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Face matching using SURF feature points

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Abstract
This paper presents a robust face matching algorithm for gray intensity images. We have used feature based approach named Speed-Up Robust Features (SURF) suggested by Herbert Bay to match faces up to certain accuracy level. Firstly, after the locations of face regions are detected, a feature based method will be used to detect ROI points on the faces. Then a matching algorithm will be used to match the interest points to take the decision. Results of experiments to the faces without spectacles show that the proposed approach is not only robust but also quite efficient.

Keywords: SURF, Face Recognition, Face Matching

Introduction
Face matching is an important application of Image processing that has wide usage in security management. It can be used to match a given face with any other face and to take the decision that the two persons are same or not. This can help to identify people from a database of faces, or can be used in live video stream to identify a particular person. For example, this system can be used in maintaining automatic attendance record which will match and recognize the employees in an office and record their attendance. There are some traditional algorithms for face recognition, which have been widely used in object detection and recognition. Among them the detector and descriptor, named Speed-Up Robust Features (SURF) suggested by Herbert Bay [1], attracts people's attentions. SURF is a scale and in-plane rotation invariant detector and descriptor. In SURF, detectors are first employed to find the interest points in an image, and then the descriptors are used to extract the feature vectors at each interest point. SURF uses Hessian-matrix approximation operating on the integral image to locate the interest points, which reduces the computation time drastically. As for the descriptor, the first-order Haar wavelet responses in x and y directions are used in SURF to describe the intensity distribution within the neighborhood of an interest point. Only 64 dimensions are usually used in SURF to reduce the time cost for both feature computation and matching. Because each of SURF feature has only 64 dimensions in general and an indexing scheme is built by using the sign of the Laplacian, SURF is much faster.

Related Works
There are some traditional algorithms for face recognition such as EigenFace [2], FisherFace [3], 2D-PCA [4] and Elastic Graph Matching [5]. The Scale Invariant Feature Transform (SIFT) proposed by David G. Lowe [6, 7] has been widely used in object detection and recognition., There are also some works on the use of SIFT features in face recognition, such as SIFT_GRID proposed by M. Bicego [8] and SIFT_CLUSTER proposed by Jun Luo [9]. In the past, a large number of approaches that tackled the problem of face recognition were based on generic face recognition algorithms such as PCA/LDA/ICA subspace analysis [10], or local binary pattern histograms (LBP) [11] and its extensions. The discrete cosine trans-form (DCT) has been used as a feature extraction step in various studies on face recognition, where the proposed local appearance-based face recognition approach in [12] outperformed e.g. the holistic approaches. Nowadays, illumination invariance, facial expressions, and partial occlusions are one of the most challenging problems in face recognition [13, 14, 15], where face images are usually analyzed locally to cope with the corresponding transformations. Local feature descriptors describe a pixel in an image through its local neighborhood content. They should be distinctive and at the same time robust to changes in viewing conditions. Many different descriptors and interest-point detectors have been proposed in the literature, and the descriptor performance often depends on the interest point detector [16]. Recently, a comparative study in [17] has shown the superior performance of local features for face recognition in unconstrained environments. SURF descriptors have been used in combination with a SVM for face components [18] only.

Proposed Schemes
In our proposed scheme we have compared two faces for matching. Firstly we have used Voila-Zones face detecting algorithm to detect faces from a picture. Then we have calculated the SURF feature points on the two faces, which are also the ROI points of the same faces. Then we have extracted different features from the both face regions by using the feature points. The results are shown in figures [Figure 1-Figure 6].

Algorithm
Start
Step 1: Input two images and extract the faces by using any face detection algorithm (e.g. Voila Zones).
Step 2: Detect SURF feature points from the corresponding faces.

Step 3: Extract SURF features.
Step 4: Compare the SURF features of two images, find the matching points and calculate the matching percentage.
Step 5: If the percentage is greater than a threshold the take the decision that the faces are matched. Otherwise reject the matching.

Stop.

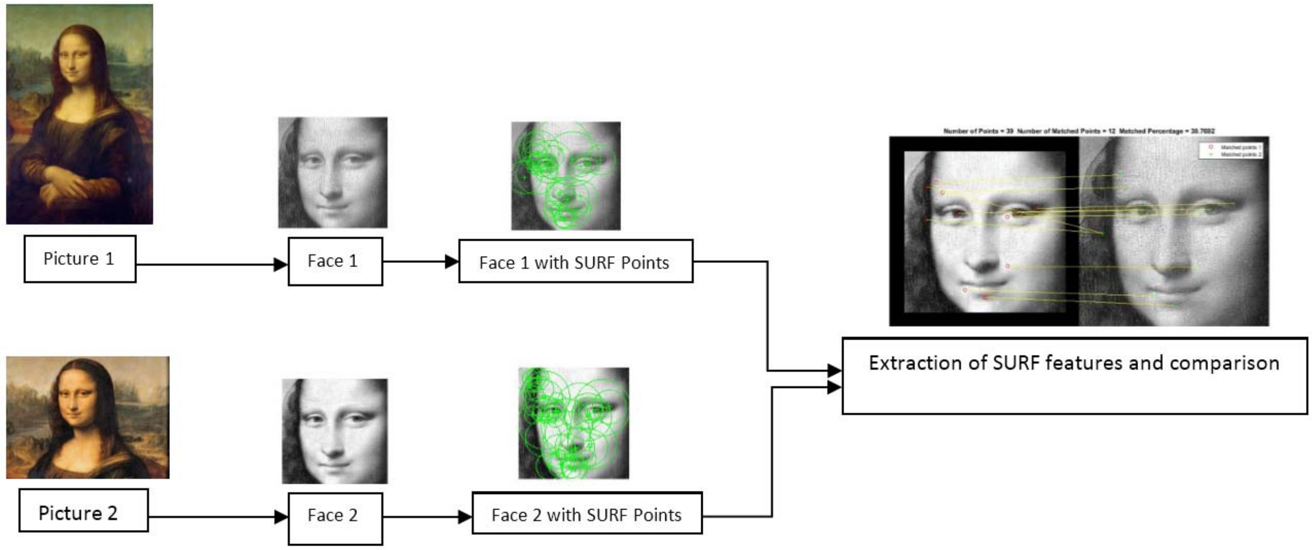

Fig 1: Steps for face matching using SURF feature points

Speeded Up Robust Features (SURF)

Speed-up robust features (SURF) is a scale and in-plane rotation invariant feature. It contains interest point detector and descriptor. The detector locates the interest points in the image, and the descriptor describes the features of the interest points and constructs the feature vectors of the interest points. Conceptually similar to the SIFT descriptor, the 64-dimensional SURF descriptor also focuses on the spatial distribution of gradient information within the interest point neighborhood, where the interest points itself can be localized by interest point detection approaches or in a regular grid. The SURF descriptor is invariant to rotation, scale, brightness and, after reduction to unit length, contrast. For the application of face recognition, invariance with respect to rotation is often not necessary. Therefore, we have used the upright version of the SURF descriptor. Due to the global integration of SURF descriptors, the authors claim that it stays more robust to various image perturbations than the more locally operating SIFT descriptor.

SURF feature extraction

SURF features can be extracted from images through SURF detectors and descriptors. Interest points are first extracted from each face image after pre-processing, such as normalization and histogram equalization. This turns out to obtain about 30-100 interest points per image. The SURF feature vectors of the set of interest points are then computed to describe the image. These features are person-specific, since the number and the positions of points selected by SURF detector as well as the features around these points computed by SURF descriptor are different in each person's image.

SURF feature matching

After SURF features have been extracted from images through SURF detectors and descriptors the features are matched against each other. We have calculated the matching percentage by using the following formula.

$$\text{Matching Percentage} = \frac{\text{Number of Matched Points}}{\text{Number of Interst points}} \times 100$$

To take the decision if the two images are matched one threshold must be selected. From our experimental result the threshold is taken as 30%.

Experimental Results

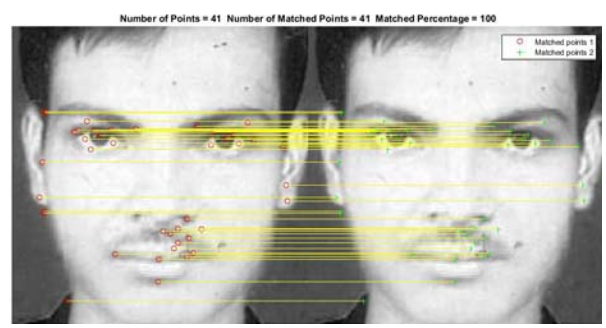

Fig 3: For same face from same picture matching is 100%.

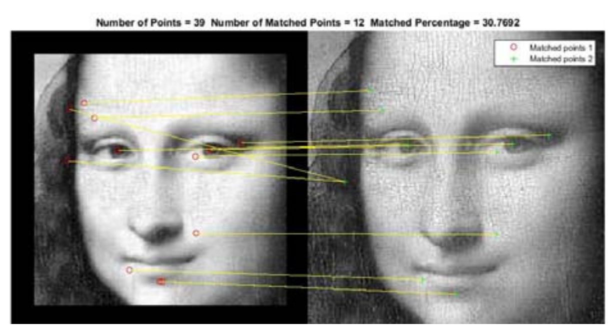

Fig 4: For same face from different picture matching is 30%

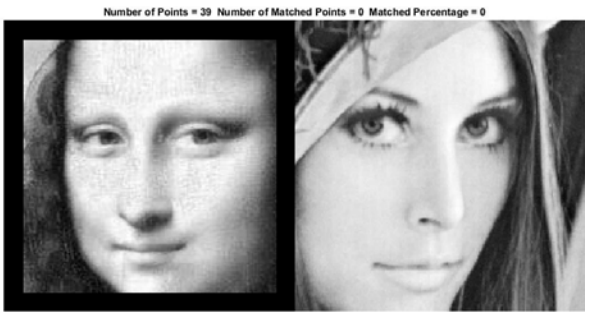

Fig 5: For different faces from different picture matching is 0%

Fig 6: For different faces from different picture matching is 4%

Conclusion

This paper deals with using SURF features in face recognition. Based on the experimental result the threshold is taken 30%. The results are quite accurate without spectacles.

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