# Efficient Fuzzy Set Theoretic Approach to Image Corner Matching

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***Abstract***— Corner matching in digital images is a key step in several applications in computer vision such as motion estimation, object recognition and localization, 3D reconstruction etc. Accuracy and reliability of corner matching algorithms are two important criteria. In this paper, corner correspondence between two images is established in the presence of intensity variations, inherent noise and motion blur using a fuzzy set theoretic similarity measure. The proposed matching algorithm needs to extract set of corner points as candidates from both the frames. Fuzzy set theoretic similarity measure is used here as fuzzy logic is a powerful tool which is able to deal with ambiguous data. Experimental results conducted with the help of various test images show that the proposed approach is superior compared existing corner matching algorithms (conventional and recent) considered in this paper under non-ideal conditions.

***Keywords****- Corner Detection, Corner Matching, Intensity Variation, Fuzzy Similarity Measure, Precision-Recall*

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## I. INTRODUCTION

Matching corners from a pair of views imaging the same scene is an important step in many computer vision applications including discrete motion estimation, object recognition and localization, image registration etc. and has been studied extensively for decades. Corners are those image points which show a big 2D-intensity change with a two dimensional structure providing the most valuable information about image motion. A matching procedure should be followed after the extraction of any local features from an object in order to identify and locate the object. When corner points are detected for the purpose of matching, the key requirement of the detector is its stability: in different views of the same scene, the detector should be able to extract the same points, despite the variations due to a change in perspective or lighting conditions. The matching process is an ill-posed problem as there will be some corners which cannot be matched, and there are also likely to be several candidate matches for some corners which are very similar. The problem is how to automatically estimate image feature correspondences between two or more images, while at the same time not assigning matches incorrectly.

There exist a significant number of approaches proposed to address the theoretical and applied issues of correspondence problem of which two approaches are more popular. One is based on some similarity or dissimilarity measures and the other uses the feature point properties. Some approaches require that the corners in a pair have similar shapes. Some matching approaches proposed must extract independently two sets of candidates from two consecutive frames, respectively. Obviously, the total time for matching process includes the cost of extracting two sets of candidates.

The remainder of this paper is structured as follows. Section 2 deals with a brief literature review, similarity measures and performance metrics that are generally used for the correspondence problem. The proposed approach for corner matching is discussed in section 3. In section 4, the superiority of the proposed approach over the other corner matching approaches are discussed with the help of experimental results. Finally, the conclusion is made in section 5.

## II. RELATED WORK

### A. *Literature Review*

Most of the approaches found in the literature solving the correspondence problem assumed that the camera displacement and the change in camera orientation between images are small. Therefore, pixels lying within small rectangular image windows (templates) centred on corresponding corners should have similar intensities and their disparities could be well approximated by the same 2D translation. Typically, different approaches use several metrics such as standard intensity cross-correlation, normalized cross-correlation and sum of squared intensity differences. The similarity values are evaluated to find potential pair matches and actual matches are found using various schemes that involve more global criteria.

Horaud and Skordas [1] used maximal cliques in a relational graph. They extracted local image structures and matched similar such structures between two images. They proposed an algorithm using straight lines and their relationships with their specific relationships. The author was able to match corners for discontinuity edges. Zhang [2] presented an iterative algorithm for image matching. The author defined a measure of matching support to allow less contribution and higher tolerance of deformation with respect to affine transformations from distant matches than from nearby ones. The algorithm was able to select only those matches having both high matching support and low matching ambiguity. The algorithm worked well in a scene with many repetitive patterns and also for image pairs with different types of scenes. Pilu [3] applied Singular Value Decomposition of a proximity matrix for matching point features across pairs of images. The algorithm did not require any specific threshold for a feature pair to be accepted. Smith et al. [4] evaluated different matching metrics and studied the effect of matching using sub-pixel information. They introduced a “Median Flow

Filter" technique in their proposed algorithm which was simple and efficient, and did not rely on any application-specific constraints. The authors also derived thresholds from the expected variance in corner location and the motion application. It detected a large number of the possible matches correctly with only a small number of outliers. Baumberg [5] presented an image feature matching that was robust to local affine distortions corresponding to the same physical point on an object seen from two arbitrary viewpoints. The algorithm required no prior knowledge about the relative camera positions and orientations. The number of false matches was reduced at the expense of total number of matches. Hansen and Morse [6] employed correlation of scale traces through multi-resolution images to find corner correspondence. Zhou et al. [7] proposed an improved SUSAN (smallest univalue segment assimilating nucleus) corner detection algorithm. They also provided an algorithm to establish corner correspondence between two images based on Delaunay triangulation. They constructed Delaunay triangulations among corners of each image and computed interior angles of the triangles to establish corner correspondences. The algorithm was not affected by scale change, less affected by rotation and translation to some extent. At the matching stage, the most similar triangle pairs were obtained first, and then extended their edges circularly until all matching corners were triangulated and mismatching corners were discarded. Lee et al. [8] developed a corner matching algorithm with uncertainty handling capability. The model was formed using available information from a corner detector to minimize the amount of calculation. The uncertainties in information due to discretization noise and geometric distortion were represented by fuzzy rule base. The algorithm extracted a matched segment list from fuzzy inference procedure and resulted segment list was used to calculate the transformation between object of model and scene. Lourakis et al. [9] proposed a fully automatic method for matching image features between two stereo pairs which exploited geometric constraints arising from the structure of a scene. Alkaabi and Deravi [10] proposed a rapid and automatic iterative corner extraction and matching for 2D mosaic construction. The algorithm combined corner extraction, matching, and transformation parameters estimation into an iterative scheme. Seo et al. [11] presented the automatic relative orientation technique with a corner matching. They used a hierarchical feature extraction to detect overlapped regions between two stereo images which were matched and filtered through the vector filtering process. Dutta et al [12, 14, 15] applied fuzzy similarity measure based approaches for finding corner correspondences between a pair of images of the same scene. Kar et al [13] suggested a fuzzy relation based similarity measure for corner matching.

### B. *Similarity Measures*

In order to match corners between images, a small region of pixels is taken around the detected corner and is compared with a similar region around each of the candidate corners in the other image. The comparison generates a score which is a measure of similarity/dissimilarity. The match is assigned to the corner with the highest/lowest matching score. The common similarity measures found in the literature are sum of absolute differences, sum of squared differences, zero-mean cross correlation coefficient etc. Moreover, in their work on corner matching, Lourakis et al. [16] used normalized mutual information (NMI) measure proposed by Studholme et al. [17] which is to be maximized to good matches defined below.

$$NMI(A,B) = \frac{H(A)+H(B)}{H(A,B)}$$

where H(A) and H(B) are the marginal entropies derived from the probability distribution functions corresponding to A and B; and H(A, B) is the joint entropy derived from the joint distribution function of A and B.

### C. *Performance Metrics*

In order to measure the effectiveness of the proposed approach, two popular performance measures, Precision (P) and Recall (R), are used in this paper based on the number of correct matches and the number of false matches obtained for an image pair representing the same scene.

$$P = \frac{CM}{CM + MM}$$

$$R = \frac{CM}{CM + FM}$$

where CM, MM and FM denote number of correct matches, missed matches and false matches respectively. The values of the measures should be close to 1 for a good corner matching.

## III. PROPOSED ALGORITHM

In every phase of computer vision, there are various sources of uncertainty such as additive and non-additive noise of various sorts and distributions in the sensing and transmission processes, vagueness in class definitions, imprecisions in computations etc. Probability theory was the major mathematical model for dealing with uncertainty problems in computer vision applications. But the recent advancement of fuzzy set theory has gained popularity in modeling and propagating uncertainty in computer vision applications. The similarity/dissimilarity measures discussed in the previous section depend upon the absolute value of all intensities in windows and hence, they fail to properly establish the correspondence in the presence of varying light as well as noise in the images. In this paper, a fuzzy similarity measure is used to establish corner correspondence between images.

### A. *Fuzzy Similarity Measure*

In the literature, many fuzzy similarity/distance measures were proposed [18, 19, 20, 21, 22] to compare objects, such as images, based on proximity measures, operations on fuzzy sets etc. Wang et al. [19] provided a comparative study on different fuzzy similarity measures. The properties of these measures are still not common for all proposed measures. The fuzzy similarity measure in [21] was applied to handwritten Arabic sentences recognition. In this paper, a similarity measure proposed in [22] is used which is specific to image processing applications. The measure S(A, B) used here is defined as:

$$S(A,B) = 1 - \frac{1}{2\ln 2}\sum_{i=1}^{n}\left(\left(\mu_A{}^i - \mu_B{}^i\right)\ln\frac{1+\mu_A{}^i}{1+\mu_B{}^i} + \left(\mu_B{}^i - \mu_A{}^i\right)\ln\frac{2-\mu_A{}^i}{2-\mu_B{}^i}\right)$$

where $\mu_A$ and $\mu_B$ denote fuzzy membership values corresponding to the crisp sets A and B, respectively. The value of S(A, B) ranges from 0 to 1. The higher value of the measure S(A, B) indicates the better correspondences between the images A and B.

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### B. *Algorithm*

In order to match corners between images properly, the basic requirement is to extract corners accurately from the images. Dutta et al [23] provided a detailed comparative study on existing popular corner detection algorithms in the literature and concluded that the algorithm proposed by Alkaabi and Deravi [24] performed better than the other algorithms under consideration in terms of accuracy, stability and computational time. In this paper, [24] is used to detect corners in images.

The algorithm given below establishes the correspondence between two images in the presence of varying illumination and noise in images sequence using fuzzy similarity measure. The intensity data in the left and right windows are fuzzified using Gaussian membership function. The reason for using Gaussian membership function for fuzzification is to eliminate the effects of intensity variation present in the images. The steps of the algorithm are as follows:

1. Corners are detected from both the images using any standard corner detector. The matching is limited to $(x_0; y_0)$ where $x - M \leq x_0 \leq x + M; y - M \leq y_0 \leq y + M$, where $(x; y)$ are the coordinates of the corner in the left image. $(x_0; y_0)$ are the coordinates of the corner in the right image.
2. Both left and right images are fuzzified using Gaussian membership function.
3. For each corner (x, y) in the left image, repeat steps 4 to 6.
4. A (2M + 1) X (2M + 1) window around the point with coordinates (x, y) in the right image is selected and the existence of corners in that window is examined.
5. If corners exist within the window, then a stationary window of size N X N, around the corner $(x; y)$ in the left image and around the corners $(x_0; y_0)$ within the window in the right image are defined. A and B are the matrices of size N X N with intensity values around $(x; y)$ and $(x_0; y_0)$ respectively. Corners are the central pixels within the windows.
6. For each window A in the left image, the best possible matched window B in the right image is obtained using the similarity measure S(A, B) given in previous subsection and the central points in each of these two windows are considered to be the candidates for the matched corners.

The values for M and N are selected in such a way that the best experimental results are obtained. If the movement of the objects in the images is more, then higher values of M and N are selected.

## IV. Results and Discussion

In order to demonstrate the effectiveness of the proposed approach, experiments are conducted on a number of test images. But for the sake of this paper, only a set of four real images such as Building, Indoor scene, House and Road scene (Figure 1). In each of the images of Figure 1, the brightness of the images is artificially reduced, motion blur (horizontal and vertical) is added, Gaussian noise is introduced and small rotation and translation is applied. In order to explain the improvement of the proposed algorithm, the comparison is preformed over two standard algorithms for corner matching proposed by Alkaabi and Deravi [10] and Laurakis et al. [14] with respect to two performance measures, precision and recall, discussed in section IIC under different conditions. The results are shown in Figure 2 and 3.

Figure 1: Representative Test Images

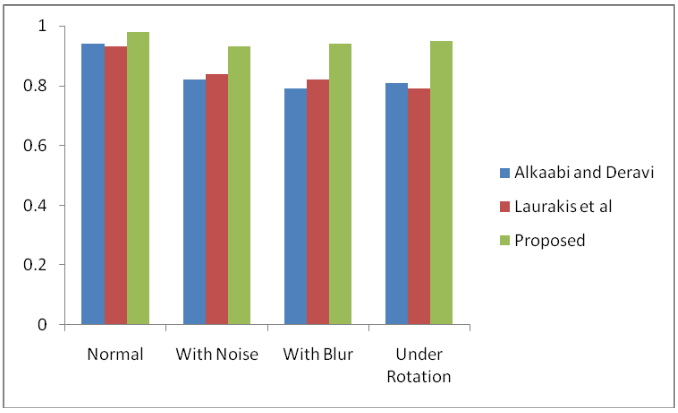


Figure 2: Improvement with respect to precision

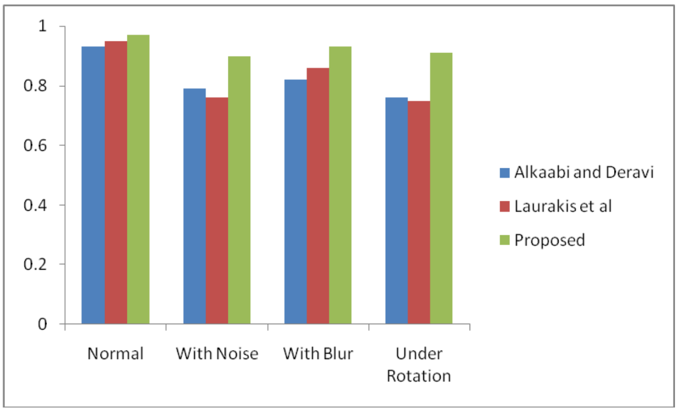


Figure 3: Improvement with respect to recall

From the figures (Figure 2 and 3), it is observed that when the comparison is performed normal lighting conditions, the performance of the proposed algorithm is almost similar (slightly better) compared to two other algorithms. But whenever noise, motion blur and/or small rotation or translation is added to the images, then the improvements of the proposed approach becomes more significant compared to other algorithms under consideration.

## V. Conclusions

Corner matching in image sequences is of fundamental importance in several important applications of stereo vision. In this paper, a corner matching algorithm based on fuzzy similarity measure is presented. Here after detecting corners from the images, the intensity values within the windows of the left and the right images are fuzzified using Gaussian membership function with the mean and the standard deviation of the intensity data of the respective windows to eliminate the effect of intensity variations between windows. The proposed algorithm is successful to match corners between two images of the same scene, even in the presence of intensity variation in corresponding windows as well as noise. The algorithm is also able to detect corners under geometrical transformations such as translation and rotation. Presently, work is going on so that corners can be matching under scaling also.

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