2012 International Conference on Education Technology and Computer (ICETC2012)
IPCSIT vol.43 (2012) © (2012) IACSIT Press, Singapore

Correlation and Probabilistic Relaxation Image Matching Approch

Xin Wang[1+], Jin Wang[2]
[1]Nanjing Institute of Railway Technology
Nanjing, China
[2]Hebei University of Science and Technology
Shijiazhuang, China

Abstract. The statistics of the neighborhood gradients in an image can yield useful descriptions of target features. This paper presents a new approach on auto-correlation relaxation algorithm by using those features to match image clips. This method is iterative and begins with the detection of all potential correspondence pairs. Each pair of matching points is assigned a number representing the probability of its correspondence. The probabilities are iteratively recomputed to get global optimum sets of pairwise relations. This method could be found wide applications of matching video frames, and industrial detection recognition, for example in the research of artificial life and factory automation.

Keywords: Image; Auto-correlation; Probabilistic elaxation; Matching; Algorithm

1. Introduction

Image matching is the problem to find correspondence points in two or more images of the same scene, traditionally. Recently, many researches also show their interest in image stream, which is large amount of information for 3-D image reconstruction from 2-D images.

Two image points p and p' match if they result from the projection of the same physical point P in the scene, a property that is often approximated by a similarity constraint requiring, for example, p and p' to have similar intensity or color. The desired output of an image correspondence algorithm is a disparity map, specifying the relative displacement of matching points between images. The image correspondence problem is inherently under constrained and further complicated in image stream and also by the fact that the images typically contain noise. Traditional approaches thus either try to only recover a subset of matches, or make additional assumptions.

The feature based matching problem can generally be fall into three categories: matching points, curves, and areas. Point based matching is, for a location in one image, to find the displacement that aligns this location with a matching location in the other image [5][7][12]; curve-based matching is by analysis of the similarity and compatibility between curves in different images [2][3][4]; area based method yield a dense disparity map by matching small image patches as whole with respect to geometry, textures [6][8][10][11]. Theoretically, point correspondences, which matches points with a certain amount of local information, are the robust way. Traditional point based approaches, however, have two foundational difficulties when applied to more general scenes. First, they usually assumed known camera geometries for stereo matching, so less point's relation in one image considered. Second, the similarity constrains are seriously required.

We depict the attributes of a target by its significant energy points. Our idea to understand a target is from its points of this target to its lines, from its points to its lines and areas. This is related to manipulate our knowledge database in our further works. If the proposed auto-correlation approach is used alone, it also gives satisfied results [14].

2. Auto-Correlation model

Let I(X) (also denoted as I), Xk =(xk, yk), X∈R2 be the image function in an image frame. Given a shift of X as ΔX and. The auto-correlation function is defined as:

+ Corresponding author. *E-mail address*: bodabo2002@sohu.com

$$f(X)=\sum_{w}\left(I(X)-I(X+\Delta X)\right)^{2} \quad (1)$$

where X presents the global position in the working window w. according to the Taylor expansion, in the case of X∈R2, we rewrite the elements in X as X =(x, y) , the item I(X+ΔX) has:

$$I(X+\Delta X)=I(X)+I_{x}(X)\Delta_{x}+I_{y}(X)\Delta \mathrm{y}+,...\approx I(X)+\nabla I(X)(\Delta X)^{\mathrm{t}} \quad (2)$$

where Ix=∂I(X)/∂x, Iy=∂I(X)/∂y. Substituting the above approximation (2) into (1),then

$$\begin{aligned} &f(x)\\ &=\sum_{w}\left(\Delta I(X)(\Delta X)^{t}\right)^{2}\\ &=\sum_{w}(\Delta X)\begin{pmatrix} I_{z}^{2} & I_{x}I_{y}\\ I_{z}I_{y} & I_{y}^{2}\end{pmatrix}(\Delta X)^{t}\\ &=(\Delta X)\left(\sum_{w}\begin{pmatrix} I_{x}^{2} & I_{z}I_{y}\\ I_{x}I_{y} & I_{y}^{2}\end{pmatrix}\right)(\Delta X)^{t}\end{aligned} \quad (3)$$

I(X) is smoothed by a Gaussian filter. Then we write W(X) as ▽I(▽I)T, build up a transform relation H(X) in a local window about X.

$$\begin{aligned} H(X)&=T(X)*\sum\left\{\Delta I(\Delta I)^{t}\right\}\\ &=T(X)*\sum\begin{Bmatrix} (G_{z}*I)^{2} & (G_{x}*I)(G_{y}*I)\\ (G_{z}*I)(G_{y}*I) & (G_{y}*I)^{2}\end{Bmatrix}\end{aligned} \quad (4)$$

where G is a Gaussian with standard deviation one, Gx= ∂G /∂x, Gx=∂G/∂y. T(X) is a weight mask to weight the derivatives over the window. In (5), I=I(X), there relations ∂I/∂x =∂/∂x*I, ∂/∂x*(G*I)=(∂/∂x*G)*I=∂G/∂x*I. The matrix H(X) captures the local structure. The eigenvectors of this matrix are the principal curvatures of the auto-correlation function. We consider a cost function M(X):

$$M(X)\alpha H_{a}H_{b} \quad (5)$$

where Ha, Hb are the determinant and trace of H(X) respectively. We can get some image energy points, called interest points, by (5) and (6). An example of M(X) is illustrated in Fig.1 and Fig.2.

Figure 1. An original image

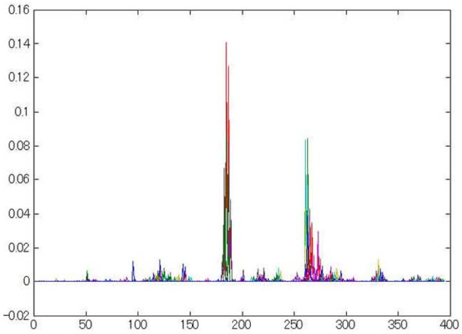

Figure 2. Distribution of the global correlation about Fig.1. M(X)is in vertical direction, and pixel position is in horizon

3. Probabilistic Relaxation Algorithm

Assume that there be two local windows Am' $\subseteq$I(X) and An' $\subseteq$ I(X+ΔX). Let Am={xm} be the set of all interest points in the first starting image that is input state space, and An={yn} the interest points in the second image that is output state space. Let cmn be a vector connecting points {xm} and {yn} (thus yn= xm+cmn). Let the probability of correspondences of two points xm and yn be Pmn. Two points xm and yn can be considered potentially corresponding if their distance satisfies the assumption of maximum velocity,

$$x_m - y_n| \le D_{max} \tag{6}$$

where Dmax is the maximum distance which a point may move in the time interval between two consecutive images. Two correspondences of points xmyn and xkyl are termed consistent of

$$c_{mn} - c_{kl}| \le D_{dif} \tag{7}$$

where Ddif is a preset constant derived from prior knowledge. Consistency of corresponding point pairs will increases the probability that a correspondence pair is correct. We determine the sets of interest points Am$\subseteq$Am' $\subseteq$Ii(X), An$\subseteq$An'$\subseteq$Ij(X), and construct a data structure as follows:

$$\left[x_{m,} \left(c_{m1}, p_{m1}\right), \left(c_{m2}, p_{m2}\right), ..., \left(SV^*, SP^*\right) \right] \tag{8}$$

where P_{mn} is defined as the probability of correspondence of points xm and yn, NV*, and NP* are special symbols indicating that no potential correspondence was found.

We initialize the probabilities P_{mn} as $P_{mn}^{(0)}$ as follows:

$$P_{mn}^{(0)} = \frac{1}{1 + k_p w_{mn}} \left(1 - P_{\left(SV^*, SP^*\right)}^{(0)}\right) \tag{9}$$

where $P_{(NV^*, NP^*)}^{(0)}$ is the initialized probability of no correspondence, kp is a constant and

$$w_{mn} = \sum_{\Delta x} \left[I_m \left(X_m \pm \Delta X\right) - I_n \left(y_n \pm \Delta X\right) \right]^2 \tag{10}$$

here, Δx defines a neighborhood for image match testing a neighborhood consists of all points (x + Δx), Δx is defined as a symmetric neighborhood around x. We iteratively determine the probability of correspondence of a point xm with all potential points yn as a weighted sum of probabilities of correspondence of all consistent pairs xkyl, xk are neighbors of xm and the consistency of xkyl is evaluated according to xm, yn. A quality qmn of the correspondence pair is defined as

$$q_{mn}^{(s-1)} = \sum_k \sum_l p_{kl}^{(s-1)} \tag{11}$$

where s denotes an iteration step, k refers to all points xk that are neighbors of xm, and l refers to all points yl$\subseteq$An that form pairs xkyl consistent with the pair xmyn.

The probabilities of correspondence are updated for each point pair xm, yn:

$$q_{mn}^{(s)} = q_{mn}^{(s-1)} \left(k_a + k_b q_{mn}^{(s-1)}\right) \tag{12}$$

where ka and kb are preset constants. They deal with the convergent speed of P_{mn}. Normalize

$$p_{mn}^{(s)} = \frac{p_{mn}^{(s)}}{\sum j p_{mn}^{(s)}} \tag{13}$$

Figure 3. Starting clip from an image stream.

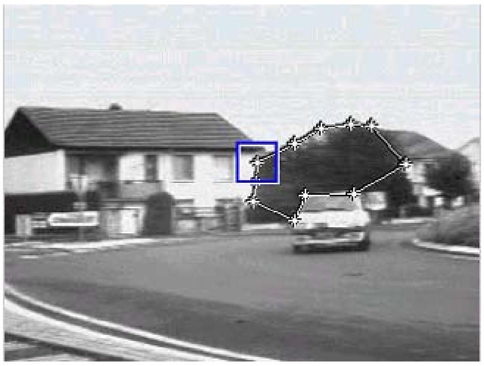

Figure 4. Slected local wiondow.

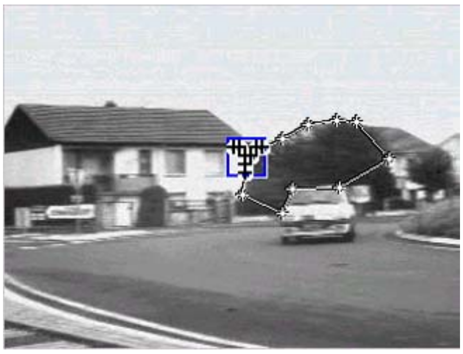

Figure 5. Maching results on Fig.4.

Those interest points that hold high probabilities that obviously differ from those interest points without correspondences finally. Repeat (11) (12) and (13) until all $P_{mn}^{(s)} > P_{thr}$ (threshold) are found for all points xm, yn.

4. Experiments and Discussions

To show availability of the presented approach, experiments are executed by matching image stream. A starting image is given in Fig.3. To illustrate the method easily, we have made an 11-points-based contour model as shown in Fig.3. Details how to make this contour can be found in [7][15][16], but beyond scope of this paper. As

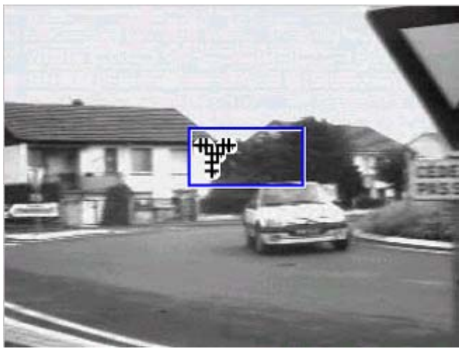

Figure 6. Maching results following Fig.4.

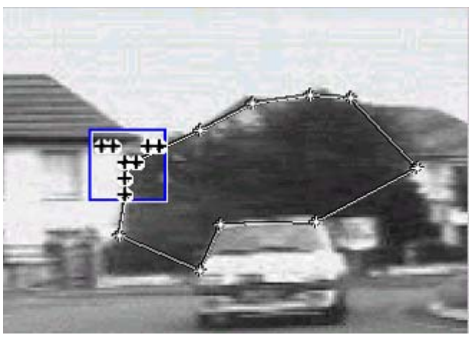

Figure 7. Fig.5 is zoomed in.

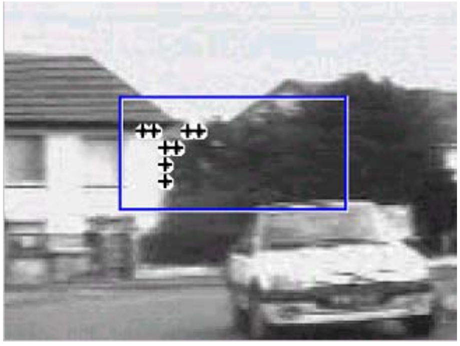

Figure 8. Fig.6 is zoomed in.

shown in Fig.4, one small window is selected in our experiment. Because the experiment is to match image stream, the second frame for matching should take into account this displacement with the respect to time t, and this is the reason why Fig.6 gives the larger window in it. The frames should be referred to the same center. Comparing Fig.5 and Fig.6, we can find 8 pairwise relations are detected from A'm and A'n. Fig.7 and Fig.8, the images zoomed in, show us surprising good results.

From Fig.3 to Fig.8, the entire experimental images are in the form of gray. In the case of color image, color images can bring us more detail image energy distribution and less similarity than gray ones. So this method is also recommended to the color case.

5. Conclusions

This paper presents a new matching approach without camera calibrations. The matching principle is based on the probabilistic relaxation under local image energy constraints. This algorithm can find contributions to image classification object tracking. We also recommend this technique to visual based intelligent navigation.

6. References

[1] D. Scharstien, *Stereo Matching with Nonlinear Diffusion*, {\it International Journal of Computer Vision}, vol.28, no.2, pp. 155-174, 1998.

[2] S. B., Pollard, J. Mayhew, and J. P. Frisby, *Implementation details of the PMF stereo algorithm*, {\it 3D Model Recognition from Stereoscopic Cues, MIT Press, Cambridge}, MA, pp. 33-41, 1991.

[3] A. Kumar, A. Tannenbaum, and G. Balas, *Optical flow: a curve evolution approach*, IEEE Trans. Image Processing, vol. 5, no. 5, pp. 598-610, 1996.

[4] R. Green, D. Gray, and J. Powers, Artificial Vision, Academic Press, London, 1997.

[5] W. Yu, K. Daniilidis, and G. Sommer, *Approximate orientation steer ability based on angular Gaussians*, IEEE Trans. Image Processing, vol. 10, no. 2, pp. 193-205, 2001.

[6] D. A. Forsyth, J. Ponce, Computer Vision, Prentice Hill, USA, 2003.

[7] B. Jähne, Image Processing for Scientific Applications, CRC Press, New York, 1997.

[8] M. Brown, D. Terzopoulos, Real Time Computer Vision, Cambridge University Press, 1994.

[9] H. Zhang, S. Roth, Camera Aided Robot Calibration, CRC Press, Boca Raton, 1996.

[10] L. Torresani, C. Bregler, *Space-time tracking*, Computer Vision- ECCV 2002, Part I, pp. 801-812, 2002.

[11] W. Kropatsch, R. Klette, F. Solina, and R. Albrecht, *Theroetical foundations of computer vision*, Springer Wien, New York, 1996.

[12] L. Zelnik, and M. Irani, *Multi-frame estimation of planar motion*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 22, no. 10, pp. 1105-1116, 2000.

[13] L. Gorelick, M. Blank, E. Shechtman, M. Irani, R. Basri, *A closed-form solution to natural image matting*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 30, no. 2, pp. 228-242, 2008.

[14] G. Medioni, I. Cohen, F. Bremond, S. Hongeng, and R. Nevatia, *Event detection and analysis from video streams*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 23, no. 8, pp. 873-889, 2001.

[15] N. Peterfreund, *Robust tracking of position and velocity with Kalman snakes* IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 21, no. 6, pp. 564-569, 1999.

[16] Y. Zhong, A. K. Jain, and M. Dubisson, P. Jolly, *Object tracking using deformable templates*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 22, no. 5, pp. 544-549, 2000.

[17] C. Rasmussen, and G. D. Hager, *Probabilistic data association methods for tracking complex visual object*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 23, no. 6, pp. 560-576, 2001.

[18] M. Kass, A. Witkin, and D. Terzopouls, *Snakes: active contour models*, Int'l J. Computer Vision, vol. 1, no. 4, pp. 321-331, 1988.

[19] L. D. Cohen, I. Cohen, *Finite-element methods for active contour models and balloons for 2-D and 3-D images*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 15, no. 11, pp. 1131-1147, 1993.

[20] C. Schmid, and R. Morh, *Local gray value invariants for image retrieval*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 5, 530-535, 1997.

[21] C. Schmid, R. Morh, and C. Bauckhage, *Evaluation of interest point detector*, Int'l J. Computer Vision, vol. 37, no. 2, pp. 151-172, 2000.

[22] G. Carneiro, and A. Jepson, *Phase-based local features*, Computer Vision - ECCV 2002, Part I, pp. 283-296, 2002.

[23] S. Sclaroof, and L. Liu, *Deformable shape detection and description via model-based region grouping*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 23, no. 5, pp. 475-489, 2001.

[24] L. Gorelick, M. Blank, E. Shechtman, M. Irani, R. Basri, *Actions as Space-Time Shapes*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 29, no. 12, 2247-2253, 2007.

[25] D. Nair, and J. K. Aggarwal, *Moving obstacle detection from a navigation robot*, IEEE Trans. Robotics and Automation, vol. 14, no. 3, pp. 404-416, 1998.

[26] N. Paragios, and R. Deriche, *Geodesic active contours and level sets for the detection and tracking of moving objects*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 22, no. 3, pp. 266-280, 2000.