Effective Scene Matching For Intelligent Video Surveillance

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ABSTRACT

This paper proposes a novel method on scene matching which aims to detect the unauthorized change of the camera’s field of view (FOV) automatically. The problem is substantially difficult due to mixed representation of FOV change and scene content variation in actual situation. In this work, a local viewpoint-invariant descriptor is firstly proposed to measure the appearance similarity of the captured scenes. And then the structural similarity constraint is adopted to further distinguish whether the current scene remains despite the content change in the scene. Experimental results demonstrate that the proposed method works well in existence of viewpoint change, partial occlusion and structural similarities in real environment. The proposed scheme has been proved to be practically applicable and reliable by its use in an actual intelligent surveillance system.

Keywords: Scene matching, Local descriptor, Structural constraint

1. INTRODUCTION

One basic requirement for the video surveillance systems is to ensure that the cameras observe desired locations. However, this condition is often violated for various reasons, for example, incorrect camera setting by an operator or unauthorized operations from outside. Because places to be monitored are usually critical in the applied field of a surveillance system, it is very important to keep the administrator notified once monitored areas are altered without a permit. Although some camera platforms are able to return to the designated area, it is still a challenging problem to detect a deviated camera from thousands of candidates. Therefore, there is an urgent need of automatic and efficient method of FOV change detection. A novel scene matching method based on SURF features and Delaunay triangulation is proposed to solve the challenges in large-scale video surveillance systems.

Three main issues are to be solved in scene matching. Firstly, varieties of scene contents require robust and unified descriptor of environments. Secondly, real environments usually contain rapid background change and occlusions such as vehicles and pedestrians. Thirdly, there are large amounts of locations needing to be processed in large-scale video surveillance systems, so the algorithm is supposed to be efficient.

The most common scene matching method currently is the normal cross-correlation method based on mask operation, that is, the normal cross-correlation between two images is computed on each location, and the location corresponding to the maximum correlation is chosen as the matched location. The simplicity makes the method can be easily implemented through parallelism, pipelining, and even hardware\cite{1}, however, the underlying matching criterion makes it unable to handle more complicated geometric deformations between images.

Global image features such as color histograms or texture features have limited utility in these real-world scenarios, and often cannot give adequate descriptions of an image’s local structures and discriminating features. In recent years, researchers have turned to use local invariant features such as Harris and SIFT\cite{2} to realize scene matching\cite{3} since they are robust to common geometric, photometric changes and partial occlusions. The SIFT descriptor has been proved to be superior to many other descriptors\cite{4} such as the distribution-based shape context\cite{5}, the geometric histogram descriptors\cite{6}, and the moment invariants\cite{7}. A number of SIFT descriptor variants and extensions, including PCA (Principal Components Analysis) SIFT\cite{8} and SURF (speeded up robust features)\cite{9} have been developed ever since.

Based on previous works, we propose a method by combining local image features with structure similarity constraints to realize the scene matching. Firstly, the SURF descriptors are extracted in the base image and the real-time image respectively. Secondly, the FANN (Fast Approximate Nearest Neighbors) and the Delaunay triangulation are used to realize the coarse-to-fine matching of key points. Finally, the similarity function is utilized to search for matching
triangular descriptors from Delaunay triangles with similarity value larger than the threshold $\mu$. These triangular descriptors, which are considered to be invariant to translation, scaling and rotation, are the precise descriptions of the scene. If the triangular descriptors are extracted successfully from the base image and the real-time image, the corresponding scenes can be regarded as matched. Fig. 1 is a summary of the proposed algorithm.

Figure 1. Flow chart of the algorithm

**2. DESCRIPTION OF SURF KEY POINT**

The major process of SURF algorithm is similar to SIFT algorithm, but it is much more efficient due to a new feature extracting strategy. The SURF detector is based on the determinant of the Hessian matrix because of its good performance in computation time and accuracy [9]. Given a point $X = (x,y)$ in an image $I$, its Hessian matrix at scales is defined as

$$H(X, \sigma) = \begin{pmatrix} L_{xx}(X, \sigma) & L_{xy}(X, \sigma) \\ L_{yx}(X, \sigma) & L_{yy}(X, \sigma) \end{pmatrix}$$

(1)

Where $L_{xx}(X, \sigma)$ represents the convolution of the Gaussian second order derivative with the image $I(x,y)$ at point $X$, and similarly for $L_{xy}(X, \sigma)$ and $L_{yy}(X, \sigma)$.

The box filter is an approximation for Gaussian second order derivative in SURF algorithm [9], through which the computational burden can be decreased greatly. The convolution of each box filter and the image can be denoted by $D_{xx}$, $D_{yy}$ and $D_{xy}$ respectively, therefore:

$$\det(H_{\text{approx}}) = D_{xx} D_{yy} - (0.9 D_{xy})^2$$

(2)

After the approximated determinant of the Hessian matrix at each scale is calculated, the non-maximum suppression in a $3 \times 3 \times 3$ neighborhood is applied to find the maxima. The stable location of SURF key point and the value of located scale can be obtained through the interpolation in both scale space and image space.

The Haar wavelet responses are calculated in both horizontal and vertical direction within a circular neighborhood of radius $6s$ around the key point. Here, $s$ is the scale at which the key point was detected. The responses are represented as points in a space with the horizontal response strength along the abscissa and the vertical response strength along the ordinate. The sum of the horizontal and vertical responses within a sliding orientation window of size 60° is calculated to yield a local orientation vector, and the longest vector over all windows defines the dominant orientation of the key point.

A 20 $\times$ 20 square region centered the key point and oriented along the dominant orientation is constructed and divided into 4 $\times$ 4 sub-regions. In each sub-region, the horizontal and vertical Haar wavelet response $dx$ and $dy$ are computed and summed up. In addition, the absolute values of the responses are also calculated and summed up. Then a 4-D feature $V = (\sum dx, \sum dy, \sum |dx|, \sum |dy|)$ is formed for each sub-region. Therefore, for each extracted SURF key point, a 4 $\times$ (4 $\times$ 4) description vector can be constructed.

**3. MATCHING OF SCENES**

After the SURF key points are detected and described in both the base image and the real-time image respectively, the coarse-to-fine matching is implemented. If there are matched triangular descriptors in base image and real-time image, the corresponding scenes can be regarded as matched.
3.1 Coarse Match based on Fast Approximate Nearest Neighbors

For many computer vision problems, the most time consuming component consists of nearest neighbor matching in high-dimensional spaces. There are no exact algorithms for solving these high-dimensional problems that are faster than linear search. (Fast Approximate Nearest Neighbors) FANN [10] are known to provide large speedups with only minor loss in accuracy, which is very suitable for our efficiency needs.

3.2 Fine Match based on Delaunay Triangulation

3.2.1 The Fuzzy Similarity of Triangulation

Delaunay triangulation is adopted in the procedure of similarity measure, due to the uniqueness of its result which is an important factor in triangles indexing. Furthermore, a circle through the three points of a Delaunay triangle contains no other points, which implies that the insertion of a new point in a Delaunay triangulation affects only the triangle whose circumcircle contains that point. Therefore, the result of Delaunay triangulation would be only affected by the noise locally. Compared to other well known topological structures in a comparison study, the Delaunay triangulation was proved to have the best structural stability under random positional perturbations because of its characteristics mentioned above [11].

In our experiments, we have used the fuzzy similarity of triangulation to evaluate the candidates. The matching criterion for the triangles is defined as follows [12]: set the two triangles are $\triangle ABC$ and $\triangle A'B'C'$, then the similarity of $\triangle A$ and $\triangle A'$ is

$$I_a = \cos^3 \left( \frac{\pi}{2} (1 - d(x)) \right), \quad I = \frac{(I_a + I_b + I_c)}{3}$$

(3)

in which $d(x) = e^{-\frac{1}{2}\phi(x-a)^2}$, $\phi = \frac{aP}{3}$, and we usually set $P$ as 0.5. For a pair of triangles, the corresponding angles' similarity can be calculated by Eq. (3), and $I$ means the three angles have the same effect. Then the candidates of similar triangles are selected by fuzzy similarity value which is greater than a threshold.

3.2.2 Mismatched Triangles Reducing based on Corresponding Edge Constraint

Fuzzy similarity matching is to find those triangles that match the sufficient condition, which includes not only the correct matching of the triangle pairs, but also the false ones, as shown in Fig.2. The reason lies in that the fuzzy similarity only measures the angles of these triangles and ignores the spatial information.

According to the correspondence between matched triangles, the constraints of the corresponding edges vector can be used to avoid wrong matches. The triangles with different spatial information may not be treated as matching when feature points are matched only. Especially for scene matching, it is necessary to avoid entire errors caused by the mismatch of local features, like the situation in Fig.2. In this paper we add constraints of spatial information into the Delaunay triangles by calculating the Euclidean Distance of the corresponding edge vectors (see Fig.3), which avoids occurrence of the errors in Fig.2.

4. EXPERIMENTS

We tested the proposed algorithm under variable situations, including viewpoint change, zooming and the structure similarities, in real scene. Fig.4 shows the match results for different scenes and the statistics are presented in Table 1.
Figure 4. The match results for different scenes. (a) scene matching by SURF and FANN. (b) scene matching by our method

Fig. 4 shows the results of SURF feature matching and our method for the different scenes. The default matched points are lined with different colors in Fig. 4(a). The SURF feature points extracted in the Fig. 4(a) are used for further processing in Fig. 4(b). The triangles drawn in Fig. 4(b) are those reach the threshold (usually 0.75), which measure the similarity of the scenes.

For the significantly different scenes, there are still many matched points in Fig. 4(a). The scenes will be mistakenly regarded as a successful match. This is mainly because SURF uses large numbers of approximates, which affects the accuracy and robustness. The matching triangular network cannot be pictured in Fig. 4(b) when the threshold is 0.75. Here, in order to display effects, μ is set to 0 to draw two similar triangles. Clearly, these two triangles’ similarity is very low, indicating that the scene matching result is correct.

Table 1. Experimental Result

<table>
<thead>
<tr>
<th>Number of samples</th>
<th>Type of FOV change</th>
<th>precision</th>
<th>recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>Viewpoint change</td>
<td>96%</td>
<td>92%</td>
</tr>
<tr>
<td>50</td>
<td>Partial occlusion</td>
<td>96.5%</td>
<td>91%</td>
</tr>
<tr>
<td>50</td>
<td>Zooming</td>
<td>95%</td>
<td>91.5%</td>
</tr>
<tr>
<td>50</td>
<td>Light change</td>
<td>97%</td>
<td>93%</td>
</tr>
</tbody>
</table>

Table 1 shows detailed results of scene matching experiments using 50 images per type. The evaluation measure is the precision-recall. For a given dissimilarity threshold δ, we define the precision and recall for an image I as:

$$
\text{precision} = \frac{N_{RS}}{N_S}, \quad \text{recall} = \frac{N_{RS}}{N_R}
$$

(4)

where $N_S$ is the number of images I whose dissimilarity values with I are smaller than the threshold δ, $N_{RS}$ is the number of relevant images among the $N_S$ images and $N_R$ is the total number of relevant images. We exploit the average of the precisions and recalls for each type of FOV change image as matching performance measure of the scenes. The precisions are all larger than 95% and the recalls are larger than 90%. The statistical results illustrate that our method can obtain good performance for those image pairs with geometric deformation like viewpoint change, partial occlusion, zooming and light change. But with the increase of geometric deformation between the base image and the real-time image, the performance of the proposed algorithm is worse inevitably. However, the necessary scenes are matched through our method.

From an implementation standpoint, the method used in this article only took 1.35 seconds and 1.81 seconds (with a resolution of 480 × 640), which can meet the standard of practical application. The higher matching efficiency demonstrates that, the scene matching based on the SURF feature matching and the Delaunay triangulation is suitable for the preset scene identification in our intelligent video surveillance system (see Fig. 5).
5. CONCLUSION

We develop an effective scene matching method to detect unpredicted alterations of monitoring cameras in an intelligent video surveillance system. The problem is addressed by combining featured-based block matching and structural-based outlier removal. Like the detection of SIFT key point, the detection of SURF key point adopts the similar scale space theory which makes the SURF feature possess excellent scale invariant property. The SURF descriptor shows excellent performance for affine transformations, scale changes, rotation, blur, and illumination changes, etc, which is ideal for the real environment in the video surveillance system. The Delaunay triangulation is used to constraint the SURF descriptors and measure the similarity of two scenes. The proposed method is robust to various image deformations. Besides, low computational cost of the SURF descriptor and Delaunay triangulation makes our approach suitable for processing large amount of data produced by the surveillance system.

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