A NEW METHOD FOR EDGE FEATURE DETECTION AND MATCHING WITH AN INTRODUCTION TO EDGE PYRAMID

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ABSTRACT

Image feature detection and matching is a fundamental task in image processing and machine vision. In this paper we present novel methods for feature detection and matching. We have used edge points and their accumulated curvature information for feature detection. The detected features are then matched using a new method called fuzzy-edge based feature matching. To increase the speed of matching algorithms, a new multi-resolution based method and edge pyramid are proposed. Experimental results have shown that the algorithms are fast and reliable and can be used in the environments with noise and illumination change. The proposed algorithms can be used in various machine vision applications such as target tracking, image registration and stereovision.

1. INTRODUCTION

One of the most important tasks in machine vision applications is the generation of image descriptors, which are more useful than the description of image with image pixels. The aim of these descriptors is to reduce the computation overhead of the machine vision algorithms by changing the large set of pixels to lists of features, which are more manageable and applicable for higher-level processes. Applications of the feature detection algorithms are numerous and they span a wide range of usages including image registration, stereovision, pattern recognition and moving target tracking, to name a few. The main purpose of feature detection algorithms in applications like target tracking, stereovision and image registration is to find corresponding points for features in different images. The use of features in these applications has two main advantages. First, since the matching process is carried out in the number of feature points, the computation overhead of the algorithm largely decreases. Second, because a feature is an image property, which image correspondence can be performed more accurately, therefore, the overall accuracy of the algorithm is improved.

There are many difficulties with feature detection and matching algorithms including the noise of image, change of scene illumination, change in objects geometry and real-time constraint, to mention a few.

Various methods have been proposed for feature extraction, such as edges [1], lines [2], corners and also regions. Among these methods corners are more popular and robust and variety of algorithms have been proposed to extract corners such as Moravec operator [3], Plessey algorithm [4], SUSAN[1] corner detector [5] and CSS[2][6].

After the features such as corners are detected in the image, in the most of the applications it is also necessary to find the matching points in the second image. For example by finding the matching points in tracking algorithms the motion vectors or motion models between two consecutive frames are calculated.

A large variety of methods have been proposed for the task of feature matching. Among these methods, similarity measure is one of the powerful tools for feature matching [7,8]. Normalized cross correlation and SSD

[1] Smallest univalue segment assimilating nucleus

[2] Curvature scale space

(sum squared difference) are well-known methods to measure similarity between two regions. Another strategy to find match points is the use of corners attributes. For example in [9] the corner brightness and the x and y components of the position of USAN center of gravity are used for matching purpose. To increase the robustness of matching algorithms, other application dependent constraints, such as target motion information in tracking applications or epipolar constraints in stereovision may be used in companion with matching algorithms.

In this paper we propose new methods for image features detection and matching. To make the algorithms robust against noise and illumination variations, we used edge points and their accumulated curvatures. We also propose methods to increase the speed of matching algorithm and also subpixel matching.

This paper is organized as follows. In the next section our feature detection algorithm is explained. In section 3 the fuzzy-edge based matching procedure is discussed. Section 4 describes the method for increasing the speed of matching process and the concept of edge pyramid. Experimental results are shown in section 5 and conclusion appears in section 6.

2. EDGE FEATURE DETECTION

As mentioned before, noise and change in illumination of the images are some of the factors that may deteriorate the performance of feature matching algorithms. In order to deal with these difficulties, it is necessary that both feature detection and feature matching algorithms have less sensitivity to the presence of noise and illumination change. Edge points are proper features of image, which have less sensitivity to the image noise and illumination variance. However when the edge points are in the form of straight lines or lines with lower curvature, the corresponding points can not be determined precisely, which is called aperture problem. To solve aperture problem and determine the precise position of corresponding points, image locations should be selected as edge features, which have enough information for matching process. The CSS corner detector is a suitable corner detector, which extracts the corners of image from the contours of edge-detected image. The detector uses the edge junctions and edge curvature, which are good features for edge matching, however the curvature of only one contour is considered. To detect more appropriate edge features, we have developed an edge feature detector algorithm, which considers the accumulated curvature of edge pixels in the match window. The algorithm also considers the number of edge pixels in the match window, which is another useful factor for correct edge matching. Our algorithm consists of following steps:

- ❑ Extract the edge contours from the input image using any good edge detector such as Canny.
- ❑ Fill small gaps in edge contours. When the gap forms a T-junction, mark it as a T-corner.
- ❑ Calculate the curvature of Gaussian smoothed edge pixels. In our algorithm it is not necessary to calculate the curvature at different scales. To calculate the curvature for edge pixels, edge contours are represented as parametric vector $r(u) = (x(u), y(u))$. Then the curvature is calculated using the following equation [6]:

$$\kappa(u,\sigma) = \frac{X_u(u,\sigma)Y_{uu}(u,\sigma) - X_{uu}(u,\sigma)Y_u(u,\sigma)}{(X_u(u,\sigma)^2 + Y_u(u,\sigma)^2)^{3/2}} \quad (1)$$

- ❑ Find the minimum and average of the absolute curvature values in the image and denote them as $\kappa_{\min}, \kappa_{ave}$.
- ❑ Assign the value of 0 to non-edge pixels and the value of $|\kappa(u,\sigma)| + \alpha\kappa_{ave} + (1-\alpha)\kappa_{\min}$ to edge pixels. Where α is a small positive number (typically $\alpha = 0.1$) and the constant term $\alpha\kappa_{ave} + (1-\alpha)\kappa_{\min}$, which is added to all edge pixels, aims to consider the density of edge pixels in the detection of proper edge features. Here $|\kappa(u,\sigma)|$ denotes absolute value of $\kappa(u,\sigma)$.
- ❑ Scan the image and calculate the accumulated curvature for each pixel. The accumulated curvature is the sum of assigned values in the previous step and summation is carried out in the small windows centered on pixels.
- ❑ Find local maximums of accumulated curvature values and apply a threshold to suppress weak features.

3. FUZZY-EDGE BASED FEATURE MATCHING

When the feature points are detected, the second step is to find the corresponding points of features in the second image. In addition to noise and illumination change of the scene, change in geometry and size of objects in the two images being matched are other factors, which might deteriorate the efficiency of the matching process. Therefore the direct matching of edge pixels, such as edge correlation is not a proper method to find corresponding points in these applications. To alleviate this problem, we have utilized a new edge matching method, which is called fuzzy-edge based feature matching. In this method edge pixels are described as fuzzy values, which are called fuzzy-edges. To describe edge points as fuzzy values, we assign the value of 1 to edge points and a value between 0 and 1 to the points that are in the neighborhood of the edge points. This value is determined based on the distance from the edge points and the fuzzy membership function, which is used for this purpose. Different membership functions [10] such as triangular and trapezoid can be used for the construction of fuzzy-edges. Since a point may take different fuzzy values from its neighborhoods, the maximum of assigned

fuzzy values is considered as a final value. When the fuzzy edges are obtained for both images being matched, SSD or normalized correlation method is used to locate the corresponding points of features in the second image.
In some applications it is also required to calculate the corresponding points with sub-pixel accuracy. Since our method is a kind of area-based matching, it is possible to calculate the sub-pixel corresponding points using parabola fitting. In our implementation we used least square parabola fitting on similarity profile in the neighborhood of the optimum value to identify the sub-pixel peak location and calculate the sub-pixel corresponding point. To reduce the computational overhead of the fitting process, two one-dimensional parabola fitting for x and y directions are used.

4. INCREASING THE SPEED OF THE MATCHING ALGORITHM USING EDGE PYRAMID

In the case large disparities, the search space for finding match points is large and this makes the computation overhead of the algorithm largely increase. Multi-resolution feature matching is one of the mostly used methods to overcome the problem of large disparities. In multi-resolution matching, different levels of resolution of the image are created and the match is usually applied in the highest level and then propagated to lowest levels. Since the disparities become small at high levels, this method considerably reduces the computational overhead of matching algorithm. Our fuzzy-edge based matching algorithm can also benefit from using multi-resolution method. Our algorithm for multi-resolution feature matching has the following steps:

- Build edge pyramids of images. The algorithm to construct edge pyramid is explained bellow.
- Perform matching at lowest resolution.
- Propagate matches down to next higher resolution.
- Correct match estimates and continue to next level.

Suppose the edge detected image g_0 is represented initially by the array of edge contours:

$$r_{0n}(u) = (x_{0n}(u), y_{0n}(u)) \quad n = 1:N \tag{2}$$

where N is the number of edge contours in the image. Also suppose that the image contains C columns and R rows of pixels. This image becomes the bottom or zero level of the edge pyramid. Pyramid level 1 image g_0, which contains $C/2$ columns and $R/2$ rows of pixels, are represented by:

$$r_{1n}(u) = (x_{1n}(u), y_{1n}(u)) \quad n = 1:N \tag{3}$$

where $r_{1n}(u)$ are reduced and low-pass filtered versions of $r_{0n}(u)$ and are calculated as follows:

$$X_{0n}(u,\sigma) = x_{0n}(u) * g(u,\sigma) \tag{4}$$

$$Y_{0n}(u,\sigma) = y_{0n}(u) * g(u,\sigma) \tag{5}$$

$$R_{0n}(u,\sigma) = (X_{0n}(u,\sigma), X_{0n}(u,\sigma)) \tag{6}$$

$$r_{1n}(u) = R_{0n}(2u,\sigma)/2 \tag{7}$$

where $g(u,\sigma)$ denotes a Gaussian function of width σ and $*$ represents one-dimensional convolution.
The pyramid level 2 image, is then obtained from image level 1 by applying the same algorithm described above. The algorithm is repeated to build all levels of edge pyramid.

5. EXPERIMENTAL RESULTS

The proposed algorithms have been implemented on a Pentium III 500Mhz under Windows 98 operating system using a Visual C++ program. We have tested the algorithms with different images including both simulated and actual sequences of images. To compare the efficiency of the different matching algorithms, matching percentage (*MP*) is calculated where this percentage is given by [9]:

$$MP = \frac{(number of\ correct matches - number of\ incorrect matches)}{maximum\ possible number of\ correct\ matches} \tag{8}$$

Figure 1 shows two image sequences, which are used for testing the proposed algorithms. The rectangular area with inverted color shows the region, which is used for testing the algorithms. Table 1 shows the average matching percentage for 200 frames of the image sequences of figure 1. The results of three matching algorithms are shown in this table, which are: 1- the proposed edge based feature detection and matching algorithms 2- SUSAN corner detector and correlation based feature matching 3- matching using SUSAN corners properties [9]. As it is shown in this table the proposed algorithm has the best results. Table 2 shows the average matching percentage for the image sequences of figure 1 with additive Gaussian noise of 10dB. In table 3 the results of different matching algorithms are shown for image sequences of figure 1 with addition of illumination change. To generate images with illumination change, the following equation is used:

$$I_{ill}(x,y) = (ax + by + c)I(x,y) + (dx + ey + c) \tag{9}$$

where $I(x,y)$ are input images, *a,b,c,d,e,f* are random numbers, which are selected differently for each frame and $I_{ill}(x,y)$ are the images with illumination changes.
One of the most important properties of the feature detection algorithms is the stability of feature detection algorithm against noise. Table 4 shows the stability of different feature detection algorithms for Gaussian noise of 10dB. To calculate the stability of different algorithms we used the following equation:

$$Stability = \frac{2(C - NC)}{N_1 + N_2} \tag{16}$$

where N_1 and N_2 are the total number of detected features in noiseless and noisy images respectively, C is the number of common feature, which are detected in both noiseless and noisy images and NC is the number of features which are detected in noiseless image, however not detected in noisy images. As it is shown in table 4, our feature detection method has a good stability compared to other methods. Also the comparison of our fuzzy-edge based method with edge correlation showed that fuzzy-edge based method enhances the average matching percentage up to 15.

(a) (b)

Figure 1: Image sequences which are used for the testing of the algorithms (a) Patrol image sequence (b) Car image sequence.

Table 1: Average matching percentage for image sequences of figure 1.

Method / Image	Correlation	Corners properties	Our method
Car	68.72	53.48	86.21
Patrol	92.05	63.46	95.51

Table 2: Average matching percentage for image sequences of figure 1 with Gaussian noise 10dB.

Method / Image	Correlation	Corners properties	Our method
Car	45.13	-15.38	70.02
Patrol	82.35	5.56	87.67

Table 3: Average matching percentage for image sequences of figure 1 with illumination change addition.

Method / Image	Correlation	Corners properties	Our method
Car	64.97	32.37	71.49
Patrol	86.5	47.78	82.45

Table 4:Stability of various feature detection algorithms for Gaussian noise of 10dB.

Method / Image	SUSAN	Moravec	Plessey	CSS	Our Method
Cameraman	0.11	0.05	0.2	0.29	0.44
Lena	0.12	0.04	0.19	0.25	0.32
Car	0.12	0.06	0.25	0.04	0.21
Patrol	0.14	0.02	0.22	0.08	0.27

We also tested the proposed algorithms with other image sequences. Results showed the accuracy of the proposed algorithms. Comparison of results generated by the proposed methods with those of other methods showed that more reliable results could be obtained with the aids of the proposed methods.

6. CONCLUSION

In this paper, new methods for detection and matching of edge features were presented. To detect features, we considered edge points and their accumulated curvatures. When the edge features are detected, they are matched with points in the second image using fuzzy-edge based feature matching. To increase the speed of matching algorithms we proposed a new multi-resolution based algorithm, which utilizes edge pyramids. The comparison of the results with those of other methods has shown that more reliable results can be obtained with the aids of proposed methods. The proposed methods also have good results in the case of noisy images or images with illumination change. The proposed algorithms can be used in various machine vision applications such as target tracking, stereovision and image registration.

7. REFERENCES

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