The Seventeenth International Symposium on Artificial Life and Robotics 2012 (AROB 17th '12),
B-Con Plaza, Beppu, Oita, Japan, January 19-21, 2012

# Hamming Distance based Gradient Orientation Pattern Matching

Prarinya Siritanawan, and Toshiaki Kondo

Sirindhorn International Institute of Technology, Thammasat University, Thailand
(Tel: +66(0)29869009, Fax: +66(0)29869112-3)
p.siritanawan@gmail.com, tkondo@siit.tu.ac.th

**Abstract:** This paper presents a novel pattern matching technique for motion estimation and visual tracking under varying illuminations, including a large amount of occlusions. To cope with the illumination problem, we previously proposed a matching technique using gradient orientation information, called gradient orientation pattern matching technique. Unlike conventional image features such as intensities and gradients, gradient orientations are known to be robust to illumination changes. In this paper, we introduce the Hamming distance to the gradient orientation pattern matching as a new similarity metric. Simulation results show that the new proposed method is robust to both illumination changes and a large amount of occlusions compared with existing matching techniques.

**Keywords:** gradient orientation pattern matching, hamming distance, object tracking, occlusion, template matching

## 1 INTRODUCTION

The purpose of this paper is to establish the novel pattern matching technique for motion estimation and visual tracking under varying illumination and partial occlusion scenarios. Various object tracking techniques have been proposed in the literature [1]. Most of them assume that illuminations are constant and occlusions are marginal, which does not always hold in real situations. To deal with the illumination variation problem, we previously proposed a matching technique using gradient orientation information, called gradient orientation pattern matching technique (GOPM) [2][3].

Unlike conventional image features such as intensities and gradients, gradient orientation information is far more independent of illumination changes over time. Generally, gradient orientation is extracted from image intensities using the trigonometric functions $\theta = arctan(I_y/I_x)$, where $I_x$ and $I_y$ are partial derivative of the intensity in $x$ and $y$ directions. This trigonometric function is slow and undesirable in the hardware implementation. GOPM technique has exhibited an alternative approach of utilizing unit gradient vectors (UGVs) to avoid the trigonometric function [3]. The efficiency of the matching method on decomposed unit gradient vectors is identical to the matching on the angular values but the calculation is reduced. We have examined it by implementing the technique on a real-time eye tracking [4][5].

For the GOPM, we can employ any traditional similarity metric, such as the sum-of-absolute differences (SAD), the sum-of-squared differences (SSD), zero-mean normalized cross-correlation (ZNCC) and so on. In this paper, we introduce the Hamming distance (HD) to the GOPM as a new similarity metric. The HD is considered robust to the occlusion problem because it is concerned with the number of pixels that match (or do not match) rather than paying attention to the differences between images. For quantitative evaluations, we have created three artificial image sequences using three still images and simulate illumination changes and occlusions in the similar fashion as in [2] and [3]. Furthermore, the new proposed technique has been examined on real video sequences and compares its efficiency over the other matching techniques. Simulation results show that the new proposed method is robust to both illumination changes and a large amount of occlusions compared with existing matching techniques.

## 2 MATCHING METHODS

### 2.1 Gradient Orientation Pattern Matching (GOPM)

The method decomposes orthogonal components of unit gradient vectors (UGVs) and performs similarity measurement on x and y gradient component separately. The UGVs could be obtained though the following normalized equations (Eq.(1))

$$\begin{aligned} n_x(x,y) &= I_x(x,y)/\sqrt{I_x^2(x,y)+I_y^2(x,y)+\epsilon} \\ n_y(x,y) &= I_y(x,y)/\sqrt{I_x^2(x,y)+I_y^2(x,y)+\epsilon} \end{aligned} \tag{1}$$

where $I_x$ and $I_y$ are gradient in x and y direction. The $\epsilon$ is a small constant added to prevent zero-division during normalization.

Using the unit gradient vectors obtained above, the best matching position is searched for with a full search strategy. In previous work, the similarity metric of GOPM are based on sum-of-absolute difference (SAD) [2] and sum-of-square difference (SSD) [5]. The SSDs for unit gradient vectors are expressed in Eqs. (2) and (3).

$$SSD\_n_x = \sum_{i=1}^{N}\sum_{j=1}^{N}(n_{x1}(x+i,y+j) - n_{x2}(i,j))^2 \quad (2)$$

$$SSD\_n_y = \sum_{j=1}^{N}\sum_{i=1}^{N}(n_{y1}(x+i,y+j) - n_{y2}(i,j))^2 \quad (3)$$

where $SSD\_n_x$ and $SSD\_n_y$ are results of similarity metric between UGVs of sample image and template at position (x,y). Note that *N* is the block size of matching, $n_{x1}$ and $n_{y1}$ are UGVs of sample image, and $n_{x2}$ and $n_{y2}$ are UGVs of template. The gradient orientation pattern matching (GOPM) is then given by Eq. (4).

$$GOPM(\vec{p},\vec{d}) = SSD\_n_x + SSD\_n_y \quad (4)$$

### 2.2 Hamming Distance based Gradient Orientation Pattern Matching

In this research, we introduce the Hamming distance (HD) as a new similarity metric of GOPM instead of SSD. General description of HD metric is defined by Eq. (5).

$$HD(x,y) = \sum_{i=1}^{N}\sum_{j=1}^{N} I_1(x+i,y+j) \oplus I_2(i,j) \quad (5)$$

where $I_1$ is intensity of sample image at position (x,y) and $I_2$ is intensity of template. Generally HD compares 2 corresponding binary pixels by exclusive OR operator. The technique is widely used in VHDL and Iris recognition [6]. HD concerns the number of pixels that match rather than overall differences and yields better results in occlusion scenarios. To apply HD with non-binary information such as intensities or gradient orientations, the exclusive OR operation would be represented by threshold absolute difference [7].

$$sim(I_1, I_2, (x,y)) = \delta(|I_1(x,y) - I_2(x,y)| > p) \quad (6)$$

Thus, we could derive the Hamming distance of gradient orientations by Eqs. (7) and (8).

$$HD\_n_x(x,y) = \sum_{i=1}^{N}\sum_{j=1}^{N}\delta(|n_{x1} - n_{x2}| > \tau_1) \quad (7)$$

$$HD\_n_y(x,y) = \sum_{i=1}^{N}\sum_{j=1}^{N}\delta(|n_{y1} - n_{y2}| > \tau_2) \quad (8)$$

where $\tau_1$ and $\tau_2$ are certain thresholds. The differences those are higher than thresholds yields distance 1 and 0 in the vice versa. The distances are accumulated over the block area and demonstrate the similarity of that block pattern to the template. After calculating Hamming distance of UGVs, the Hamming distance based gradient orientation pattern matching is then calculated by OR operator as shown in Eq. (9).

$$HDGOPM = HD\_n_x \vee HD\_n_y \quad (9)$$

(a) (b) (c)

**Fig. 1.** (a) Part of the Lena image, and corresponding gradient orientations in x and y directions, (b) $n_x$ and (c) $n_y$

## 3 EXPERIMENTAL RESULTS

In the experiment, we established 3 kinds of simulation: i) Illumination change test, ii) Occlusion problem in illumination change situation, and iii) Testing all of problems out in the video sequences.

In the first three simulations, we create an artificial motion sequence on still image. The standard test images; Lena, Cameraman, and House with size 512 by 512 pixels are used as first frames. The second frames of sequence are then generated by translating the first frames by 5 pixels in both vertical and horizontal direction. To compute the motion vector over the entire scene, we defined 961 blocks in the first frame as reference blocks, and each block have size 16 by 16 pixels. The 961 motion vectors are estimated by measuring the similarity of reference pattern and the pattern in the second frame. The search range in the second frame is set around reference block areas by +/- 8 pixels (32 by 32 pixels search range).

**Fig. 2.** (a) The standard test image House, (b) the image translated by 55 pixels, and (c) the translated image under non-uniform illumination

### 3.1 Illumination change test

To simulate the illumination change situation in the artificial motion sequence, we re-simulate the worst case condition of illumination change test in previous research [2][3]. The second frame is translated (5,5) pixels under Gaussian noise with SNR 40dB and non-uniform illumination change of intensities, which the image intensities within vertical and horizontal stripes are rapidly reduced to half and the intensity in the areas where two stripes overlap are reduce to one forth.

**Table 1.** Successful motion estimation rate (%) under non-uniform illumination change

| Image | Standard SSD | GOPM with SSD | GOPM with HD |
|---|---|---|---|
| Lena | 21.23 | 99.89 | 100 |
| Cameraman | 26.74 | 99.89 | 100 |
| House | 23.10 | 99.37 | 100 |

Successful motion estimation rate (%) of 961 motion vector estimated by standard SSD, GOPM with SSD metric, and HD based GOPM are shown in Table 1. GOPM is obviously overcome lighting change problem (successful rate approximately 99% by SSD similarity metric and 100% successful rate by HD metric). Meanwhile SSD on intensity features is incapable to estimate the motion (successful rates are approximately 20%).

### 3.2 Occlusion test under illumination change situation

In the second experiment, the second frame of sequences are also translated by (5,5) pixels and 40dB Gaussian noise added. The non-uniform illumination is varied in the same way as in the first experiment. To simulate the occlusion situations in the sequences, the pattern of reference block are then occluded by *mxm* zeros square (Fig. 3), where *m* iterate from 0 to 13, which is approximately 81% covered. The successful motion estimation rates of SSD, GOPM with SSD metric and GOPM with HD metric on each standard test images are plotted against occlusion size over the pattern (Fig. 6). According to the graphs, GOPM with HD metric yields the highest successful motion estimation rates, while the successful rates of GOPM with SSD metric are slightly lower than HD metric. For standard SSD, it is severely fail to estimate the motion vector under the circumstances. This shows the advantage of HD based GOPM under occlusion and non-uniform illumination change.

### 3.3 Test in video sequences

Finally the last simulation shows the performance of proposed matching technique on the video sequences. In this experiment, the face template is initialized manually in the first frame. The video sequences consisted of 4 different scenarios; *normal* situation, *illumination change* by shot the flashlight in various angle and distance, *occlusion* which an unknown object cover some part of the face and the last scenario is *occlusion problem under illumination change* situation (Fig. 4). As a result, all matching techniques; SSD on intensities, GOPM with SSD metric and GOPM with HD metric could perform a tracking very well under normal situation. However in the case of illumination change, SSD fails

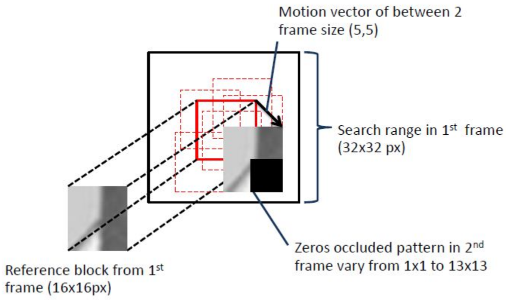


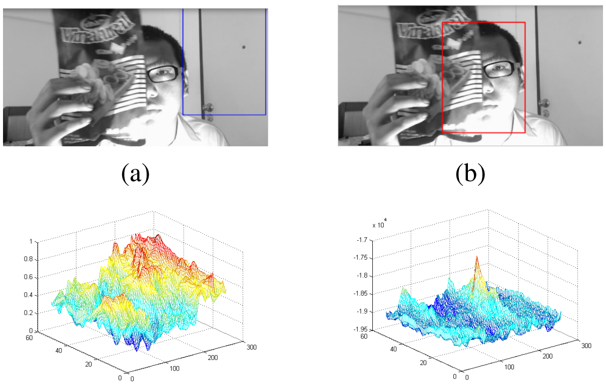

**Fig. 3.** Motion estimation on artificial motion sequence with (5,5) pixel translation, illumination change, 40dB Gaussian noise and zeros occlusion.

to archive the tracking, while both GOPM with SSD metric and GOPM with HD metric are fine. For occlusion problem (and occlusion under illumination change), only GOPM with HD metric could keep track the object almost of the entire video sequence. The similarity measurement results in Fig. 5 demonstrate the advantage of GOPM with HD metric over other techniques which matching results are disturbed due to the occlusion existence.

**Fig. 4.** Four real image sequences; constant light without occlusion, irregular lighting without occlusion, constant lighting with occlusion, and irregular lighting with occlusion.

## 4 CONCLUSION

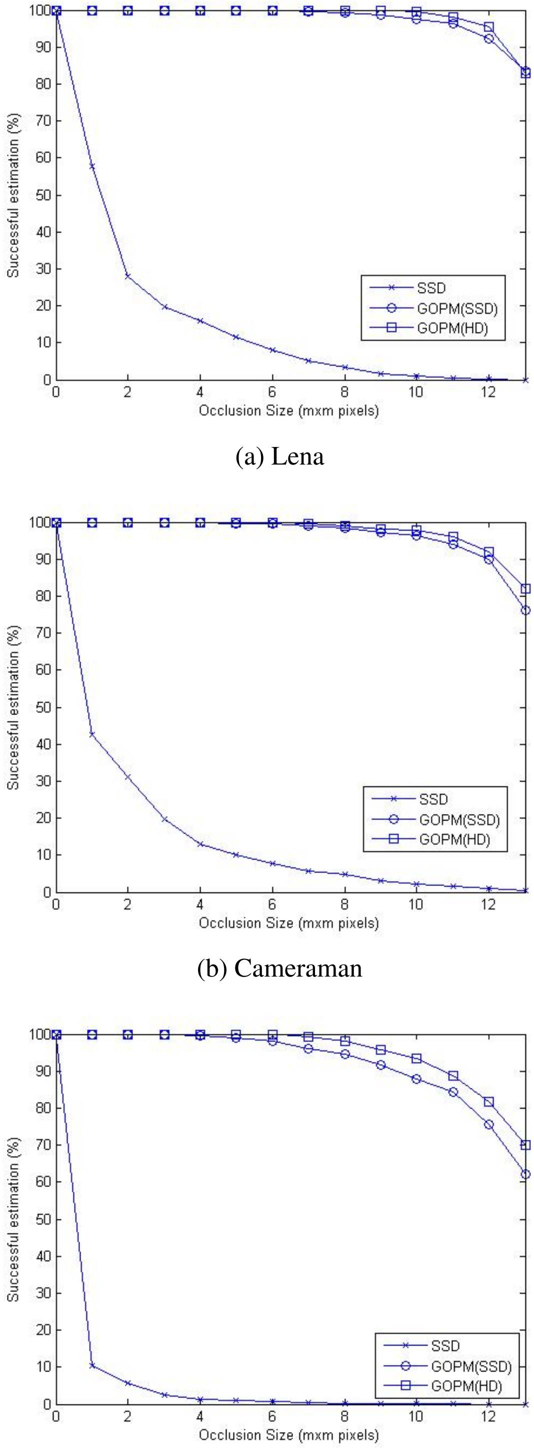
In this paper, we have proposed a novel pattern matching technique for motion estimation and visual tracking, which combines the advantages of gradient orientation features and Hamming distance metric. Unit gradient vectors are computed from template and input images before measuring the similarity between them using the Hamming distance. The Hamming distance is equivalent to the number of pixels whose unit gradient vectors are similar to each other between the template and images. The proposed method can perform robustly in time-varying lighting conditions with partial occlusions. Our simulation results have shown those advantages over existing matching techniques on both synthetic and real image sequences.



(a) (b)

(c) (d)

**Fig. 5.** Tracking results under irregular lighting with occlusion by (a) GOPM with SSD, (b) GOPM with HD, (c) and (d) the distributions of the corresponding similarity measurements




(a) Lena

(b) Cameraman

(c) House

**Fig. 6.** Successful rate motion estimation of occlusion testing under non-uniform illumination change on artificial motion sequences by using (a) Lena, (b) Cameraman, and (c) House image. The sizes of occlusion block are varied from 0x0 to 13x13 pixels

## REFERENCES

[1] Yilmaz A, Javed O, Shah M (2006), Object Tracking: A Survey. ACM Computing Surveys 38(4), Article 13, Dec 2006

[2] Kondo T, Kongprawechnon W (2009), A Block Matching Technique Using Unit Gradient Vectors, Proceedings of MVA2009 IAPR Conference on Machine Vision Applications, Yokohama, Japan, May 20-22, 2009

[3] Kondo T, Kongprawechnon W (2009), A matching technique using gradient orientation patterns, Thammasat Int. J. Sc. Tech. 14(3)

[4] Hotrakool W, Siritanawan P, Kondo T (2010), "Real-time Gradient Orientation Pattern Matching, Proceedings of International Conference on Embedded System and Information Technology, Chaing Mai, Thailand, 2010

[5] Hotrakool W, Siritanawan P, Kondo T, A Real-time Eye-tracking Method using Time-varying Gradient Orientation Patterns, Proceedings of ECTI-CON, Thailand, 2010

[6] Gupta S, Doshi V, Jain A, Iyer S, Iris Recognition System using Biometric Template Matching Technology, JACSA International Journal of Advanced Computer Science and Applications 1(2):24-28

[7] Ofir Pele and Michel Werman, Robust Real-time Pattern Matching Using Bayesian Sequential Hypothesis Testing, IEEE Transaction on Pattern Analysis and Machine Intelligence, August 2008