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DAISY Descriptor Based Automatic Multiple Panorama Generation

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Abstract: Panorama creation is one of the applications of Image Registration. Image Registration is geometrically align two or more images of the same scene taken from different times, depth, view point etc. Existing Image Registration algorithm lack accuracy and perfection and most of them are designed for a particular application only. Multiple image pairs are registered relatively to each other to form a panorama. Even though creation of panorama is common in nowadays, most of the algorithm are focused on a creation of a single panorama. Consider the case if the input database contain images from more than one location, then a separate algorithm is necessary for automatically create multiple panorama, so the process of multiple panorama creation is a challenging issue today. As a solution to these problems, DAISY descriptor based automatic multiple panorama creation algorithm is proposed. A high performance DAISY descriptor is used to detect and extract features from the input images. A clustering algorithm which separates images corresponds to each location according to the image match. Individual group of images are stitched together to form separate panoramas.

Keywords: Image Registration, DAISY descriptor, stitching, feature matching.

1. INTRODUCTION

The procedure of image stitching is an extension of feature based image registration. Image Registration [1] involves the following steps they are feature extraction, feature matching, mapping function building and finally merging or Image Registration. Image Registration is used in computer vision, medical imaging, military automatic target recognition, compiling and analyzing images and data from satellites. Most of the Image Registration algorithms are designed for a particular application only. Image Registration algorithm can be classified in to intensity based and feature based methods [2]. Feature point based methods [3] are preferred over intensity based methods because of its ability to handle complex distortion, illumination changes and less registration time

For an accurate image registration algorithm, the selection of suitable descriptor to detect and extract features from images is also important since only with best match leads to a perfect match. DAISY descriptor [4] is a rich, high performance local descriptor which retains the robustness of SIFT [5] and GLOH [6]. Multiple image pairs are registered relatively to each other to form panorama. In case of panoramic view the FOV is 360° x 180°. Even though creation of panorama is common nowadays most of the algorithm are focused on creation of a single panorama. Consider the case if the input database contain images from more than one location, then the problem become more complex. In this paper discussing an automatic multiple panorama creation algorithm based on DAISY descriptor. After extracting feature points from each images using DAISY descriptor a clustering algorithm is used which separate images corresponds to each location. Finally

individual group of image pairs are stitched iteratively to form separate panoramas.

2. METHODOLOGY

The proposed system of automatic multiple panorama creation consist of various stages such as feature detection, feature matching, clustering, merging and blending. First collect different images from more than one location. Extract features from each images using DAISY descriptor. Randomly select one of the image from input database and find minimum Euclidian distance between the selected image and all other images in the database. Set a threshold value and Euclidian distances less than threshold are considered as inliers i.e. they are considered for matching. So the matched images are move to a stack. Repeat the whole process recursively for each images currently in the stack until all images in the stack have been used. Thus the images currently in the stack are from one location only.

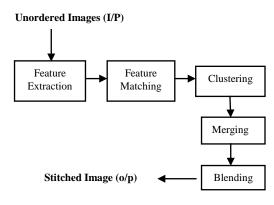


Figure 1: Basic block diagram

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Remove all those images and store all the matched images in to a new directory and the entire process applied recursively until no images are left in the input database. Thus get a number of directories contain images from separate locations. By using homography two images with largest number of key point matches inside each directory are used for stitching. More specifically matched images inside each directory are merged and blended together to get the stitched panoramic view of each location.

2.1 Feature Detection

Features from the input images can be accurately determined using a rich robust descriptor. DAISY descriptor is a local descriptor having improved performance and also suitable for dense computation. DAISY descriptor can be computed quickly at every single image pixel. For every input image compute H number of orientation map $G_{\rm O},\ 1 \le o \le H,$ one for each quantized direction where $Go(u\ ,v\)$ equals the image gradient norm at locations $(u,\ v)$ for directions "o" if it is bigger than zero, else it is equals to zero. This preserves the intensity of the polarity changes. Formally orientation map are written as

$$G_o = (\partial I/\partial o)^+ \tag{1}$$

To obtain convolved orientation map for different sized region, convolve each orientation map several times with Gaussian kernel of different Σ values.

$$G_0^{\Sigma} = G_{\Sigma} * (\partial I/\partial o)^{+}$$
 (2)

Where I is the input image, o is the orientation of the derivative and G_{Σ} is the Gaussian kernel. The Σ values are varied in order to control the size of the aggregation region. Convolution with large Gaussian kernel can be obtained from several consecutive convolution with smaller kernel. This incremental computation flow is shown figure 3.

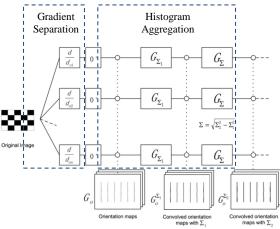


Figure 2: Calculation process of convolved orientation map in DAISY^[4]

Let $h_{\Sigma}(u, v)$ is the vector made of the values at location (u, v) in the orientation map after convolution by a Gaussian kernel of standard deviation Σ .

$$h_{\Sigma}(u, v) = [G_1^{\Sigma}(u, v), \dots, G_H^{\Sigma}(u, v)]^T$$
 (3)

Here $G_1^{\;\Sigma}$, $G_2^{\;\Sigma}$ and $G_H^{\;\;\Sigma}$ denotes the Σ convolved orientation map in different directions. Normalize these vectors to unit norms. The normalization is performed in each histogram independently, this is to represent the pixel near occlusion as correct as possible.

Let Q represents the number of circular ring, then the full DAISY descriptor D(u, v) for location (u, v) is the concatenation of normalized vectors.

$$\begin{split} D(u,\,v) &= \, \big[h^{\tilde{}}_{\Sigma l}{}^{T}(u,\,v), \\ &\quad h^{\tilde{}}_{\Sigma l}{}^{T}(\,I_{l}(u,\,v,\!R_{l})), \ldots \, h^{\tilde{}}_{\Sigma l}{}^{T}(\,I_{T}(u,\,v,\!R_{l})), \\ &\quad h^{\tilde{}}_{\Sigma l}{}^{T}(\,I_{l}(u,\,v,\!R_{2})), \ldots \, h^{\tilde{}}_{\Sigma l}{}^{T}(\,I_{T}(u,\,v,\!R_{2})), \\ &\quad h^{\tilde{}}_{\Sigma l}{}^{T}(\,I_{l}(u,\,v,\!R_{3})), \ldots \, h^{\tilde{}}_{\Sigma l}{}^{T}(\,I_{l}(u,\,v,\!R_{3})), \\ &\quad \ldots \ldots \\ &\quad h^{\tilde{}}_{\Sigma Q}{}^{T}(\,I_{l}(u,\,v,\,R_{Q})), \ldots \, h^{\tilde{}}_{\Sigma Q}{}^{T}(\,I_{l}(u,\,v,\,R_{Q}))]^{T} \end{split}$$

Table 1 DAISY parameter

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Parameter	Symbol	Descriptor and Default Value
Name		
Radius	R	Distance from center pixel to
		the outermost grid point. (15)
Angular	T	Number of histogram at a
Quantization		single ring. (8)
No		
Radius	Q	Number of circular ring. (3)
Quantization		
No		
Histogram	H	Number of bins in the
Quantization		histogram. (8)
No		
Grid Point	S	Number of histogram used in
No		the descriptor = $Q * T + 1$
Descriptor	Ds	The total size of the vector
Size		= s * H

Where $I_j(u, v, r)$ is the location with distance R from (u, v) in the direction given by j where the direction are quantized in to the T values of Table 1.

2.2 Feature Matching

The extracted features are compared to find matches between every possible combination of two images in order to find matches. The matching process was performed by finding the

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features in the first image which had minimum Euclidian distances from each features in the second image. Set a threshold value and based on this predetermined threshold value consider the set of images as inliers, i.e. matched pairs, where those set of images have Euclidian distance less than the threshold value and others as outliers.

2.3 Clustering

In case the input image directory contain different images from more than one location, then a clustering algorithm is needed to determine which images corresponds to separate panorama. First randomly select one image from input directory. Match the selected image with each of the input in the input directory and move the matched images to a separate directory, thus get a new directory contain images of one location. Iteratively do the same procedure for rest of the images in the input directory until no image left in the input database. Thus get separate directory for each location.

2.4 Merging

Two images with largest number of feature matches inside each directory are used for stitching. First step in stitching is homography calculation. Using the homography one image is warped to be in the same frame as the other and a new image of all black pixel is created which can fit both image in the new frame. The properly arranged images are combined to form stitched image.

2.5 Blending

Pixel on opposite side of a seam comes from different image that overlap. The seam is the result of an abrupt transition from one image to another. In order to do blending use weighted average of pixel from different images in the region of overlap. Blending hides seams but preserve sharp details.

3. PROPOSED ALGORITHM

Step 1: Detect feature point from all input images.

• Use DAISY descriptor.

Step 2: Set a threshold value.

Step 3: Calculate Euclidian distance.

• Randomly select one image say IMG1 and compute Euclidian distance between IMG1 and all the other images.

Step 4: Move matched images to a stack.

• Move images if the Euclidian distance is less than threshold value.

Step 5: Repeat recursively step 3- step 4.

• For each image currently in the stack until all images in the stack have been used.

Step 6: Move all images in the stack to a new directory and repeat step 3-6 until no images left in input database Step 7: Stitch images.

• Individual group of images are merged and blend together to form stitched image.

4. EXPERIMENTAL RESULT

The input databases [10]-[12] used contain 60 images from different locations.

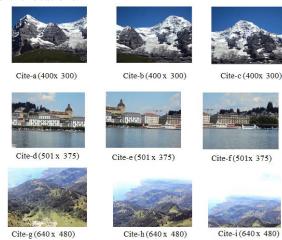


Figure 3: Input Images

Created a total of 18 directories which contain 7 separate panoramas and 11 unmatched images. Got 7 panoramas by stitching together the matched images. Experimental results are shown in figure 5.



Figure 4: Input Images

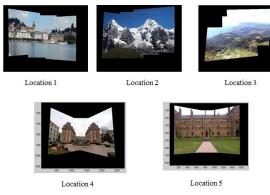


Figure 5: Output panoramas

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5. CONCLUSION

Experimental results are obtained successfully. In summary, an automatic multiple panorama creation based on DAISY descriptor is proposed. A clustering algorithm is included which separate image corresponding to each location. The individual set of image pairs are stitched iteratively to form different panorama. The proposed algorithm is a novel method and overcome the limitations of existing algorithm and is easy to use also.

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