ESTIMATION AND SEGMENTATION OF A DENSE DISPARITY MAP FOR 3D RECONSTRUCTION

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ABSTRACT

This paper presents a new algorithm of disparity map segmentation in planar facets. Originalities of this method lies in the process of dense disparity map estimation, using the dynamic programming subject to interest points previously extracted. The segmentation of this map uses the normal vector at each pixel surface. The matching of pixels between the two images by dynamic programming provides us with a scattered disparity map. So the densification of this map is achieved by matching contour points extracted between the two available images. Experiments with real images have validated our method and have clearly shown the improvement over the existing methods. The dense disparity map obtained is reliable when compared to classical methods. We also get a normal vector map segmented in contours and in homogeneous regions reflecting 3D planar facets.

INTRODUCTION

One of the main research field in computer vision is the matching of stereoscopic images. This matching enables the building up of a 3D surface of the scene. This matching step consisting in identifying the homologous points in the two pictures constitutes the key point of the stereo-reconstitution, but presents a difficult problem. Indeed, the geometric properties of the picture vary, one from the other because of geometric distortions; moreover objects visibility is often different in the two images. The presence of noise or a variation of lighting conditions can also transform the photometric properties of the different pictures.

In order to solve these problems, we have developed a new algorithm of matching, subject to interest points.
The interest points have properties and particular features (points of Moravec [5], edge points, corners, junctions, etc). There are numerous algorithms to match such interest points between views. Among these well known algorithm we can mention the correlation technique, methods of optimization, and the dynamic programming [8,11].

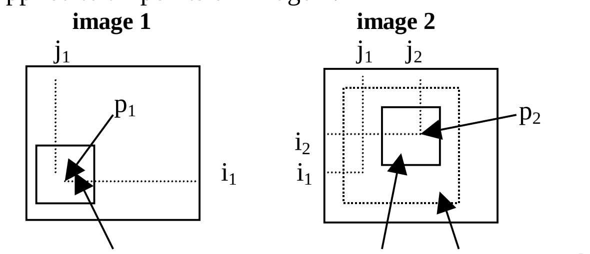
In this paper, our focus here is on a couple of rectified images, obtained from a fixed polyhedral scene. Paragraph 2 describes briefly the correlation-based technique and the dynamic programming method. In paragraph 3, the main improvement and process associated with the utilization of the dynamic programming are introduced. Paragraph 3-3 suggests a densification technique in order to improve the disparity map. The segmentation of this disparity map is investigated in paragraph 4. Finally, paragraph 5 shows the experimental results obtained by the method suggested; in addition to a comparison between this method and the correlation technique.

2. MATCHING METHODS

2-1 Correlation-Based Method

The technique of matching points by correlation is described as follow: If we look for the correspondent of a point p_1 of the picture 1 (figure 1), we first of all start by a defining a research zone in picture 2. We use a fixed window of correlation F_1 in picture 1, centered in point p_1. We also use a slippery window F_2 in picture 2 that browses the research zone. For each F_2 position, a correlation value is calculated between F_1 and F_2. The calculated values on the research zone defines a correlation surface associated to point p_1. The chosen point is the one having the biggest correlation value if the measure of this correlation corresponds to a measure of similarity; otherwise we use the smallest value in the case of a dissimilarity measure.

If we wish to get a dense matching, this process will be applied to all points of image 1.



F_1correlation window, **F_2** slippery window, zone of research

Figure 1. Research of a correspondence by correlation

2-2 Dynamic Programming

This technique is particularly adapted to problems of optimization subject to constraints. The dynamic programming uses the local associations of features to condition the global optimization research. The principal idea of this technique is to minimize a cost function in a bidimensional graph. The research of corresponding points is done subject to conjugated epipolar lines. Order constraints and disparity domain enable the reduction of possible paths and allow the intra-line consistency [2]. The advantage of this technique is that it allows the subdivision of the problem of matching in to a set of under-problems (restriction to couples of epipolar lines). Each under-problem can be solved globally, thus avoiding error propagation problems on the same line. The principal problem of this approach consists in the choice of the cost function and also in saving the inter-line consistency.

3. PROPOSED MATCHING APPROACH

3-1 General Gait

Our objective is to improve the dynamic programming technique [8] by integrating a phase of point feature detection (interest points and edge points). Our algorithm is divided in two steps: The first step consists in extracting interest points by the detector of Harris and Stephens[5] then in matching them by a bi-directional correlation technique including a step of relaxation in order to eliminate the aberrant matching points [10]. This technique provides a sparse disparity map. Au second step is introduced for densification of disparity map by using the edge points.

3-2 Constrained Dynamic Programming

After extracting and matching interest points [5][10], we can match two conjugated epipolar lines D_g and D_d globally (see figure 2). For that, we have arranged the signals on the left and the right epipolar lines in two array axis.

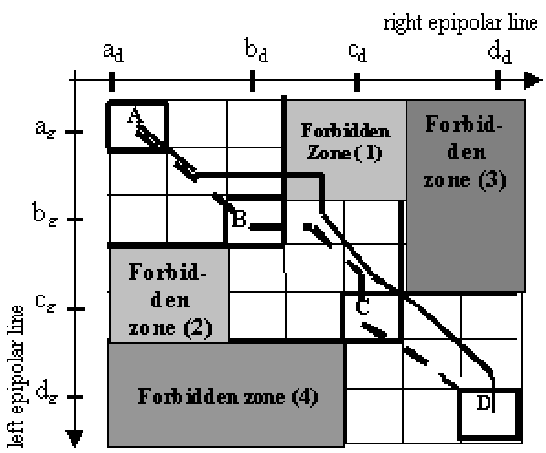


Figure 2. dynamic programming constrained by interest points.

We have associated a cost function to this array. For each element of the array a potential matching is allowed with a cost value. The goal is to find the optimal path between points A and D. The introduction of interest points permits to constrain the optimal path by restricting research zone. This path is constrained to contain points B and C representing the couples of homologous interest points (b_d,b_g) and (c_d,c_g). Assuming that the order constraint is verified, the homologous points of points between c_d and d_d are located between points c_g and d_g (and vice versa). This scheme defines two forbidden zones. Zone 3 permits to avoid the matching the points of $]c_d,d_d[$ interval with the $]a_g,c_g[$ points . Zone 4 permits to avoid matching the points of $]c_g,d_g[$ interval with the $]a_d,c_d[$ points. Therefore, all horizontal, vertical or diagonal displacement that can browse a forbidden zone is excluded. This restriction permits a best constrained matching of epipolar lines with a reduced execution time.

3-3 Densification Of The Disparity Map

The interest points extraction method does not provide interest points on all epipolar line. Therefore the disparity map obtained by the dynamic programming method constrained by interest points (matching epipolar lines that contain interest points) remains a scattered map. For a disparity map densification, H. Maitre [6], proposed to approximate the disparity map on each region by the model z=ax+by+c. The main difficulty of his approach is the imprecision of the segmentation. Each pixel affected to an incorrect region seems to distort the parameters estimation. To remedy this problem, an approach based on four steps for the model estimation has been proposed [4]. This technique remains always biased by the segmentation technique. For this reason we are interested to edges points, often corresponding to the physical discontinuities of the scene.

3-3-1 Matching Of Edge Points

In our experiments, the edge points are obtained by applying the canny filter [3]. These points are then matched by bi-directional correlation, followed by a relaxation step to eliminate the false matching [10]. The obtained homologous points permit to constrain dynamic programming correspondence on the epipolar lines that do not contain interest points. For the epipolar lines that contain neither interest points nor edge points, the disparity is calculated by unconstrained dynamic programming method [8].

4. SEGMENTATION IN PLANAR FACETS

We have segmented the obtained disparity map in regions that present 3D planar facets. We have used the normal vector to distinguish two adjacent facets in the same polyhedral object. The originality of our method is based on the estimation of the normal in each pixel. Here, we have presented equations of the normal vector in each pixel in the calibrated case (intrinsic parameters are known) and in the uncalibrated one (intrinsic parameters are not known). In the two cases the stereo system is supposed to be rectified [9].

4-1 Equation Of The Normal In A Calibrated Case

A 3D facet can be represented by the equation:

$$a\,x + b\,y + c\,z = d \qquad \textbf{(1)}$$

The normal vector N in each point P of the facet is expressed as :

$$\vec{N} = \left(-\frac{\partial z}{\partial x}, -\frac{\partial z}{\partial y}, 1 \right)^T = (Nx, Ny, 1)^T = \lambda (a, b, c)^T \quad \textbf{(2)}$$

By using the projection equation of a perspective projection model and the relation between the depth and the disparity : $\delta = f \cdot B/z$ **(3)**

f: the focal, B: the baseline, z: the depth.

we can show that :

$$N_x = \frac{f\delta \, u \dfrac{\partial\left(\frac{1}{\delta}\right)}{\partial u}}{1 + \delta \, u \dfrac{\partial\left(\frac{1}{\delta}\right)}{\partial u} + \delta \, v \dfrac{\partial\left(\frac{1}{\delta}\right)}{\partial v}}$$

and

$$N_y = \frac{f\delta \, v \dfrac{\partial\left(\frac{1}{\delta}\right)}{\partial v}}{1 + \delta \, u \dfrac{\partial\left(\frac{1}{\delta}\right)}{\partial u} + \delta \, v \dfrac{\partial\left(\frac{1}{\delta}\right)}{\partial v}}$$

(u ,v) : are the picture coordinates in the camera repere.

4-2 Equation Of The Normal In Uncalibrated Case

To calculate the coordinates N_x and N_y, the camera needs to be calibrated. Yet, we can work with the uncalibrated camera. To solve this problem, we have worked out the equation (1) in a 3D space, called space disparity space (equation (5)).

We can show that the new 3D facet equation is :

$$AX_p + EY_p + C\delta = D \quad \textbf{(5)}$$

$$\text{with} \quad A = \frac{a}{F_x}, \quad E = \frac{b}{F_y}, \quad C = -\frac{d}{Bf}$$

$$\text{and} \quad D = \frac{aX_c}{F_x} + \frac{bY_c}{F_y} - c$$

and X_p, Y_p : the image coordinates in the pixel repere and X_c, Y_c, F_x, F_y, f : are the intrinsic parameters.

Coordinates of the normal vector N can be expressed as followed :

$$N' = (N'_x, N'_y, 1)^T = \left(-\frac{\partial\delta}{\partial X_p}, -\frac{\partial\delta}{\partial Y_p}, 1 \right)^T = \lambda (A, E, C)^T \quad \textbf{(6)}$$

4-3 Segmentation Of The Disparity Map

We have used two algorithms for planar facets segmentation : the first algorithm achieves a direct segmentation of the disparity map in homogeneous regions in terms of a brightness affine model related to the equation (5). This provides one region by planar facet. For this segmentation we use the algorithm of Victor Nzomgni [7]. In the second algorithm segmentation, the normal vector map is calculated from the disparity map, then segmented in uniform regions by a level curve algorithm.

5. EXPERIMENTAL RESULTS

We have processed 2 couples of polyhedral stereoscopic images (Fig. 3a, 3b, 4a and 4b). The disparity maps obtained from the proposed method are presented in figures 3c and 4c. The disparity map obtained from our method (fig. 3c) is better than the disparity map obtained from correlation matching [1] (fig. 3d). The segmentation maps based on a normal vector computing (fig. 3f and 4e) provides the true different contours of 3D facets. The results of segmentation can show different facets 3D in the scene, two facets appear in "BOX" image and four facets in "BD" image. We have also tested these methods on a complex image (images of tree in fig. 5a and 5b). The disparity map (fig. 5d) obtained from the proposed method is better than the one obtained from the correlation technique (fig. 5c). We can here note that the step of differentiation is sensitive to noise.

6. CONCLUSIONS

In this paper, We have presented a segmentation method of stereoscopic images in planar facets based on a disparity map estimation which is improved by both the introduction of interest points and a normal vectors. The results presented have shown the relevance of our approach. Yet, to completely validate the algorithm, a 3D reconstruction is needed.

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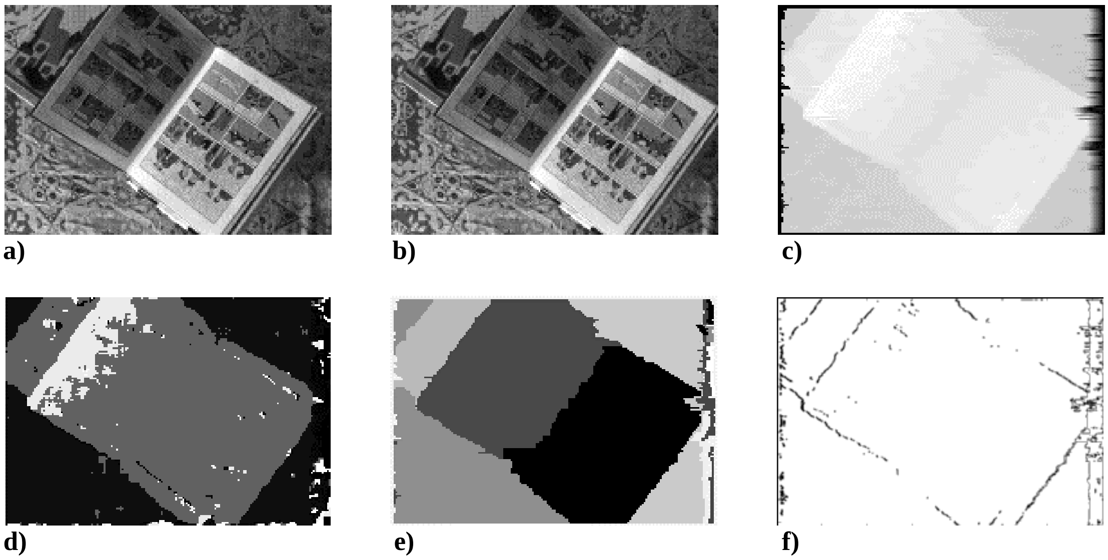

Figure 3. **a)** left image of BD, **b)** right image of BD, **c)** proposed method dense disparity map, **d)** disparity map by correlation, **e)** V. Nzomigni segmentation, **f)** based normal edge segmentation.

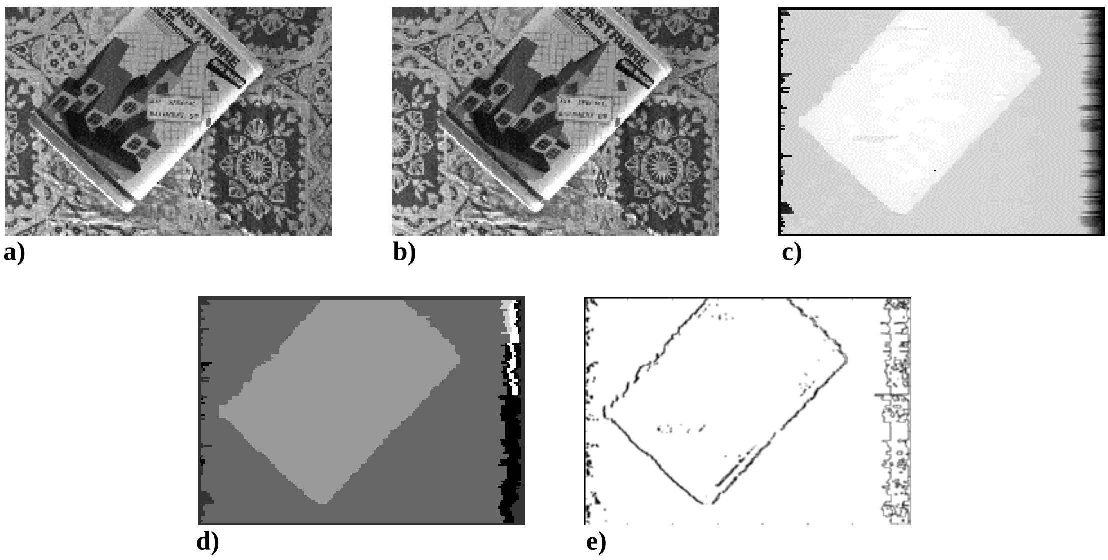

Figure 4. **a)** left image of box, **b)** right image of box, **c)** proposed disparity map, **d)** V. Nzomigni segmentation, **e)** edge segmentation using normal vector

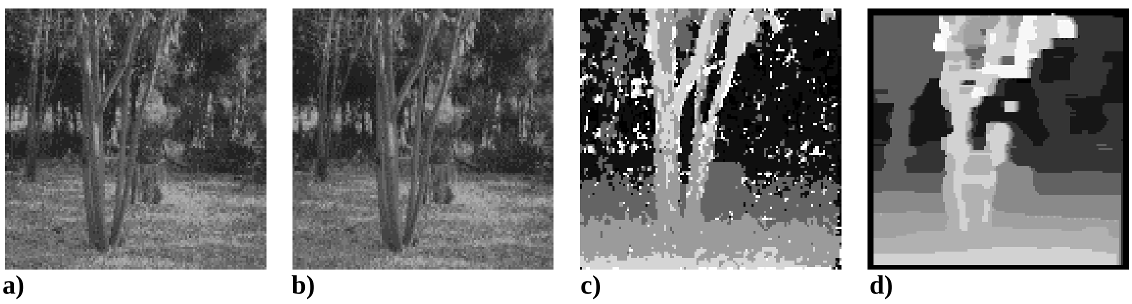

Figure 5. **a)** left image of tree, **b**) right image of tree , **c)** correlation disparity map, **d)** based dynamic programming disparity map