

Construction of Delaunay Triangles for Face Recognition in Images

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Abstract—A Delaunay graph method is a proposed solution to the matching issue in facial recognition. The techniques for feature matching and feature detection are scale-invariant feature transform (SIFT) and speeded-up robust features (SURF). In the existing method, the major drawback is that each algorithm only extracts particular features, leading to many mismatches in matched features. To avoid those mismatches, this paper concatenates the SIFTSURFLBPCNN together. Input images are pre-processed and key points are detected using sift algorithm. For each Detected key point, textural, and geometrical utilizing, characteristics are extracted scale-invariant feature transform(SIFT), speeded-up robust features (SURF), local binary pattern(LBP), Convolution neural network(CNN) and concatenated to form a feature vector. Using the lows method, the key points between the input images are filtered out. Then the Delaunay triangles are constructed for the input images from their respective filtered key points using the Delaunay triangulation method. Testing is done and each algorithm's performance is evaluated.

Index Terms— Convolution neural network, Local binary patterns, Delaunay triangles.

I. INTRODUCTION

The face matching algorithm is a Process to detect the comparison of a face in an image with another face (or faces) to see if there is a match. Feature extraction methods are applied to raw images to extract features. The features are then used as input data for the matching algorithms. There are many algorithms are in existence for feature extraction methods. SIFT, SURF, and LBP are one of those. This algorithm [3] uses only particular features for matching, they are not produce accurate matching results because all features are not taken into consideration and most times mismatches will occur, these are the major drawback of feature matching. The accurate matching results can be obtained only if all features are considered. In this paper, we use SIFTSURFLBPCNN for feature extraction.

Each algorithm posse's unique advantages over one another. Scale-invariant feature transform (SIFT) extracts the local features of images, Speeded-up robust features (SURF) identifies the neighbors' Intensity [6], and Local binary patterns it extracts the textural information of a feature. Finally Applying PCA [5], the dimension is reduced to 128 using VGG-16 trained on the Image net. Using Lower matching technique, unique critical points are eliminated. Images from the Labelled Face in the Wild face dataset are utilized images are produced in an unrestricted environment with significant changes in scale, rotation, and illumination.

To increase matching accuracy graph matching algorithms can be used. To perform the graph matching

algorithms Delaunay triangles are constructed. The advantage of using Delaunay triangles are creating a triangular mesh by connecting a group of points. In Delaunay triangulations, narrow triangles are typically avoided.

II. RELATED WORK

A. Comparison of SIFT, PCA_SIFT, SURF

Luo jian & Oubang (2009) describes a comparison of sift, PCA-sift, surf [8]. The Performance of the robust features is compared with the scale changes, rotation blur and illumination changes. K-nearest neighbors (KNN), Random sample consensus (RANSAC) [7] are the methods used for SIFT, SURF, PCA-SIFT algorithms in order to finding the matching recognition between the images. This paper evaluates that while sift is invariant to rotation, scale changes, and affine transformations, it is sluggish and not good at changing illumination. Surf has the same performance as the same sift and is faster than sift. But pca sift is the best choice and giving best improvements in the results.

B. Linear programming formulation

All geometric restrictions should be able to be precisely or roughly reformulated into a linear form once a model has been established and the matching problem is solved [1]. This poses a significant challenge for this particular matching method. Unlike previous linear programming-based solutions, the technique developed in this work, popularly called new local produce remote keyless entry constraint, can be exactly normalised and requires far fewer auxiliary variables. Its basic premise is that each position in the configuration point sequence can be accurately depicted by an interpolation blending of its successive points, the weights of which can be easily calculated using least squares [11].

C. Comparison of sift surf approaches

SIFT [10] is the most well-known key point descriptor in the literature because it offers a high level of resilience and individuality. Ke and Sukthankar [9] devised PCASIFT to decrease the dimension of the descriptor from 128 to 36 in order to increase the effectiveness of SIFT. In [2] the authors describe a comparison of sift and surf approaches in different set of Noisy images, Blur images, rotation of images 90 degrees & 180 degrees. This paper proposes a SIFT and SURF algorithm comparison. Scale space extreme detection, key point localization, and key point description techniques in the SIFT algorithm are used and in surf algorithm interest point detection, interest point description methods are used for feature detection.

In feature extraction every set of images is compared with SIFT and SURF algorithm and the performance is evaluated. In some images the sift algorithms provides the good results and in some images the surf algorithms provide the better results. Tested the different types of images like blur, noisy, wrap transform images, rotation with 90 degrees of images. As a result, SURF is three times better than SIFT because of using integral images and box filter. SURF is providing good results in matching features in blur, noisy images. SIFT provides good results in different scale of images.

D. Robust point set matching for partial face recognition

In [4] the strong point set matching between the photos is described. The scale invariant feature transform (SIFT) feature detector is used to detect key points in each image. Each key point has geometric characteristics that record its posture in the current frame and texture analysis that serve as its feature descriptor. A scale-invariant binarization pattern is used to acquire more relevant information of facial expression textures while also accommodating scaling. The test is made on AR datasets. The dataset consists of partial images and holistic images which varies from scale, illumination changes.

These features are concatenated as the single descriptor is coined as SIFTSURFLBP. From the detected key points to facilitate the matching process, we choose a subset of the key points. Lastly, the suggested SIFTSURFLBPCNN algorithm for matching all the features between the images and construct the Delaunay triangles in the matched features. By taking input as holistic image and partial images, Only the sift detects the key points in the images and all other algorithms like SURF, LBP, CNN produces the descriptions for the detected keypoints. The dataset used for the test was labelled face in the wild (LFW). The images are produced in an unrestricted environment with significant scale, rotation, illumination, and occlusion variation.

III. PROPOSED MODEL

In this section, we model the Delaunay triangles as a task of matching geometric graphs. After key point extraction, we apply Delaunay triangulation to build a graph for each image in order to take into account the structural information. Extraction of features and key point selection. To build the graph, we first extract key points and associated descriptions from facial photos. We then use coarse matching to filter the candidate key points. First, we utilize Scale-Invariant Feature Transform (SIFT), a popular method for key point extraction, to find key points. After that, we mix the CNN descriptor with the "SiftSurfSILBP" to create the "SiftSurfSILBPCNN" for key point description. To increase the resilience to changes in illumination, we particularly combine the SIFT descriptor with the Speeded Up Robust Features (SURF) [9] and then apply the Scale $\{P, R\}$: $\{8,1\}$, $\{8,2\}$, $\{16,2\}$ and $\{16,3\}$. Finally, we use VGG-16 trained on ImageNet to reduce dimensionality to 128 with PCA. The proposed "SiftSurfSILBPCNN" combines the capabilities of SIFT, SURF, SILBP, and CNN, demonstrating reliability to spinning, scale, and illumination, all of which are essential for key point characterization. SIFT can detect 100s of key points in a typical 128 128 face recognition system, which would incur considerable computational price if we applied graph matching to all key points directly. As a result, we first use Lower matching strategy to filter out apparent anomalies before applying our graph-matching methodologies to the candidate key points.

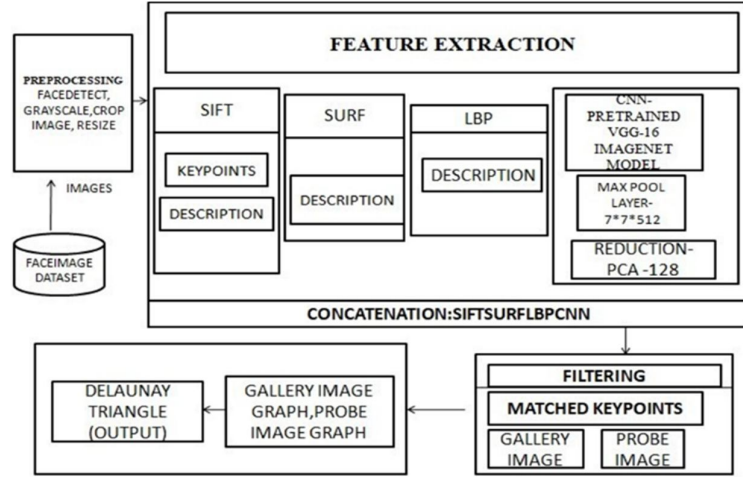


Figure 1. Flow Diagram

The flow diagram in Figure 1 shows the overall architecture of constructing a Delaunay triangle for graph matching for face recognition.

A. Algorithm: Sift Surf Lbp

```

//detect keypoints
For all pixels p in image
{
  If (is key point(p)) Keypoint_list.add (p);
}
For all pixels kp in keypoint_list
{
  Sift and surf Extract features(kp)
}
//extract local binary patterns
For all keypoint in keypoints(list)
{
  Consider 8*8 region
  Lbp extract features () region, p=8, r=1)
  Lbp extract features () region, p=8, r=2)
  Lbp extract features () region, p=16, r=2)

```

```

    Lbp extract features () region, p=16, r=3)
  }
  //extract VGG 16
  For all key point in key points(list)
  {
    Consider 8*8 region
    Extract CNN features (in max pool layer)
    Reduce dimension using PCA (128)
    Concatenate siftsurflbpcnn
  }

```

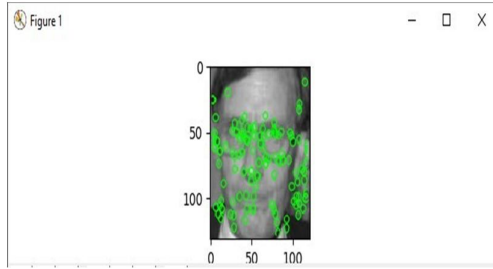


Fig 2. The SIFT detected keypoints in full image

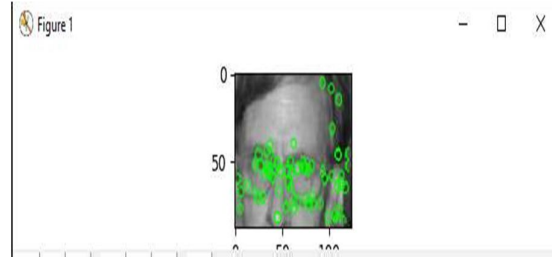


Fig 3. The SIFT detected keypoints in partial image

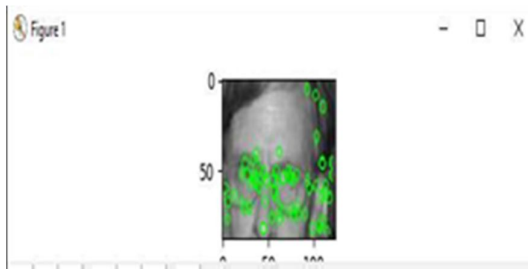


Fig4 Results of Delaunay triangles from the LFW dataset

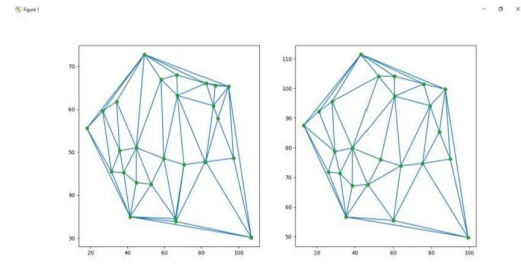


Figure 2, 3 and 4 shows the SIFT detected keypoints in full image, partial image and Delaunay triangles from the LFW dataset respectively.

IV. EXPERIMENTAL EVALUATION

To evaluate the performance of the system. Each algorithm is separately evaluated Overall results shows that siftsurflbpcnn gives the best performance.

A. Comparison of siftsurflbpcnn (matching features) in gaussian median filters

TABLE 1. COMPARISON OF SIFTSURFLBPCNN (MATCHING FEATURES) IN GAUSSIAN MEDIAN FILTERS

ALGORITHM	SIFT	SURF	LBP	CNN	SSLC
GASSUSIAN	1	4	1	4	13
MEDIAN	1	9	2	18	11

B. Comparison of SIFTSURFLBPCNN (timecost) in gaussian median filters

TABLE II. COMPARISON OF SIFTSURFLBPCNN (TIMECOST) IN GAUSSIAN MEDIAN FILTERS

ALGORITHM	SIFT	SURF	LBP	CNN	SSLC
GASSUSIAN	0.03	0.4	0.09	17.1	13.2SEC
MEDIAN	11	0.2	0.4	0.09	31SEC

C. Performance of rotating images 90/180 degrees matching features and timecost

TABLE II. PERFORMANCE OF ROTATING IMAGES

ALGORITHM	SIFT	SURF	LBP	CNN	SSLC
90DEGREE	19	13	1	14	19
180DEGREE	34	18	3	13	33
ALGORITHM	SIFT	SURF	LBP	CNN	SSLC
90DEGREE-TIMECOST	0.4	0.4	1	50	51
180DEGREE-TIMECOST	0.6	0.4	0.2	109	106

D. Comparison of sift, surf, lbp, cnn, siftsurfllbpcnn / blurimage gaussian filters

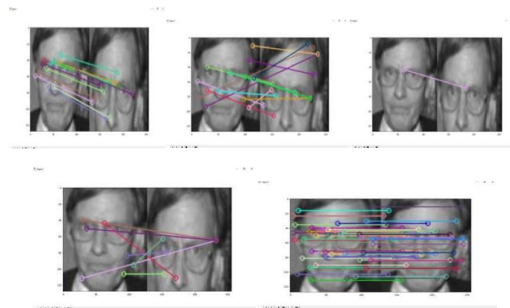


Fig 5 the results of SIFT, SURF, LBP, CNN, SIFTSURFLBPCNN

V. CONCLUSION

SIFT, SURF, LBP, CNN all these algorithms are robust methods to find the feature detection. The major drawback is each algorithm uses only particular features for matching the holistic face image and partial image, it results in many features being unmatched. To get accurate matching results since we use the combination of SIFT SURF LBP CNN Algorithms. Thus gaining advantages of the features matching is obtained. Direct matching of all the key points suffers from high computational cost, so by using the Lowes matching method the Candidate key points are filtered out. Delaunay triangles are constructed. For further extending the application of proposed techniques more accurate matching results can be produced by comparing the Delaunay structures.

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