A NEW APPROACH FOR DETECTING LOCAL FEATURES

Giang Phuong Nguyen and Hans Jørgen Andersen
Department of Media Technology, Aalborg University, Denmark

Keywords: Local descriptors, Image features, Triangular representation, Image retrieval/recognition.

Abstract: Local features up to now are often mentioned in the meaning of interest points. A patch around each point is formed to compute descriptors or feature vectors. Therefore, in order to satisfy different invariant imaging conditions such as scales and viewpoints, an input image is often represented in a scale-space, i.e. size of patches are defined by their corresponding scales. Our proposed technique for detecting local features is different, where no scale-space is required, by dividing the given image into a number of triangles with sizes dependent on the content of the image at the location of each triangle. In this paper, we demonstrate that the triangular representation of images provide invariant features of the image. Experiments using these features show higher retrieval performance over existing methods.

1 INTRODUCTION

At the beginning of image retrieval systems, global features such as color histograms were commonly used. Recently, local features is taking the role. There are several advantages of local features over global features including robustness to occlusion and clutter, distinctiveness for differentiating in a large set of objects, a large quantity can be extracted in a single image, and invariant to translation, rotation etc. These advantages lead to the increasing number of researches on exploring these types of features. Comprehensive overviews can be found in (Mikolajczyk and Schmid, 2005; Tuytelaars and Mikolajczyk, 2008).

Up to now, local features is mostly known as descriptors extracted from areas located at interest points (Tuytelaars and Mikolajczyk, 2008). This means that, existing methods first detect interest points, for example using Harris corner detector (Harris and Stephens, 1988). Then a patch is drawn which is centered at the corresponding interest point, and descriptors are computed from each patch. So, the main issue is how to define the size of the patch. In other words, how to make these descriptors scale invariant. To satisfy this requirement, these methods need to locate a given image at different scales, or so called the scale-space approach. A given image is represented in a scale-space using difference of Gaussian and down sampling (Lowe, 2004; Brown and Lowe, 2007; Nguyen and Andersen, 2008). The size of a patch depends on the corresponding scale where the interest point is detected. The computation of the scale space and descriptors is often expensive and complicated.

In this paper, we propose a different approach for detecting local features that does not require the scale-space representation nor the detection of interest points. Given an input image, we divide the image into a number of right triangles where a triangle defines a homogenous region. The size of each triangle depends on the content of the image at the location of the triangle. This process is done automatically. This means that if an object appears at different scales, the triangular representation will adapt to draw the corresponding triangle size. The technique of using triangle representation of images is originally introduced by Distasi in (Distasi et al., 1997) for image compression. Moreover, in this reference, only intensity images are taken into account. Following the current trend, where color based local features are of interest, we also investigate the use of color information for describing local features. The distinctiveness in color is much larger, therefore, using color information for locating local features can be of great importance when matching images. We develop a new technique to extract local features using the color based triangular representation of images.

The paper is organized as follows. In the next section, we will give a description of our approach in using triangular representation of color images, and how to compute local descriptors. In section 2.4, we

Phuong Nguyen G. and Jørgen Andersen H. (2010).
A NEW APPROACH FOR DETECTING LOCAL FEATURES.
In *Proceedings of the International Conference on Computer Vision Theory and Applications*, pages 221-226
DOI: 10.5220/0002848402210226
Copyright © SciTePress

evaluate the proposed features with repeatability criteria in (Mikolajczyk and Schmid, 2005). Experimental results in a image retrieval system are carried out in section 3.

2 BTREE TRIANGULAR CODING (BTTC) FOR COLOR IMAGE

In this section, we discuss the extension of the triangular representation for intensity images to color images. We then evaluate the repeatability of our local features under different imaging conditions.

2.1 1D-BTTC

As mentioned above, the BTree triangular coding (BTTC) is a method originally designed for image compression purpose (Distasi et al., 1997). An input image is an intensity image, so we denote it as 1D-BTTC. For compression purpose, the method tries to find a set of pixels from a given image that is able to represent the content of the whole image. This means that given a set of pixels, the rest of pixels can be interpolated using this set. In the reference, the authors divide an image into a number of triangles, where pixels within a triangle can be interpolated using information of the three vertices. The same idea can be applied to segment an image into a number of local areas, where each area is a homogenous triangle.

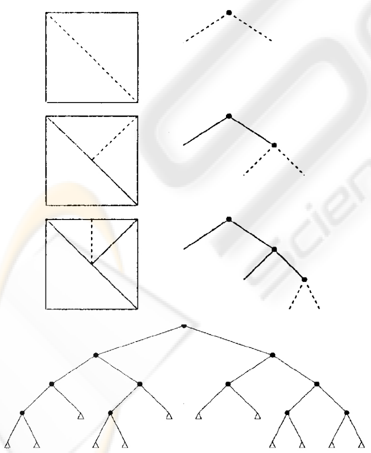


Figure 1: An illustration of building BTree using BTTC. The last figure shows an example of a final BTree.

A given image I is considered as a finite set of points in a 3-dimensional space, i.e. $I = \{(x,y,c)|c = F(x,y)\}$ where (x,y) denotes pixel position, and c is an intensity value. BTTC tries to approximate I with a discrete surface $B = \{(x,y,d)|d = G(x,y)\}$, defined by a finite set of polyhedrons. In this case, a polyhedron is a right-angled triangle (RAT). Assuming a RAT with three vertices (x_1,y_1), (x_2,y_2), (x_3,y_3) and $c_1 = F(x_1,y_1)$, $c_2 = F(x_2,y_2)$, $c_3 = F(x_3,y_3)$, we have a set $\{x_i,y_i,c_i\}_{i=1..3} \in I$. The approximating function $G(x,y)$ is computed by linear interpolation:

$$G(x,y) = c_1 + \alpha(c_2 - c_1) + \beta(c_3 - c_1) \qquad (1)$$

where α and β are defined by the two relations:

$$\alpha = \frac{(x-x_1)(y_3-y_1)-(y-y_1)(x_3-x_1)}{(x_2-x_1)(y_3-y_1)-(y_2-y_1)(x_3-x_1)} \qquad (2)$$

$$\beta = \frac{(x_2-x_1)(y-y_1)-(y_2-y_1)(x-x_1)}{(x_2-x_1)(y_3-y_1)-(y_2-y_1)(x_3-x_1)} \qquad (3)$$

An error function is used to check the approximation:

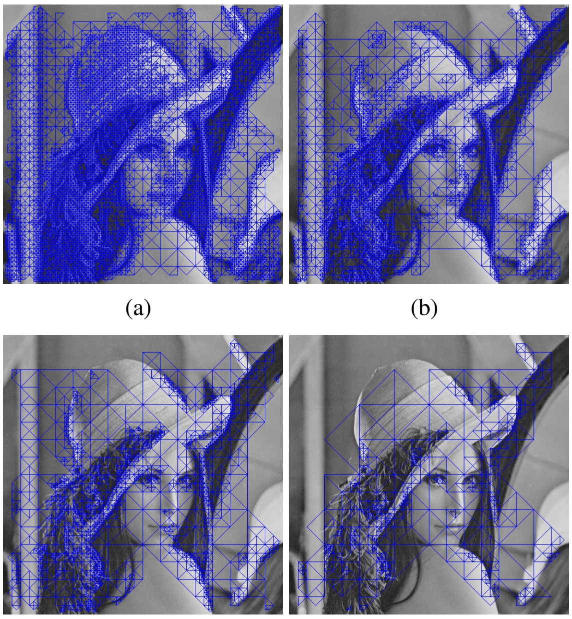
$$\text{err} = |F(x,y) - G(x,y)| \leq \varepsilon, \varepsilon > 0 \qquad (4)$$

If the above condition is not met then the triangle is divided along its height relative to the hypotenuse, replacing itself with two new RATs. The coding scheme runs recursively until no more division takes place. In the worst case, the process is stopped when it reaches to the pixel level i.e. three vertices of a RAT are three neighbor pixels and err=0. The decomposition is arranged in a binary tree. Without loss of generality, the given image is assumed having square shape, otherwise the image is padded in a suitable way. With this assumption, all RAT will be isosceles. Finally, all points at the leave level are used for the compression process. Figure 1 shows an illustration of the above process.

In the reference (Distasi et al., 1997), experiments prove that BTTC produces images of satisfactory quality in objective and subjective point of view. Furthermore, this method has shown very fast in execution time, which is also an essential factor in any processing system. We note here that for encoding purpose, the number of points (or RAT) is very high (up to several ten thousand vertices depending on the image content). However, we do not need that detail level, so by increasing the error threshold in Eq.(4) larger we obtain fewer RATs while still fulfilling the homogenous region criteria. Examples using BTTC to represent image content with different threshold values are shown in figure 2.

2.2 3D-BTTC

In this section, we extend the 1D-BTTC to color image. As we mentioned above, the use of color information can be of great importance for matching images. To get a triangular representation on the color image, we consider the 3-color channels at the same time, so the technique is called 3D-BTTC.



(a) (b)

(c) (d)

Figure 2: Examples using 1D-BTTC embedded in the input image: with different values of the threshold, the higher the threshold, the rougher the triangular representation.

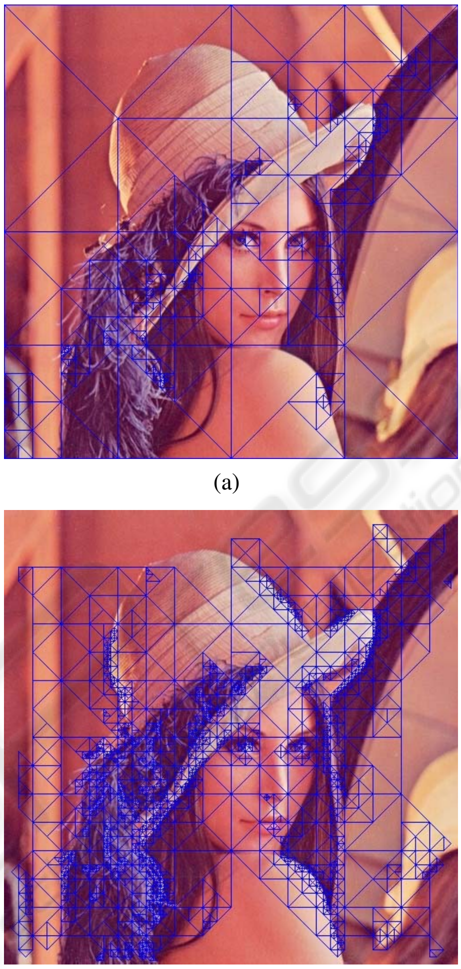
First of all, we consider the color space of the given image. Because of common variations in imaging conditions such as shading, shadows, or reflectance, the components of the RGB color space are correlated and very sensitive to illumination changes. Therefore, different color spaces are investigated, for instance, normalized RGB, HSI, or Lab. There are several comprehensive overviews on characteristics of existing color spaces (Niblack, 1985; Gevers et al., 2006; Geusbroek et al., 2001; Gevers and Smeulders, 1999), where each color system is evaluated under different invariant criteria. HSI (Hue, Saturation and Intensity) is among one of the best color space that overcomes shading, shadows, reflectance, and only color differences are taken into account. We, therefore, convert all input images into the HSI color space.

Given an RGB image, the HSI color space is computed by the following equation:

$$\begin{pmatrix} H \\ S \\ I \end{pmatrix} = \begin{pmatrix} \tan^{-1}(\frac{o_1}{o_2}) \\ \sqrt{o_1^2 + o_2^2} \\ o_3 \end{pmatrix}, \tag{5}$$

where

$$\begin{pmatrix} o_1 \\ o_2 \\ o_3 \end{pmatrix} = \begin{pmatrix} \frac{R-G}{\sqrt{2}} \\ \frac{R+G-2B}{\sqrt{6}} \\ \frac{R+G+B}{\sqrt{3}} \end{pmatrix}. \tag{6}$$



(a)

(b)

Figure 3: An example of triangular representation using 1D-BTTC (a) and 3D-BTTC (b) embedded to the input image.

An input image I is now represented as $I = \{(x,y,c)\}$ where (x,y) denotes pixel position, and $c = \{H,S,I\}$. Similar to 1D-BTTC, the HSI image is first divided into two triangles along the diagonal of the given image. The condition in Eq.(4) must be satisfied for all three channels. This means that for each pixel within a triangle, we compute the interpolated color based on the color of the three vertices. Eq.(1) is extended as:

$$G_H(x,y) = H_1 + \alpha(H_2 - H_1) + \beta(H_3 - H_1) \tag{7}$$

$$G_S(x,y) = S_1 + \alpha(S_2 - S_1) + \beta(S_3 - S_1) \tag{8}$$

$$G_I(x,y) = I_1 + \alpha(I_2 - I_1) + \beta(I_3 - I_1) \tag{9}$$

where α and β are computed by Eq.(2). H_i, S_i and I_i $(i = 1,2,3)$ are HSI values of the three vertices of the current triangle. For 3D-BTTC, Eq.(4) changes as follows

Figure 4: The "boat" test set for evaluating the repeatability when changing rotations and scales.

$$|F_H(x,y) - G_H(x,y)| \leq \varepsilon_H, \quad \varepsilon_H > 0 \qquad (10)$$
$$|F_S(x,y) - G_S(x,y)| \leq \varepsilon_S, \quad \varepsilon_S > 0 \qquad (11)$$
$$|F_I(x,y) - G_I(x,y)| \leq \varepsilon_I, \quad \varepsilon_I > 0 \qquad (12)$$

If all the color channels meet the above equations, then the division stops, otherwise two new triangles are created. The process is repeated, the stopping criteria is similar to the 1D-BTTC.

In figure 3, we show an example of using 1D-BTTC and 3D-BTTC. The input image is converted to an intensity image and a HSI image, respectively. The threshold are set equal in both cases. We can observe that there are a lot interesting area where color changes and they are ignored when using 1D-BTTC, but captured in case of 3D-BTTC.

2.3 Computing Descriptors

When the triangular representation of the given image are drawn, we calculate the HSI color histogram of each right triangle. The color histogram is used as descriptor of the triangle.

2.4 Repeatability Experiment

In this section, we evaluate the repeatability of our local features. In (Mikolajczyk et al., 2005), the authors suggest a test for the quality of local features under different challenges. Each challenge contains of a set of 6 images with a reference image and 5 other images show the same scene under predefined changes including blurring, rotation, zooming, viewpoint, and lighting. Figure 4 shows an example of a set with different rotations and scales.

The repeatability rate is defined as the ratio between the number of actual corresponding features and the total number of features that occur in the area common to both images. To compute the rate, local features are extracted from all test images. Then, features from the reference image will be mapped to each images of the other five images using a predefined transformation matrix (Mikolajczyk et al., 2005). All features outside the common area between two images are removed. After that, we calculate the overlap between features from the reference image to features of the other images. Similar to (Mikolajczyk et al., 2005), we also set the overlap error threshold to 40%.

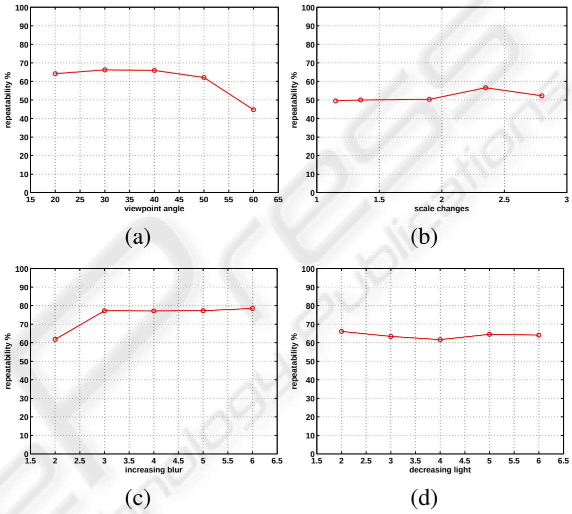


Figure 5: Repeatability of 3D-BTTC under different imaging conditions. (a) With different viewpoint angles. (b) With different scales (including zooming and rotation). (c) With different blurring factors. (d) With different illumination.

In figure 5, we show results with four different test sets corresponding to four different challenges: viewpoint changes, scale changes, increasing blurring, and decreasing lighting. Results show that our local features give very stable repeatability rate in different imaging conditions. For examples, with viewpoints changes of 40^0 to the reference image, the repeatability rate is 65%, this is compatible to methods presented in (Mikolajczyk et al., 2005). In case of rotation and zooming applied, our local features is stable even with large scale changes. In (Mikolajczyk et al., 2005), other methods go down quite significantly with larger scales. In this reference, the best performance reaches 30% rate at the highest scale, and our method stays at 50% rate. Given very high challenging test sets, on average, we obtain 60% repeatability rate for all cases.

Figure 6: An example of images taken from the same building.

3 EXPERIMENTAL RESULTS

Our experiments are carried out with a dataset, which contains of 135 images. This dataset is called the AAU dataset, where images are captured from 21 buildings/objects in the area of Aalborg University. There are from 4 to 7 images for each building. It should be noted that all the buildings are quite similar in their textures (for examples, brick wall or glasses). Images of the same building are taken at different viewpoints, rotations, and scales. In figure 6, we show example images of the same building.

Evaluation of local features is based on image retrieval performance. To do so, we sequentially use images from the given dataset as a query image. Local features are extracted from the query image and compared to features of all images in the dataset. The $\varepsilon_i (i = 1, 2, 3)$ in Eq.(10) are all set to 150. For comparing HSI histograms, we use the Euclidean distance as a similarity function. The top 5 best matching are returned, and groundtruth is manually assigned to corresponding building to compute the precision rate:

$$\text{precision} = \frac{\text{\# of correct matches}}{\text{\# of returned images}} (\%). \tag{13}$$

The average retrieval rate is shown in figure 7. We also reported the retrieval performance using the multi-scale oriented patches (MOPS) (Brown et al., 2005), which applies the common approach using scale-space representation, for comparison. Matching using 1D-BTTC also used as a reference. Results show that using color information instead of intensity boot up the retrieval performance. Moreover, our system using 3D-BTTC give a higher retrieval rate compared to MOPS.

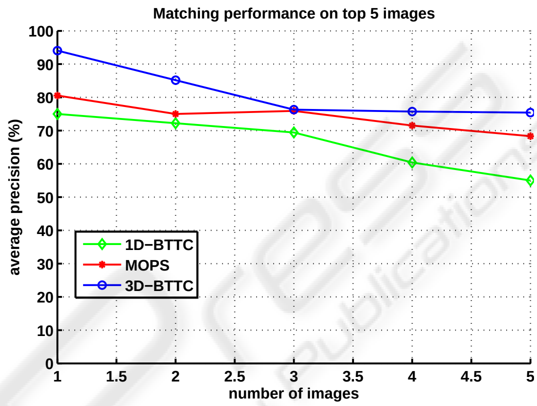


Figure 7: Precision vs. number of returned images.

4 CONCLUSIONS

In this paper, we present a new approach to detect local features in color images. We use triangular representation to detect local features. Depends on the content of the area inside the input image, different sizes of triangles are drawn. Therefore, our proposed approach is independent of changing scales without using the scale-space representation. The technique is much simpler and, hence, faster. Besides, the repeatability rate of our local features in different imaging conditions is compatible to existing techniques. Our first experimental results on image retrieval show that the proposed approach gives better performance compared to other method using scale-space representation. We obtain a high precision rate, i.e. 95% correct matches in the best matching results.

ACKNOWLEDGEMENTS

This research is supported by the IPCity project (FP-2004-IST-4-27571), a EU-funded Sixth Framework program Integrated project on Interaction and Presence in Urban Environments.

REFERENCES

Brown, M. and Lowe, D. (2007). Automatic panoramic image stitching using invariant features. *International Journal of Computer Vision*, 74(1):59–73.

Brown, M., Szeliski, R., and Winder, S. (2005). Multi-image matching using multi-scale oriented patches. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, volume 1, pages 510–517.

Distasi, R., Nappi, M., and Vitulano, S. (1997). Image compression by B-Tree triangular coding. *IEEE Transactions on Communications*, 45(9):1095–1100.

Geusbroek, J., Boomgaard, R., and Smeulders, A. (2001). Color invariance. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(12):1338–1350.

Gevers, T. and Smeulders, A. (1999). Color based object recognition. *Pattern Recognition*, 32:453–464.

Gevers, T., Weijer, J., and Stokman, H. (2006). Color feature detection. *Color Image Processing: Methods and Applications, editors R. Lukac and K.N. Plataniotis, CRC Press*.

Harris, C. and Stephens, M. (1988). A combined corner and edge detector. *Proceedings of the Alvey Vision Conference*, pages 147–151.

Lowe, D. (2004). Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*, 60(2):91–110.

Mikolajczyk, K. and Schmid, C. (2005). A performance evaluation of local descriptors. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, 27(10):1615–1630.

Mikolajczyk, K., Tuytelaars, T., Schmid, C., Zisserman, A., Matas, J., Schaffalitzky, F., Kadir, T., and Van-Gool, L. (2005). A comparison of affine region detectors. *International Journal of Computer Vision*, 1/2(65):43–72.

Nguyen, G. and Andersen, H. (2008). Urban building recognition during significant temporal variations. In *Proceedings of the IEEE Workshop on Applications of Computer Vision*, pages 1–6.

Niblack, W. (1985). *An introduction to digital image processing*. Strandberg Publishing Company, Birkeroed, Denmark, Denmark.

Tuytelaars, T. and Mikolajczyk, K. (2008). Local invariant feature detectors. *Foundations and Trends in Computer Graphics and Vision*, 3(3):177–280.