# Face Recognition Using Phase-Based Correspondence Matching

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*Abstract*— **This paper proposes a 2D face recognition algorithm using phase-based correspondence matching. The phase information obtained from 2D DFT (Discrete Fourier Transform) of images contains important information of image representation. The phase-based image matching is successfully applied to sub-pixel image registration tasks for computer vision applications and image recognition tasks for biometric authentication applications. Hierarchical block matching using phase information, i.e, phase-based correspondence matching, can find the corresponding points on the input image from the reference points on the registered image with sub-pixel accuracy. For face recognition, the phase-based correspondence matching is useful for minute change of texture, such as facial expression change, illumination change, etc. Experimental evaluation using the CSU Face Identification Evaluation System with the FERET database demonstrates efficient recognition performance of the proposed algorithm compared with the conventional face recognition algorithms.**

## I. Introduction

With the needs for reliable human authentication in various applications such as access control, etc., biometric authentication has been receiving extensive attention over the past decade [4]. Among all the biometric techniques, face recognition has been an area of intense research [6].

Face recognition approaches can be classified into two categories: holistic and feature-based approaches. Holistic approaches such as PCA (Principle Component Analysis) [11], LDA (Linear Discriminant Analysis) [13] project input face images onto a low dimension feature space. These approaches have achieved a level of success in face recognition. However, these approaches are not robust against facial expression changes, illumination changes, and pose variation. Feature-based approaches such as Active Appearance Model (AAM) [3] and Elastic Bunch Graph Matching (EBGM) [12] recognize faces using facial components: eyes, nose, mouth, etc. These approaches are robust against facial expression changes, pose variation, etc. However, AAM needs time-consuming semi-automatic annotation process and EBGM needs accurate landmark extraction. Also, the face description using LBP (Local Binary Patterns) proposed by Ahonen, et al. [1] exhibits good performance for face recognition. The recognition performance of the LBP-based algorithm, however, may drop for face images with minute changes, i.e., expression changes, etc.

In this paper, we propose a face recognition algorithm using phase-based correspondence matching. The phase-based correspondence matching proposed by Takita, et al. [10] can find the corresponding points on the input image from the reference points on the registered image with sub-pixel accuracy. The proposed algorithm is robust against (i) illumination changes by using phase information of 2D DFT and (ii) facial expression changes, since facial expression can be approximated by minute translations. Also, the proposed algorithm does not need landmark extraction, since reference points can be freely put on the face region. Experimental evaluation using the CSU Face Identification Evaluation System [2] with the FERET database [8] demonstrates efficient performance of the proposed algorithm compared with conventional face recognition algorithms.

## II. Phase-Based Correspondence Matching

This section describes Phase-Only Correlation (POC) function which is the fundamental technique for the phase-based correspondence matching used in this paper. We also present the detailed description of the phase-based correspondence matching.

### A. Phase-Only Correlation (POC) function

We briefly introduce a Phase-Only Correlation (POC) function (which is sometimes called the "phase-correlation function") proposed in [5], [9], [10]. The POC function is defined as the inverse DFT of normalized cross-power spectrum. When two images are similar, their POC function gives a distinct sharp peak. When two images are not similar, the peak drops significantly. The height of the peak gives a good similarity measure for image matching, and the location of the peak shows the translational displacement between the images.

Takita, et al. [9] proposed a high-accuracy translational displacement estimation method, which employs (i) an analytical function fitting technique to estimate the sub-pixel position of the correlation peak, (ii) a windowing technique to eliminate the effect of periodicity in 2D DFT, and (iii) a spectrum weighting technique to reduce the effect of aliasing and noise. The experimental observation in [9] shows that POC-based matching can estimate displacement between two images with 0.01-pixel accuracy when image size is about $100 \times 100$ pixels. Other important properties of POC function are that the POC-based image matching is not influenced by image shift and brightness change, and it is highly robust

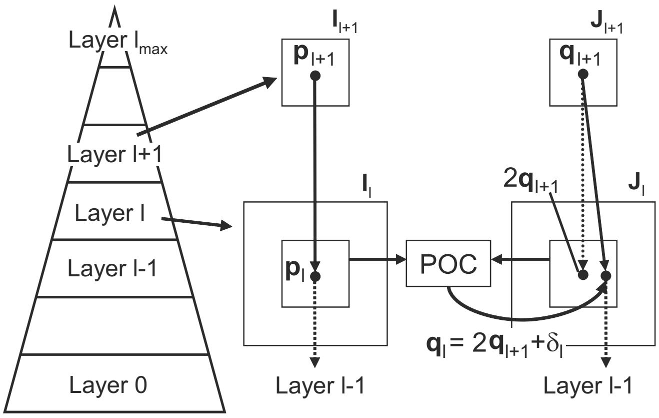


Fig. 1. Phase-based correspondence matching.

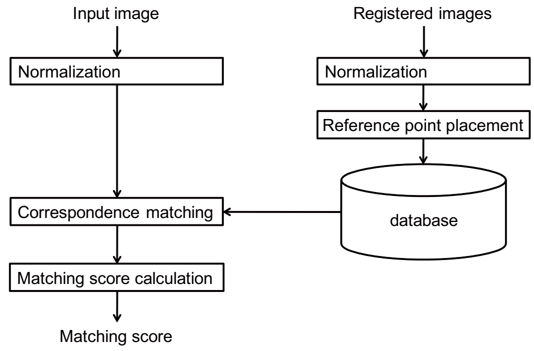


Fig. 2. Flow diagram of the proposed algorithm.

against noise. These properties allow us to develop a robust and accurate face recognition algorithm.

### B. Phase-Based Correspondence Matching

The phase-based correspondence matching [10] employs (i) a coarse-to-fine strategy using image pyramids for robust correspondence search and (ii) a sub-pixel window alignment technique for finding a pair of corresponding points with sub-pixel displacement accuracy. Let $\boldsymbol{p}$ be a coordinate vector of a reference pixel in the reference $I(n_1, n_2)$. The problem of sub-pixel correspondence search is to find a real-number coordinate vector $\boldsymbol{q}$ in the input image $J(n_1, n_2)$ that corresponds to the reference pixel $\boldsymbol{p}$ in $I(n_1, n_2)$. We briefly explain the procedure as follows (Fig. 1).

**Step 1**: For $l = 1, 2, \cdots, l_{max}$, create the $l$-th layer images $I_l(n_1, n_2)$ and $J_l(n_1, n_2)$, i.e., coarser versions of $I_0(n_1, n_2)$ and $J_0(n_1, n_2)$, recursively as follows:

$$I_l(n_1,n_2) = \frac{1}{4}\sum_{i_1=0}^{1}\sum_{i_2=0}^{1} I_{l-1}(2n_1+i_1, 2n_2+i_2),$$
$$J_l(n_1,n_2) = \frac{1}{4}\sum_{i_1=0}^{1}\sum_{i_2=0}^{1} J_{l-1}(2n_1+i_1, 2n_2+i_2).$$

In this paper, we employ $l_{max} = 3$.

**Step 2**: For every layer $l = 1, 2, \cdots, l_{max}$, calculate the coordinate $\boldsymbol{p}_l = (p_{l1}, p_{l2})$ corresponding to the original reference point $\boldsymbol{p}_0$ recursively as follows:

$$\boldsymbol{p}_l = \lfloor \tfrac{1}{2}\boldsymbol{p}_{l-1} \rfloor = (\lfloor \tfrac{1}{2}p_{l-1\ 1} \rfloor, \lfloor \tfrac{1}{2}p_{l-1\ 2} \rfloor), \quad (1)$$

where $\lfloor z \rfloor$ denotes the operation to round the element of $z$ to the nearest integer towards minus infinity.

**Step 3**: We assume that $\boldsymbol{q}_{l_{max}} = \boldsymbol{p}_{l_{max}}$ in the coarsest layer. Let $l = l_{max} - 1$.

**Step 4**: From the $l$-th layer images $I_l(n_1, n_2)$ and $J_l(n_1, n_2)$, extract two sub-images (or image blocks) $f_l(n_1, n_2)$ and $g_l(n_1, n_2)$ with their centers on $\boldsymbol{p}_l$ and $2\boldsymbol{q}_{l+1}$, respectively. The size of image blocks is $W \times W$ pixels. In this paper, we employ $W = 32$.

**Step 5**: Estimate the displacement between $f_l(n_1, n_2)$ and $g_l(n_1, n_2)$ with pixel accuracy using POC-based image matching. Let the estimated displacement vector be $\boldsymbol{\delta}_l$. The $l$-th layer correspondence $\boldsymbol{q}_l$ is determined as follows:

$$\boldsymbol{q}_l = 2\boldsymbol{q}_{l+1} + \boldsymbol{\delta}_l. \quad (2)$$

**Step 6**: Decrement the counter by 1 as $l = l - 1$ and repeat from Step 4 to Step 6 while $l \geq 0$.

**Step 7**: From the original images $I_0(n_1, n_2)$ and $J_0(n_1, n_2)$, extract two image blocks with their centers on $\boldsymbol{p}_0$ and $\boldsymbol{q}_0$, respectively. Estimate the displacement between the two blocks with sub-pixel accuracy using POC-based image matching. Let the estimated displacement vector with sub-pixel accuracy be denoted by $\boldsymbol{\delta} = (\delta_1, \delta_2)$. Update the corresponding point as follows:

$$\boldsymbol{q} = \boldsymbol{q}_0 + \boldsymbol{\delta}. \quad (3)$$

Also, the peak value of the POC function is also obtained as a measure of reliability in local block matching.

□

## III. Proposed Face Recognition Algorithm

This section presents a face recognition algorithm using phase-based correspondence matching proposed in this paper. The proposed algorithm consists of 2 stages: (i) enrollment stage and (ii) matching stage. Fig. 2 shows the flow diagram of the proposed algorithm. We describe the details of each stage as follows.

### A. Enrollment Stage

The enrollment stage consists of 2 steps: (i) normalization and (ii) reference point placement.

**(i) Normalization**

This step is to normalize scale, rotation and illumination of the registered face image. In this paper, we employ the normalization process used in the CSU Face Identification Evaluation System [2]. The normalization process converts the color image into the gray scale image, normalizes geometry based on eye coordinates, makes an elliptical mask including only face, applies histogram equalization to normalize illumination change, and normalizes the pixel values having a mean zero and a standard deviation of one. Instead of the above normalization process used in the CSU Face Identification Evaluation System, we can use AAM

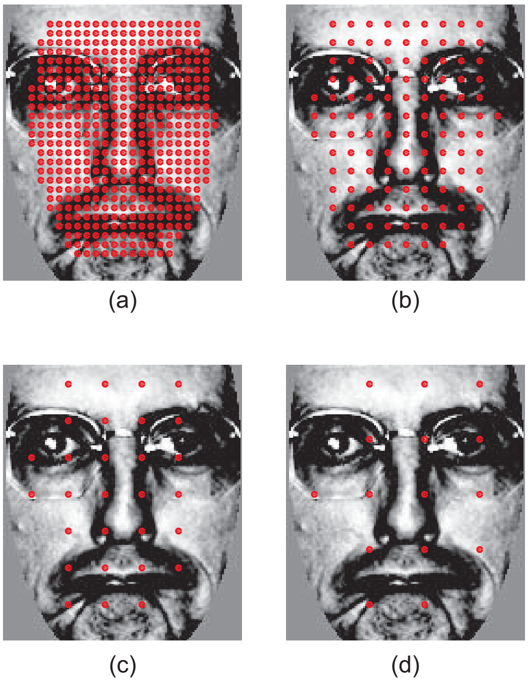


Fig. 3. Example of reference points on normalized face image: (a) POC_05, (b) POC_10, (c) POC_20 and (d) POC_30.

proposed by Cootes, et al.[3] for achieving more accurate face image normalization against facial expression changes and pose variation.

**(ii) Reference point placement**

This step is to place a set of reference points $\boldsymbol{p}$ on the normalized face image. The number of reference points should be determined depending on applications. Many reference points result in high recognition performance and slow computation, while a few reference points result in low recognition performance and fast computation. In this paper, we consider 4 situations such as 463, 116, 29, 15 points with a spacing of 5, 10, 20, and 30 pixels, respectively, as shown in Fig. 3. We also denote these settings as POC_05, POC_10, POC_20 and POC_30, respectively.

### B. Matching Stage

The matching stage consists of 3 steps: (i) normalization, (ii) correspondence matching and (iii) matching score calculation.

**(i) Normalization**

This step is the same as the normalization process of the enrollment stage.

**(ii) Correspondence matching**

This step is to find the corresponding points $\boldsymbol{q}$ on the input image from the reference points $\boldsymbol{p}$ on the registered image using the phase-based correspondence matching as described in Sect. II-B. After the correspondence matching, we obtain a set of coordinates and similarity values for each corresponding point pair, where the similarity value is defined by the peak value of POC function.

**(iii) Matching score calculation**

This step is to calculate the matching score between the input and registered images. If the similarity value of the corresponding point pair is below the specified value, we eliminate the corresponding point pair as an outlier. In this paper, we employ 0.5 as a threshold. The matching score is defined as

$$Matching\ score = \frac{\#\ of\ correct\ corresponding\ points}{\#\ of\ reference\ points}. \quad (4)$$

## IV. Experiments and Discussion

This section describes a set of experiments to evaluate performance of the proposed algorithm. In this paper, we employ the CSU Face Identification Evaluation System [2] with the FERET database [8].

The FERET database contains 3,368 face images of 1,209 subjects. The face images in the FERET database are organized into a gallery set (*fa*) and 4 probe sets such as *fb*, *fc*, *dup1* and *dup2*. The images in *fa* and *fb* set were taken in the same session with the same camera and illumination condition, but with different expression. The images in *fc* set were taken in the same session using the different camera and lighting. The images in *dup1* set were taken later in time. The images in *dup2* set which is a subset of *dup1* set were taken at least a year. Using the FERET database, we perform 4 experiments denoted by *fafb*, *fafc*, *dup1* and *dup2*.

The CSU Face Identification Evaluation System includes conventional face recognition algorithms for comparison. The conventional algorithms compared in the experiments are 2 Bayesian algorithms (Bayesian_MAP and Bayesian_ML) [7], 4 EBGM algorithms (EBGM_Optimal_FGMagnitude, EBGM_Optimal_FGNarrowingLocalSearch, EBGM_Optimal_FGPredictiveStep and EBGM_Standard) [12], 2 LDA-based algorithms (LDA_Euclidean and LDA_ldaSoft) [13] and 2 PCA-based algorithms (PCA_Euclidean and PCA_MahCosine) [11]. We also employ LBP-based face recognition algorithms [1] to demonstrate effectiveness of the proposed algorithm.

We evaluate recognition performance of face recognition algorithms according to the performance metrics employed in the CSU Face Evaluation Identification System such as the Cumulative Match Characteristic (CMC) curve, the recognition rates of genuine pairs at rank 1, and the mean recognition rate of the permutation test with a 95 percent confidence interval. See Ref. [2] for more detailed description.

Fig. 4 shows the CMC curves for each experiment. Table I shows the recognition rates of genuine pairs at rank 1 for each experiment in the first four columns and the mean recognition rate of the permutation test in the last three columns. Table II shows the recognition rates at rank 1 and the computation time of the proposed algorithms. The computation time is evaluated by using MATLAB 7.4 (64 bit) on Intel Xeon E5450 (3.00GHz). As for experiments *fafb* and *fafc*, the recognition rate for the proposed algorithms (POC_05, POC_10, POC_20 and POC_30) is more than 96% at rank 1. This result indicates that the proposed algorithm

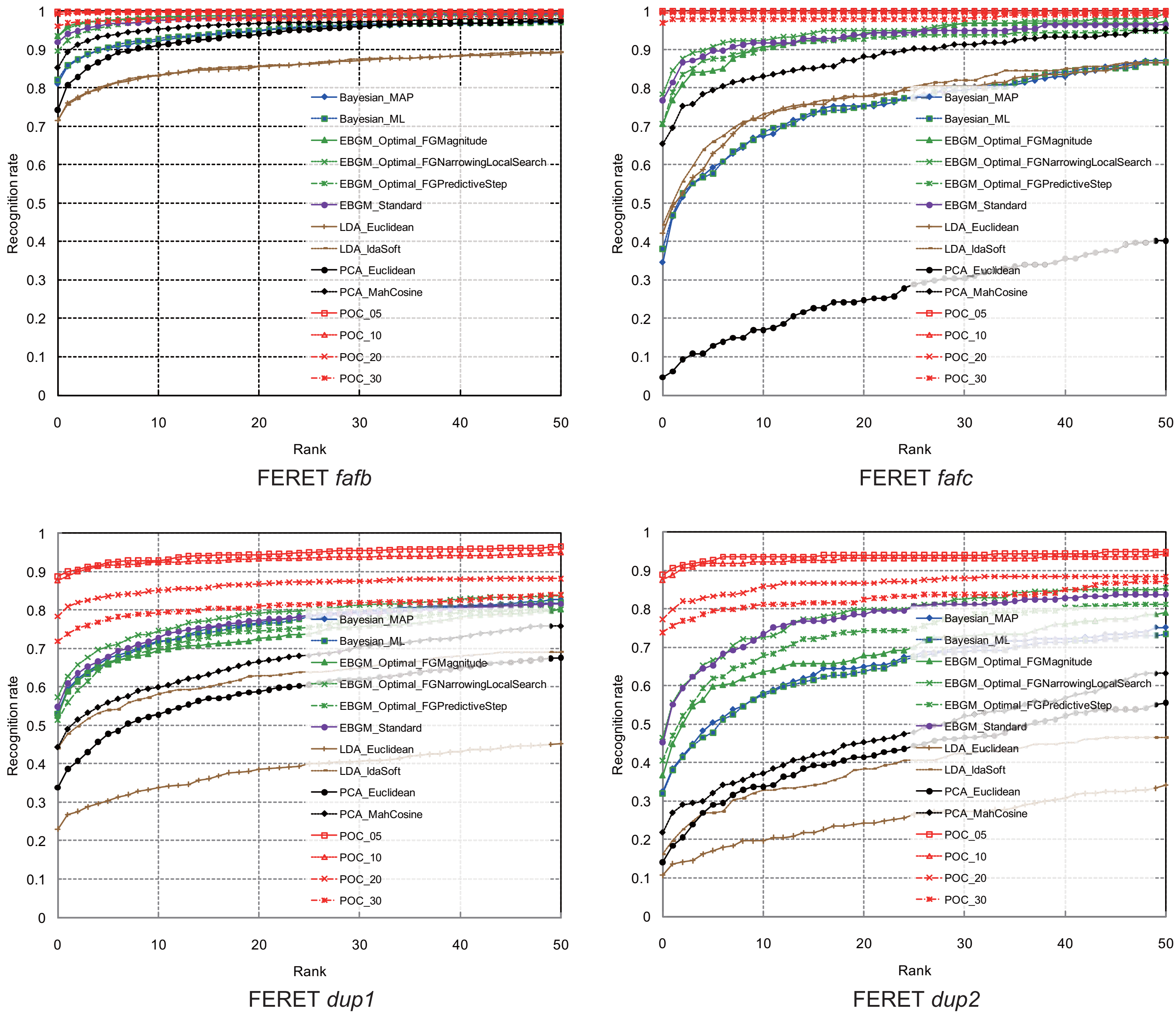


Fig. 4. CMC curves for the proposed algorithm and comparison algorithms using the FERET database.

TABLE I

RECOGNITION RATE FOR THE PROPOSED ALGORITHM AND COMPARISON ALGORITHMS USING THE FERET DATABASE.

| Algorithm | *fafb* | *fafc* | *dup1* | *dup2* | Lower | Mean | Upper |
|---|---|---|---|---|---|---|---|
| Bayesian_MAP | 81.2% | 34.5% | 53.3% | 32.5% | 66.9% | 72.2% | 77.5% |
| Bayesian_ML | 82.1% | 38.1% | 53.0% | 32.1% | 68.1% | 72.9% | 78.1% |
| EBGM_Optimal_FGMagnitude | 93.4% | 70.6% | 52.5% | 36.8% | 63.8% | 68.8% | 73.8% |
| EBGM_Optimal_FGNarrowingLocalSearch | 93.5% | 78.4% | 57.3% | 46.6% | 67.5% | 72.4% | 77.5% |
| EBGM_Optimal_FGPredictiveStep | 89.6% | 70.6% | 51.4% | 40.6% | 63.8% | 69.0% | 74.4% |
| EBGM_Standard | 91.9% | 76.8% | 54.8% | 45.3% | 65.6% | 70.9% | 76.2% |
| LDA_Euclidean | 71.5% | 42.3% | 23.0% | 10.7% | 48.8% | 54.9% | 61.2% |
| LDA_ldaSoft | 71.6% | 44.3% | 44.0% | 16.2% | 63.8% | 69.1% | 74.4% |
| PCA_Euclidean | 74.3% | 4.6% | 33.8% | 14.1% | 57.5% | 62.6% | 67.5% |
| PCA_MahCosine | 85.3% | 65.5% | 44.3% | 21.8% | 66.2% | 72.1% | 77.5% |
| LBP_weighted [1] | 97.0% | 79.0% | 66.0% | 64.0% | 76.0% | 81.0% | 85.0% |
| LBP_nonweighted [1] | 93.0% | 51.0% | 61.0% | 50.0% | 71.0% | 76.0% | 81.0% |
| POC_05 | 99.7% | 100.0% | 88.8% | 88.9% | 91.9% | 94.6% | 97.5% |
| POC_10 | 99.7% | 100.0% | 87.7% | 87.6% | 90.6% | 93.9% | 96.9% |
| POC_20 | 99.2% | 99.5% | 78.4% | 77.4% | 85.0% | 88.7% | 92.5% |
| POC_30 | 96.1% | 96.9% | 71.9% | 73.9% | 79.4% | 84.2% | 88.8% |

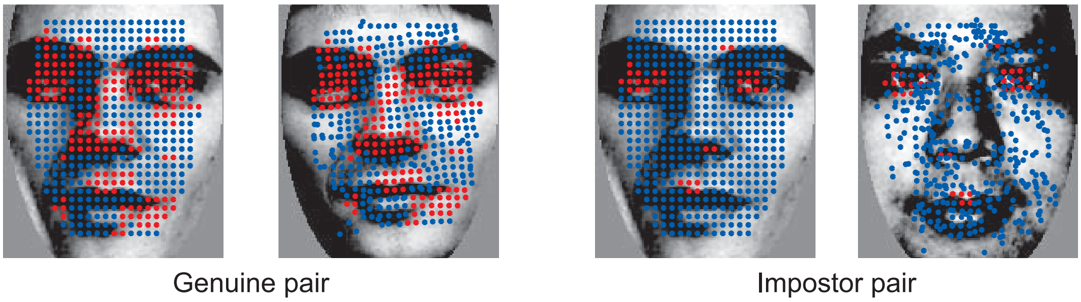


Fig. 5. Matching result for POC_05: red points are corresponding points and blue points are outlier points.

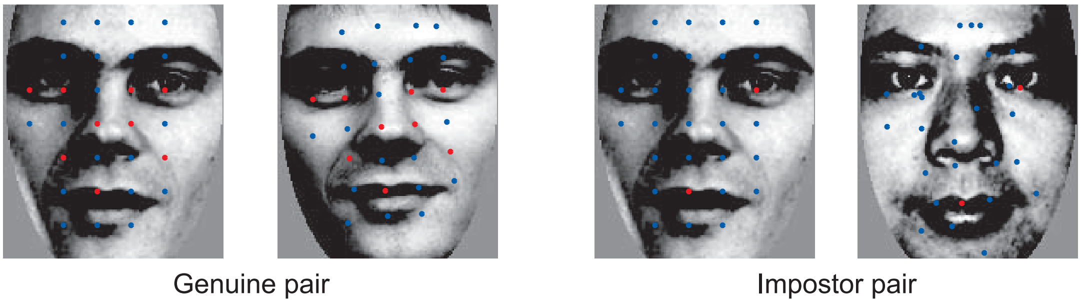


Fig. 6. Matching result for POC_20: red points are corresponding points and blue points are outlier points.

TABLE II
COMPUTATION TIME AND RECOGNITION RATE OF THE PROPOSED ALGORITHM.

| Algorithm (# of ref. points) | Recognition rate [%] | Computation time [sec.] |
|---|---|---|
| POC_05 (463) | 94.6 | 0.137 |
| POC_10 (116) | 93.9 | 0.036 |
| POC_20 (29) | 88.7 | 0.011 |
| POC_30 (15) | 84.2 | 0.006 |

are robust against facial expression changes and illumination changes. As for experiments *dup1* and *dup2*, the recognition rate of POC_05 and POC_10 is more than 87% at rank 1, while that for POC_20 and POC_30 is below 80% at rank1. The reason is that a few number of reference points is not enough to recognize face images having expression changes, illumination changes, aging, etc. Nevertheless, the recognition rate of the proposed algorithm is still higher than the conventional algorithms. As a result, the proposed algorithm is robust against illumination change, facial expression change and aging compared with the conventional algorithms.

Figs. 5 and 6 show example of matching results for POC_05 and POC_20, respectively. The *red* dots denote the correct corresponding point pairs, while the *blue* dots denote wrong corresponding point pairs, i.e., outliers. In the case of genuine pair, the corresponding points accurately put on eyes, nose and mouth. In the case of impostor pair, the position of the corresponding points is not correct and the number of correct is few.

## V. CONCLUSION

This paper has proposed the face recognition algorithm using the phase-based correspondence matching. Through a set of experiments using the CSU Face Identification Evaluation System with the FERET database, we demonstrate that the proposed algorithm is robust against facial expression changes, illumination changes, aging, etc. and exhibit higher recognition performance than the conventional face recognition algorithms. In future work, we will evaluate the proposed algorithm using other face image databases such as FRGC (Face Recognition Grand Challenge), MBGC (Multiple Biometric Grand Challenge) and LFW (Labeled Faces in the Wild). We will also consider to develop the practical and real-time face recognition system using the proposed algorithm.

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