Journal of Theoretical and Applied Information Technology
30th November 2013. Vol. 57 No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

FACE LOCALIZATION-BASED TEMPLATE MATCHING APPROACH USING NEW SIMILARITY MEASUREMENTS

GHASSAN MARWAN ABDULFATTAH[1], MOHAMMAD NAZIR AHMAD[2]

[1]Faculty of Computing, 81310,Universiti Teknologi Malaysia
Skudai, Johor.

[2]Faculty of Computing, 81310,Universiti Teknologi Malaysia
Skudai, Johor.

E-mail: [1]g_h_assan@hotmail.com, [2]drmnazir09@gmail.com

ABSTRACT

In this paper, a number of similarity measurements have been developed, namely: Sum of Absolute Difference (OSAD), Sum of Square Difference (SSD) and Normalized Cross Correlation (NCC) in order to measure the correlation between the input image and the template image. In addition, two metrics were proposed, specifically: Sum Square T-distribution Normalized (SSTN) and Chi-Square distribution (Chi2) by which to measure matching between the two images. The result showed that optimized measurements overcome any drawbacks of NCC. Moreover, our results show SSTN and Chi2 as having the highest performance compared with other measurements. Sets of faces including: Yale, MIT-CBCL, BioID, Indian and Caltech were used to evaluate our techniques with success localization accuracy of up to 100%.

Keywords: *Face Localization, Template Matching, Similarity Measurements*

1. INTRODUCTION

The concept of face recognition has caught the attention of many researchers over the last few decades. As a result, numerous research efforts have been conducted on a wide range of facial biometrics [17] to introduce reliable features for many applications such as: security systems, E-government, object tracking, etc. Before extracting these features, there is a need to determine the region of interest (ROI) which contains only the face, since some parts of the input images are not needed for the recognition process. In real-time face recognition systems, locating faces in the input image should be fast and accurate. Thus, the need to introduce a face localization method with less complexity has arisen. Essentially, face localization is considered as the first step whenever a specialized case of face detection is involved. With regard to the face localization problem, an existing face already exists in the input image and the goal is to determine the location of the face. In other words, it is a matching process between two images and it can best be described as follows: input image A and template image B from the database to find the best matching correlation in image A. However, face localization from the input image is considered to be a challenging task due to variations in, specifically: scale, pose, occlusion, illumination, facial expressions and clutter backgrounds. One of the important surveys undertaken on face recognition and some detection techniques can be found in [1]. Recently, an outstanding survey concerning relevant literature studies of face detection and localization was authored by Yang et al. [2]. The survey covered the problems of detection and clearly highlighted a research gap. Moreover, it introduced some solutions for these existing problems. Another critical survey can be found in [12]. Recently, a template matching approach demonstrated its superiority against other face localization methods. The most popular template matching methods are similarity measurements such as: sum of absolute difference (SAD), sum of squared difference (SSD) and normalized cross correlation (NCC). These methods are fast and simple (qualities which are required for real time systems); however, they still show a weakness against images with high illumination. Thus the need to optimize the existing measurement to increase the matching process rises. Also, the application of a new similarity measurement will represent a strong addition to the template matching approach.

In this paper, a number of similarity measurements have been optimized so as to compute the similarity matching between the face template and rectangular blocks of the input image used to locate the face. Further, new similarity measurements are proposed and compared with the

Journal of Theoretical and Applied Information Technology
30th November 2013. Vol. 57 No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

existing measurements as well as other face localization methods.

The rest of this paper is organized as follows: in the following section we explain related and previous works and highlight the research gaps in the localization problem. In Section 3, we introduce the proposed method. In Section 4, experimental results and comparisons with (the) recent methods will be presented; while the last section is allocated for the conclusion and recommendation for further studies.

2. RELATED WORK

With regard to extant literature studies, face detection (localization) methods are classified into four main categories as follows: Knowledge-based method [3], Feature invariant method [4-13], Template matching method [5-15] and Appearance-based method [6-14]. Template matching approaches have been widely used for face localization due to their accuracy and appropriateness for real-time systems [15]. In such approaches, the first step is to create a template based on human face criteria stored in the system database. Later, correlations between the stored template and the input image parts are computed so as to locate the faces. The advantages of these methods lie in the fact that they are, specifically: resistant to noise, simple to implement and do not require a significant length of time to locate the candidates' faces from the input images [7]. However, it is not sufficient for locating faces in images with clutter background and illumination, because of some image parts appear as face location regarding to image variations. One of the simplest methods of the template-matching approach is to gather set face samples in order to obtain an average face and then save them in the database as a template. Later, for the localization process, the template is then called up and passed through the input image and the image block; the highest similarity correlation score is supposed to be the correct face location. Using this method, the process can be called the filter match method where the input image constantly convolves or interacts with a flipped version of the average face as a filter. Statistically, filter matching assumes additive white Gaussian noise (AWGN) which is very detrimental for image variations such as clutter background, illumination and expressions [7]. To reduce the effect of high face variation problems, the Eigenface approach is adopted to enhance matched filter performance [8]. This enables linear combination for Eigenfaces of the average face and also assumes that each face should be closed to this linear combination. Nevertheless, the Eigenface approach has problems which are reflected in the variations of the face, as well as in noise [9]. Due to this problem, there is always some localization error where non-face blocks may provide high matching similarity to the linear combination of the average face and its Eigenfaces are subsequently more than face blocks. Therefore, the Eigenface method can render a good detection rate when the noise is composed of white-noised clutter. Meng et al. [7] proposed a new method to localize human faces using linear discriminants from grey scale images. To minimize the Bayesian error, they developed an optimal discriminant template by modelling faces and non-faces as Gaussian distribution. In addition, they compared their results with the matched filter and the Eigenface methods and obtained a result of 92.7% using the University of Michigan's face database. Some researchers used another method to locate faces in the input images by using face anthropometric templates such as eyes, mouth and nose. Campadelli et al [16] introduced a beneficial survey relating to face location using an anthropometric template based on the eye as *a* reference.

One of the more widely-used methods to compute the correlation between two images is through the use of similarity measurements such as Normalized Cross Correlation (NCC) [10-11]. However, NCC still does not give suitable matching accuracy because the variation in illumination and clutter background sometimes produces mismatching face localizations. This problem can be eliminated by using a filtering process which changes the properties of the image and increases the similarity process which will reflect on the localization accuracy. Huaibin et al [18] proposed a new method based on an anisotropic filter, for de-noising and smoothing images which can also be used for edge detection; however, it is still not entirely effective for images having illumination and clutter background variations.

3. PROPOSED METHOD

In this paper, a number of optimized metrics are used to measure the similarity correlation between the template image and the dynamic window through the input image. The image window then corresponds to the minimum value in the record matrix which will be extracted as the face region. Actually, those metrics optimize the Sum of Absolute Difference (SAD) and Sum of Square Difference (SSD) metrics which are widely used in

Journal of Theoretical and Applied Information Technology
30th November 2013. Vol. 57 No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

video tracking and image compressing; it is a simple procedure and very easy to implement in order to find a relationship between two images. The idea of those metrics is based on calculating the difference between each element in the template image corresponding element in the dynamic window through the input image. The absolute or square values of the difference will be calculated and gathered together. There are many applications for SAD and SSD including: motion estimation, object recognition and video compression.

As the first step in the proposed method, the template face will be created by gathering together a set of faces from the users of the system as shown in Figure1.

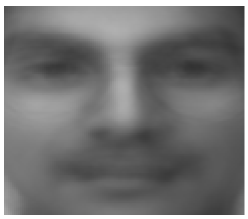

Figure 1: Template Face

A number of similarity measurements will then be used to measure correlation between the two images. The process in Figure 2 can provide an example of SAD and SSD methods after the subtraction of the two matrixes. In the resulting matrix there are some negative values. Therefore, we will take the absolute value of all matrix elements and then sum up these elements. The result of this summation gives SAD between the image window and face template image. SAD can be computed by using the equation below:

Suppose we have three matrixes (see Figure 2):

$$\underset{A}{\begin{array}{|c|c|c|}\hline 1 & 2 & 3 \\ \hline 4 & 5 & 6 \\ \hline 7 & 8 & 9 \\ \hline\end{array}} - \underset{B}{\begin{array}{|c|c|c|}\hline 6 & 3 & 0 \\ \hline 2 & 5 & 1 \\ \hline 8 & 7 & 1 \\ \hline\end{array}} = \begin{array}{|c|c|c|}\hline -5 & -1 & 3 \\ \hline 2 & 0 & 5 \\ \hline -1 & 1 & 8 \\ \hline\end{array}$$

Figure 2: The difference of two matrixes

$$d(A,B) = \sum_i \sum_j \left| A(i,j) - B(i,j) \right| \tag{1}$$

SAD of the two matrixes =5+1+3+2+0+5+1+1+8=26

While

$$d(A,B) = \sum_i \sum_j \left(A(i,j) - B(i,j) \right)^2 \tag{2}$$

SSD of the two matrixes=25+1+9+4+0+25+1+1+64=130

In contrast with the other common correlation-based similarity methods, namely: Normalized Cross Correlation (NCC) and Sum of Hamming Distances (SHD), SAD and SSD are very simple and more accurate as well as being also less sensitive to illumination. However, there are some localization errors which may be due to two neighbour windows having the face and almost the same SAD or SSD. To improve those metrics, we need to optimize equations (1) and (2) to find the optimum image window that contains the face exactly. The following equations give Optimized (SAD) and Optimized (SSD):

$$OSAD_1(A,B) = \sum_i \sum_j \frac{\left| A(i,j) - B(i,j) \right|}{\max(A(i,j), B(i,j))} \tag{3}$$

$$OSAD_2(A,B) = \sum_i \sum_j \frac{\left| A(i,j) - B(i,j) \right|}{\left| (A(i,j) + B(i,j)) \right|} \tag{4}$$

$$OSAD_3(A,B) = \sum_i \sum_j \frac{\left| A(i,j) - B(i,j) \right|}{\sqrt{A(i,j) + B(i,j)}} \tag{5}$$

$$OSSD_1(A,B) = \sum_i \sum_j \frac{\left(A(i,j) - B(i,j) \right)^2}{\left(A(i,j) + B(i,j) \right)} \tag{6}$$

$$OSSD_2(A,B) = \sum_i \sum_j \frac{\left(A(i,j) - B(i,j) \right)^2}{\left(A(i,j) + B(i,j) \right)^2} \tag{7}$$

In addition to the previous optimized metrics, two optimized error measurement metrics were proposed to find the face location in the input image. The first metric is the chi-square test which can be used to measure the difference between the expected frequencies and the observed frequencies in one or more categories of faces. In general, the chi-square test statistic is calculated as follows:

$$x^2 = \sum \frac{(Observed - Expected)^2}{Expected} \tag{8}$$

If the computed test statistic is high, then the difference between the observed and the expected is significant and the model is deemed poor to fit the data.

In our case, the sample is the set of n human faces, mainly frontal faces, noted as below:

$S = \{A_i, 1 \le i \le n\}.$

The expected face model is the dynamic window within the image that contains a face, noted as B. Chi2 quantifies the similarity between the Joint Probability Distribution (dynamic windows) and the sample (set of human face). The Chi2 formula for these data is defined as follows:

$$\chi^2_{u \times v - 1} = \sum_{i=1}^{u} \sum_{j=1}^{v} \frac{\left(\overline{A(i,j)} - B(i,j) \right)^2}{B(i,j)}, \tag{9}$$

Journal of Theoretical and Applied Information Technology
30th November 2013. Vol. 57 No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

where u and v are face sizes and the template is defined as being the average of a face image sample noted by:

$$\overline{A}(i,j)=\frac{\sum_{k=1}^{n}A_k(i,j)}{n},\quad 1\le i\le u;1\le j\le v.$$

We calculated the statistic test for each dynamic window in order to find the most likely location of any given face, which is the one corresponding to the minimum chi-square value. To decrease the error of localization, it is better to take into consideration the location of lower locals minimum, which are close to the global minimum, as suspected face locations.

The second metric is Sum Square of Student's t-distribution, which is used to measure the difference between the template and the dynamic windows. Our assumption in this case is to consider all pixel values of image as independent variables and to make a decision regarding the face of the dynamic windows. If they are of adequate face capability, that is sufficient to test the null Hypothesis. Dynamic windows are face; against the alternative hypothesis, dynamic windows are not face. This can be proven by using the following statistic test:

$$SST=\sum_{i=1}^{n}\sum_{j=1}^{v}\left(\frac{\overline{A}(i,j)-B(i,j)}{S(i,j)/\sqrt{n}}\right)^2, \tag{10}$$

where

$$S^2(i,j)=\sum_{i=1}^{n}\left(A_k(i,j)-\overline{A}(i,j)\right)^2/(n-1).$$

Using the Central Limit Theorem and the fact that t-distribution square of freedom n-1 is Fisher distribution of freedom 1 and n-1, the Sum Square t-distribution Normalized (SSTN) converges in distribution to standard normal distribution:

$$SSTN=\frac{SST-u\times v(n-1)/(n-2)}{\sqrt{u\times v\frac{2(n-1)^2(n-2)}{(n-3)^2(n-5)}}}\approx N(0,1). \tag{11}$$

We calculate SSTN for all dynamic windows to extract all suspected windows and to be face-corresponding to the location of the lower locals minimum which approaches the global minimum.

The proposed method can now be summarized as in the following diagram (see Figure 3):

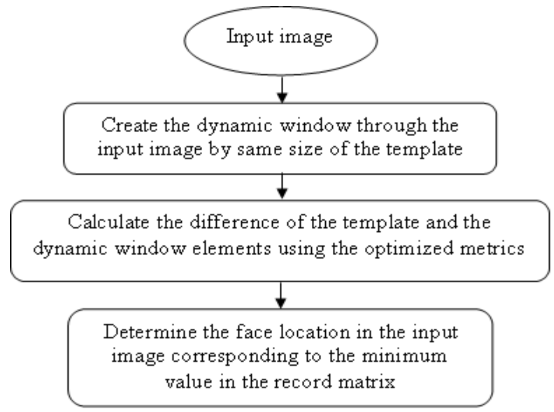

Figure 3: Face Localization Using Optimized Metrics

4. RESULT AND DISCUSSION

During the tests, a number of face datasets were used to evaluate the proposed method and included Yale [19] and MIT-CBCL [20] databases. A few examples of these images are shown in Figures 4 and 5 below:

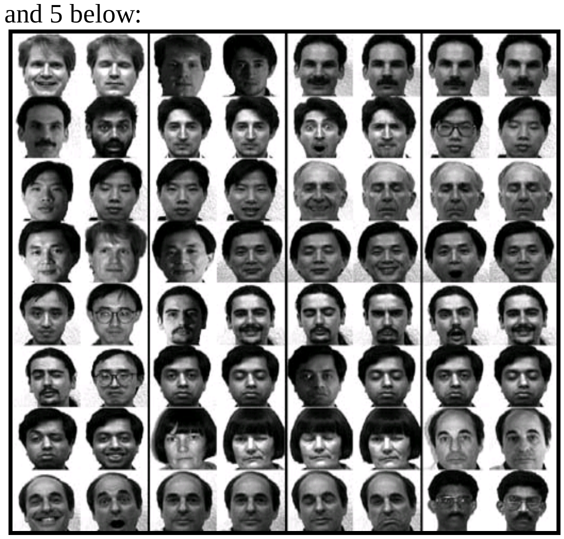

Figure4: Samples From Yale Database

Figure 5: Samples From MIT-CBCL Dataset For Localization

Journal of Theoretical and Applied Information Technology
30th November 2013. Vol. 57 No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

At the beginning, the template image was prepared and saved in the system database; the face template size used was 100×120 (see Figure 6). The similarity between the reference image (template) and the target image (dynamic window) was then calculated by similarity measurements equations 3 to 10. Table 1 shows the result of face localization established using ten different Statistical measurements. The results clearly demonstrate the increase in accuracy by using our statistical metrics, Chi2, SSTN, in addition to the optimized metrics against the other measurements.

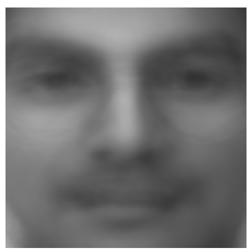

Figure 6: Template face

The results in Table 1 clearly show the efficiency of the face localization using our statistical metrics, which provide accuracy of up to 100%. This result gains more importance in the knowledge that our algorithm is able to determine precisely the face location. Further, it can also establish whether or not there is variation in illumination, expressions and shade in the input image. In the table, the accuracy of the face localization using Chi2, SSTN and OSAD (1, 2 and 3) are 100% when using Yale dataset. Thus, OSAD overcame the drawback of the NC since there is no effect resulting from the illumination variation. For the SAD, the accuracy is 98% which is acceptable in comparison with the other metrics. This localization error referring to the adjacent windows have almost the same SAD. However, these windows have the appropriate face, but one of them is more correct than the other. This case will produce an error percentage for locating the face, but it is only a small localization error. Figure 7 shows examples of the face localization by using OSAD and SAD on Yale dataset. For the SSD, the accuracy is acceptable but its complexity is higher than OSAD and SAD, thus the error rate is maximized. In addition, if there are two windows with pixel values close to each other, SSD cannot be considered as a useful mechanism to determine which one is similar to the template. Thus, OSSD (1 and 2) minimized this complexity and increased the accuracy of SSD up to 98%. In the case of NCC, there is a significant increase in the error rate and that is referring to the illumination problem. Since the illumination changed the pixel values of some image parts, this will cause the maximum percentage of NCC to be in the wrong place. In contrast to the SSD error, the error in NCC gives a completely wrong location of the face. SHD gives a poor localization rate because it normally calculates the distance between two strings, not between matrices. Therefore, SHD is not useful for face localization or detection but it can be used to calculate the difference between the signals.

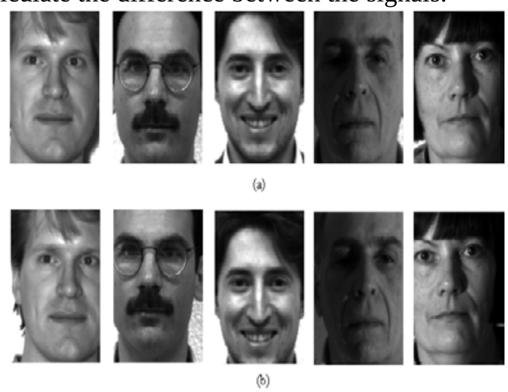

Figure 7: Samples Of Face Localization: OSAD In The Top And SAD In The Bottom

Table 1: Comparison Between Similarity Measures And The Proposed Metrics On YALE Dataset

Similarity Measure	Accuracy (%)
Sum Square T-distribution Normalized (SSTN)	100
Chi-Square distribution (Chi2)	100
Optimized Sum of Absolute Difference ($OSAD_1$ & $OSAD_2$ & $OSAD_3$)	100
Optimized Sum of Squared Differences ($OSSD_1$ & $OSSD_2$)	98
Sum of Absolute Differences (SAD)	98
Zero-mean Sum of Absolute Differences (ZSAD)	98
Locally scaled Sum of Absolute Differences (LSAD)	98
Sum of Squared Differences (SSD)	95
Zero-mean Sum of Squared Differences (ZSSD)	95
Locally-scaled Sum of Squared Differences (LSSD)	95
Normalized Cross Correlation (NCC)	80
Zero-mean Normalized Cross Correlation (ZNCC)	80
Sum of Hamming Distances (SHD)	43

The result in Table 2 showed that the proposed metrics achieved high localization accuracy in

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

comparison with the other metrics on MIT-CBCL dataset. Unlike the Yale dataset, the images used in this test have variations in the background and the face pose.

Table 2: Comparison Between Similarity Measures And Proposed Metrics On MIT-CBCL Dataset

Similarity Measure	Accuracy for Pose (%)	Accuracy for Clutter Background (%)
SSTN	100	100
Chi2	100	100
OSAD1	100	96
OSAD2	100	96
OSAD3	100	96
OSSD1	98	92
OSSD2	98	92
SAD	98	94
ZSAD	98	94
LSAD	98	94
SSD	95	89
ZSSD	95	89
LSSD	95	89
NCC	80	73
ZNCC	80	73
SHD	43	40

Table 2 shows the comparison between the proposed metrics and other measurements on the MIT-CBCL Dataset. In this test, the concern is in relation to a high variation in poses from 30 degrees left to 30 degrees right, as well as clutter background. From Table 2 we can see that a template matching using SSNT and Chi2 will not be affected by the variation in poses. However, OSAD (1, 2 and 3) will not be affected by clutter background due to the existence of some objects in the background. Consequently, some windows in input images will have exactly the same or very close classical metrics values as the template image. This problem increases the error rate in general and then affects the result. This result can be explained as follows: calculation of the error of two couples of values 1 and 11 then 100 and 110. The error is the same for both cases, which is 10, but the relative errors are different. Thus, we introduce the idea to divide the error by the average of the values.

In order to obtain a fair empirical evaluation of face localization, it is important to test our approaches by using the most commented-upon datasets and compare our results with other techniques. Although several face localization methods have been developed over the past decade, only a few of them have been tested on the same dataset. Table 3 shows the reported performance among several face localization methods on five standard datasets. The result shows the performance of our Sum Square T-distribution Normalized (SSTN) approach over the five datasets and the results provide clear evidence that the SSTN approach provides high superiority performance compared with other techniques.

Table 3: Comparison Between SSTN And Chi2 With Other Techniques On Different Databases

Method	DataSet	Result	Our Result by SSTN	Our Result by Chi2
Orientation Template Matching [24]	BioID database [21]	94.6%	98.7%	97.2%
Gradient Vector Flow [25]	Indian database [22]	97.2%	100%	100%
Features Invariant Method [26]	Yale database	94.73 %	100%	100%
Skin Colour [27]	Caltech database [23]	93.5%	99.5%	99%
AdaBoost and Artificial Neural Network [28]	MIT-CBCL database	85.34 %	100%	100%

5. CONCLUSION

The work in this paper concerns the development of similarity measurements methods to locate faces in an input image. We examined the performance of several measurement methods on images with various face situations and image illumination changes. In particular, we optimized a number of the existing measurement methods and two new metrics were proposed to measure the relation between the template image and dynamic window in the input image as well. A comparison between the optimized metrics and other similarity measurement metrics shows that optimized metrics increase the accuracy of SAD and SSD from 98% and 95% respectively up to 100% on the Yale dataset and from 90% and 87% up to 100% on the MIT-CBCL dataset. Meanwhile, the other metrics achieved high localization results only against

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

expressions and poses and poor results against illumination and small background changes. In addition, the proposed error measurement metrics achieved high localization accuracy up to 95% and 96% on BioID and Caltech databases respectively as indoor and outdoor localization databases.
However, the proposed measurements need developing against clutter background. Therefore, further work will focus on developing these metrics to locate faces in the input image with clutter background.

REFERENCES:

[1]. R. Chellappa, C. L. Wilson and S. Sirohey, "Human and machine recognition of faces: a survey," Proceedings of the IEEE, vol. 83, pp. 705-741, 1995.
[2]. Ming-Hsuan Yang, D. J. Kriegman and N. Ahuja, "Detecting faces in images: a survey," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 24, pp. 34-58, 2002.
[3]. Zhao Fei and Qiao Qiang, "Face detection based on rectangular knowledge rule and face structure," in Information Science and Engineering (ICISE), 2009 1st International Conference on, 2009, pp. 1235-1239.
[4]. S. Jeng, H. Y. M. Liao, C. C. Han, M. Y. Chern and Y. T. Liu, "Facial feature detection using geometrical face model: An efficient approach," Pattern Recognit, vol. 31, pp. 273-282, 3, 1998.
[5]. A. K. Jain, Y. Zhong and M. Dubuisson-Jolly, "Deformable template models: A review," Signal Process, vol. 71, pp. 109-129, 12/15, 1998.
[6]. M. -. Yang, N. Ahuja and D. Kriegman, "Face recognition using kernel eigenfaces," in Image Processing, 2000. Proceedings. 2000 International Conference on, 2000, pp. 37-40 vol.1.
[7]. Lingmin Meng and T. Q. Nguyen, "Frontal face localization using linear discriminant," in Signals, Systems, and Computers, 1999. Conference Record of the Thirty-Third Asilomar Conference on, 1999, pp. 745-749 vol.1.
[8]. A. Pentland, B. Moghaddam and T. Starner, "View-based and modular eigenspaces for face recognition," in Computer Vision and Pattern Recognition, 1994. Proceedings CVPR '94, 1994 IEEE Computer Society Conference on, 1994, pp. 84-91.
[21]. "BioID : BioID Support : Downloads : BioID Face Database " vol. 2011, .
[9]. Lingmin.Meng and Truong.Q.Nguyen, "Frontal face detection using multi-segment and wavelet," in 1999.
[10]. D. Tsai and C. Lin, "Fast normalized cross correlation for defect detection," Pattern Recog. Lett., vol. 24, pp. 2625-2631, 11, 2003.
[11]. Shou-Der Wei and Shang-Hong Lai, "Fast Template Matching Based on Normalized Cross Correlation With Adaptive Multilevel Winner Update," Image Processing, IEEE Transactions on, vol. 17, pp. 2227-2235, 2008.
[12]. J. Ddaugman, "Face detection: a survey," Journal of computer vision and image understanding, vol. 83, no.3, pp. 236-274, 2001.
[13]. Jing-Wein Wang, "Face Localization in Clutter Background," in Intelligent Hiding and Multimedia signal processing, 2008 International Conference on, 2008, pp. 1235-1239.
[14]. S. M. Hassan, Wei-Yun, E. K. Teoh," Fast Face Detection and Localization from Multi-Views using Statistical Approach" in Information Science and Engineering (ICISE), 2011 International Conference on, 2011, pp. 1235-1239.
[15]. A. Perez, M. Carlos, I. Juan, A. Pablo, M. Claudio," Face and Iris Localization using Templates Designed by Particle Swarm Optimization" Pattern Recognition Letters, vol. 31, pp. 857-868, 2010.
[16]. P. Campadelli, R. Lanzarotti," Eye Localization: A Survey," The Fundamentals of Verbal and Nonverbal Communication and their Biometrical Issues, Vol.18, pp. 234-245, 2007.
[17]. W. Zhao, R. Chellappa, A. Rosenfeld and P. J. Phillips, "Face Recognition: A Literature Survey," vol. 35, pp. 399-458, December, 2003.
[18]. H. Wang, Y. Wang, W. Ren," Image Denoising Using Anisotropic Second and Fourth Order Diffusions Based on Gradient Vector Convolution," Computer Science and Information Systems, Vol. 9, pp. 1493-1512, December, 2012.
[19]. Yale Face Database, http://cvc.yale.edu/projects/yalefaces/yalefaces.html vol. 2010.
[20]. CBCL Database, "http://cbcl.mit.edu/software-datasets/heisele/facerecognition-database.html," vol. 2010, .

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[22]. http://vis-www.cs.umass.edu/~vidit/IndianFaceDatabase/.

[23]. http://www.vision.caltech.edu/html-files/archive.html.

[24]. B. Froba and C. Kublbeck, "Orientation template matching for face localization in complex visual scenes," in Image Processing, 2000. Proceedings. 2000 International Conference on, 2000, pp. 251-254 vol.2.

[25]. M. Vatsa, R. Singh and P. Gupta, "Face detection using gradient vector flow," in Machine Learning and Cybernetics, 2003 International Conference on, 2003, pp. 3259-3263 Vol.5.

[26]. Jiatao Song, Jilin Liu, Zheru Chi and Wei Wang, "Locatization of human eyes based on a series of binary images," in Multimedia and Expo, 2004. ICME '04. 2004 IEEE International Conference on, 2004, pp. 1199-1202 Vol.2.

[27]. M. H. Khan, N. A. Khan and A. Zuberi, "Fast and accurate localization of human faces," in Communications and Information Technology, 2004. ISCIT 2004. IEEE International Symposium on, 2004, pp. 1232-1237 vol.2.

[28]. Thai Hoang Le and Len Tien Bui, "A hybrid approach of AdaBoost and artificial neural network for detecting human faces," in Research, Innovation and Vision for the Future, 2008. RIVF 2008. IEEE International Conference on, 2008, pp. 79-85.