Fast Panoramic Stereo Matching Using Cylindrical Maximum Surfaces

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***Abstract*—This paper presents a fast panoramic stereo matching algorithm using a cylindrical maximum surface technique. The disparity for a pair of panoramic images is found in a cylindrical shaped correlation coefficient volume by obtaining the maximum surface rather than simply choosing a position that gives the maximum correlation coefficient value. The use of our cylindrical maximum surface technique ensures that the disparities obtained at the left and the right columns of the panoramic stereo images are properly constrained. Typical running time for a pair of 1324 × 120 images is about 0.33 s on a 1.7-GHz PC. A variety of real images have been tested, and good results have been obtained.**

***Index Terms*—Circular shortest path, cylindrical maximum surface, cylindrical volume, dynamic programming, fast cross-correlation, fast panoramic stereo matching.**

I. Introduction

Panoramic images are becoming increasingly popular in image-based virtual environment representations and digital photography. Different techniques have been developed for creating panoramic images [1], [2]. Panoramic stereo images are also becoming available for three-dimensional (3-D) applications. These include 3-D scene visualizations [3]–[5] and 3-D reconstructions [2], [6]–[10]. The panoramic stereo images that we are interested in are the 360° stereo images on a cylindrical surface.

The correspondence problem in stereo vision and photogrammetry concerns the matching of points or other kinds of primitives such as edges and regions in two images such that the matched points or primitives are the projections of the same point or primitive in the scene. The disparity map obtained from the matching stage may then be used to compute the 3-D position of the scene points given the knowledge about the imaging geometry of the cameras.

Numerous stereo matching methods that appeared in the literature were developed for the standard stereo images (see review papers in [11]–[13]). Some matching methods for panoramic stereo images use standard window-based correlation search [2], [9], [10]. Because of the special wrap-around property for the panoramic stereo images, special care needs to be taken during the stereo matching process. Zheng and Tsuji used circular dynamic programming for matching vertical features in panoramic images [14]. They did not carry out dense matching, and the matching process was iterative. Li *et al.* used tensor voting techniques for matching multiperspective panoramas [15].

In this paper, we propose to use cylindrical maximum surface techniques for carrying out dense panoramic stereo matching. The algorithm also uses fast correlation calculation techniques for fast calculation of similarity measure and obtains the cylindrical maximum surface in a multi-resolution or coarse-to-fine scheme. The disparity is obtained from the cylindrically shaped 3-D correlation coefficient volume by finding the cylindrical maximum surface considering the continuity of neighboring epipolar scanlines. The rest of the paper is organized as follows: Section II presents our new method for panoramic stereo matching by finding the cylindrical maximum surface in the 3-D cylindrical correlation volume by using circular shortest path techniques. The detailed matching steps are described in Section III. Section IV shows the experimental results obtained using our fast panoramic stereo matching method applied to a variety of images. Section V gives concluding remarks.

Manuscript received August 15, 2002; revised November 19, 2002. This work was supported in part by the Israeli Ministry of Science. This paper was recommended by Associate Editor P. Bhattacharya.

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Digital Object Identifier 10.1109/TSMCB.2003.816997

II. Panoramic Stereo Matching

Panoramic stereo images can be obtained by a number of methods. They can be generated by mosaicking images from a rotating camera [10], [16] or by using special imaging optics [2], [17]–[20].

In traditional stereo images, even for the rectified epipolar images, points that are close to the left or right image boundaries usually do not have matching points in the other image. For panoramic stereo images, each of the image contains the whole 360° view. There are no nonoverlap regions for panoramic stereo images except those occlusion areas.

For a flattened [from cylindrical surface to two-dimensional (2-D) matrix] panoramic image, the left and right image boundaries are actually neighboring columns of the actual panoramic image. A panoramic image is a circular image. It is therefore necessary to make special considerations for designing algorithms to perform panoramic stereo matching.

A. Image Boundary Padding

Images are stored as a 2-D array or matrix, but for panoramic images, the left and right boundaries are actually neighbors. We need to take this information into account when carrying out panoramic stereo matching. The similarity measure that we are going to use is windowed correlation. In order to work up to the image boundaries, we need to pad the images with some extra pixels. The padding of the left and the right boundaries are copies of the boundary regions of the original image. The width of this padding is related to the correlation window size and disparity search range. The padding of the top and the bottom of the image can take simple mirror reflection of the original image pixels. This process is used for both similarity calculation and circular shortest path extraction algorithms (to be described later).

B. Fast Similarity Measure

Similarity is the guiding principle for solving the correspondence problem. The most commonly used similarity measure is the cross-correlation coefficient. The sum of absolute differences (SAD) and the sum of square differences (SSD), which are both dissimilarity measures, can also be used. It has also been shown that the zero-mean normalized cross-correlation (ZNCC) and the zero-mean sum of squared differences tend to give better matching results [21]–[23]. The estimate is independent of differences in brightness and contrast due to the normalization with respect to mean and standard deviation. We will use the ZNCC coefficient as the similarity measure between the candidate matching areas, but direct calculation of ZNCC is computationally expensive. Faugeras *et al.* developed a recursive technique to calculate the correlation coefficients which are invariant to the correlation window size [21]. Sun used the box-filtering concept for fast cross correlation calculation [24].

We can use the techniques described in [21] or [24] on the boundary padded panoramic stereo images for fast correlation calculation. As a result of the fast similarity measure, we obtain a 3-D correlation volume. The size of the volume depends upon the image row and column numbers M, N and the maximum disparity search range

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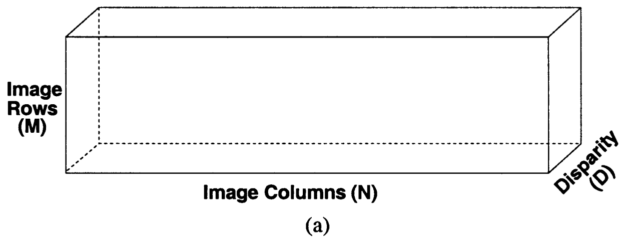

Fig. 1. Illustration of the 3-D correlation coefficient volume for panoramic stereo images obtained after using the fast correlation method. (a) 3-D volume. (b) Same volume in cylindrical shape.

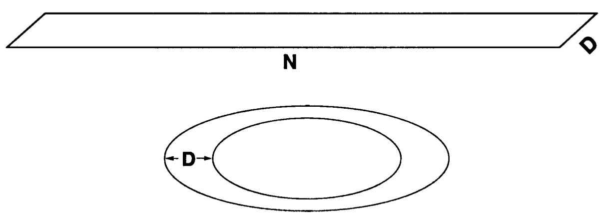

Fig. 2. One slice of the 3-D cylindrical volume shown in Fig. 1.

D as shown in Fig. 1(a). The algorithm used for the fast correlation calculation is based on the moving average or moving window's technique. The complexity of the fast algorithm for similarity measure is $O(MND)$, which is independent of the correlation window size, similar to the standard stereo cases as in [21] and [24]. For detailed description for fast correlation calculation, see [24] or [25].

As the inputs are panoramic stereo images, the 3-D correlation coefficient volume obtained actually forms a cylindrical volume as shown in Fig. 1(b). We will find a maximum surface within this cylindrical volume for disparity estimation.

C. Circular Shortest Path in 2-D Matrix

In panoramic stereo matching, a horizontal slice of the cylindrical volume as shown in Fig. 2 has the property that the left most and the right most columns are connected. This 2-D slice can also be shown in the format of a cylindrical surface as in [26]. In traditional stereo matching, dynamic programming (DP) techniques have been used to obtain shortest paths to estimate disparities [24], [27], [28]. For panoramic stereo matching, we can use circular shortest path (CSP) extraction technique to obtain a CSP in each 2-D correlation matrix (sized ND, as shown in Fig. 2) so that the starting and ending positions of this path are connected.

Five algorithms (MSA: multiple search algorithm; IPA: image patching algorithm; MBTA: multiple backtracking algorithm; combination algorithm of IPA and MBTA; and approximate algorithm) in [26] and one (BBCSP: circular shortest path by branch and bound) in [29] have been developed for CSP extraction on regular grids or images when the left and the right columns of the grid are neighbors. The basic algorithm within these five algorithms is the use of DP technique. MSA is the slowest as multiple DP (D times) operations are necessary. The complexity of this algorithm is $O(ND^2)$. BBCSP is faster than MSA but slower than other methods. The BBCSP algorithm gives $O(ND^{1.6})$ average running time. The combination algorithm of IPA and MBTA takes roughly the same time as IPA, MBTA, or the approximate algorithm and achieves a higher probability and speed in finding the optimum circular shortest path. These algorithms have the computation complexity of $O(ND)$. The algorithms used for IPA and MBTA are essentially dynamic programming algorithms. We will use the combination algorithm of IPA and MBTA for our panoramic stereo matching as it is fast and guarantees to find a circular path.

The patching of a 2-D matrix for the IPA algorithm is carried out in the x-direction on the left and the right sides of one slice of the cylindrical volume. The values of the patched regions come from the input matrix itself. A shortest path is obtained from this patched matrix, and a CSP may be extracted from the 2-D slice of correlation matrix. For detailed description of the IAP algorithm, see [26]. The steps of the IPA algorithm for CSP extraction for a 2-D slice of correlation matrix are as follows.

1) Patch the input 2-D matrix on the left and the right sides with portions of the input matrix itself to obtain a patched matrix.
2) Perform ordinary shortest path extraction using ordinary dynamic programming on the patched matrix.
3) Extract the shortest path which lies inside the original matrix.

When carrying out the ordinary shortest path extraction using dynamic programming, we can also store the cost value for each node and the corresponding predecessor matrix. From each node on the last column, we can backtrack a path from this node to a certain node on the first column. This path has a certain cost. If the starting and the ending positions of this path are neighbors, then we say this path is a possible CSP. We backtrack all the nodes on the last column, and we may find several possible CSPs. We can then choose the CSP with the minimum cost as the final result. For detailed description of the MBTA algorithm, see [26]. The steps for the MBTA algorithm are as follows.

1) Carry out ordinary dynamic programming to build a cost matrix and a predecessor matrix.
2) Carry out backtracking from each position on the last column, and record the cost for a circular path.
3) Choose a circular path with the minimum cost as the result of this algorithm.

The combination algorithm involves running each of the IPA and MBTA algorithms once. That is using the IPA algorithm to find a path, if this path is not circular, we use the path obtained by the MBTA algorithm. If the path obtained from running the IPA algorithm is circular, we choose the path with the minimum cost from the IPA and the MBTA algorithms.

One can simply use the CSP extraction algorithm mentioned earlier to obtain a CSP for each slice of the 3-D cylindrical volume independently for the disparity estimation of the panoramic stereo images. However, this approach does not take information from neighboring scanlines into account (apart from the windowing effect during correlation). In the following subsection, we use this CSP extraction technique to obtain a 3-D surface in the cylindrical volume for panoramic stereo matching. We intend to obtain a maximum 3-D cylindrical surface rather than a number of independent CSP's.

D. Maximum Surface in a Cylindrical Volume

There are a number of researchers who obtain ordinary stereo disparity from 3-D correlation volume. Roy and Cox [30] and Chen and Medioni [31] use 3-D volume information to find disparities. The average running time for Roy and Cox's algorithm is $O((MN)^{1.2}D^{1.3})$ [30]. The typical running time for 256 $\times$ 256 images is anywhere between 1 to 30 min on a 160-MHz Pentium machine depending on the

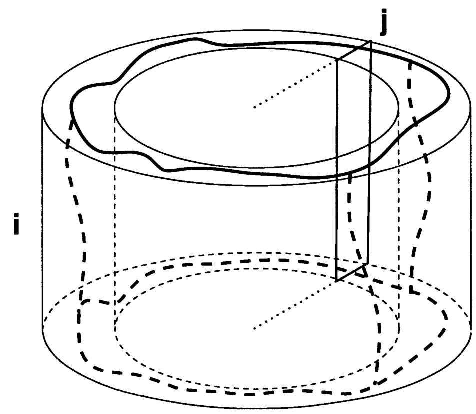

Fig. 3. Cylindrical maximum surface that gives the maximum accumulation of cross correlation values in the cylindrical volume. The vertical rectangle in the figure shows one vertical slice at position j of the cylindrical volume.

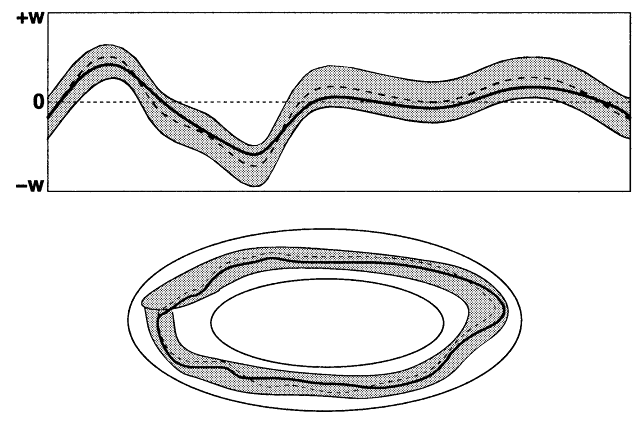

Fig. 4. Circular shortest path obtained for each horizontal slice of the Y volume. The horizontal axis is the image column. The vertical axis is the disparity. The dashed curves are the path obtained in the previous slice. The solid curves are the path obtained in the current slice. The top drawing gives 2-D matrix form while the bottom drawing shows a ring form.

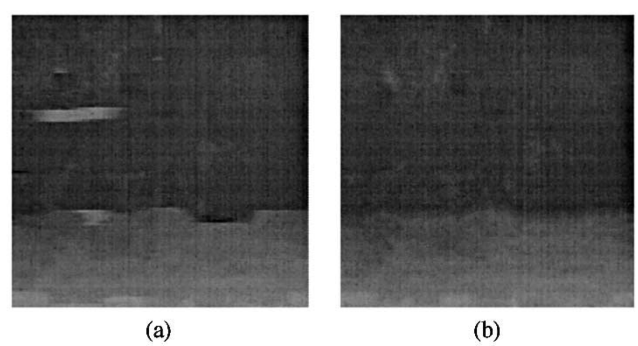

Fig. 5. Different disparity results obtained for a portion of the panoramic stereo images. (a) Disparity obtained using CSP for each horizontal slice of the 3-D correlation volume. (b) Disparity obtained using the cylindrical maximum surface technique.

depth resolution used. There was no mentioning about the speed issues in [31]. Yang and Yuille proposed a nonlinear filter for detecting disparity surface in a 3-D volume [32]. They first apply the filter to the 3-D volume and then simply use maximum picking. Sun developed a fast two-stage dynamic programming technique for maximum surface extraction in a 3-D volume for ordinary stereo matching [25].

In this subsection, we will approach the issue of obtaining the panoramic stereo disparity map from the cylindrical shaped 3-D correlation coefficient volume using a CSP technique, which is computationally efficient. A cylindrical maximum surface that cuts through the cylindrical volume from the top to the bottom as shown in Fig. 3 is obtained in two steps. The cylindrical maximum surface gives the maximum summation of the correlation coefficients along the surface inside the cylindrical volume.

Now, we describe our algorithm for the maximum surface extraction in a 3-D cylindrical shaped volume of size MND. Assume $C(i,j,d)$ is the correlation coefficient value in the 3-D volume at position (i,j,d), where $0 \leq i < M$, $0 \leq j < N$, and $0 \leq d < D$ (i,j are the indices of image rows and columns; and d is index for disparity). This C is obtained in Section II-B. Note that plane $j=0$ and plane $j=N-1$ in the 3-D volume are neighboring planes. In the first step, we obtain a temporary volume Y, which contains the maximum value accumulation from top to bottom. Volume $Y(i,j,d)$ contains the accumulated values of the maximum cross correlation coefficients along each vertical slice at position j in the same volume from top to bottom. One of these vertical slices at position j is shown in Fig. 3. For the top horizontal slice of the volume, i.e., when $i=0$

$$Y(0,j,d) = C(0,j,d) \tag{1}$$

i.e., the top (horizontal) slice of Y is a copy of the top slice of C. For the remaining horizontal slices of the volume Y, the value at each position is obtained using the following recursion:

$$Y(i,j,d) = C(i,j,d) + \max_{t:|t|\leq p} Y(i-1,j,d+t) \tag{2}$$

where p determines the number of local values that need to be checked. If $p=1$, only three values in Y need to be evaluated. These three values are $Y(i-1,j,d-1)$, $Y(i-1,j,d)$, and $Y(i-1,j,d+1)$. If $p>1$, more than three values need to be checked. The recursion in (2) gives the maximum accumulation of C in the vertical direction for each and every j. For each j, we have one vertical slice. At the end of recursion for every vertical slice from top to bottom, we have the accumulated maximum values in volume Y.

In the second step, we use volume Y to obtain the disparity map for the input panoramic stereo images. In step one, while we obtain Y, the maximum accumulation is only carried out along the vertical direction. In this step, we carry out a second accumulation horizontally based on Y. Starting from the bottom of the 3-D volume Y, we select the 2-D horizontal slice with $i=M-1$. From this 2-D matrix with size ND, a CSP, as illustrated by the dashed line in Fig. 4, is obtained using the combination of the IPA and the MBTA algorithms. The summation of the values along this path gives the maximum value while making sure that a circular path is obtained. This obtained path is related to the disparities for the last or bottom row of the input panoramic stereo images. The distance of each point along this path to the middle dashed line in Fig. 4 is the obtained disparity for the same x-positioned point of the input image.

We then move from the bottom slice upwards for obtaining CSPs. When calculating the disparity for row number $i-1$, we use the result obtained for row number i. We now select the horizontal slice number $i-1$ of the 3-D volume Y and mask out those values outside the gray region that are p position away from the circular shortest path obtained from row number i, as shown in Fig. 4. Then, a new CSP, which is constrained to lie inside this gray region, is obtained in this matrix ring. This process of obtaining a CSP is repeated for each horizontal slice of Y until the disparity for the first row of the image is obtained. When obtaining the CSP for the very bottom slice, the whole 2-D matrix should be used without masking out any pixel values.

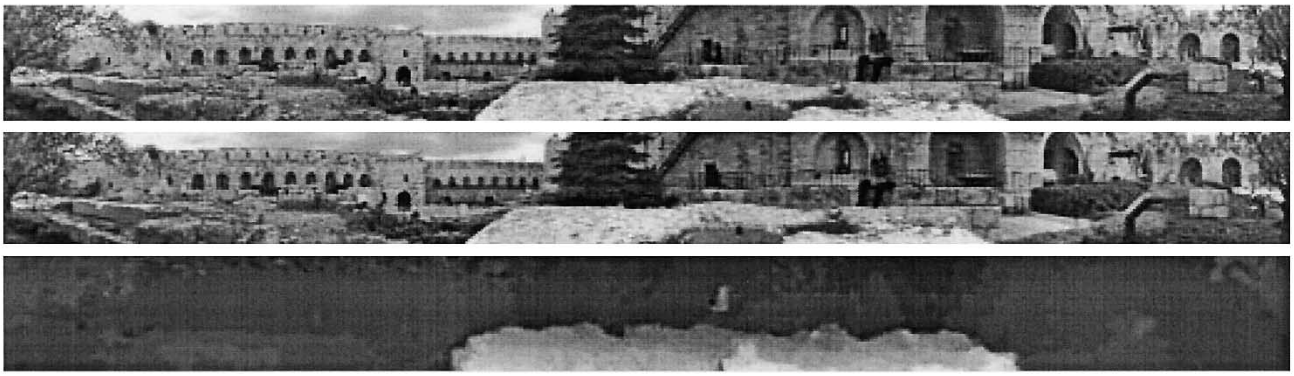

Fig. 6. First and second images are the left and right input images [18]. The third image gives the matching results using our method described in this paper.

In a process of finding a shortest path in an image or 2-D matrix by the use of ordinary dynamic programming technique, two steps are usually involved. The first step is the value accumulation or distance transformation, say, from left to right of the image. The second step is the backtracking from an optimum point in the last column. Our accumulation process for obtaining the $Y(i, j, d)$ volume is similar to the value accumulation or distance transformation step for an ordinary dynamic programming process. In 2-D case, one finds a single point in the last column to start the backtracking process. In our 3-D case, we find a single CSP in the last slice of the $Y(i, j, d)$ volume to backtrack. The recursion for obtaining Y does not have to start from the top. It can start from the bottom. If the process of obtaining Y starts from the bottom and finishes at the top, then the process of obtaining a circular shortest path should start from the top of Y. The 3-D surface obtained from the 3-D volume should be very similar, if not exactly the same, whether one starts the recursion from the top or from the bottom of the volume. Pixels with different disparity results if different starting recursions are used may come from tie values during the DP process.

Occlusion is not explicitly modeled in our matching process. Therefore, if there are regions with large disparity jumps, a smooth transition may result. Path finding techniques such as those described in [28] can be used to model occlusion. This will increase the computational cost.

Putting all the CSPs obtained for each of the scanline together form a 3-D cylindrical surface within the 3-D volume of Y. Because successive CSP for each scanline is obtained in the neighborhood of the previous path position, the cylindrical maximum surface gives more consistent disparities.

The result of obtaining this cylindrical surface is that the summation of the correlation values on this surface is maximum. Note that the surface has certain smoothness constraints that during the process of obtaining this surface the neighborhood search is only carried out around the neighboring $2p + 1$ points.

III. Algorithm Steps

It has been shown that a multiresolution or pyramid data structure approach to stereo matching is faster than one without multiresolution [33], as the search range in each level is small. Besides fast computation, a more reliable disparity map can be obtained by exploiting the multiresolution data structure. The upper levels of the pyramids are ideal to get an overview of the image scene. The details can be found down the pyramid at higher resolution. Subpixel accuracy can be obtained by fitting a second degree curve to the correlation coefficients in the neighborhood of the disparity, and the extrema of the curve can be obtained analytically.

The steps of our proposed algorithm for fast panoramic stereo matching are as follows.

1) Perform image padding for panoramic stereo images.
2) Build image pyramids with P levels (from 0 to $P - 1$), with the reduction ratio of r (e.g., $r = 2$), from the original left and right images. The upper or coarse resolution levels are obtained by averaging the corresponding $r \times r$ pixels in the lower or finer resolution level.
3) Initialize the disparity map as zero for level $k = P - 1$, and start panoramic stereo matching at this level.
4) Perform panoramic image matching using the method described in Section II, which includes the following.
   a) Perform fast ZNCC to obtain the correlation coefficients and build a 3-D correlation coefficient volume.
   b) Use the cylindrical maximum surface technique to find the maximum surface, which will then give the disparity map as described in Section II-C and D.
5) If $k \neq 0$, propagate the disparity map to the next level in the pyramid using bilinear interpolation, set $k = k - 1$, and then go back to Step 4; otherwise, go to Step 6.
6) Fit parabola function to obtain sub-pixel accuracy if necessary.
7) Display disparity map.

IV. Experimental Results

This section shows some of the results obtained using our method described in previous sections. The input left and right panoramic stereo images are assumed to be rectified epipolar images.

Fig. 5 shows the different results obtained for a portion of a panoramic stereo images by using just the CSP algorithm or the cylindrical maximum surface technique. Fig. 5(a) is the result obtained using the CSP algorithm for each horizontal slice of the 3-D correlation volume independently. Fig. 5(b) gives the result obtained using the cylindrical maximum surface technique. Note that there is a white streaking around the top left region and a dark streaking around the bottom right region in Fig. 5(a). These streakings appear mainly because there is not much constraints between neighboring epipolar lines if CSP is applied to each slice of the 3-D correlation coefficient volume. Fig. 5(b) gives a smoother result due to the use of the cylindrical maximum surface technique. Only one level of image pyramid is used for this test. If multiple levels of image pyramid are used, as in Fig. 6 and Fig. 7, the difference between the results obtained by using just the CSP algorithm or the cylindrical maximum surface technique will become smaller.

Figs. 6 and 7 give some of the results obtained by using our methods described in previous sections. In each of these figures, the first two images are the left and the right input panoramic stereo images. The third images are the disparity map obtained. The values of the disparities have been normalized to the range of [0, 255] for viewing purposes.

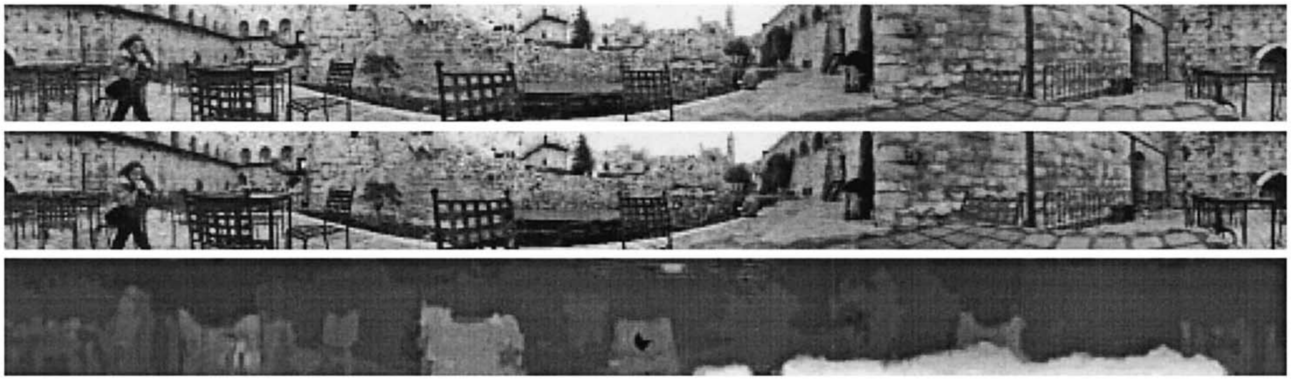

Fig. 7. First and second images are the left and right input images. The third image gives the matching results using the method described in this paper.

The running time for the algorithm on a 1324×120 image is about 0.33 s on a 1.7-GHz Linux PC. The size of the correlation window used for the images is 9×9. The reduction ratio r used in the pyramid generation process is 2. Levels of pyramid is 3. Disparity search range is $[-13, +13]$. Disparity search range is a parameter to be provided by users. The density of our disparity field is 100%. We are showing the disparity for every points of the stereo images. The work by Li *et al.* [15] for depth estimation from multiperspective panoramas by the use of tensor voting techniques seems to give good results. Their algorithm, however, takes about 60 min on a Pentium III 550 MHz PC.

The reliable results of our algorithm are achieved by applying the combination of the following techniques.

1) Multiresolution or coarse-to-fine strategy is used.
2) The ZNCC similarity measure is used, which is independent of differences in brightness and contrast due to the normalization with respect to mean and standard deviation. Because the correlation step is window based, the correlation value (similarity measure) may not be accurate at object boundaries where occlusion or depth changes occurs. This inaccurate result can be improved by using multiple window techniques at object boundaries.
3) The correlation coefficient value is used as input to the CSP extraction stage. A number of approaches that use dynamic programming method just use the intensity value along the left and right epipolar lines. These approaches do not take the neighborhood information from the successive scanlines into account.
4) CSP technique is used to find a maximum surface in the cylindrical correlation volume. By using the cylindrical maximum surface technique on the input correlation coefficient volume, one will obtain a more smooth surface within the volume. The maximum surface method takes all the information into account, rather than work individually for each pair of the epipolar lines. The left and the right columns are also properly constrained. Currently, we do not model occlusion in our matching process. In addition, as our matching is area correlation based, if the input images contains large regions without texture, our algorithms may not work like most of other matching algorithms.

The fast computational speed of our algorithm is achieved in conjunction with some of the factors mentioned above for achieving reliability of the algorithm. Some of the factors are as follows

1) Fast ZNCC is used.
2) Apart from having the advantages of increasing the reliability, the coarse-to-fine approach is also faster than one without using it.
3) Computationally efficient two step techniques are used to find a cylindrical maximum surface in the 3-D cylindrical correlation volume.

V. Conclusions

We have developed a fast panoramic stereo matching method using cylindrical maximum surface techniques together with fast correlation calculation in the coarse-to-fine framework. The cylindrical maximum surface is obtained from the 3-D correlation volume using our two step techniques: the vertical accumulation step to obtain the maximum accumulation volume and, based on this volume, a second step to obtain the cylindrical maximum surface using CSP techniques. By using the ZNCC similarity measure together with the multiresolution scheme and cylindrical maximum surface techniques, the reliability of the algorithm was increased. The typical running time for a 1324×120 image is about 0.33 s. The algorithm was shown to be fast and reliable by testing on several different types of real images.

Acknowledgment

The authors would like to thank Dr. X. Wu of CSIRO and the anonymous reviewers for their comments and suggestions. The panoramic stereo images used in this paper were acquired at the School of Computer Science and Engineering, The Hebrew University, 91 904 Jerusalem, Israel.

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