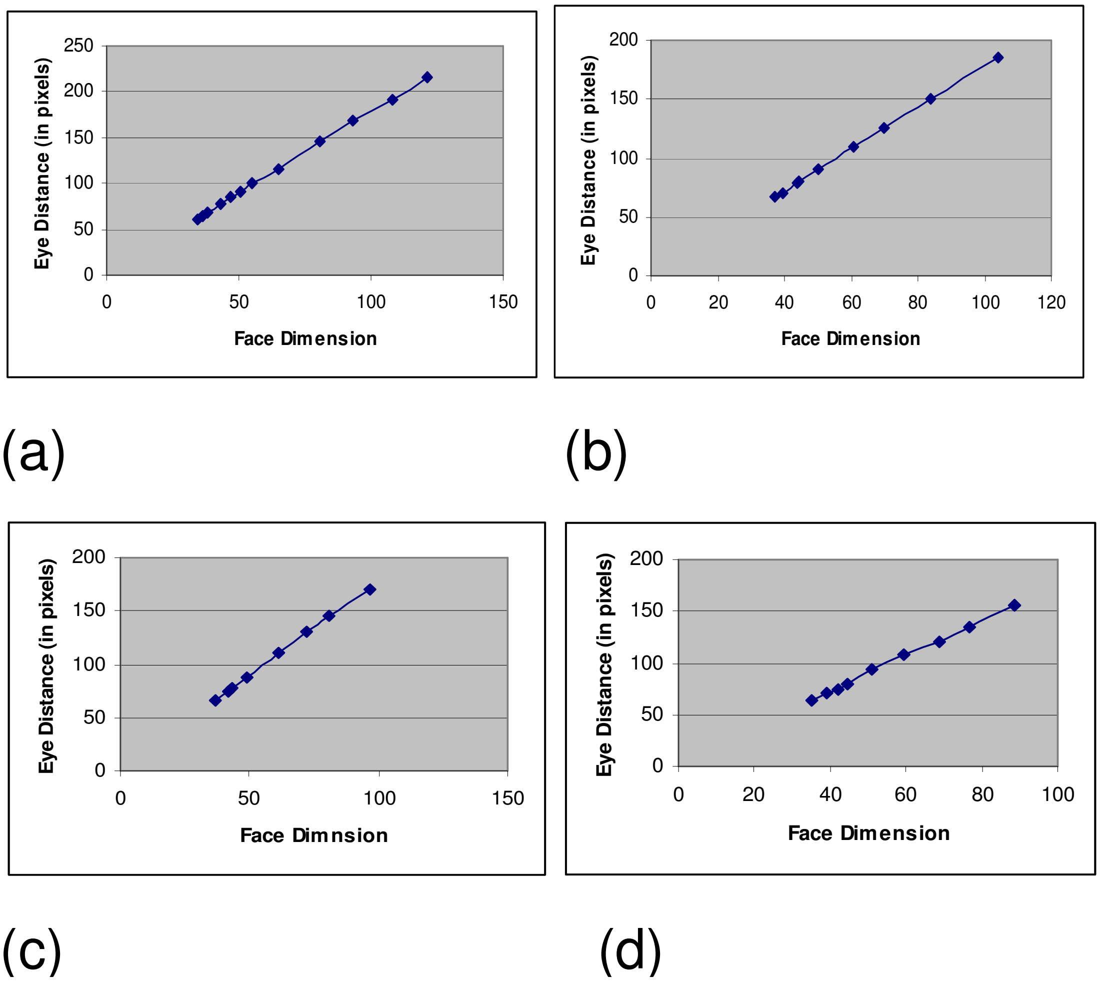

Figure 6. Relation between eye distance and face size, (a) height ranging over 5' 8'', (b) height ranging between 5' 4'' and 5' 7'', (c) height ranging between 5' and 5' 3'', (d) height ranging bellow 5'.

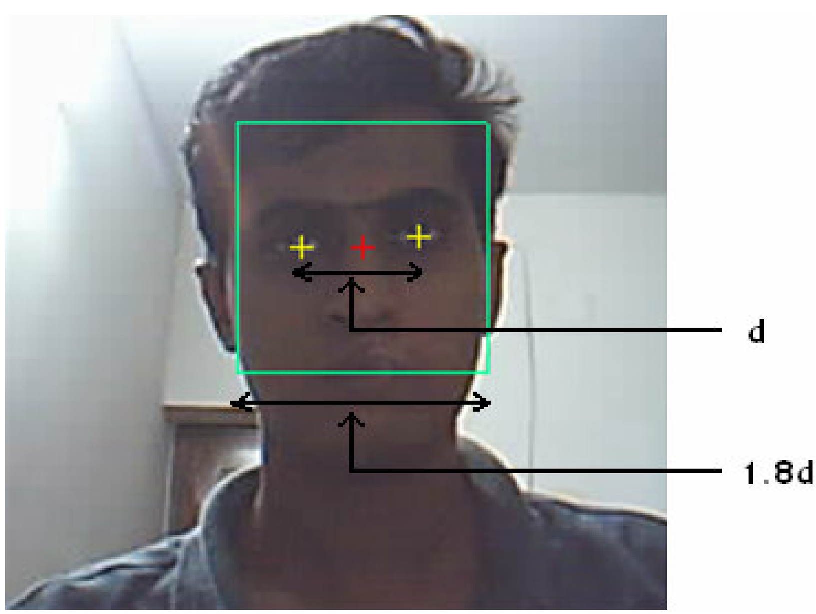

Figure 7. Relation between eye distance and mask size.

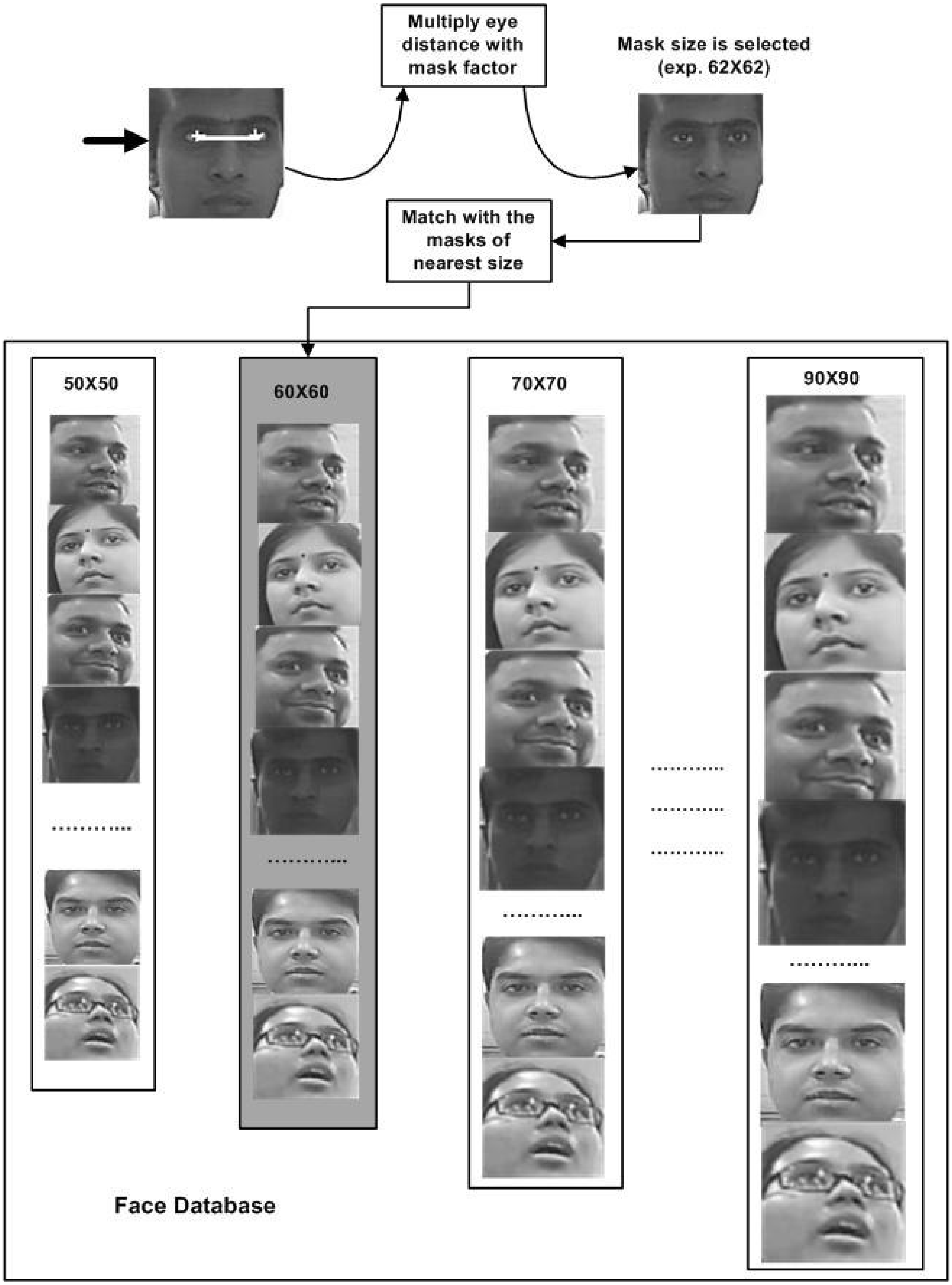

Figure 8. Person identification.

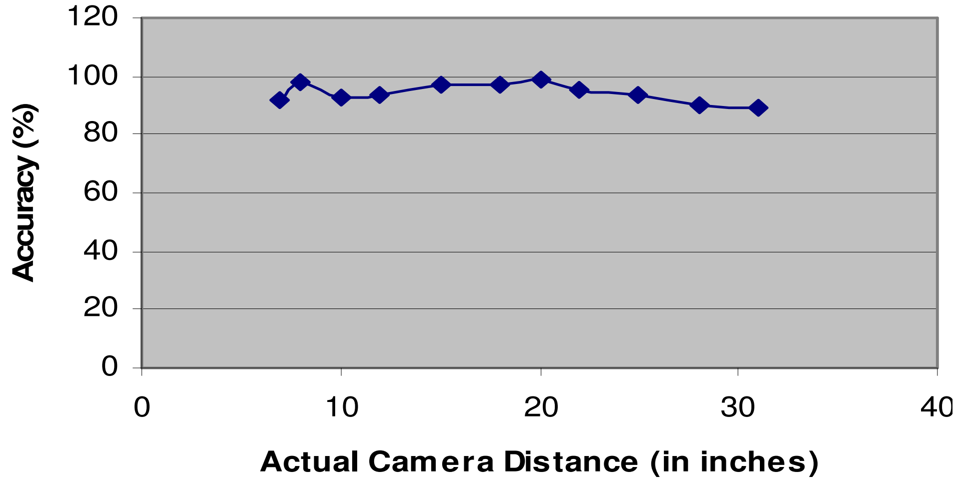

Figure 9. Accuracy (%) of the measured distance with the actual distance.

$M' \times N'$ = $M_s \times d_{ep}$ where M_s is the Mask Size Factor and d_{ep} is the eye distance.

Step 4: For i = 1 to K, calculate Manhattan Distance, δ^i between I_{ts} and all the training images with nearest dimension by the following equation,

$$\delta^i = \sum_{j=1}^{M' \times N'} \left| I_{ij} - I_{ts} \right| ,$$

Where I_{ts} is the test image I_{ij} is the jth pixel of ith training image and K is the number of images in the face database.

Step 5: Calculate the minimum Manhattan Distance, η_M from Step 4 by the equation

η_M = Min (δ^i),

Where δ^i is the ith Manhattan Distance

Step 6: If minimum Manhattan distance, $\eta_M \leq T$ for a test image and threshold value, T then person is identified

Step 7: Else person is not identified and should be adapted and trained for future identification.

EXPERIMENTAL RESULTS

This system uses *A4 Tech PK-336MB* CCD camera for image acquisition (a4tech.com, 2009). Each captured image is digitized into a 320 × 320 matrix with 24 bit color. The system captures 30 image frames per second. The system considers every 5th frame captured by camera for further processing. Thus the system processes 6 image frames per second for face area and eye detection (FaceVACS SDK). Accuracy of person to camera distance measurement results using the proposed method are shown in Table 4, where real distances, measured distances, and accuracy (for distances from 7 - 31 inches) of 35 persons are recorded. Figure 9 shows the accuracy (%) of the proposed system at different predefined distances. The average accuracy of 94.11% is obtained. Though other conventional measuring results shows slight accurate where error rates range from 1 - 8% (Wang, 2006; Lu, 2006), the proposed system validated its' superiority in terms of simplicity and cost effectiveness.

Comparison between single and eye-distance based multi-resolution masks has been done by analyzing precision and recall rates over twenty three persons. The accuracy (%) which is compared on thirty five persons with different eye distances. The precision and recall rates for both single resolution mask and eye-distance based multi-resolution masks is presented in Table 5.

It can be inferred from Table 5 that, both precision and recall rates are significantly higher for eye-distance based multi-resolution mask than single resolution mask based person identification and thus outperforms the single resolution mask counterpart. Figure 10 and 11 show the comparison between precision and recall rates with multi-resolution and single resolution mask respectively. Figure 12 shows the sample matching probability of the system for both single mask and multi-resolution masks. Table 6 shows the performance comparison in terms of matching probability. Figure 13 shows the matching probability comparison graph of single resolution mask and eye-distance based multi-resolution mask for person identification. It is noticeable from the above figure that,

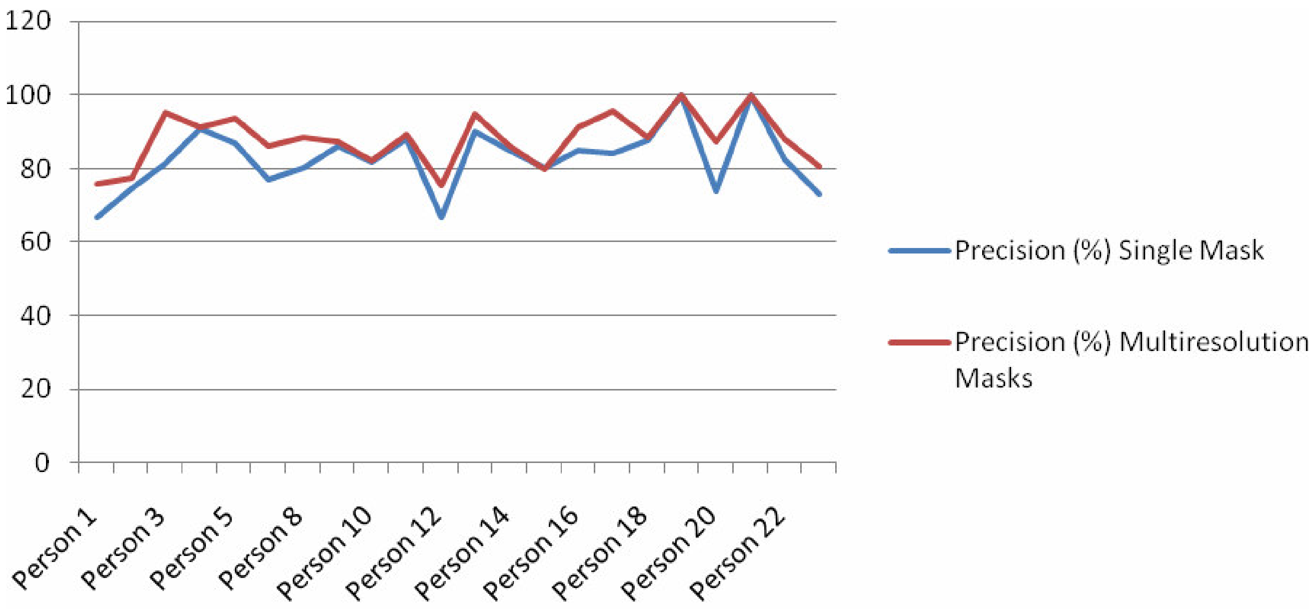

Figure 10. Performance comparison between multi-resolution masks and single resolution mask in terms of precision rates.

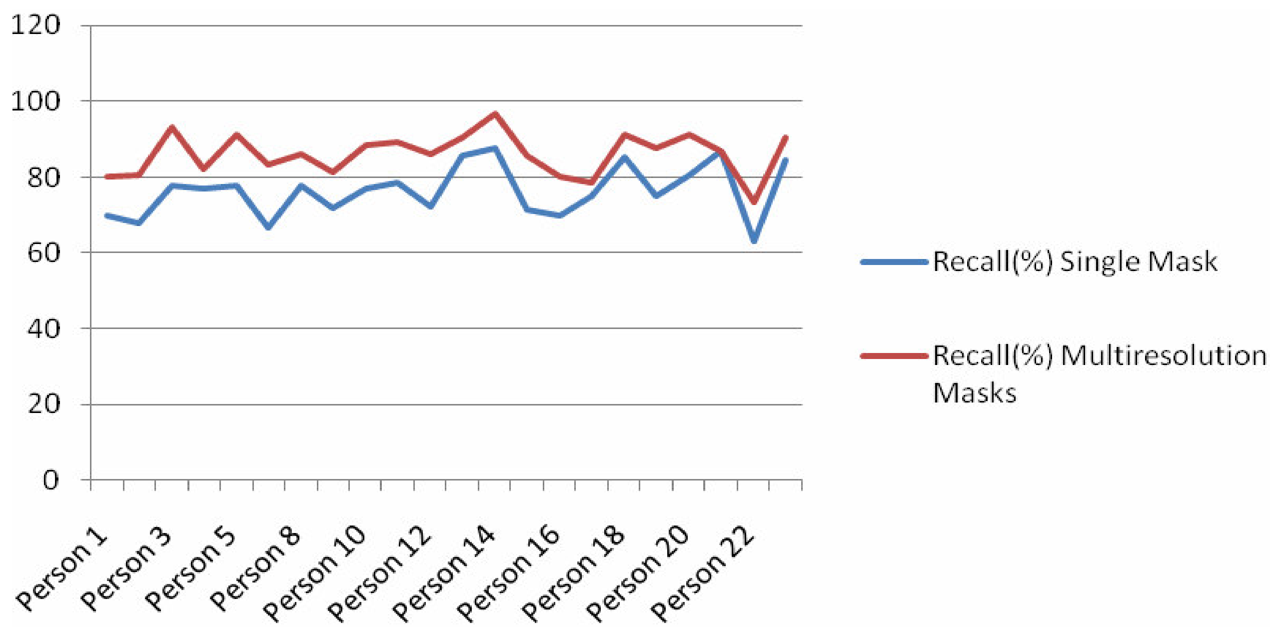

Figure 11. Performance comparison between multi-resolution masks and single resolution mask in terms of recall rates

accuracy is declining with the increment of eye-distance.

CONCLUSION

In this paper, an improved mask selection criterion from multi-resolution masks is proposed for person identification thus making a major contribution in areas of face recognition and person identification. There are several systems for choosing the mask size for person identification but the proposed eye-distance based mask selection is more robust and reliable as it reduces the computation time drastically. The system can now easily predict the best possible size of the mask and ignore other sizes at the very beginning. The proposed system has an average precision rate of 88.25% and average

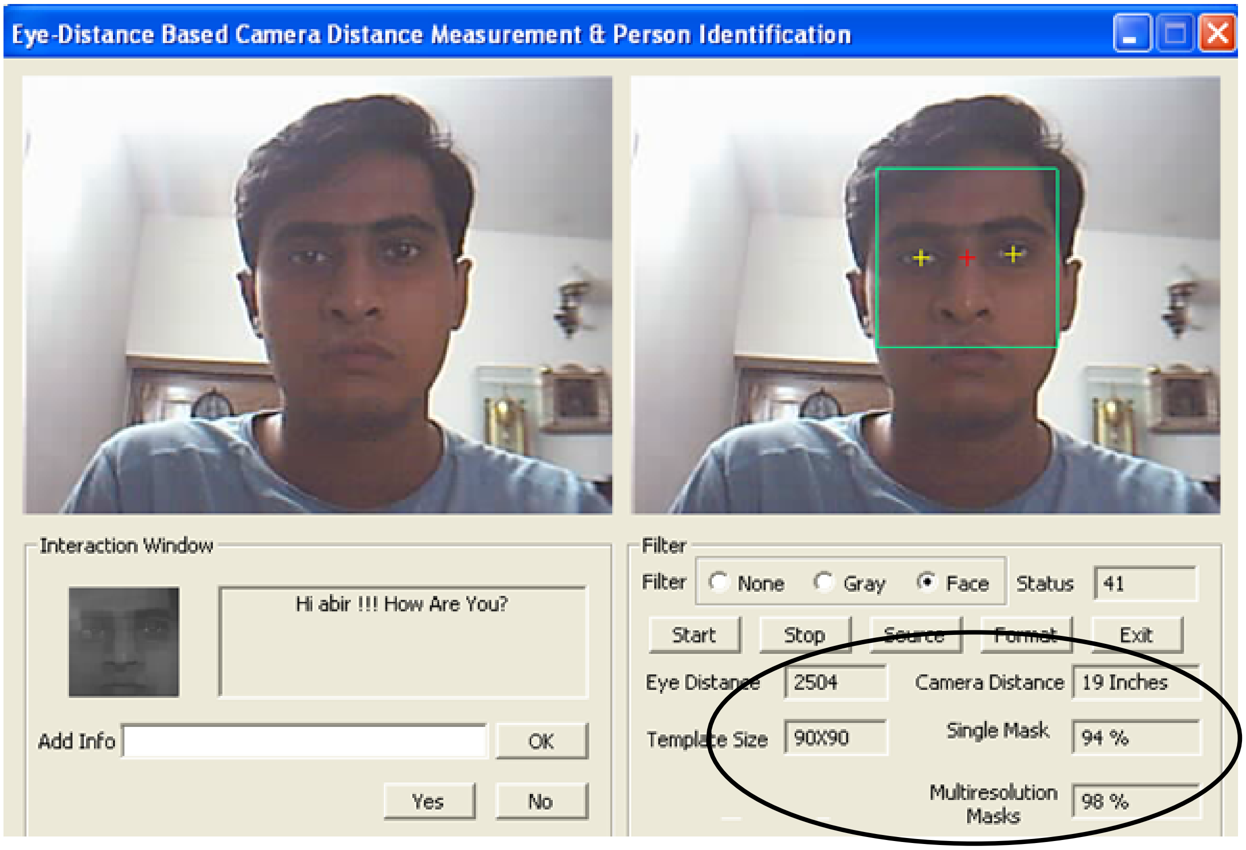

Figure 12. Matching probability of person identification for both single resolution mask and multi-resolution masks (eye distance = 50 pixels).

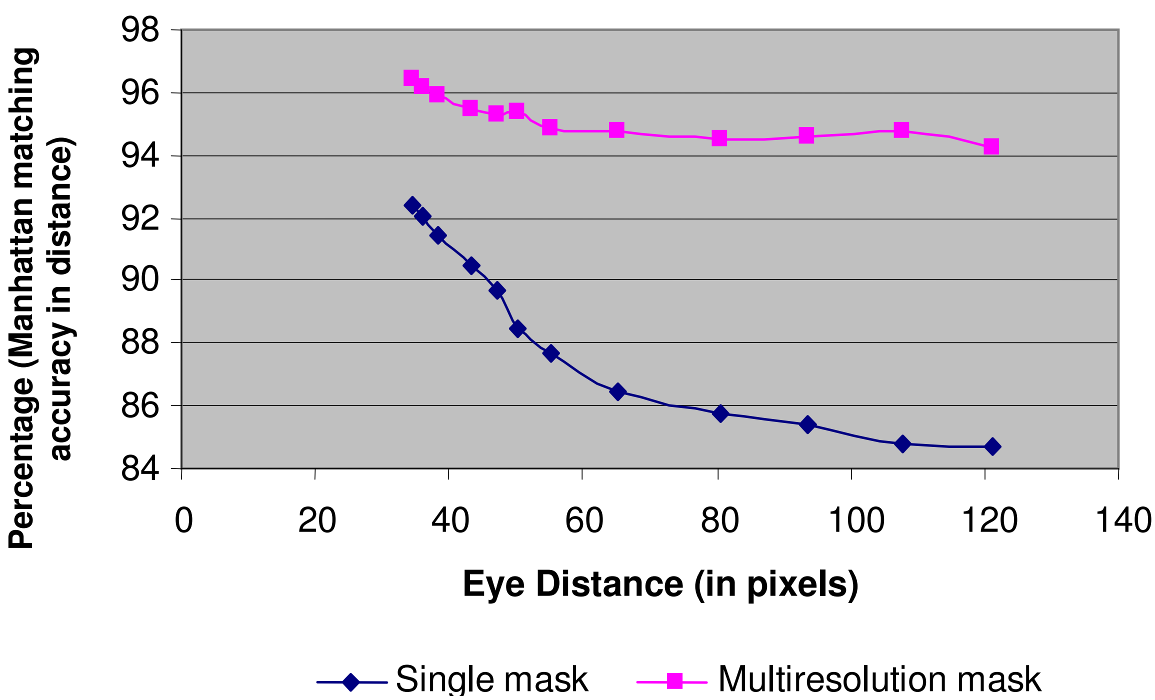

Figure 13. Matching probability comparison of single resolution mask and eye-distance based multi-resolution masks for person identification.

Table 4. Accuracy of the distance measurement method.

Actual person to camera distance (in inches)	System person to camera distance (in inches)	Accuracy (%)
31	33.8	88.96
28	31	90.25
25	26.7	93.2
22	23	95.45
20	20.3	98.5
18	18.2	96.88
15	14.5	96.66
12	10.71	93.25
10	9.24	92.4
8	8	97.55
7	7.76	92.14

Table 5. Performance comparison of single resolution mask and eye-distance based multi-resolution masks.

Person	Single resolution mask		Multi-resolution mask (based on eye-distance)	
	Precision (%)	Recall (%)	Precision (%)	Recall (%)
Person 1	66.66	70	76.19	80
Person 2	74.5	67.85	77.58	80.35
Person 3	81.39	77.77	95.45	93.33
Person 4	90.9	76.92	91.42	82.05
Person 5	86.88	77.94	93.54	91.17
Person 6	76.92	66.66	86.2	83.33
Person 8	80	77.77	88.57	86.11
Person 9	86.11	72.09	87.5	81.39
Person 10	81.63	76.92	82.14	88.46
Person 11	88	78.57	89.28	89.28
Person 12	66.67	72.22	75.6	86.11
Person 13	90	85.71	95	90.47
Person 14	84.85	87.5	86.11	96.87
Person 15	80	71.42	80	85.71
Person 16	84.85	70	91.42	80
Person 17	84	75	95.65	78.57
Person 18	87.88	85.29	88.57	91.17
Person 19	100	75	100	87.5
Person 20	74	80.43	87.5	91.3
Person 21	100	86.84	100	86.84
Person 22	82.6	63.33	88	73.33
Person 23	72.97	84.37	80.55	90.62

recall rate of 86.05%, which is much higher comparing with the single resolution mask based person identification (Rahman, 2009). The matching probability of the system which is near to approximately 90%, is also significantly higer than single resolution mask based person identification. This paper also presents a simple image-based person to camera distance measuring system. The proposed method has significant importance because of its lower cost and simpler algorithm for real-time implementation. Because of the simplicity of the proposed approach, hardware-intensive techniques, such as echo detection, additional CCD cameras, laser projector (Rahman, 2009; Wang, 2007), flash lights etc. are no longer required for obtaining a satisfactory person to camera distance measurement. One of the major limitations of this system is that, the system requires more secondary memory space for storing masks with different dimensions than single resolution mask based

Table 6. Comparison of matching probability between single resolution mask and multi-resolution masks.

Average eye distance (in pixels)	Matching probability(%) with single resolution mask	Matching probability (%) with multi-resolution masks
34.33	90.42	96.39
36.07	92.07	96.15
38.19	91.43	95.87
43.32	90.47	95.48
47.09	89.7	95.27
50.38	88.49	95.34
55.31	87.68	94.89
65.11	86.44	94.72
80.46	85.77	94.5
93.43	85.43	94.6
107.90	84.79	94.78
121.29	84.72	94.2

person identification approach because it scales the training images to different dimensions. The ultimate goal of this research is to implement the proposed person identification system in the field of robotics, biometric devices and other related fields.

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