Point pattern matching by line segments and labels

Wen-Hao Wang and Yung-Chang Chen

Indexing terms: Pattern matching, Image processing

A point pattern matching method is proposed using the intrinsic invariant properties of a line segment which contains any two labelled points. Consequently, only the patterns which are judged to be affine-related are used to estimate the affine parameters so that efficient invariant image matching can be attained.

Introduction: Image matching is an application of image registration which utilises control points to estimate a mapping function. By using the same principle, image matching invariant to affine transformation can be accomplished by using the extracted point sets for initial matching where each pair of points in images are produced by the same process, i.e. the two points can be engaged with the same label.

Labelled point pattern matching [1, 2] has been proposed for the purpose of matching constellations by using the magnitude of each star as the label. It is prominent that point patterns with labels can be matched more easily than non-labelled point patterns. Therefore, the 'label' is a very important factor for speeding up point pattern matching. In addition, the intrinsic invariant properties [3] of a line segment, which consists of any two points, is also conducive to point matching when geometric deformation occurs. Yuen [4] utilised three successive points on a contour as a set of control points, which can be used for occluded object recognition. The line length ratio and the interior angle of the set of control points (three points) are defined for matching.

The registration-based image matching method [5] has lately been exploited, which is invariant to translation, rotation, and scaling. Each test image is registered with a reference image before matching. The requisite control points are centroids of the segmented regions, each of which corresponds to a specific grey level interval chosen from the reference in advance. Hence, the control points can be automatically paired as soon as they are produced from the same grey level interval. Thus, these points are referred to as 'labelled points'. Note that these labels are unique. They are different from the labels of the magnitude of stars because different stars may have the same magnitude. In general, control point pairing is a cumbersome and inevitable task in conventional registration; however, it has been eliminated from [5].

Proposed method: Considering that there exists a set of affine parameters for any two point patterns even if they are quite different, it will be time-consuming if affine parameters estimation, affine transformation, and image correlation are to be performed in that case. Thus, this Letter proposes a preprocessing stage by means of the intrinsic properties of line segments intending to remove the unnecessary computations in order that only the point patterns, which have high initial matching score, are used to estimate the affine parameters and perform what follows.

Let A and B denote the control point sets of the reference and test images, respectively:

$$A = \{a_i | i = 1, ..., N\} \qquad (1)$$

$$B = \{b_i | i = 1, ..., N\} \qquad (2)$$

Each point a_i or b_i has the same label 'i' which reveals that a_i and b_i are generated from the same (i)th grey level intervals. N is the number of the control points in one image. The line segments are defined as $\overline{a_ia_j}$ and $\overline{b_ib_j}$, $i = 1, ..., N, j = i + 1$ where $a_{N+1} = a_1$ and $b_{N+1} = b_1$. Hence, the number of line segments in one image is N. If the line segments are chosen as the whole combinations of points (i.e. C_2^N), the computational cost will be somewhat larger than the evaluation of least squares error. By using the designed sequentially and circularly point-connected line segments, the computational cost for the initial matching score will be greatly reduced.

Let $l_1(i,j)$ and $l_2(i,j)$ denote the line lengths of line segments $\overline{a_ia_j}$ and $\overline{b_ib_j}$, respectively. Then we can compute the line length ratio as

$$\eta(i,j) = l_1(i,j)/l_1(i,j) \qquad (3)$$

Let $\theta_1(i,j)$ and $\theta_2(i,j)$ denote the orientations of the line segments $\overline{a_ia_j}$ and $\overline{b_ib_j}$, respectively. The orientation distinction is defined as

$$\phi(i,j) = \begin{cases} (\theta_1(i,j) - \theta_2(i,j))/\pi & \theta_1(i,j) - \theta_2(i,j) \geq 0 \\ (\theta_1(i,j) - \theta_2(i,j))/\pi + 2 & \theta_1(i,j) - \theta_2(i,j) < 0 \end{cases} \qquad (4)$$

The division of π is to keep the order of ϕ consistent with η. Let $(\eta(i,j), \phi(i,j))$ be a feature point in the (η,ϕ) domain. The fundamental principle of the proposed method is the use of the intrinsic invariant property of (η,ϕ) which tends to be concentrated on a small area if the two point patterns have affine relationship; otherwise, (η,ϕ) will be scattered over a wide range of area. Hence, the initial matching score M of two point patterns is defined as the reciprocal of the deviation σ of the feature points.

$$\sigma^2 = \frac{1}{N} \sum_{i=1,...,N} ((\eta(i,i+1) - \bar{\eta})^2 + (\phi(i,i+1)\bar{\phi})^2) \qquad (5)$$

$\bar{\eta}$ and $\bar{\phi}$ are the means of $\eta(i,j)$ and $\phi(i,j)$, respectively. Smaller σ will result in a more coherent transformation for each corresponding line pair. Let T be a threshold. If $M \geq T$, the affine parameters estimation becomes necessary, i.e., there exists an affine transformation such that the two point patterns can be matched with less least squares error. Therefore, the affine parameter estimation, affine transformation, and correlation can then be performed to achieve the invariant matching of two images.

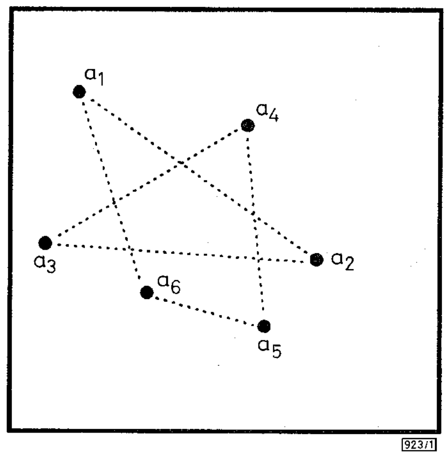

Fig. 1 *Point pattern p1*

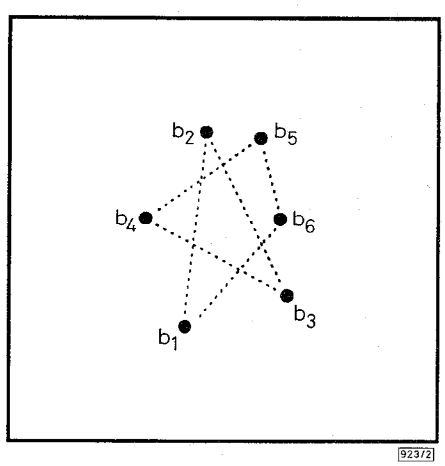

Fig. 2 *Point pattern p2*

Experimental results: Fig. 1 shows the point pattern p1 of the reference image with six labelled points ($N = 6$). Fig. 2 depicts the point pattern p2 of the test image which is the affine transformed version of the reference image. It is clear that these two patterns are similar to each other. Hence, the matching index of p1 and p2 is very high; i.e. it is necessary to compute the affine parameters for p1 and p2. The matching indexes are shown in Table 1. Fig. 3 shows the point pattern p3 which is another test image. Since p1 and p3 do not have an affine relationship, the matching index is very low; thus, affine parameter estimation is not required. Fig. 4 shows the scatter plot for the feature points (η,ϕ). The upper-right small region indicates the locations of the feature points of p1 and p2. It is obvious that the round marks in that region are densely distributed; nevertheless, there is a larger deviation between the triangular marks for the feature points of p1 and p3.

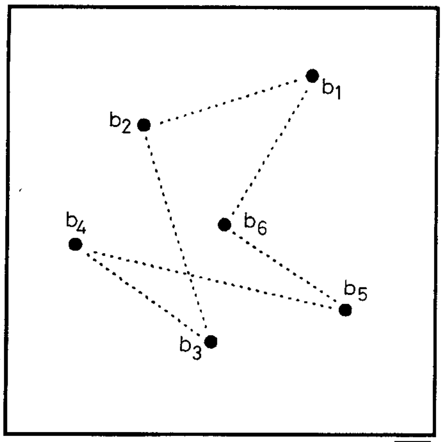

Fig. 3 *Point pattern p3*

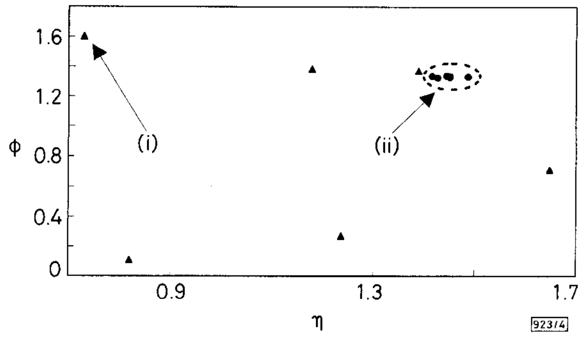

Fig. 4 *Scatter plot of feature points*

(i) feature points of p1 and p3
(ii) feature points of p1 and p2

Table 1: Matching index

p1 and p2	p3 and p3
50.0	1.5

Conclusions: Points without any labels are most involved in the matching. Labelling like that of the magnitude of stars is helpful to the matching of point patterns. Consequently, it is obvious that paired labels can facilitate point pattern matching because the pairing procedure is obviated. In addition, only a moderate number of line segments are involved. Hence, the proposed method can be used to remove the unnecessary parameter estimation, transformation, and image correlation procedures such that efficient invariant image matching can be achieved.

 13 January 1997
Electronics Letters Online No: 19970337

Wen-Hao Wang and Yung-Chang Chen (*Institute of Electrical Engineering, National Tsing Hua University, Hsinchu, Taiwan 30043, Republic of China*)

E-mail: ycchen@ee.ntu.edu.tw

References

1 OGAWA, H.: 'Labelled point pattern matching by fuzzy relaxation', *Pattern Recognit.*, 1984, **17**, (5), pp. 569–573

2 MURTAGH, F.: 'A new approach to point-pattern matching', *Astron. Soc. Pac.*, 1992, **104**, pp. 301–307

3 SKEA, D., BARRODALE, I., KUWAHARA, R., and POECKERT, R.: 'A control point matching algorithm', *Pattern Recognit.*, 1993, **26**, (2), pp. 269–276

4 YUEN, P.C.: 'Dominant point matching algorithm', *Electron. Lett.*, 1993, **29**, (23) pp. 2023–2024

5 WANG, W.-H., and CHEN, Y.-C.: 'A new approach for scale, rotation, and translation invariant pattern recognition', *Optical Engineering*, 1997, **36**, (4), (to be published)

Using target variance for optimum zoom setting in ATR

M. Mirmehdi, P.L. Palmer and J. Kittler

Indexing terms: Computer vision, Image recognition

The authors describe a technique for determining the best magnification to zoom in onto a target object while it is still at long range. The zoom process is modelled on the expected signal from the object and the background. The variance in a region of interest is shown to be an SNR indicator for the optimal zoom.

Introduction: It is desirable in automatic target recognition (ATR) systems to have the ability to both detect targets at long ranges (low crossing rate) and track targets at short ranges (high crossing rate due to increased velocity). However, to combine these will impose compromises in both scenarios. In long range recognition, a long stare time is necessary to ensure that the target signature is not adversely affected by the system noise, while in short range recognition a high frame rate and a short stare time would suffice to minimise the range when the target fills the field of view [1]. To avoid compromised systems, adaptive zoom optics must be developed to allow the sensor to zoom in on the object of interest once it is detected at long range. Sensor parameters are considered by Trabanis *et al.* [2], but they use geometrical models of the environment, optical models of the vision sensors, and models of the task to be achieved. In this Letter we mathematically model and implement the best optimal zoom factor for a sensor, by progressively locating the maximum of a simple signal measure. This acts as a (performance) evaluation measure which may be used for target identification and recognition.

Zoom process modelling: We are interested in locating objects in the sky when they are very distant. The background is assumed to be constant and we expect a tracking system to have detected and locked on the target. Given the aspect ratio a of the image is fixed, and the camera is in wide field view, the range of the axis visible in the image is $-w \le x \le w$ and $-aw \le y \le aw$. We shall presume that the object lies in the range $-1 \le x,y \le 1$ and that due to the constant background the image luminance function is $f(x, y) = 0$ outside these limits. The image variance σ_f which we shall adopt as an indicator of useful signal strength is by definition given by

$$\sigma_f^2 = \frac{1}{4aw^2}\int_{-w}^{w}\int_{-aw}^{aw} f^2(x,y)dxdy - \left[\frac{1}{4aw^2}\int_{-w}^{w}\int_{-aw}^{aw} f(x,y)dxdy\right]^2 \quad (1)$$

which can be shown to simplify to

$$\sigma_f^2 = \frac{\sigma_o^2 + \mu_o^2}{aw^2} - \frac{\mu_o^2}{a^2w^4} \quad (2)$$

where μ_o and σ_o are the object mean and variance.

Its maximum occurs at

$$w_{max} = \frac{\sqrt{2}\mu_o}{\sqrt{a(\sigma_o^2 + \mu_o^2)}} \quad (3)$$

As the image window w becomes smaller, the object contributes more, the background contributes less, and the variance becomes increasingly dominated by the variation in brightness of the object itself. If we allow the window to become smaller than the object, then the variance again reduces to zero once the window becomes smaller than the smallest scale variation within the object. We can therefore expect that the variance shows a maximum value once