Improvement of image matching by using the proximity criterion

Ibrahim GUELZIM
LRIT Laboratory, associated unit to CNRST, URAC 29
Physics Department, Faculty of Science
University Mohammed V-Agdal
B.P 1014, Rabat, Morocco
ibr_guelzim@yahoo.fr

Ahmed HAMMOUCH
LRIT Laboratory, associated unit to CNRST, URAC 29
Physics Department, Faculty of Science
University Mohammed V-Agdal
B.P 1014, Rabat, Morocco

Driss ABOUTAJDINE
LRIT Laboratory, associated unit to CNRST, URAC 29
Physics Department, Faculty of Science
University Mohammed V-Souissi
Rabat, Morocco

Abstract— The aim of this work is to develop a new algorithm for matching stereo images to the 3D reconstruction. We propose the use of a proximity criterion, to improve performance, and applying of the second chance algorithm. The similarity measures used are mutual information and correlation coefficient. The matching is done between neighborhoods of points of interest extracted from the images. We work in case which the sensor has a slight displacement between two images. The tests are performed on grayscale images.

Keywords- computer vision; 3D reconstruction; stereoscopic images; robotics;

I. INTRODUCTION

Approaching the human visual system is one of the major goals of computer vision. In this context, the stereoscopic image processing was the subject of much research during recent decades.

The idea is to make a 3D reconstruction from at least two images of the same scene. These images can be taken by two different cameras or a single camera captures the scene at two very close moments.

The matching is done between points of interest extracted from two images as it may apply to the contours. The outline approach consumes more time compared with the global issues of interest because of the considerable number of points that must match. For this reason, most research focuses on the method based on point of interest initiated by Moravec [10]. In this case, through the epipolar constraints, the correspondence between neighborhoods of points of the image left and right allows the determination of 3D coordinates. If the neighborhood size is reduced, the information available for matching is depleted by cons if the neighborhood size is large the information is more reliable statistically, but the probability of occultation is higher [11]. In [6] the authors proposed to vary the window size depending on the texture.

The epipolar constraint comes directly from the geometry of the stereoscopic sensor. It greatly reduces the search space corresponding to the entire image on the epipolar line (Fig. 1). It can apply in cases where the system is first calibrated or not [8] [20]. It is also applicable to other primitives that point [17], ie segments [15] [2] or regions [5] [19]. However, the calculated epipolar segment of each item consumes a considerable time and it must know in advance the parameters of the sensor.

Among the applications of stereovision found the construction of map, navigation for robotics [10], reconstruction of objects, face recognition [13] and others.

We propose a new matching method that we introduced a criterion of proximity to improve performance. We compare the results of matching with and without use of the criterion introduced. We also applied the second chance algorithm. The similarity measures used are mutual information and correlation coefficient.

In the following we present the similarity measures used, then we present the proposed method, and finish with a conclusion and perspectives.

II. SIMILARITY MEASURE USED

A. Mutual information

The mutual information (MI) between two random variables measures the amount of information that knowledge of one variable can make on another. The mutual information

![Fig 1. Epipolar constraint: the corresponding $m_g$ is on the segment $E_m$](image)

978-1-61284-732-0/11/$26.00 ©2010 IEEE
between two random variables \( X=\{x_1, x_2, \ldots, x_k\} \) and 
\( Y=\{y_1, y_2, \ldots, y_n\} \) is:
\[
MI(X,Y) = H(X) - H(X \mid Y) \\
= H(Y) - H(Y \mid X) \\
= H(X) + H(Y) - H(X, Y)
\]

Such that \( H \) is the entropy function and is equal to:
\[
H(X) = E[h(x_i)] = - \sum p_i \log_2 (p_i(x_i))
\]

with \( p_i = P(X = x_i) / i \in \{1, 2, \ldots, k\} \)

\( h(x) = -\log(p(x)) \)

Mutual information is a positive quantity, symmetric and is cancelled if the random variables are independent.

It follows the principle of no information creation (or Data Processing Theorem):
If \( g_1 \) and \( g_2 \) are measurable functions then:
\[
MI(g_1(X), g_2(Y)) \leq MI(X,Y)
\]

The inequality (5) means that no processing on raw data can reveal information.

The MI is a universal similarity measure [23][3][13] which is used in stereo matching [21], image registration[1], parameter selection[22].

B. Correlation coefficient

The correlation coefficient (CC) between two random variables calculates the degree of linear dependence between them. It is equal to the ratio of their covariance and nonzero product of their standard deviations (equation 6)
\[
\rho = \frac{\sigma_{xy}}{\sigma_x \sigma_y}
\]

where:
\( \rho \) : correlation coefficient;
\( \sigma_{xy} \) : covariance between X and Y;
\( \sigma_x \) : standard deviation of variable X;
\( \sigma_y \) : standard deviation of variable Y.

The CC is symmetrical and can vary from -1 to 1, values where linearity between two variables is perfect.
If two variables are totally independent, then their correlation is zero. However, the converse is not necessarily true, because there may be a nonlinear relationship between the two variables.

The difference between correlation coefficient and mutual information is that MI allows measurement of linear and nonlinear dependencies between random variables whereas CC calculates only the degree of linear dependence between variables.

III. PROPOSED METHOD

We chose to match the points of interest extracted from two images.

A. Detection of points of interest

To choose a detection algorithm, we must take into account two criteria: quality and detection time. Depending on the type of application, one is led to focus on one criterion at the expense of another.

There are two main families of interest point detectors:
- Detectors based on mathematical operators: Harris [4], Shi and Tomasi [14], Lindeberg [7], Harris-Laplace [9]
- Detector based on the change of appearance: Moravec [10], SUSAN [16], FAST [12]

We chose the use of Harris detector because it is stable, invariant to rotation and has good repeatability. We can also control the number of points detected for each image by changing the parameters of the Harris detector for the purpose of alleviating the calculations.

B. Followed algorithm

First, we introduce a criterion of proximity taking into account the condition that the images are supposed to be taken at times very close.

We consider the distance between the point P in the left image and the point Q in the right image as:
\[
QPd(\text{x}_P, \text{y}_P, \text{x}_Q, \text{y}_Q) = \sqrt{\text{x}_P^2 + \text{y}_P^2}
\]

Then, for a detected point of interest \( P \) in the left image, we seek the corresponding points in the right image. For this, we calculate the similarity (MID and CCD) between the neighborhood of the point P and the respective neighborhoods of interest points extracted in the image on the right (Fig 2).

If the corresponding point Q is the point P, then it is decided that P and Q are related, else we introduce the notion of second chance by using a confidence level. It measures the relative difference between the maximum similarity measure and the next smallest. It is very useful in cases where the maximum similarity measure is achieved by two points or if the values are very close.
We consider R, the second point chosen from right image, using the second chance. If the corresponding point on left image is P, then it is decided that P and R are related, else the point P has no correspondent in the right image.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

We have made tests on eight pairs of stereoscopic images of size 187x250 pixels (Fig. 5). We chose various images, which contain different structures to better evaluate our method. The number of points detected in the left images is 113. The neighborhood size used is 9x9. We used this size of neighborhood to have a rich sample (81 items) for the calculation of probabilities in order to have a correct measure of similarity.

The number of points detected in the left images is 113. The neighborhood size used is 9x9. We used this size of neighborhood to have a rich sample (81 items) for the calculation of probabilities in order to have a correct measure of similarity.

The threshold used varies with the type of images.

For a given point in left image, a good correspondence is realised if the corresponding actual is found or decide that it does not correspondent if it did not.

In the case in Figure 4, the algorithm without proximity criterion chooses a very distant point (R) from the true corresponding (Q) of point P, but by introducing the criterion the algorithm selects the correct corresponding.

Taking into account the condition that the images are supposed to be taken at times very close, the introduction of proximity criterion improves the results of matching by 15.9% in case of mutual information and 14.3% in case of coefficient correlation. This is due to the fact that the nearest points are more likely to be chosen for correspondence (Table 1 and Graph 1).

The same work was done on noised images by Gaussian noise multiplied by 25, the result of improvement is 32.1% in case of mutual information and 20.0% in case of correlation coefficient (Table 2).

V. CONCLUSION AND PROSPECTS

In this paper we presented a new matching method based on a criterion of proximity. The similarity measures used are mutual information and correlation coefficient. Considering that the images are supposed to be taken at times very close, the introduction of the proximity criterion improved significantly the results.

The results are promising, which encourages us to apply our method to the mobile robotics after compared it with existing methods.

TABLE I. RESULTS OF GOOD CORRESPONDENCE BETWEEN THE FEATURES EXTRACTED ON LEFT AND RIGHT IMAGES

|                        | mutual information | correlation coefficient |
|------------------------|--------------------|-------------------------|
| without proximity criterion | 77.9%              | 80.5%                   |
| with proximity criterion        | 90.3%              | 92.0%                   |

TABLE II. RESULTS OF IMPROVEMENT OF MATCHING CAUSED BY INTRODUCING PROXIMITY CRITERION FOR NORMAL AND NOISED IMAGES

|                        | mutual information | correlation coefficient |
|------------------------|--------------------|-------------------------|
| Simple images          | 15.9%              | 14.3%                   |
| Noised images          | 32.1%              | 20.0%                   |
Figure 2. Search the correspondent of the point P in the right image using MID.

Figure 3. Confirmation of correspondence between P and Q.

Figure 4. Need to introduce proximity criterion
References:

[1] J. Atif. "Recalage non-rigide multimodal des images radiologiques par information mutuelle quadratique normalisée". Université de Paris XI – Orsay. 29 Octobre 2004

[2] N. Ayache. Construction et fusion de représentations visuelles 3D. Applications à la robotique mobile. PhD thesis, Université Paris-Sud, 1988.

[3] Guoyan Zheng and Xuan Zhang. A Unifying MAP-MRF Framework for Deriving New Point Similarity Measures for Intensity-based 2D-3D Registration. IEEE conference. ICPR 2006.

[4] C. Harris & M. Stephens (1988). A combined corner and edge detector Proceedings of the 4th Alvey Vision Conference: pages 147--151.

[5] A. Gagalowicz and L. Vinet. Regions matching for stereo pairs. In Sixth scandinavian conference on image analysis, pages 63–70, Juin 1989.

[6] T. Kanade and M. Okutomi. A stereo matching algorithm with an adaptive window : Theory and experiment. IEEE Transactions on Pattern Analysis and Machine Intelligence, 16(9):920–932, 1994.

[7] T. Lindeberg, "Feature detection with automatic scale selection". International Journal of Computer Vision 30 (2). 1998

[8] Q.T. Luong and O. Faugeras. Self-calibration of a stereo rig from unknown camera motions and points correspondences. Technical Report 2014, INRIA, Juillet 1993.

[9] K. Mikolajczyk, C. Schmid(2004). "Scale and affine invariant interest point detectors" IJCV, Volume 60, Number 1 - 2004

[10] Moravec H. "Obstacle Avoidance and Navigation in the Real World by a Seeing Robot Rover", Ph.D. thesis, Stanford University, Stanford, California, May 1980. Available as Stanford AIM-340, CS-80-813 and CMU-RI-TR-3

[11] C. Rabaud, "Une nouvelle approche de mise en correspondance stéréoscopique dense par méthodes possibilistes". Université Montpellier II. 15 Juillet 2005.

[12] Edward Rosten (2006), Tom Drummond."Machine Learning for High-Speed Corner Detection". ECCV 2006. p 430-443

[13] D.B. Russakoff, C.Tomasi, T.Rohlfing, Calvin and R.Maurer, Jr. Image Similarity Using Mutual Information of Regions. ECCV 2004.

[14] J. Shi and C. Tomasi (June 1994). "Good Features to Track,". 9th IEEE Conference on Computer Vision and Pattern Recognition, Springer.

[15] Skordas and R. Horauld. Mise en correspondance structurelle pour la vision stéréoscopique.TSI, 7(6):591–608, 1988.

[16] S. M. Smith and J. M. Brady (May 1997). "SUSAN - a new approach to low level image processing.". International Journal of Computer Vision 23: 45-78.

[17] L. Sommellier, "Mise en correspondance d’images stéréoscopiques utilisant un modèle topologique". Université CLAUDE BERNARD - LYON 1. 23 septembre 1997

[18] R. VAILLANT, I. SURIN, "Reconstruction de visages par stéréovision active". Traitement du Signal [Trait. Signal], Vol. 12, N° 2-NS, p. 201-211. 1995

[19] L. Vinet. Segmentation et mise en correspondance de régions de paires d’images stéréoscopiques. PhD thesis, Université Paris IX Dauphine, juillet 1991.

[20] Z. Zhang, R. Deriche, O. Faugeras, and Q.T. Luong. A robust technique for matching two uncalibrated images through the recovery of the unknown epipolar geometry. Technical Report 2273, INRIA, Mai 1994.

[21] Yong Seok Heo, Kyoung Mu Lee, Sang Uk Lee: Mutual information-based stereo matching combined with SIFT descriptor in log-chromaticity color space. CVPR 2009: 445-452.

[22] M.A. Kerroum, and A. Hammouch, and D. Aboutajdine. Textural feature selection by joint mutual information based on Gaussian mixture model for multispectral image classification. Pattern Recognition Letters. Volume 31. N°10, pp : 1168-1174. July 2010.

[23] Skerl D, Tomazevic D, Likar B, Perrus F. Evaluation of similarity measures for reconstruction-based registration in image-guided radiotherapy and surgery. Int J Radiat Oncol Biol Phys. Volume 65, Issue 3, Pages 943-953, 1 July 2006.