A Study on Similarity Computations in Template Matching Technique for Identity Verification

Lam, S. K., Yeong, C. Y., Yew, C. T., Chai, W. S., Suandi, S. A.
Intelligent Biometric Group, School of Electrical and Electronic Engineering
Engineering Campus, Universiti Sains Malaysia
14300 Nibong Tebal, Pulau Pinang, MALAYSIA
Email: shahrel@eng.usm.my

***Abstract* — This paper describes a study on the development of a human face verification system by merely using template matching (TM) as the main verification engine. In contrast to common face recognition techniques, our approach for the identity verification (face recognition) consists of matching the facial features extracted from the detected face. These facial features namely left eye, right eye and mouth regions; are detected using a system known as EMoTracker. As TM is sensitive to lighting, this study considered different type of lighting directions and similarity computation in TM. Three types of TM functions are evaluated in this paper: Sum of Squared Difference, Cross Correlation and Correlation Coefficient. In the experiments, YaleB Database is used. Based on the observation results, using Correlation Coefficient is shown to be the most reliable similarity computation to handle different lighting conditions using TM.**

Keywords - template matching; eyes and mouth; identity verification; similarity

I. INTRODUCTION

The main challenge in human face detection and verification is the amount of variation in visual appearance. It is challenging to build robust classifiers which are able to detect and verify face in different image situations and face conditions. For example, face may vary in shape, skin color, expression, and facial features (e.g. moustache or hair).

The appearance of the face depends on its pose; that is, the head position and orientation with respect to the camera. The view of the face can be totally changed depending on the position of the person captured by camera. Visual appearance also depends on the surrounding environment. Face appearance may vary a lot in different lighting conditions, including the type of illumination, intensity and the angle of the incident light. Nearby objects may cast shadows or reflect additional light on the face.

Various approaches to face verification are introduced to overcome these problems. Principle Component Analysis (PCA) which introduces Eigenface concept is widely used now due to its high reliability [5, 6]. Another popular approach is Linear discriminant analysis (LDA), which outperforms PCA approach when the number of samples per class is large [2, 7]. However, both methods required huge amount of data [2, 10].

In this paper, we propose template matching in the face verification due to its simplicity and reliability. Only one reference is used in this system. In contrast to common face recognition methods, facial features such as left eye, right eye and mouth regions are used in our work. These features are extracted from the face image for matching purpose using EMoTracker [9]. Based on the experiments carried out, we observed that by considering each feature independently, we may overcome lighting problems especially when only one part of these facial features are affected by the lighting. For similarity computation, 3 types of correlation calculation methods have been tested, which are sum of squared difference, cross correlation and correlation coefficient. Among these, correlation coefficient is shown to be the most reliable and efficient method to be used in the verification process.

The rest of the paper is organized as follows: Section II describes the face and facial features detection technique employed in our work. In Section III, we describe the identity verification process using TM technique including the 3 correlation calculation methods. In Section IV and V, we present the experiments and results, respectively. Finally, we conclude this paper in Section VI.

II. FACE DETECTION

Face detection is the prior step to the face verification. The face detection is realized by the object detection functions as well as some of the image processing functions available in OpenCV computer vision library. The robust object detection method proposed by Viola and Jones [11] based on AdaBoost training algorithm, is used for face detection. Their method achieves high detection rate (≈ 80%) when compared to the previous best systems.

The developed face detection system is able to detect one or multiple human faces, on both input image (test image) and reference image. If either input image or reference image is not able to detect any human face, the face verification stage cannot be done and the system will give warning to the user. In addition to this, if there are multiple faces detected on both images, the user has to select which face is to be matched with the reference face. Figure 1 depicts if only one face is detected by the face detection system.

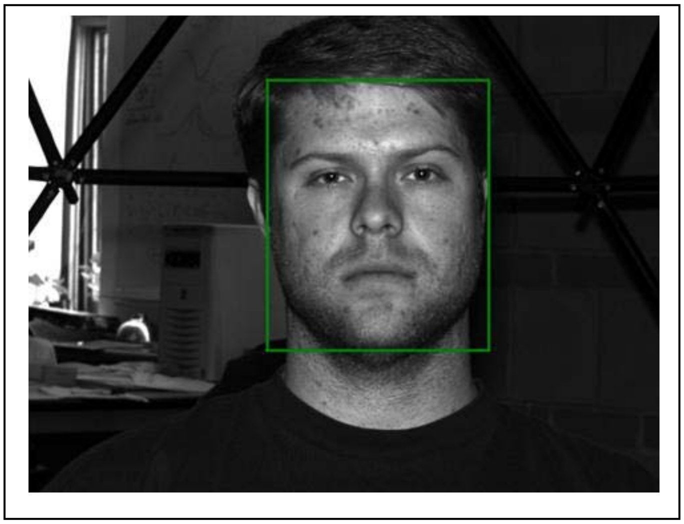

Figure 1. Face detected from input image.

III. FACE VERIFICATION

In face verification, it is a one-to-one match where the detected face from the input image will be matched to the reference image. From the input image, facial features are extracted using EMoTracker [9]. In template matching technique, an object is searched based on the template which has been prepared beforehand. Since the template has a fixed size, different region sizes from the input image have to be rescaled according to the template size during searching process. This is called 'normalization' process. In our work, the template size is 10×10. However, since the size of detected facial features have been adjusted according to the detected face size [8], it is sufficient to use the detected facial features as it is during the verification process. As a result, no more searching with different patch size is required and less time is used for verification.

A. Template Matching

In template matching, all possible locations to be matched with the template are stored in a resultant matrix **R**, which stores the coefficient value for each matched location in pixel [4]. With the size of the source image is $W \times H$ where W and H representing the width and height, respectively, and $w \times h$ is the product of width and height of the template image, the matrix size is given by $(W - w + 1) \times (H - h + 1)$. The reference size and the illustrative representation of template matching processes are shown in Figure 2 and 3, respectively. In Figure 4, it is shown the final matrix after one template matching process.

There are several types of template matching methods, which are the Sum of Squared Difference, Cross Correlation, and Coefficient Correlation method. Depending on its matching algorithm, the matching result may be slightly different. Consider T is the template image and I is the input source image, $SSD(x,y)$, $CC(x,y)$, and $\varrho(x,y)$ are numerical

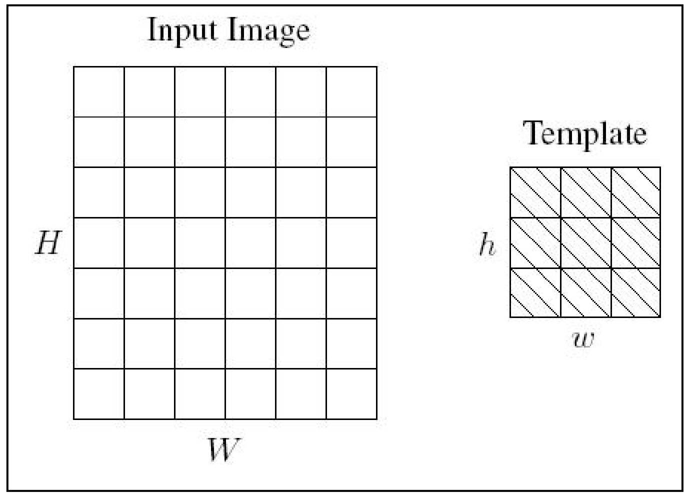

Figure 2. Finding the input image regions that are similar to the given template.

index for Sum of Squared Difference, Cross Correlation, and Correlation Coefficient, respectively, in the range [0,1] at position *(x,y)* after matching. However, since the interpretation of SSD will be opposite of the other two methods, i.e., 0 shows the best while 1 shows the worst, we invert the result for SSD by subtracting 1 from its' result so that the results we observe will be consistent. In the implementation, only normalized template matching functions are used. The equations for the three methods are shown below:

$$SSD(x,y) = \frac{\sum_{x',y'}[T(x',y') - I(x+x',y+y')]^2}{\sqrt{\sum_{x',y'} T(x',y')^2 \sum_{x',y'} I(x+x',y+y')^2}} \quad (1)$$

$$CC(x,y) = \frac{\sum_{x',y'} T(x',y') I(x+x',y+y')}{\sqrt{\sum_{x',y'} T(x',y')^2 \sum_{x',y'} I(x+x',y+y')^2}} \quad (2)$$

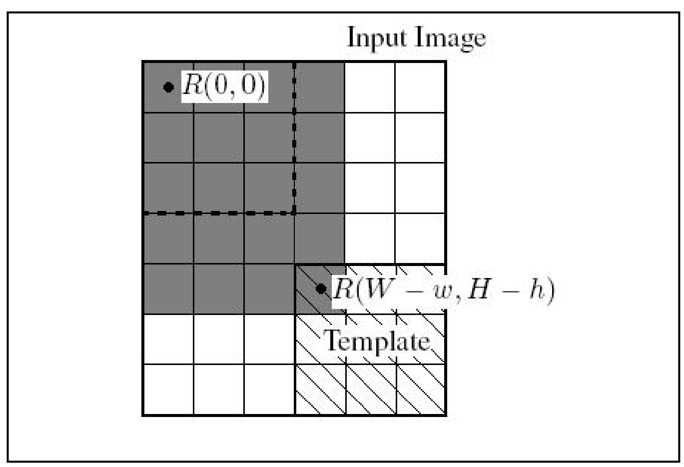

Figure 3. The pixel value in each location *(x,y)* characterizes the similarity between the template and the input image rectangle with the top-left corner at *(x,y)*.

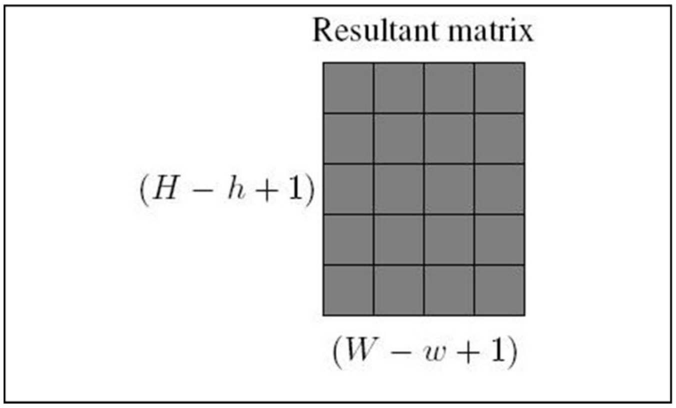

Figure 4. Resultant Matrix.

$$\varrho(x,y) = \frac{\sum_{x',y'} T'(x',y') I'(x+x',y+y')}{\sqrt{\sum_{x',y'} T'(x',y')^2 \sum_{x',y'} I'(x+x',y+y')^2}} \qquad (3)$$

where *T'(x',y')* is the average value of template *T*, given by

$$T'(x',y') = T(x',y') - \frac{1}{wh}\sum_{x',y'} T(x',y') \qquad (4)$$

and *I'(x+x',y+y')* is the average value of *I* in the region coincide with *T*, given by

$$I'(x+x',y+y') = I(x+x',y+y') - \frac{1}{wh}\sum_{x',y'} I(x+x',y+y') \qquad (5)$$

where $x' = 0 \ldots w-1$ and $y' = 0 \ldots h-1$ for all three methods.

B. EMoTracker

Shahrel et al. [9] introduce a novel approach for online facial components tracking based on energy minimization criterion. The tracker, known as EMoTracker, employs template matching as the principal technique. As feature appearance changes during tracking, template matching suffers in providing good detection results. Therefore, instead of utilizing only the similarity (correlation values) independently, global constraints of facial components placement is added on face as additional parameters when searching corresponding components. Figure 5 shows one of the results using EMoTracker. From the detected face (on left), eyes and mouth are detected and labeled with yellow, blue and white for right, left eye and mouth, respectively.

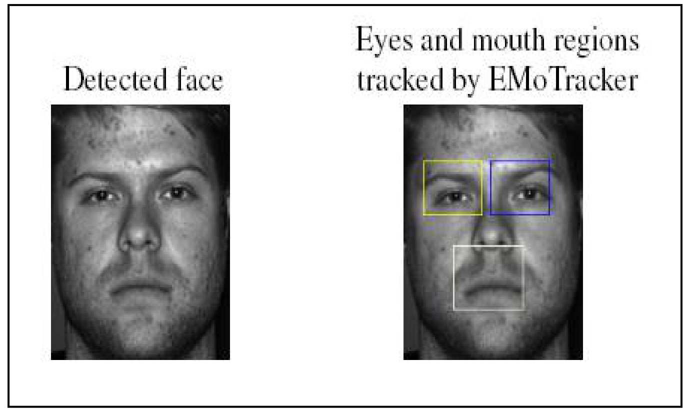

Figure 5. Facial regions tracked by the EMoTracker.

IV. EXPERIMENTS

Experiments are carried out to analyze the performance of proposed identity verification approach under different lighting angles, for each type of correlation calculation method mentioned in Section III. The experiment data set used is the YaleB Face Database [1]. The tested face images consist of frontal face pose with small lighting angle variation, from ±20° azimuth angle and ±20° elevation angle. Tested subjects are yaleB01_P00, yaleB05_P00 and yaleB09_P00 (shown in Figure 6).

The experiments evaluate the performance of each type of correlation calculation method for identity verification under different lighting angles. In the results, we compare mainly *FF* and *EF,* where *FF* is the 'facial features average correlation value' and *EF* is the 'entire face correlation value'. *FF* is computed by calculating the mean of left eye (L_Eye), right eye (R_Eye) and mouth (Mouth). In other words, we are interested in the results using holistic method and facial features method. Apart from this, we also evaluate the effectiveness of using template matching in terms of accuracy, i.e. which of the correlation calculation method is robust towards impostors.

V. EXPERIMENT RESULTS

Table 1, Table 2 and Table 3 show the comparison of each subject being referenced to him and other subjects with different template matching methods (in terms of coefficient value) under various lighting angles. For the three methods used, the coefficient values for the correctly verified subject are significantly higher than the verified value to other subjects, regardless of the angle variation.

As a matter of fact, the matching coefficient values achieved from the facial features are generally slightly higher than the matching value of the entire face region. This suggests that matching using facial features are better than matching

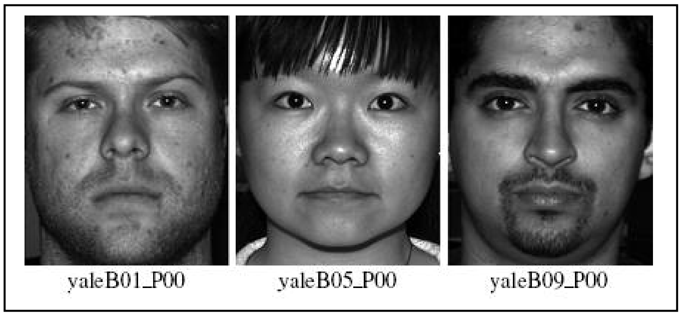

Figure 6. Subjects face image in YaleB Database used in the experiments.

using the entire face region. However, the problem arises in this approach is that it causes the coefficient value for other mismatched face image increase significantly. The coefficient values for each template matching method have a significant difference. Therefore, the threshold value that considers a subject in the input image is different for each method used.

Figure 7, 8 and 9 show the distribution plots of the coefficient values. The total angle is the summation of absolute value of azimuth angle, A and absolute value of elevation angle, E. From the distribution plots for each method used, we notice that when the reference image is matched with the image set of the same person, the coefficient values are clearly distinguished from other image sets of another person. As a comparison for each method used, the margin between the match and not match data set is measured. For Sum of Squared Difference method, it gives a margin about 0.05 to 0.2, Cross Correlation gives about 0.04 to 0.06 and Correlation Coefficient gives about 0.20 to 0.35.

Among the three methods used, the Correlation Coefficient gives the highest margin that differentiates among the correctly matched data set from the other wrongly matched data set. The large margin can be considered as safety margins that avoid the system wrongly verify/recognize a person. From this plots, we can determine the threshold or cut-off point of the coefficient value for the chosen type of template matching method. The Sum of Squared Difference and Cross Correlation template matching methods are not feasible to be used by the system, as the margin for both methods are smaller than Correlation Coefficient. The recommended cut-off point for the Correlation Coefficient is ≥ 0.8 for lighting angles varying from $\pm 20°$. For angle beyond $\pm 20°$, the cut-off point can be slightly lower.

Also notice that the coefficient values are generally decreased as the total angle (summation of azimuth, A and elevation, *E*) is increased. This implies that when the lighting angle from the frontal is large, the matching performance generally will be decreasing. Therefore, the system cannot be used for large lighting angle variation.

VI. CONCLUSION

The problem of human face detection and recognition is challenging, due to the fact that human faces are not rigid and difficult to be defined by machine. Human faces vary from person to person, and may appear differently under the effects of different condition such as face pose, lighting condition, facial appearance etc. The approach proposed in this paper is to use facial features that relatively experience less susceptible to different facial expression. The selected facial features; the eyes and mouth region, used to identify a person identity. Template matching technique is shown to be feasible for identity verification.

Experiments are performed to evaluate template matching performance when entire face and only facial features are used. Although many current researches utilize entire face, we have observed that verifying an identity using facial features outperforms entire face technique when different lighting conditions are taken into account.

We also compare correlation calculation methods in template matching. The best method is Correlation Coefficient based template matching. From the experiment results, this method shows that the coefficient values of correctly matched image is clearly higher than those coefficient values of mismatched images (impostors). A large margin separates the true and false verified dataset; reducing the chances of false identified as imposter.

ACKNOWLEDGMENT

This work has been supported by Universiti Sains Malaysia Short Term Grant (304/PELECT/6035270).

REFERENCES

[1] A. Georghiades, P. Belhumeur, and D. Kriegman, “From few to many: illumination cone models for face recognition under variable lighting and pose”, IEEE Trans. Pattern Anal. Mach. Intelligence, Vol. 23, No. 6, pp. 643–660, 2001.

[2] L.-H. Chan, S.-H. Salleh, C.-M. Ting, and A. K. Ariff, “Face identification and verification using PCA and LDA”, Vol. 2, pp. 1 – 6, Aug. 2008.

[3] Y. Freund and R. E. Schapire, “A decision-theoretic generalization of on-line learning and an application to boosting”.

[4] I. S. Group, “Open Source Computer Vision Library Reference Manual”, Intel Corporation.

[5] K.-B. Kim, A. suk Oh, and Y.-W. Woo, “PCA-based face verification and passport code recognition using improved FKCN algorithm”, Vol. 2, pp. 51 –57, Nov. 2008.

[6] M. Kirby and L. Sirovich, “Application of the Karhunen-Loeve procedure for the characterization of human faces”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 12, No. 1, pp. 103 – 108, Jan. 1990.

[7] A. Martinez and A. Kak, “PCA versus LDA”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 23, No. 2, pp. 228 –233, Feb. 2001.

[8] H. C. Lim, L. N. Rasid and S. A. Suandi, “A study on the effectivess of different patch size and shape for eyes and mouth detection”, International Journal on Computer Science and Engineering, Vol. 2, No. 3, 2010, pp. 424—432.

[9] S. A. Suandi, S. Enokida, and T. Ejima, “EMoTracker: eyes and mouth tracker based on energy minimization criterion”, 4th Indian Conference on Computer Vision, Graphics and Image Processing (ICVGIP 2004), 2004.

[10] X. Tan, S. Chen, Z.-H. Zhou, and F. Zhang, “Face recognition from a single image per person: a survey”, Pattern Recognition, Vol. 39, No. 9, pp. 1725 – 1745, 2006.

[11] P. Viola and M. J. Jones, “Robust real-time object detection”, IEEE ICCV Workshop Statistical and Computational Theories of Vision, 2001.

TABLE 1. Sum of Squared Difference

Input	Template		yaleB01_P00					yaleB05_P00					yaleB09_P00				
	A	E	EF	L_Eye	R_Eye	Mouth	FF	EF	L_Eye	R_Eye	Mouth	FF	EF	L_Eye	R_Eye	Mouth	FF
yaleB01_P00	00	20	0.911	0.942	0.946	0.970	0.953	0.656	0.924	0.899	0.938	0.920	0.789	0.765	0.730	0.824	0.773
	00	-20	0.841	0.948	0.954	0.975	0.959	0.672	0.909	0.911	0.924	0.915	0.806	0.774	0.750	0.834	0.786
	05	10	0.923	0.963	0.965	0.985	0.971	0.658	0.932	0.911	0.959	0.934	0.772	0.751	0.605	0.812	0.723
	05	-10	0.942	0.971	0.971	0.986	0.976	0.709	0.899	0.898	0.948	0.915	0.833	0.715	0.710	0.805	0.743
	10	00	0.961	0.974	0.941	0.973	0.963	0.673	0.921	0.886	0.945	0.917	0.793	0.722	0.624	0.779	0.708
	20	10	0.925	0.931	0.949	0.955	0.945	0.659	0.938	0.885	0.932	0.918	0.801	0.834	0.640	0.844	0.772
	20	-10	0.878	0.926	0.964	0.965	0.951	0.641	0.903	0.906	0.934	0.914	0.804	0.771	0.712	0.831	0.771
	-05	10	0.955	0.963	0.948	0.976	0.962	0.688	0.910	0.911	0.924	0.915	0.854	0.751	0.797	0.877	0.808
	-05	-10	0.970	0.961	0.981	0.982	0.975	0.717	0.919	0.913	0.946	0.926	0.806	0.757	0.616	0.763	0.712
	-10	00	0.972	0.971	0.982	0.987	0.980	0.693	0.930	0.929	0.944	0.934	0.819	0.716	0.728	0.822	0.755
	-20	10	0.877	0.916	0.947	0.942	0.935	0.635	0.901	0.909	0.915	0.909	0.719	0.710	0.774	0.795	0.760
	-20	-10	0.919	0.962	0.938	0.971	0.957	0.684	0.907	0.917	0.915	0.913	0.807	0.763	0.725	0.823	0.770
yaleB05_P00	00	20	0.572	0.926	0.888	0.906	0.906	0.815	0.965	0.972	0.947	0.961	0.554	0.705	0.666	0.853	0.741
	00	-20	0.687	0.917	0.894	0.942	0.918	0.899	0.973	0.976	0.976	0.975	0.551	0.666	0.603	0.773	0.681
	05	10	0.701	0.916	0.897	0.927	0.913	0.917	0.985	0.985	0.984	0.984	0.622	0.670	0.605	0.810	0.695
	05	-10	0.687	0.918	0.899	0.943	0.920	0.943	0.991	0.984	0.981	0.985	0.559	0.670	0.604	0.773	0.682
	10	00	0.648	0.912	0.895	0.927	0.911	0.929	0.988	0.964	0.975	0.975	0.537	0.729	0.576	0.757	0.687
	20	10	0.628	0.915	0.893	0.917	0.908	0.849	0.930	0.967	0.962	0.953	0.592	0.776	0.642	0.841	0.753
	20	-10	0.617	0.918	0.885	0.924	0.909	0.875	0.920	0.968	0.966	0.951	0.525	0.736	0.579	0.797	0.704
	-05	10	0.592	0.920	0.903	0.940	0.921	0.858	0.972	0.957	0.947	0.959	0.588	0.686	0.697	0.860	0.748
	-05	-10	0.675	0.916	0.883	0.932	0.910	0.903	0.968	0.983	0.978	0.976	0.511	0.582	0.613	0.727	0.641
	-10	00	0.643	0.899	0.907	0.941	0.916	0.941	0.984	0.985	0.987	0.985	0.538	0.614	0.678	0.801	0.697
	-20	10	0.624	0.875	0.906	0.894	0.891	0.865	0.941	0.960	0.948	0.950	0.520	0.622	0.666	0.780	0.689
	-20	-10	0.641	0.897	0.890	0.941	0.909	0.902	0.970	0.951	0.973	0.965	0.520	0.639	0.707	0.789	0.711
yaleB09_P00	00	20	0.822	0.856	0.832	0.849	0.845	0.485	0.849	0.847	0.868	0.855	0.916	0.919	0.917	0.912	0.916
	00	-20	0.789	0.866	0.884	0.905	0.885	0.647	0.874	0.883	0.888	0.881	0.932	0.963	0.959	0.968	0.963
	05	10	0.858	0.871	0.859	0.866	0.865	0.550	0.867	0.868	0.889	0.875	0.893	0.941	0.950	0.951	0.947
	05	-10	0.849	0.887	0.884	0.896	0.889	0.656	0.885	0.899	0.911	0.898	0.968	0.975	0.967	0.982	0.975
	10	00	0.860	0.899	0.867	0.889	0.885	0.605	0.883	0.873	0.897	0.884	0.930	0.977	0.945	0.965	0.962
	20	10	0.795	0.873	0.861	0.860	0.864	0.505	0.885	0.850	0.890	0.875	0.906	0.863	0.928	0.893	0.895
	20	-10	0.777	0.882	0.887	0.915	0.895	0.575	0.884	0.888	0.913	0.895	0.889	0.888	0.940	0.943	0.923
	-05	10	0.804	0.873	0.870	0.857	0.867	0.513	0.873	0.892	0.893	0.886	0.936	0.948	0.901	0.927	0.925
	-05	-10	0.862	0.879	0.899	0.889	0.889	0.665	0.890	0.899	0.907	0.899	0.970	0.959	0.973	0.974	0.969
	-10	00	0.836	0.858	0.889	0.870	0.873	0.610	0.882	0.891	0.880	0.885	0.940	0.966	0.961	0.979	0.969
	-20	10	0.796	0.838	0.887	0.825	0.850	0.530	0.885	0.874	0.851	0.870	0.851	0.922	0.863	0.909	0.898
	-20	-10	0.790	0.883	0.893	0.891	0.889	0.617	0.892	0.888	0.897	0.892	0.923	0.950	0.908	0.954	0.937

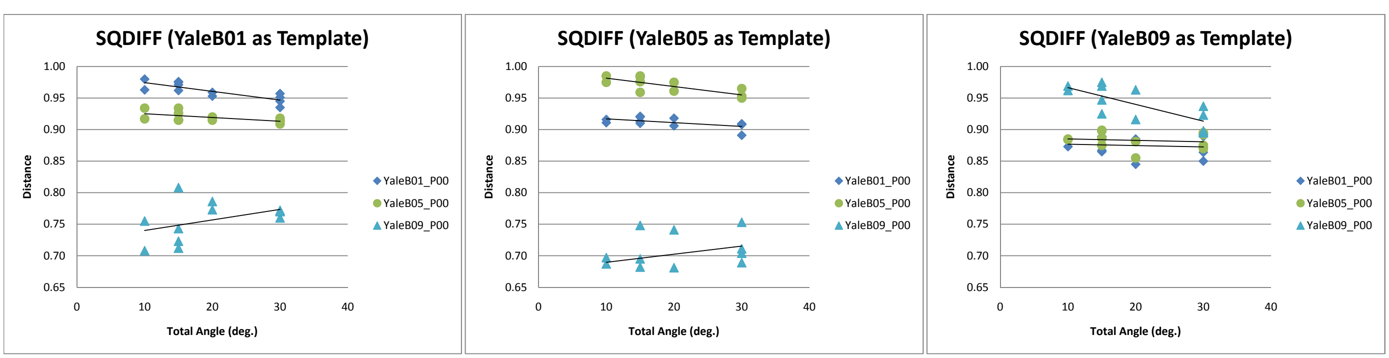

Figure 7. Sum of squared difference matching plot.

TABLE 2. Cross Correlation

Input	Template		yaleB01_P00					yaleB05_P00					yaleB09_P00				
	A	E	EF	L_Eye	R_Eye	Mouth	FF	EF	L_Eye	R_Eye	Mouth	FF	EF	L_Eye	R_Eye	Mouth	FF
yaleB01_P00	00	20	0.962	0.973	0.976	0.985	0.978	0.835	0.963	0.955	0.971	0.963	0.933	0.926	0.937	0.942	0.935
	00	-20	0.932	0.975	0.978	0.988	0.980	0.847	0.955	0.957	0.965	0.959	0.903	0.894	0.886	0.934	0.904
	05	10	0.972	0.982	0.984	0.994	0.986	0.841	0.968	0.956	0.979	0.968	0.935	0.920	0.928	0.948	0.932
	05	-10	0.972	0.986	0.990	0.994	0.990	0.855	0.958	0.950	0.974	0.961	0.924	0.894	0.901	0.944	0.913
	10	00	0.986	0.988	0.992	0.994	0.991	0.842	0.966	0.949	0.975	0.964	0.932	0.912	0.914	0.947	0.924
	20	10	0.963	0.972	0.979	0.978	0.976	0.830	0.969	0.946	0.966	0.960	0.920	0.920	0.914	0.938	0.924
	20	-10	0.946	0.980	0.986	0.983	0.983	0.827	0.956	0.953	0.968	0.959	0.903	0.888	0.893	0.930	0.903
	-05	10	0.978	0.984	0.988	0.994	0.989	0.844	0.965	0.962	0.977	0.968	0.937	0.915	0.935	0.948	0.932
	-05	-10	0.986	0.990	0.992	0.995	0.993	0.861	0.960	0.957	0.973	0.963	0.928	0.893	0.906	0.944	0.914
	-10	00	0.987	0.990	0.993	0.994	0.992	0.848	0.965	0.965	0.974	0.968	0.931	0.905	0.925	0.945	0.925
	-20	10	0.951	0.982	0.981	0.973	0.979	0.832	0.961	0.968	0.960	0.963	0.912	0.903	0.932	0.930	0.922
	-20	-10	0.961	0.985	0.980	0.986	0.984	0.843	0.955	0.960	0.963	0.959	0.910	0.884	0.895	0.935	0.905
yaleB05_P00	00	20	0.803	0.965	0.952	0.967	0.961	0.924	0.987	0.988	0.982	0.985	0.777	0.881	0.885	0.939	0.901
	00	-20	0.844	0.959	0.954	0.976	0.963	0.950	0.987	0.988	0.991	0.988	0.794	0.873	0.884	0.940	0.899
	05	10	0.852	0.966	0.950	0.975	0.963	0.960	0.994	0.993	0.993	0.993	0.817	0.881	0.897	0.948	0.909
	05	-10	0.845	0.963	0.954	0.976	0.965	0.973	0.996	0.995	0.996	0.995	0.804	0.868	0.885	0.941	0.898
	10	00	0.826	0.962	0.949	0.969	0.960	0.967	0.994	0.994	0.994	0.994	0.794	0.878	0.889	0.940	0.902
	20	10	0.824	0.968	0.947	0.959	0.958	0.934	0.989	0.984	0.982	0.985	0.796	0.903	0.891	0.931	0.908
	20	-10	0.810	0.961	0.947	0.971	0.960	0.939	0.979	0.985	0.985	0.983	0.769	0.876	0.879	0.932	0.896
	-05	10	0.818	0.961	0.955	0.971	0.962	0.950	0.994	0.995	0.992	0.994	0.795	0.862	0.884	0.944	0.897
	-05	-10	0.844	0.960	0.957	0.977	0.965	0.959	0.994	0.993	0.995	0.994	0.795	0.864	0.880	0.944	0.896
	-10	00	0.822	0.956	0.956	0.971	0.961	0.971	0.995	0.995	0.994	0.994	0.780	0.858	0.887	0.939	0.895
	-20	10	0.812	0.940	0.957	0.958	0.952	0.932	0.986	0.986	0.976	0.983	0.775	0.843	0.890	0.927	0.887
	-20	-10	0.821	0.955	0.957	0.971	0.961	0.951	0.988	0.983	0.987	0.986	0.771	0.859	0.881	0.935	0.892
yaleB09_P00	00	20	0.915	0.943	0.947	0.958	0.950	0.745	0.937	0.940	0.959	0.945	0.962	0.972	0.967	0.961	0.967
	00	-20	0.932	0.954	0.950	0.962	0.955	0.859	0.952	0.949	0.961	0.954	0.972	0.982	0.980	0.984	0.982
	05	10	0.929	0.950	0.950	0.964	0.955	0.776	0.943	0.947	0.963	0.951	0.955	0.978	0.975	0.976	0.976
	05	-10	0.939	0.958	0.951	0.960	0.956	0.841	0.954	0.950	0.963	0.955	0.984	0.988	0.988	0.992	0.989
	10	00	0.932	0.956	0.947	0.963	0.955	0.804	0.949	0.946	0.961	0.952	0.971	0.989	0.989	0.985	0.987
	20	10	0.905	0.949	0.944	0.961	0.951	0.759	0.943	0.938	0.964	0.948	0.954	0.970	0.972	0.949	0.964
	20	-10	0.914	0.957	0.944	0.958	0.953	0.812	0.953	0.946	0.963	0.954	0.946	0.974	0.976	0.972	0.974
	-05	10	0.928	0.947	0.948	0.961	0.952	0.781	0.944	0.946	0.957	0.949	0.970	0.988	0.984	0.986	0.986
	-05	-10	0.938	0.956	0.955	0.959	0.956	0.839	0.958	0.950	0.963	0.957	0.986	0.991	0.987	0.990	0.989
	-10	00	0.926	0.949	0.949	0.959	0.952	0.812	0.953	0.946	0.955	0.951	0.971	0.992	0.985	0.990	0.989
	-20	10	0.898	0.943	0.949	0.957	0.949	0.765	0.944	0.944	0.957	0.948	0.940	0.974	0.955	0.955	0.961
	-20	-10	0.914	0.951	0.953	0.955	0.953	0.826	0.955	0.948	0.950	0.951	0.962	0.986	0.972	0.977	0.978

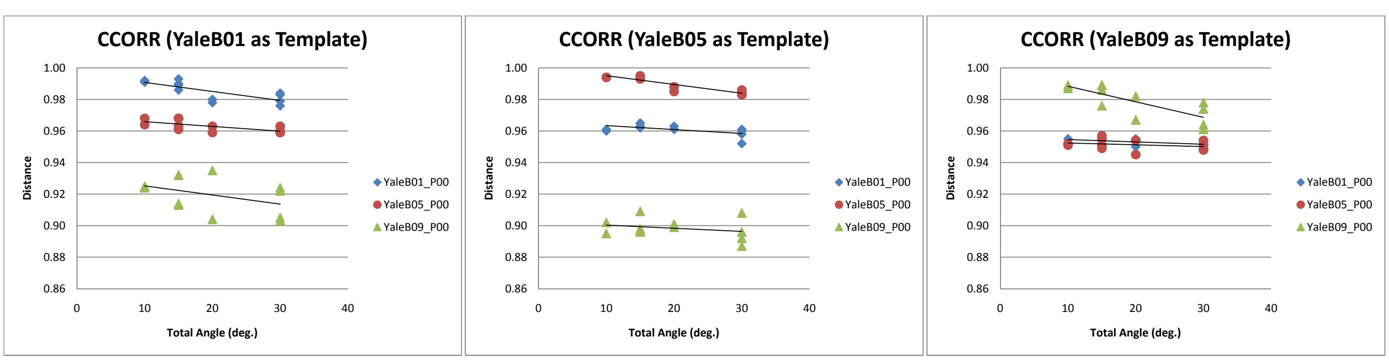

Figure 8. Cross correlation matching plot.

TABLE 3. Correlation Coefficient

Input	Template		yaleB01_P00					yaleB05_P00					yaleB09_P00				
	A	E	EF	L_Eye	R_Eye	Mouth	FF	EF	L_Eye	R_Eye	Mouth	FF	EF	L_Eye	R_Eye	Mouth	FF
yaleB01_P00	00	20	0.830	0.789	0.831	0.840	0.820	0.382	0.713	0.634	0.635	0.661	0.758	0.744	0.755	0.504	0.668
	00	-20	0.698	0.784	0.785	0.816	0.795	0.430	0.554	0.597	0.540	0.564	0.648	0.609	0.483	0.426	0.506
	05	10	0.866	0.845	0.853	0.905	0.867	0.363	0.730	0.626	0.694	0.683	0.764	0.731	0.730	0.530	0.664
	05	-10	0.873	0.871	0.900	0.900	0.891	0.458	0.626	0.538	0.586	0.583	0.728	0.601	0.583	0.483	0.556
	10	00	0.937	0.894	0.922	0.906	0.907	0.412	0.706	0.519	0.625	0.617	0.755	0.688	0.667	0.522	0.626
	20	10	0.834	0.803	0.802	0.755	0.787	0.364	0.741	0.514	0.577	0.611	0.710	0.714	0.651	0.481	0.615
	20	-10	0.771	0.858	0.858	0.773	0.830	0.371	0.611	0.554	0.584	0.583	0.653	0.616	0.529	0.432	0.526
	-05	10	0.896	0.859	0.896	0.916	0.890	0.395	0.696	0.674	0.671	0.680	0.771	0.711	0.760	0.536	0.669
	-05	-10	0.937	0.911	0.927	0.922	0.920	0.470	0.620	0.607	0.576	0.601	0.736	0.612	0.604	0.485	0.567
	-10	00	0.939	0.912	0.944	0.902	0.919	0.421	0.685	0.685	0.612	0.660	0.750	0.676	0.703	0.505	0.628
	-20	10	0.804	0.832	0.897	0.703	0.811	0.406	0.650	0.721	0.535	0.635	0.694	0.656	0.730	0.419	0.602
	-20	-10	0.830	0.861	0.848	0.812	0.840	0.421	0.568	0.636	0.533	0.579	0.675	0.559	0.552	0.425	0.512
yaleB05_P00	00	20	0.395	0.673	0.563	0.561	0.599	0.796	0.904	0.916	0.828	0.883	0.370	0.545	0.530	0.472	0.516
	00	-20	0.441	0.577	0.441	0.629	0.549	0.841	0.893	0.908	0.873	0.891	0.345	0.524	0.484	0.453	0.487
	05	10	0.465	0.661	0.452	0.659	0.590	0.871	0.954	0.943	0.905	0.934	0.410	0.572	0.559	0.552	0.561
	05	-10	0.426	0.610	0.437	0.607	0.551	0.913	0.966	0.964	0.935	0.955	0.360	0.498	0.506	0.454	0.486
	10	00	0.385	0.602	0.372	0.530	0.502	0.897	0.954	0.951	0.917	0.941	0.351	0.582	0.516	0.481	0.526
	20	10	0.423	0.685	0.373	0.557	0.538	0.807	0.930	0.873	0.815	0.873	0.394	0.681	0.523	0.461	0.555
	20	-10	0.368	0.586	0.400	0.509	0.498	0.819	0.859	0.883	0.811	0.851	0.306	0.546	0.462	0.413	0.474
	-05	10	0.377	0.616	0.503	0.570	0.563	0.849	0.951	0.967	0.899	0.939	0.372	0.425	0.524	0.503	0.484
	-05	-10	0.421	0.575	0.456	0.622	0.551	0.865	0.955	0.951	0.926	0.944	0.330	0.487	0.499	0.481	0.489
	-10	00	0.366	0.513	0.455	0.539	0.502	0.908	0.960	0.965	0.915	0.947	0.310	0.443	0.514	0.458	0.472
	-20	10	0.389	0.494	0.533	0.483	0.503	0.807	0.892	0.935	0.771	0.866	0.336	0.465	0.510	0.398	0.457
	-20	-10	0.393	0.523	0.459	0.573	0.518	0.854	0.906	0.898	0.828	0.877	0.304	0.513	0.528	0.425	0.489
yaleB09_P00	00	20	0.750	0.649	0.704	0.478	0.610	0.242	0.713	0.604	0.611	0.643	0.893	0.926	0.904	0.840	0.890
	00	-20	0.727	0.786	0.724	0.561	0.690	0.506	0.691	0.611	0.636	0.646	0.904	0.941	0.928	0.880	0.917
	05	10	0.733	0.680	0.696	0.526	0.634	0.235	0.715	0.607	0.621	0.647	0.848	0.936	0.916	0.852	0.901
	05	-10	0.757	0.771	0.722	0.568	0.687	0.444	0.727	0.615	0.645	0.663	0.946	0.962	0.955	0.937	0.951
	10	00	0.744	0.748	0.726	0.542	0.672	0.338	0.735	0.608	0.608	0.651	0.901	0.969	0.958	0.898	0.942
	20	10	0.702	0.736	0.722	0.490	0.649	0.269	0.718	0.593	0.610	0.640	0.864	0.928	0.903	0.775	0.869
	20	-10	0.672	0.777	0.702	0.545	0.675	0.363	0.690	0.597	0.613	0.633	0.820	0.928	0.912	0.811	0.884
	-05	10	0.749	0.686	0.707	0.516	0.636	0.287	0.715	0.621	0.616	0.651	0.904	0.965	0.955	0.914	0.945
	-05	-10	0.761	0.760	0.725	0.544	0.676	0.447	0.733	0.649	0.630	0.671	0.953	0.971	0.954	0.925	0.950
	-10	00	0.745	0.732	0.721	0.496	0.649	0.392	0.723	0.642	0.578	0.647	0.907	0.974	0.958	0.929	0.953
	-20	10	0.678	0.643	0.688	0.421	0.584	0.287	0.704	0.648	0.544	0.632	0.822	0.919	0.891	0.756	0.855
	-20	-10	0.688	0.746	0.710	0.488	0.648	0.429	0.715	0.663	0.557	0.645	0.876	0.953	0.922	0.839	0.904

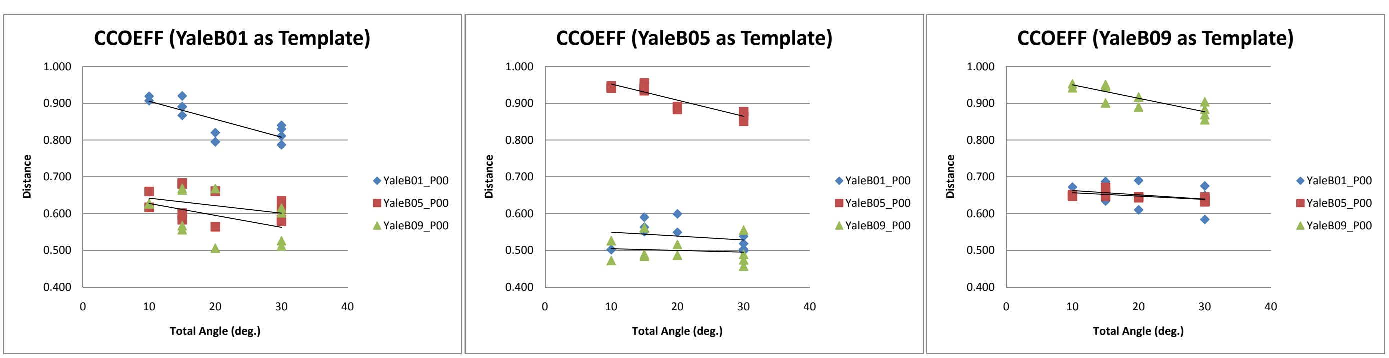

Figure 9. Correlation coefficient matching plot.