A new approach for detecting local features

Nguyen, Phuong Giang; Andersen, Hans Jørgen

Published in:
International Conference on Computer Vision Theory and Applications

Publication date:
2010

Document Version
Early version, also known as pre-print

Link to publication from Aalborg University

Citation for published version (APA):
A NEW APPROACH FOR DETECTING LOCAL FEATURES

Giang Phuong Nguyen, Hans Jørgen Andersen

Department of Media Technology, Aalborg University, Denmark
gnp@imi.aau.dk, hja@imi.aau.dk

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 prove 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 interesting points (Tuytelaars and Mikolajczyk, 2008). This means that, existing methods first detect interesting 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 downsampling (Lowe, 2004; Brown et al., 2005; 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 interesting 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 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 BTTree 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 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.

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 $\{x_i,y_i,c_i\}_{i=1,3} \subseteq I$. The approximating function $G(x,y)$ is computed by linear interpolation:

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

where $\alpha$ and $\beta$ are defined by the two relations:

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

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

An error function is used to check the approximation:

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

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 $\text{err}=0$. 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 is 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 homoge-

![Figure 1: An illustration of building BTree using BTTC. The last figure shows an example of a final BTree.](image)
nous region criteria. Examples using BTTC to repre-
sent 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 im-
age. As we mentioned above, the use of color infor-
mation can be of great importance for matching im-
ages. 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.

First of all, we consider the color space of the
given image. Because of common variations in
imaging conditions such as shading, shadows, or re-

ductance, 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 (Gevers et al., 2006; Geus-
broek 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 differ-
ces are taken into account. We, therefore, convert
all input images into the HSI color space.

Given an RGB image, the HSI color space is com-
puted by the following equation:

\[
\begin{pmatrix}
H \\
S \\
I
\end{pmatrix}
= \left( \begin{pmatrix}
\tan^{-1} \left( \frac{o_1}{o_2} \right) \\
\frac{\sqrt{o_1^2 + o_2^2}}{o_3}
\end{pmatrix}
\right),
\]

where

\[
\begin{pmatrix}
o_1 \\
o_2 \\
o_3
\end{pmatrix}
= \left( \begin{pmatrix}
R - G \\
\sqrt{2} \left( R + G - 2B \right) \\
R + G + B \sqrt{3}
\end{pmatrix}
\right).
\]

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.

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 im-
age. 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 \(\alpha\) and \(\beta\) 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

\[
|F_H(x,y) - G_H(x,y)| \leq \varepsilon_H, \quad \varepsilon_H > 0 \tag{10}
\]
\[
|F_S(x,y) - G_S(x,y)| \leq \varepsilon_S, \quad \varepsilon_S > 0 \tag{11}
\]
\[
|F_I(x,y) - G_I(x,y)| \leq \varepsilon_I, \quad \varepsilon_I > 0 \tag{12}
\]

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. 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. The overlap error threshold is set 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° 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.

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 ε_\(i\) (\(i = 1, 2, 3\)) 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:

\[
\text{precision} = \frac{\# \text{ of correct matches}}{\# \text{ of returned images}} \times 100\% \tag{13}
\]

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.

4 CONCLUSION

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


