MVA2005 IAPR Conference on Machine VIsion Applications, May 16-18, 2005 Tsukuba Science City, Japan

8-34

Using Orientation Code Difference Histogram (OCDH) for Robust Rotation-invariant Search

Takahiro Urano*
takahiro@ssc.ssi.ist.hokudai.ac.jp

Shun'ichi Kaneko*
kaneko@ssi.ist.hokudai.ac.jp

Takayuki Tanaka*
ttanaka@ssi.ist.hokudai.ac.jp

Munatoshi Imada†
imada.munetoshi@sharp.co.jp

Abstract

We propose a fast and rotate-invariant template matching using an Orientation Code Difference Histogram (OCDH). It is fast in order to prune by OCDH, and robust for template matching even in presence of some irregularities like shading, highlighting, occlusion or their combination. This method is based on Orientation Code Matching (OCM)[1, 2] and Orientation Code Histogram (OH)[3].

1 Introduction

Template matching is an important technique for one of the major problems in pattern recognition and image understanding. In the field of template matching, there are many difficult problems, for example rotation image search, occlusion, scaling, change of light condition, and so on. We proposed Orientation Code Difference Histogram (OCDH). This method can estimate rotation angle of the image accurately and designed for a gray scale image. It is based on Orientation Code Matching (OCM)[1, 2] and Orientation Code Histogram (OH)[3]. It is fast and robust for template matching even in presence of some irregularities like shading, highlighting, occlusion or their combination.

2 Orientation Code Difference Histogram

2.1 Orientation Code (OC)

Define a blightness of the image for a pixel location (m,n) is represented by $f_{m,n}$, and its horizontal and vertical derivatives by $\nabla f_x = \partial f/\partial x$ and $\nabla f_y = \partial f/\partial y$, respectively. An orientation angle $\theta_{m,n}$ is computed as $\theta = \tan^{-1}\left(\nabla f_y/\nabla f_x\right)$. The orientation code is obtained by quantizing $\theta_{m,n}$ into $N(=2\pi/\Delta\theta)$ levels with a quantization width $\Delta\theta$ as

$$c_{m,n} = \begin{cases} \left\lceil \frac{\theta_{m,n}}{\Delta\theta} \right\rceil & : |\nabla f_x| + |\nabla f_y| > \Gamma, \\ N & : \text{otherwise}, \end{cases} \quad (1)$$

where $\lceil x \rceil$ is the maximum integer exceeding x. If there are N pieces of orientation codes then $c_{m,n}$ is ranges between 0 and $N-1$. We assign the particular code N for low contrast pixels for which it is not possible to stably compute the gradient angles. Γ is a parameter for suppressing the effects of noise from low contrast neighborhoods. Hereafter, the suffix orientation code represents location or coordinates in the image. An example of the orientation codes is depicted in Fig. 1, which in the case of $\Delta\theta = 22.5$[deg]$(N = 16)$.

2.2 Definition of OCDH

A difference between any two orientation codes is expected not to change even if the image rotates. We use this orientation code difference (OCD) as a rotate-invariant feature. Define s as a difference between the codes c_a and c_b

$$s(c_a, c_b) = \begin{cases} c_b - c_a, & c_a \le c_b < N \text{ or } c_a = c_b = N, \\ c_b - c_a + N, & N > c_a > c_b, \\ N, & (c_a = N \text{ and } c_b \ne N) \text{ or } (c_a \ne N \text{ and } c_b = N), \end{cases} \quad (2)$$

where it has a value from 0 to N. It is equivalent to the number of the counting orientation codes counterclockwise from c_a to c_b. In the case that either c_a or c_b is the particular code N, s is assigned to N. For example, $s(14, 2)$ is 4 and $s(2, 14)$ is 12.

We shows the difference between any two orientation codes does not change even if the image rotates. The difference after rotation is given by

$$s((c_a + g) \bmod N, (c_b + g) \bmod N) = s(c_a, c_b), \quad (3)$$

where g is an offset caused by rotation by the angle ϕ, which is defined as $g = \lceil \phi/\Delta\theta \rceil$. Fig. 2 shows an

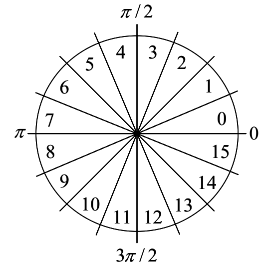


Fig. 1: 16 Orientation Codes($\Delta\theta = \frac{\pi}{8}$).

* Graduate School of Information Science and Technology, Hokkaido University, Kita 14, Nishi 9, Kita-ku, Sapporo, 060-0814, JAPAN.
† Sharp Manufacturing System, 4-1-33, Atobehonmachi, Yao City, Osaka, Japan

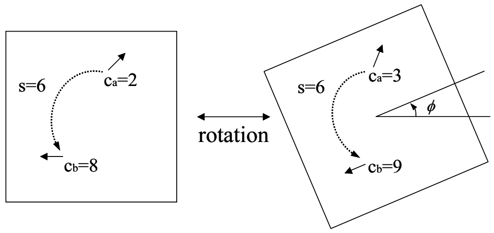


Fig. 2: The difference of orientation code $\phi = 22.5[\mathrm{deg}](g=1)$.

example of the differense of orientation codes in the case of image rotations.

We show an example the case $N+g > c_a+g > N > c_b+g$. Here,

$$
\begin{aligned}
c_a + g \bmod N &= c_a + g - N, \\
c_b + g \bmod N &= c_b + g.
\end{aligned}
$$

And then

$$
\begin{aligned}
s(c_a+g-N, c_b+g) &= c_b + g - (c_a + g - N) \\
&= c_b - c_a + N \\
&= s(c_a, c_b).
\end{aligned}
$$

When calculating the difference, we generally have to know corresponding pixels of after rotation, It is, however, very troublesome to draw these correspondences from images, such as in stereo visions and optical flow detection. Because we have the purpose to design a robust and rotation-invariant image search algorithm, we introduced OCD as the first key feature for this task. We showed it is rotation-invariant and can be calculated from any two pixels which are preferred to be a part from one another for keeping a level on precision of rotation measurement.

In order to realize a faster and simpler algorithm, however, we should avoid some complicated procedures for searching these target pixel pairs.

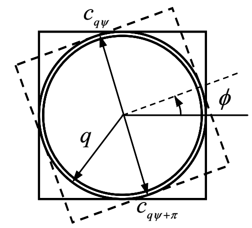
Therefore we introduce two techniques to resolve. Local-feature-based histograms are effective for rotation-invariant search. We propose here a combination of this histogram and ring calculation. When a center of rotation is assumed through scanning, the target pixel pairs should locate on the rings around the center. By utilizing the ring regions for calculation of OCD and summing up them into the histogram, we can have a search algorithm of efficient computation.

We define concentric rings at the image center as shown in Fig. 3(a). We calculate OCD $c_{q\psi}$ and $c_{q\psi+\pi}$ on the diameter which consists of the pixel (q,ψ) and $(q,\psi+\pi)$, where the coordinates system of pixels are expressed by polar coordinates system.

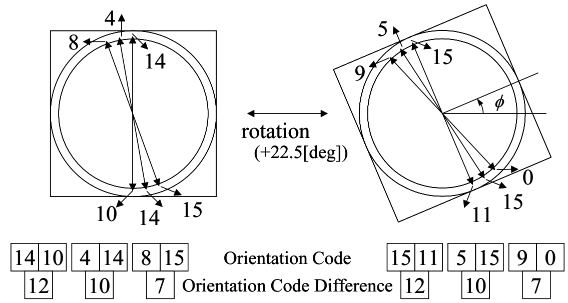
$v_q = (v_q(0), v_q(1), \ldots, v_q(N))$ is given by

$$
v_q(k) = \sum_{\psi=0}^{\pi} \delta\big(k - s(c_{q\psi}, c_{q\psi+\pi})\big), \tag{4}
$$

where $\delta()$ is Kronecker's delta. A similarity measure based on the histogram intersection[4] is designed to evaluate the difference between a template histogram v_q^T and an object histogram v_q from the template image



(a) The rotation of image



(b) The difference of orientation code on ring

Fig. 3: The difference of orientation code of rotation of image.

and the subimage, as respectively

$$
S_q = \frac{1}{A_q} \sum_{k=0}^{N} \min\{v_q(k), v_q^T(k)\}, \tag{5}
$$

where A_q represents the pixel amount on the rings of radius q.

Fig. 4(b) shows the histograms and their intersection for the image in Fig. 4(a). The dissimilarity D_1 of the orientation code difference histograms is given by

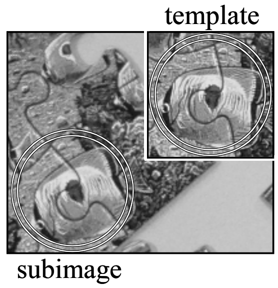
$$
D_1 = \frac{\sum_{q=1}^{n} A_q(1-S_q)}{\sum_{q=1}^{n} A_q}. \tag{6}
$$

Upper formula normalized R_q from 0 to 1.

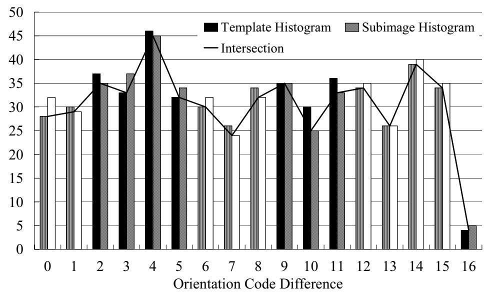
2.3 Verification

In the previous sections, we have designed the OCD-based histogram algorithm for rotation-invariant search. Generally, image search tasks consist of the two phases: search and verification, so two matching procedures, Orientation code histogram (OH)[3] for rotation angle estimation, and then Orientation code matching (OCM)[1, 2] for precise matching, are used for the verification. These two matching procedures have been proposed by ourselves for respective independent tasks [1, 2, 3], here we design the combination of these procedures in order to realize robust and rotation-invariant image search.

OH consists of the histogram feature made from pixel-wise orientation codes in the image and the shifted intersection for evaluating histogram similarity. Fig. 5 shows their examples, where in Fig. 5(a) a template histogram is directly compared to an object one, and in Fig. 5 the shifted version of the object histogram. As shown in the figures, we can simultaneously evaluate their similarity and estimate the angle $\hat{\phi}$

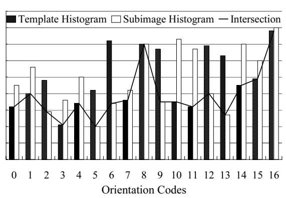


(a) An example of ring

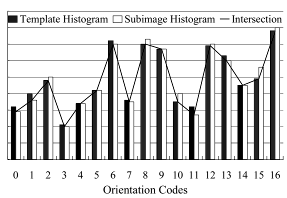


(b) OCDH

Fig. 4: An example of OCDH.



(a) Original histograms



(b) Shifted histograms for subimage

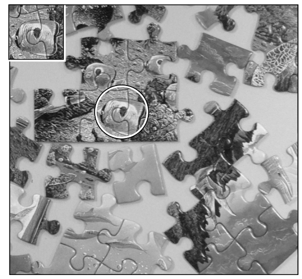
Fig. 5: Orientation code histogram.

of image rotation. In the shifted intersection, the frequency in the Nth bin that reveals an irregular pixel number helps the evaluation precision. Each dissimilarity measure corresponding to the shift k is calculated directly based on bin-wise comparison, and then their maximum D_2 can be used as component in the final step.

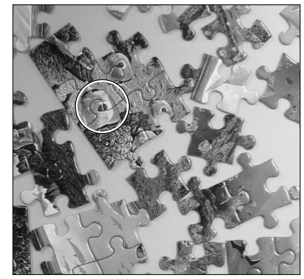
For reliability of matching, we use another verification by Orientation code matching (OCM) using a rotated version of the template image by the estimated rotation angle $\hat{\phi}$. We need a different scheme $d(c_a, c_b)$ of calculating difference from Eq.2, which reflects circularity of orientation, for example, $d(14, 2)$ and $d(2, 14)$ are the same as 4. The dissimilarity D_3 based on pixel-wise local evaluation of difference between corresponding pixels is used for verification in this step.

3 Image search algorithm

By combination three procedures abovementioned, we propose a robust and rotation-invariant image search algorithm. In many applications of image search in real industry, we are provided with larger images called scene including some subimages corresponding to the template image. For each target image of the same size as the template drawn from the scene, we first calculate D_1 for candidate search. The candidate images are selected by comparing D_2 with a threshold level Th, and their rotation angle estimations $\hat{\phi}$ are obtained by use of OH. In the third step, after generating rotated version of the template by $\hat{\phi}$, D_3 is computed.

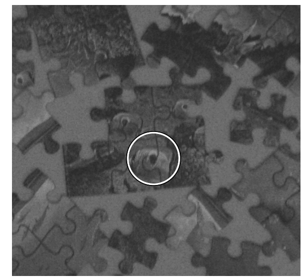


(a)



(b)

(c)



(d)

Fig. 6: Search experiment.

Finally, we compute the overall dissimilarity which is a weighted sum of dissimilarities in OCDH, OH and OCM.

$$D = (\alpha D_1 + \beta D_2 + \gamma D_3)/(\alpha + \beta + \gamma), \tag{7}$$

where α, β, γ are the weighting factors.

4 Experiments

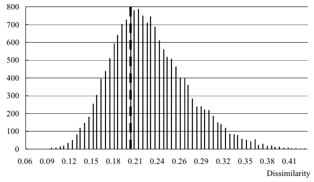
For the experimental verification of the search algorithm proposed above, we have conducted fundamental search experiment as shown in Fig. 6, in which the white circle shows the detected target image.

Fig. 7 shows the distribution of the dissimilarities around the searched position for Fig.6(a), when the ring number n is $1, 3, 5, 7$, and dotted lines in these figures represent the pruning threshold level Th.

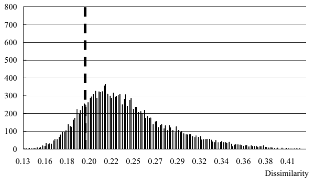
And Fig. 8 shows the pruning area, which are shown by dark tone. We can find that accuracy of the search increase as the number of rings n, because the pruning area increase with the number.

Fig. 9 shows the computation cost for the code number N. We could find when we use OCDH, the computation cost doesn't change with increasing number of codes.

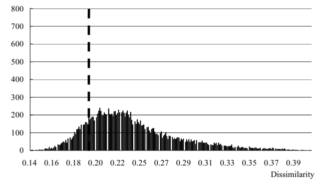
The dissimilarity profiles for Fig.6(b) are shown in Fig.10. Fig.10(a) shows the dissimilarity surface around the true position of the object in the scene. Fig.10(b) shows the dissimilarity of each angle of image rotation at the true position. When $\hat{\phi} = 292.5[deg]$, peak values correspond to the correct angle.



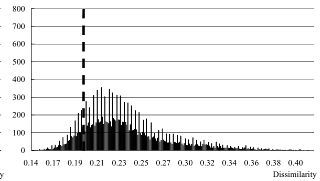
(a)n=1



(b)n=3



(c)n=5



(d)n=7

Fig. 7: Dissimilarity histogram for Fig.6(a)

(a) $n : 3, Th = 0.2$

(b) $n : 5, Th = 0.2$

Fig. 8: Pruning area for Fig.6(b).

5 Conclusins

A novel algorithm for fast, robust and rotation-invariant template search has been proposed. It is fundamentally based on orientation code difference histogram which can be designed by using histogramming robust features and ring structures for fast computation. The effectiveness and efficiency of the proposed algorithm could be experimentally verified with real images. The proposed algorithm can be widely used in real industry for product handling in many irregular conditions of illumination change and fluctuation of positioning and rotation.

References

[1] Farhan Ullah, Shun'ichi Kaneko, Satoru Igarashi, "Orientation Code Matching for Robust Object Search", IEICE Trans. on Inf. Sys., Vol.E84-D, No.8, pp.999-1006 (2001).

[2] Farhan Ullah, Shun'ichi Kaneko, Satoru Igarashi, "Tracking Looming and Receding Objects by Orientation Code Matching",The Journal of the IIEEJ, Vol.31, no.1, pp91-102(2002).

[3] Farhan Ullah, Shun'ichi Kaneko, "Using orientation codes for rotation-invariant template matching", Pattern Recognition, Vol.37, No.2, pp.201-209 (2004).

[4] M.J.Swain, D.H.Ballard, "Color Indexing", IJCV, Vol.7, No.1, pp.11-32,1991.

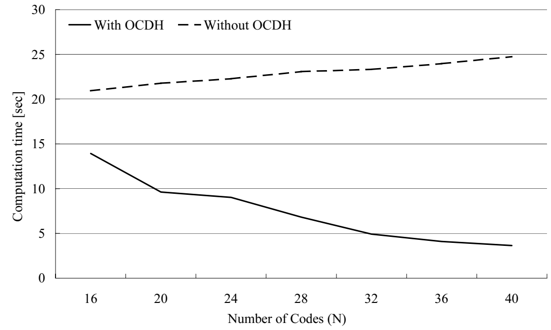
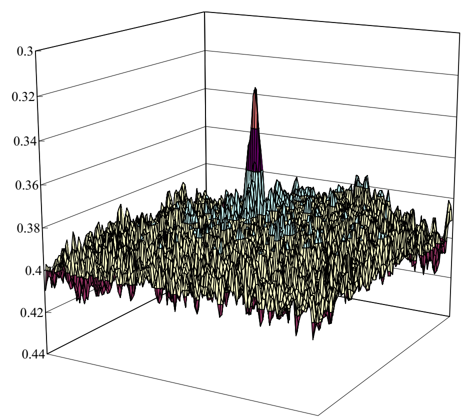
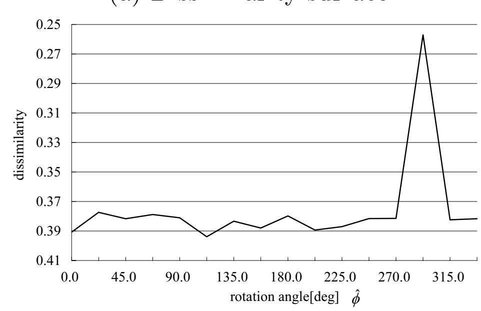


Fig. 9: Computation time for code number.



(a) Dissimilarity surface.



(b) Dissimilarity of each angle.

Fig. 10: Dissimilarity profiles for Fig.6(b)