

We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

4,800

Open access books available

122,000

International authors and editors

135M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.

For more information visit www.intechopen.com



Real-time Stereo Disparity Map for Continuous Distance Sensing Applications - A Method of Sparse Correspondence

Kunio Takaya
University of Saskatchewan
Canada

1. Introduction

The dense stereo disparity map, i.e. image based distance measurement has been developed for applications such as robotic vision and video surveillance. Two small video cameras embedded in the hand-held computer or game controller can be turned into a distance image sensor or a range finder. Electrical retina stimulation with the implanted 2D electrode array that has recently been reported is potentially capable for blind people to regain vision with the technology of BMI (Brain Machine Interface). The dense disparity map is definitely one important mode of artificial vision to sense the distance by vision, when such BMI is fully developed. The challenge is to perform frame-by-frame image processing fast enough to keep up with a video rate. (1) The objective of study is to develop a robust and fast stereo matching algorithm usable in the real time video environment.

To calculate and render the stereo disparity map in real time at a video rate is a challenging problem. In the approach to use two cameras posed to have their optical axes in parallel, typically local cross-correlations are measured from a point in the left image to that in the right image along the same raster scan line, then stereo correspondence is searched for every pixel by finding the maximum among the local cross-correlations. The time warp algorithm based on the dynamic programming (DP) optimizes the search for the entire raster scan line. To ensure the accuracy up to a pixel distance or even to a fractional distance, the pixel-to-pixel similarity matrix of size N^2 needs to be calculated for a raster length N . This imposes a large computational burden to calculate a dense stereo disparity map, and to keep up with a video rate such as 30 frames/sec.

The Dynamic Time Warp Algorithm (DTW), an implementation of Dynamic Programming (DP) is a well accepted method for the problem of stereo matching, because DTW has a time constraint that the sequence of data is retained when matching two sequences. In another word, a pixel in a sequence is matched to a pixel after the pixel following a previously matched pixel in the other sequence to be matched. Therefore, DTW is particularly useful to match two raster profiles which are basically a time sequence. Since the DTW matches all pixels in the raster according to the cost function to minimize, the stereo correspondence for all pixels in the raster is calculated as a result. However, the search for matching is exhaustively done for each and every pixel in the raster, thus the process is time consuming particularly to calculate

the N^2 similarity matrix which determines the correlation between a pixel in one raster and a pixel in the other matching raster.

To alleviate this computational burden, sampling sparsely the raster waveform (profile) can reduce the number of calculations N^2 as N becomes considerably smaller than the raster size. Down sampling is one approach, but this reduces the resolution of disparity measurement at the same time, thus defeats the ultimate goal of producing the dense disparity map. Alternative approach is to extract features common to the right and left image at the accuracy of the pixel distance. Those features must be sampled sequentially, so that the DTW can determine the correspondence among all extracted common features. For example, peak points and step edges can be candidates for such a common feature.

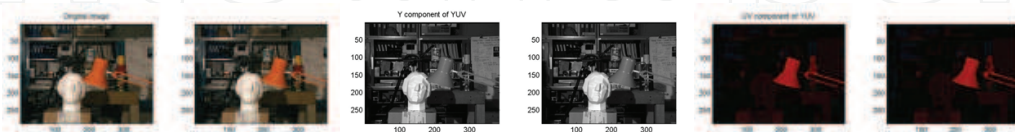


Fig. 1. A pair of original stereo images, Y and UV image pairs in YUV color space (or V and HS in HVS color space)

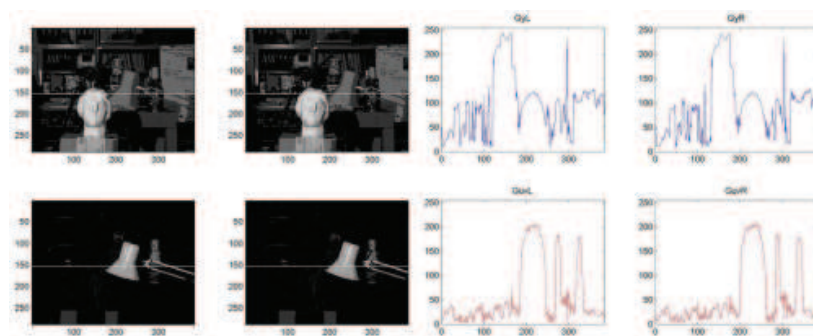


Fig. 2. Y (luma) image and UV (chroma) image of a pair of stereo images and raster waveforms sampled at the white horizontal line

Successful works in producing good quality dense disparity maps have rather used image processing (6) (5) (2) than digital signal processing (DSP) which is more advantageous for raster scanning video to gain the speed in time critical situations. Image based disparity maps adopt image segmentation to break down the whole image into many small patches often in terms of color. Then, the disparities among the segmented patches are calculated to produce a dense disparity map of the segmented image. In this paper, we do the image segmentation in terms of 1D raster image (waveform) to perform sparse sampling based on the 1D patches. We propose coarse quantization applied to the luma image which is Y-component in the YUV color space or V-component in the HSV color space, and to the chroma image as well which is the UV-component in YUV or the HS component in HSV as shown in Fig. 1. Stereo matching can usually be performed well only with the luma image segmentation. But for some images dominated by color, color based image segmentation is better suited. The run-lengths at coarsely quantized levels are thought to be the 1D patch which is used as a feature to represent a given raster waveform. Thus, we can realize the sparse sampling to reduce the size of the similarity matrix, much smaller than N^2 . We also consider humps observed in the denoised raster profiles by the median filter as a 1D patch similar to the 2D patches resulting from image segmentation. In this paper, we studied two methods of finding sparse correspondence for stereo matching, (1) run-lengths at the coarsely quantized raster waveform and (2) humps

found in the denoised raster waveform. Typical raster waveforms observed in the Y and UV image are shown in Fig. 2 for a pair of the right and left image.

2. Dynamic Time Warp algorithm

Stereo matching in the binocular image pair is to find two corresponding feature points, one in the left image and the other in the right image. The distance between the corresponding points are referred to as stereo disparity that is inversely proportional to the distance to the point in the 3D space. Stereo matching is a problem of optimization to match all points in a raster scan line so that the error criterion that reflects the degree of mismatching is minimized. The time warp algorithm of the dynamic programming is one of the robust algorithms which is known to work even for the image having some occluded objects, meaning that an object is seen from a camera but not from the other. This method (7) called dynamic time warp algorithm (DTW) matches two sequences in the order of the sequence allowing multiple correspondence to a given point. This condition is regarded as a constraint imposed in the optimization. Therefore, the DTW is particularly useful to find stereo correspondence in the raster scanned 1D raster profiles (waveforms). There is another useful stereo matching method called Scott and Longuet-Higgins algorithm (8) that utilizes the singular decomposition method (SVD) applied to the proximity matrix \mathbf{G} . The element of \mathbf{G} is given by

$$G_{ij} = e^{-r_{ij}^2/2\sigma^2}, \quad i = 1, \dots, m; j = 1, \dots, n$$

where, \mathbf{G} is Gaussian weighted distance between two features $I_i (i = 1, \dots, m)$ and $J_j (j = 1, \dots, n)$, and $r_{ij} = ||I_i - J_j||$. Unlike the DTW algorithm, this matching method is not constrained by the data sequence. Thus, the method is applicable to the 2D or multi-dimensional data. Since we chose to use 1D raster waveforms for stereo matching in order to reduce overall computation time to keep up with the video rate, we ruled out the SVD based Scott and Longuet-Higgins algorithm.

In the DTW algorithm (7), the similarity matrix \mathbf{S} and the cost matrix \mathbf{C} play the key role in the optimization process. The similarity matrix for two raster profiles I_ℓ and I_r of size N is given by

$$\mathbf{S} = \{s(n, m), \quad n = 1, \dots, N \text{ and } m = 1, \dots, N\}$$

\mathbf{S} indicates how similar the n th pixel point of the sequence I_ℓ is to the m th pixel point of I_r .

$$s(n, m) = \sum_{k=-L/2}^{L/2} |I_\ell(n+k) - I_r(m+k)|$$

for a window size $L + 1$. Stereo matching is the problem to minimize the penalty to match dissimilar points to match all points in I_ℓ and I_r . Define the left pixel array up to the n th element, and the right pixel array up to the m th element as

$$\begin{aligned} X_{1\dots n} &= \{I_\ell(1), I_\ell(2), \dots, I_\ell(i), \dots, I_\ell(n)\} \\ Y_{1\dots m} &= \{I_r(1), I_r(2), \dots, I_r(j), \dots, I_r(m)\} \end{aligned}$$

which is the sum of absolute difference (SAD) in correlation.

The element of the cost matrix \mathbf{C} is given by

$$C(X_{1\dots n}, Y_{1\dots m}) = s(n, m) + \min \begin{cases} C(X_{1\dots n-1}, Y_{1\dots m-1}) \\ C(X_{1\dots n}, Y_{1\dots m-1}) \\ C(X_{1\dots n-1}, Y_{1\dots m}) \end{cases}$$

$C(X_{1\dots n}, Y_{1\dots m})$ is the minimum cost to match the n th pixel point of I_ℓ and the m th pixel point of I_r among all previous matches of $\leq n$ and $\leq m$. There are only three choices to match $I_\ell(n)$ and $I_r(m)$. Given the costs to match upto $I_\ell(n-1)$ and $I_r(m-1)$, $I_\ell(n-1)$ and $I_r(m)$, $I_\ell(n)$ and $I_r(m-1)$, the smallest of the three costs plus the similarity $s(n, m)$ is the cost to match $I_\ell(n)$ and $I_r(m)$. Back tracking the matrix \mathbf{C} shown in Fig. 3 from the right most column or from the bottom most row yields the optimum path that defines the best matching of all pixels.

.			$I_\ell(n-1)$	$I_\ell(n)$
.			.	.
.			.	.
.			.	.
$I_r(m-1)$			$C(X_{1\dots n-1}, Y_{1\dots m-1})$	$C(X_{1\dots n}, Y_{1\dots m-1})$
$I_r(m)$			$C(X_{1\dots n-1}, Y_{1\dots m})$	$s(n, m) + \min. \text{ of } 3 \text{ neighbours}$
.			.	.

Fig. 3. Local decision making in the cost matrix \mathbf{C} by the DTW dynamic programming

The size of a raster waveform is $N = 320$ for the CIF image. The size of the similarity matrix \mathbf{S} and that of the cost matrix \mathbf{C} is $N^2 = 102,400$. Furthermore, the window size is practically as large as $L = 10$. The required computation for \mathbf{S} and \mathbf{C} is about 1 million calculations, which substantially make the implementation of the DTW algorithm difficult in video applications.

3. DTW implementation for run-lengths in coarsely quantized Y and/or UV image

In Fig. 2, the gray scale image of the luma component Y and that of the chroma component UV combined (or V and HS in HVS color space) are shown along with the raster waveforms at the white position line of the left and right images. The luma image represents the light intensity of all wave lengths and the chroma image carries color information, hue at all saturation levels. The disparity measurement can be applied to either image or both depending on the objects of interest in the scene. In order to demonstrate the sparse feature extraction for the DTW algorithm to accomplish stereo matching, we use the luma Y image as an example to illustrate the steps of digital signal processing (DSP) illustrated in Fig. 4.

The raster waveform captured from a video camera is affected by various sources of noise such as photon noise, thermal noise, and electronic noise. The source video signal is, therefore, first filtered with the 1D median filter of a length of 5 or 7 to eliminate salt and pepper type noise which produces faulty break in a run-length. The denoised waveforms are then coarsely quantized to produced 4 non-zero quantization levels as shown in the top row of Fig. 4. Then run-lengths measured at each of the 4 quantized levels are calculated and shown in the middle and bottom row. Level 4 is the largest and level 1 is the smallest quantization level. The run-length traces in red is for the left image and blue is for the right image. Notice that the number of runs are not necessarily the same between the right and left, but similar in the numbers. The run at a coarsely quantized level means that the gray scale values within the run

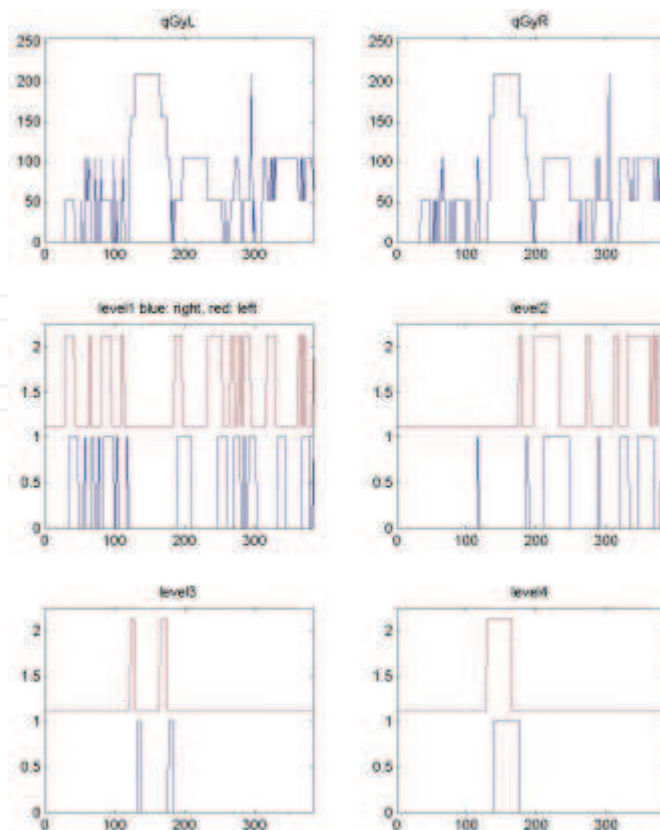


Fig. 4. Coarse quantization and run-lengths of level wise binary waveforms

fall in the range greater than the quantization level, but less than the next higher quantization level. We regard that such a run indicates a contiguous block of almost the same gray scale value, meaning a 1D patch of image segmentation. Such runs are generally a feature common to the left and right stereo images. Associated with the run-length, the position of centroid and the positions of edges constitutes the sparse samples for stereo matching. Since the number of runs found for all 4 levels are much smaller than the size of the raster waveform N , we can save the computational time to calculate \mathbf{S} and \mathbf{C} .

The coarse quantization applied to the raster waveform produces four binary runs at the four levels of quantization, i.e. $\text{Level4} > \text{Level3} > \text{Level2} > \text{Level1}$, so that the higher the level number the more intense is the image object. The middle level such as Level3 and Level2 contains the transitions to a higher intensity. Let $r_L(i, k)$ denote the k th run-length of the left raster at the i th level. Let $r_R(j, \ell)$ denote the ℓ th run-length of the right raster at the j th level. The indices k and ℓ are the sequential index to encompass all levels, $0 < k \leq N_L$ and $0 < \ell \leq N_R$ where N_L and N_R are the total number of runs found in the left and right raster, respectively. Let

$$q(i, j) = \begin{cases} 1 & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases}$$

The element of the similarity matrix \mathbf{S} is defined as

$$s(k, \ell) = |r_L(i, k) - r_R(j, \ell)| + \alpha q(i, j)$$

to make $s(k, \ell)$ take a smaller value if the ℓ th right run and the k th left run are similar in length and belong to the same quantization level. The size of the similarity matrix is $N_L \times N_R$.

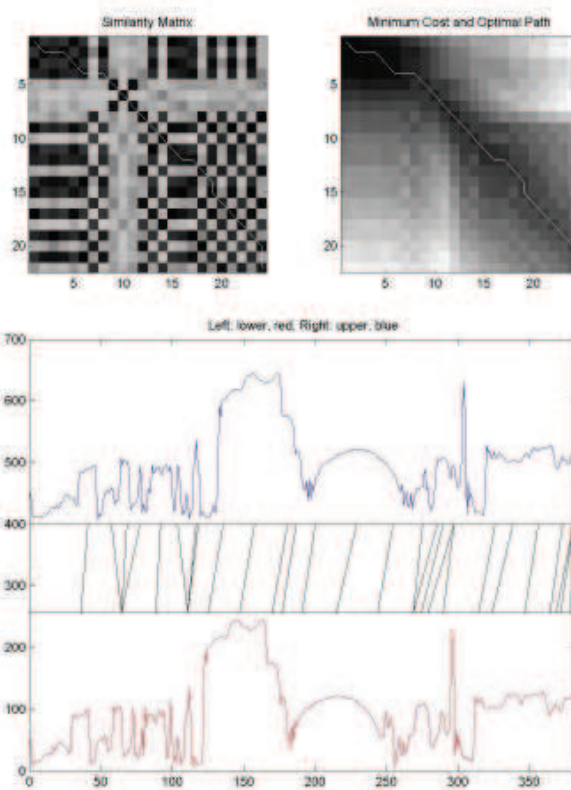


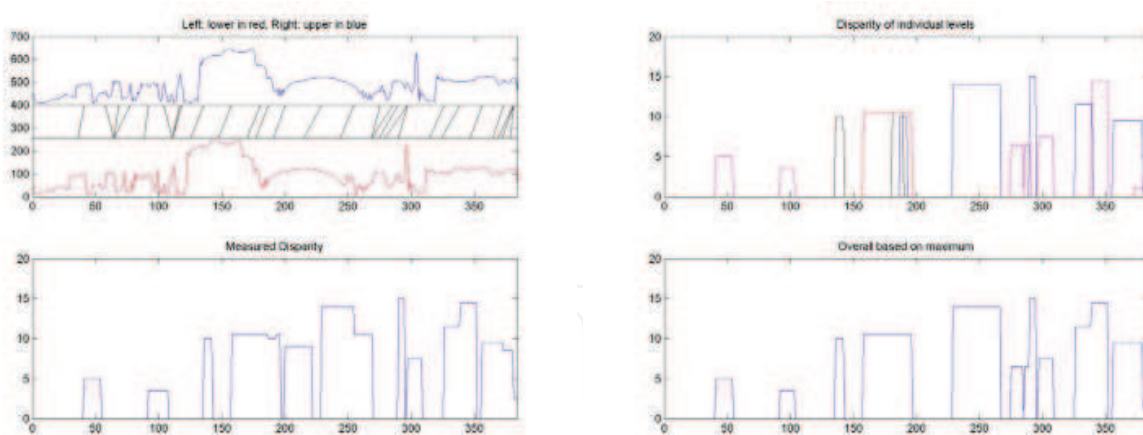
Fig. 5. The similarity matrix \mathbf{S} and the cost matrix \mathbf{C} of the DTW algorithm and stereo matching for the sparse feature points defined by the runs at coarse quantization levels

Where, α is the penalty to associate the runs in different levels. Another approach is to match runs with in the same quantization level. we define the similarity matrix \mathbf{S} at level i as

$$s(k, \ell) = |r_L(i, k) - r_R(i, \ell)|$$

In this case, we deal with four similarity matrices of the size, $N_{L,i} \times N_{R,i}$ for $i = 1, 2, 3$ and 4. For the coarse quantization shown in Fig. 4, the size of the similarity matrix that considers all the runs in all 4 levels is $\mathbf{S}(23 \times 25) = 575$, whereas the sizes of the individual similarity matrices are of size $\mathbf{S}_1(13 \times 15) = 195$, $\mathbf{S}_2(7 \times 7) = 49$, $\mathbf{S}_3(2 \times 2) = 4$ and $\mathbf{S}_4(1 \times 1) = 1$. Thus, the total number of the elements is 249. The latter approach to match individually within a quantization level was resulted in a less number of calculations to evaluate the four similarity matrices compared to a single \mathbf{S} in the former case.

The DTW algorithm is applied to the sparse features derived from the binary runs defined by the coarsely quantized raster waveform. The rising and trailing edge and the centroid of each run were used as sparse samples. The similarity matrix \mathbf{S} and the cost matrix \mathbf{C} for the combined runs of all 4 levels are shown in the upper images in Fig. 5, in which the minimum path (optimal solution) of matching is shown by the white zig-zag line. All correspondences between the sparse features in the left and those in the right are shown in the lower frame of Fig. 5. Matching with multiple points are resulted from the horizontal or vertical sliding of the minimum path in the cost matrix \mathbf{C} . Multiple points matching with a single point generally means that those multiple points failed to find a better matching feature (partner) likely due to the occlusion that occurred in the image of the single corresponding point. The disparities



(a) by a combined S

(b) by 4 S's at 4 levels

Fig. 6. Bottom frames show the 1D disparity profiles determined (a) by the combined similarity matrix S, and (b) by the 4 S's at 4 quantization levels

at the extracted sparse feature points are then calculated. Since the sparse feature is the run of a binary level, the disparity applies to the range of the run as shown in Fig. 6. The disparities found from the DTW individually applied for 4 different quantization levels are shown in the right column (b) in Fig. 6 which agrees well with the combined case in the left column (a) in Fig. 6.

4. Sparse correspondence based on major humps in the raster profile

Another approach to determine the sparse correspondence of features is to use major humps that exist in a raster waveform. The previous method approximated a raster waveform by a coarsely quantized step-wise waveform, then applied the measurement of runs at each of the quantization level in order to determine the sparsely sampled feature points. The approach to detect major humps involved in a raster waveform works equally well because those humps are generally the features representing the image in the raster scan line. The hump here means an upward convex shape defined by a sharp rising and a falling edge. Mathematically, a hump is defined for the waveform $f(t)$ for $t \in [t_1, t_2]$ with the condition that satisfies,

$$\frac{df(t_1)}{dt} > +\epsilon, \quad \frac{df(t_2)}{dt} < -\epsilon$$

ϵ specifies the steepness of the slope. Since the hump here is defined only in terms of the derivatives of the raster waveform, a hump is not necessarily a single modal hump, but it could have multiple modal points, or peaks in another word. We regard whatever the waveform that begins with a slope greater than $+\epsilon$ and ends with the slope less than $-\epsilon$ is a hump. Small wiggles that often exist in a major hump can be ignored and included in the big hump with an appropriate value of ϵ as the slopes of such wiggles are small when they appear minor profiles in the hump.

Since this hump detection uses the derivative waveforms, it is quite important to carefully denoise waveforms without altering major hump profiles in the waveform. The following digital signal processing procedure was adopted to successfully accomplish hump detection and extraction of sparse features.

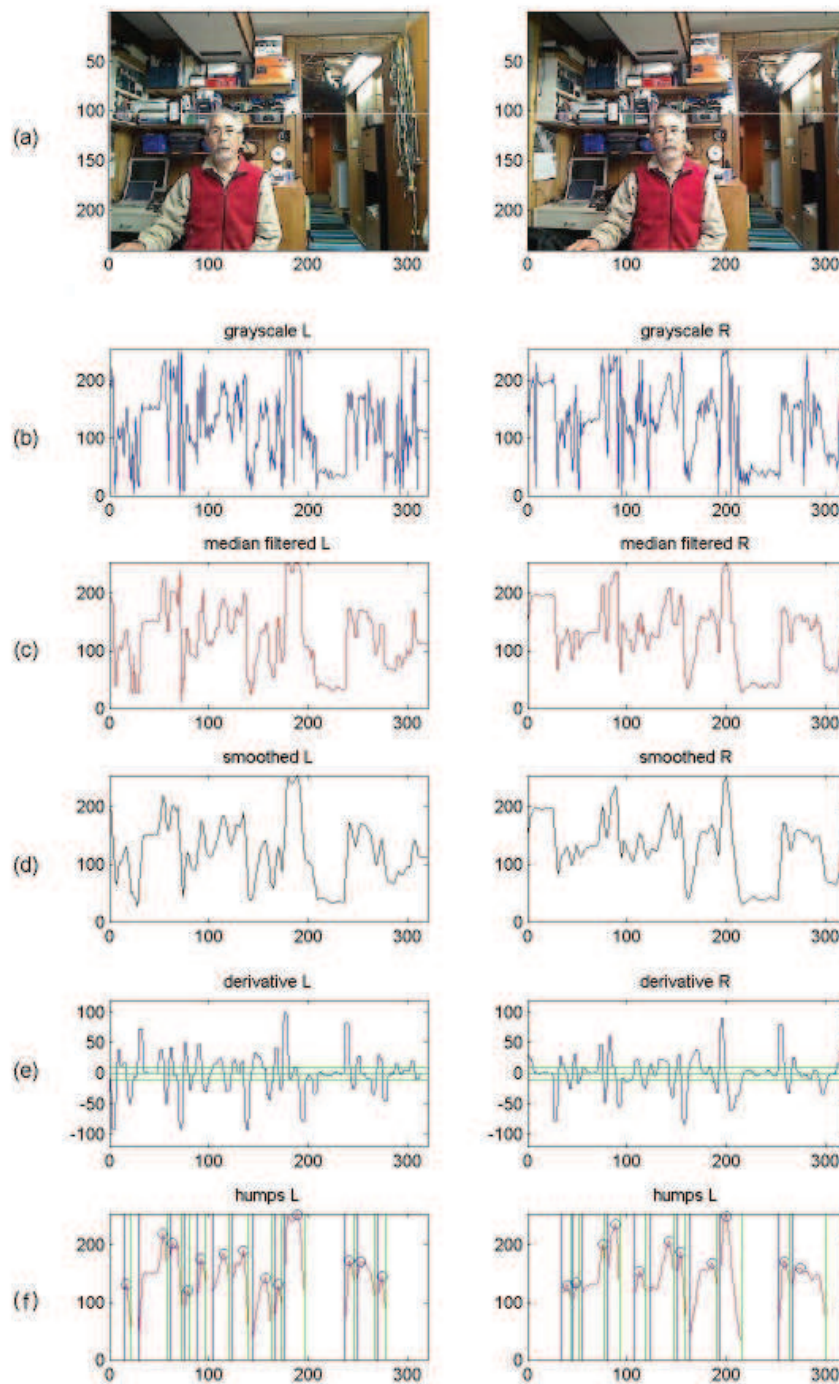


Fig. 7. Sequence of digital signal processings (DSP) for hump detection: (a) Original left and right image, (b) Raster waveforms at the cursor line of (a), (c) Processed by 7 point 1D median filter, (d) processed by 5 point FIR smoothing filter, (e) First derivative of waveforms in (d) and the threshold $\pm\epsilon$, (f) Detected humps indicated by a start line in black, a stop line in green, and a circle at the peak of the hump.

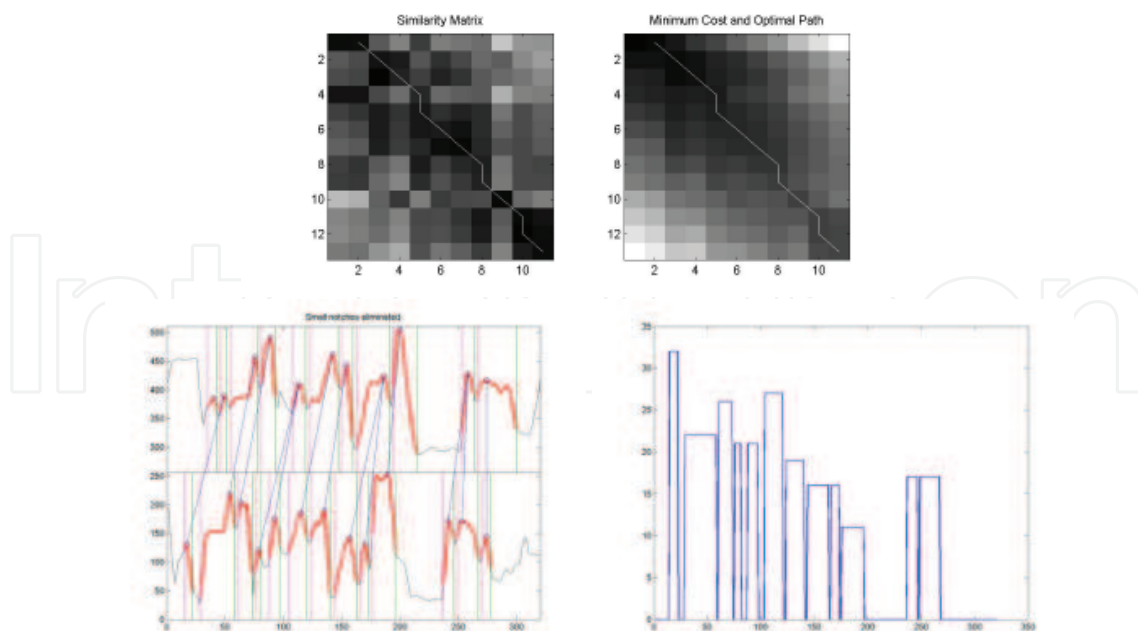


Fig. 8. The similarity matrix S and the cost matrix C of the DTW algorithm based on the major humps as sparse features (upper frame), correspondence of humps in the left and right waveforms, and the calculated disparities (lower frames) of the same waveforms as in Fig. 7.

1. Capture a pair of raster waveforms, left and right.
2. Apply a 7 point median filter to denoise the left and right waveforms.
3. Apply a 5 point symmetric smoothing FIR filter.
4. Differentiate the denoised and smoothed left and right waveforms.
5. Apply threshold ϵ to find the beginning and end of humps, and record the duration, peak position, peak value of each hump.

The sequence of digital signal processings (DSP) is illustrated in Fig. 7. The position of the raster scan line is indicated by a white line in (a) of Fig. 7. The humps found by this stream of DSP processings are shown in (f) of Fig. 7 for the left and right waveform. Features comparable between the left and right are seen in (f) of Fig. 7. Some detected humps have more than one peak, i.e. multi-modal. The threshold applied to waveforms of the first derivative, $\pm\epsilon$ are shown in (e) of Fig. 7.

For each hump detected, say i th hump of the left, duration $d_L(i)$ of the hump, peak value $v_L(i)$ are recorded. Similarly, duration $d_R(j)$ and peak value $v_R(j)$ are recorded for the j th hump of the right waveform. The element of the similarity matrix S is defined as

$$s(i, j) = \alpha |d_L(i) - d_R(j)| + \beta |v_L(i) - v_R(j)| + \gamma |i - j|$$

Fig. 8 shows the stereo matching with the DTW algorithm applied to the sparse features (humps). The numbers of humps found for this particular scan line are 11 for the left, and 13 for the right waveform. In this optimization, a set of parameters $(\alpha, \beta, \gamma) = (0, 0.67, 0.33)$ was used. Using the correspondence between the left and right humps, the disparities were calculated and shown in the lower panel of Fig. 8. The graph of the disparities indicates that images in Fig. 7 have relatively near background in the left edge of the image and far background in the left edge.

5. Experimental system and results

An experimental system that aims at the realization of real-time display of continuous changes of disparity maps at a video rate of 30 fps, was built for the Windows platform. The system is a software based system except that two USB CCD cameras (Webcam) were used. As two identical USB cameras are simultaneously used for video capturing, the driver has to be of type that recognizes different units of the same camera as separate units. Only a few USB cameras such as QuickCam Pro 4000, QuickCam Pro 9000, Watchport/V2 and Microsoft LifeCam VX-700 can be used in the multi-camera applications. The spacing between the two cameras is set between 6 cm to 10 cm. The programs were written in Visual C# 2008 Express (C language). XVideoOCX (Marvelsoft) was used to interface USB cameras to the programs, mainly utilizing its real-time video capturing capability. For video rate control of the developed programs, the timer interrupt caused by the end of frame was used.

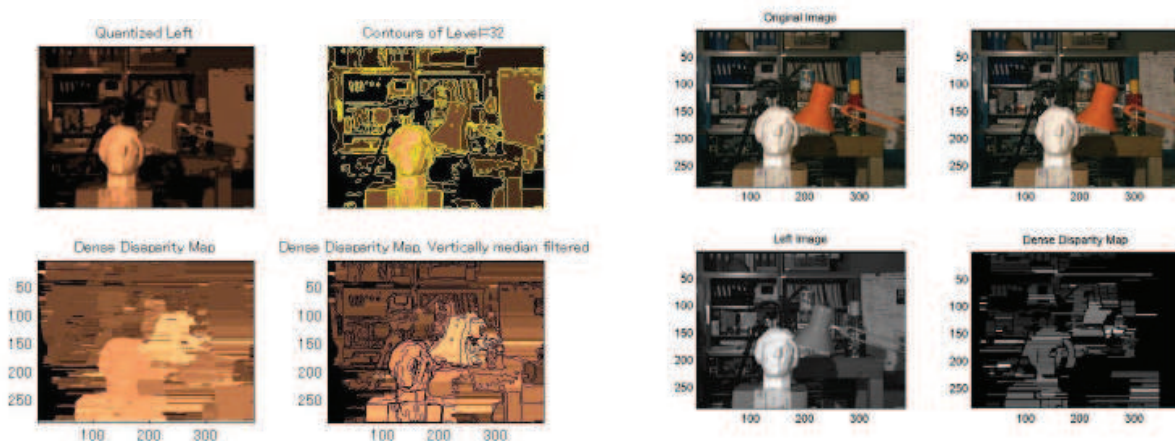


Fig. 9. Dense disparity map by the coarse quantization method (left), and dense disparity map by the hump detector method (right) are shown in the right-bottom frame for the data set "statue"

The proposed two methods, the coarse quantization method and the hump detector method, were applied to various stereo pair images, (Tsukuba database etc.) to find out what degree of reduction is possible for the size of the similarity matrix S . The major interest of this paper is to construct a compact similarity matrix S using sparse sampling of the features involved in a raster waveform of the image. The actual implementation of the proposed methods in an embedded system is in progress using the system mentioned above, however, it is beyond the scope of this paper. The DDM for the data set "statue" is shown in Fig. 9 (left) for the coarse quantization method, and in Fig. 9 (right) for the hump detector method. The DDM for another data set "buildings" is shown in Fig. 10. Figures for the coarse quantization methods, Fig. 9 and Fig. 10 (left), show the image of coarse quantization and the resulting DDM with and without contour lines superimposed. Figures for the hump detector method, Fig. 9 and Fig. 10 (right), show the original image and the resulting DDM in which borders are shown dark as no disparity is measured in between the adjacent humps. Dark border lines serve for the same purpose of contours. In DDM, the greater the disparity, the brighter is the pixel. The closer objects are shown by the brighter intensity. Vertically, the raster scan lines were down sampled by 4:1 for all DDM's shown here to further reduce computation time.

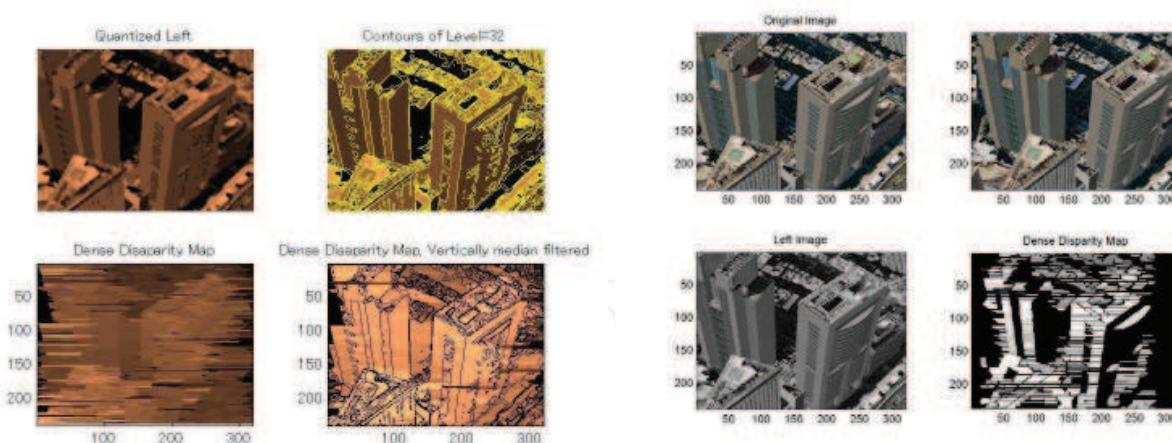


Fig. 10. Dense disparity map by the coarse quantization method (left), and dense disparity map by the hump detector method (right) are shown in the right-bottom frame for the data set “buildings”

6. Conclusive remarks

Dynamic dense disparity map showing the distance to the video objects in real-time at a video rate is a challenging problem. Raster based 1D stereo matching for the camera pose that the lens axes are in parallel is more straightforward and faster than the image based 2D matching. The dynamic time warp (DTW) algorithm of the dynamic programming is a well accepted robust optimization method for matching two 1D raster waveforms of the left and right image. This method requires the similarity matrix \mathbf{S} of the size N^2 for the raster size N . The large size of \mathbf{S} , N^2 is the obstacle to continuously display the disparity map, DDM at a video rate of 30 fps since the elements of \mathbf{S} require local correlations amongst all points in the left image and all points in the right image. In order to realize real time display of the DDM, it is crucially important to reduce N down to a much smaller number of feature points. Thus, the computation time to calculate \mathbf{S} can be dramatically reduced by the square of the size reduction. Down sampling to reduce N defeats the purpose of disparity measurement because the spatial resolution is also reduced resulting less accurate disparity measurement. Two methods to significantly reduce the size N to create the sparse feature samples without sacrificing the spatial resolution of stereo matching, are proposed and tested.

One approach is to use the binary runs at the levels of coarse quantization from the rising and falling edges and the centroids of the runs. The second method is to use major humps detected in the raster waveforms. The sparse feature points in this case are the starting and ending points and the peaks of humps. For the CIF image of 352×288 , $N = 352$ and $N^2 = 123,904$. The size of the sparse set for the first method based on the binary runs is typically $N = 30$ and $N^2 = 900$. The second method based on the humps was around $N = 15$ and $N^2 = 225$. Roughly speaking, reduction is 10:1, whereas the second method of hump detector extracting 10~20 humps gives a reduction of 20:1. In the previously developed system which performs the DTW algorithm for every pixel of the raster size $N = 352$, it took approximately 7 second to complete a dense disparity map. The raster scan lines are down sampled by the ratio of 4:1, so that the time for one raster waveform is $7000/72=97$ ms. The reduction of the calculation time for \mathbf{S} from $N^2 = 123,904$ down to $N^2 = 225$ is 550:1, and down to $N^2 = 900$ is 138:1. This means that the sparse feature points can be reduced to 0.176 ms per raster or 12.7 ms per frame if we use the hump detector. Including the overhead time to apply the 7 point

median filter followed by the 5 point smoothing FIR filter, then the first derivatives, a frame time of the video rate 30 fps that is 33 ms, is sufficient to complete the digital signal processing (preprocessing) and the DTW algorithm to generate DDM.

7. References

- [1] S. Forestmann, Y. Kanou, J. Ohya, S. Thuring, Real-Time Stereo by Using Dynamic Programming, *Computer Vision and Pattern Recognition Workshop*, vol. 27, issue 02 June 2004.
- [2] A. Klaus, M. Sormann, K. Karner, Segment-Based Stereo Matching Using Belief Propagation and a Self-Adapting Dissimilarity Measure. *ICPR 2006*, Vol. 3, pp. 15-18, Hong Kong, Aug. 20-24, 2006.
- [3] Christopher M. Christoudias, Bogdan Georgescu and Peter Meer, Synergism in Low Level Vision, *Int. Conf. on Pattern Recognition. ICPR 2002*, Vol. 4, p. 40150 Quebec City, Aug. 11-15, 2002
- [4] S. Birchfield and C. Tomasi, Depth Discontinuity by Pixel-to-Pixel Stereo, *The 6th IEEE Int. Conf. on Computer Vision*, Bombay, Mumbai, India, pages 1073-1080, January 1998.
- [5] M. Gong and Y-H Yang, Fast Stereo Matching Using Reliability-Based Dynamic Programming and Consistency Constraints, *Proc. of the 9th Int. Conf. on Computer Vision (ICCV 2003)* pp. 610-617. Nice, 2003.
- [6] H. Hirschmuller, Stereo Vision in Structured Environments by Consistent Semi-Global Matching, *IEEE Int. Conf. on Computer Vision and Pattern Recognition (CVPR 2006)* New York, June, 2006.
- [7] Dan Ellis, Dynamic Time Warp (DTW) in Matlab, <http://labrosa.ee.columbia.edu/matlab/dtw/>
- [8] Maurizio Pilu, A Direct Method for Stereo Correspondence based on Singular Value Decomposition, *In IEEE Conf. on Computer Vision and Pattern Recognition (CVPR 1997)*, pp.261-266, Puerto Rico June, 1997.

IntechOpen



Video Surveillance

Edited by Prof. Weiyao Lin

ISBN 978-953-307-436-8

Hard cover, 486 pages

Publisher InTech

Published online 03, February, 2011

Published in print edition February, 2011

This book presents the latest achievements and developments in the field of video surveillance. The chapters selected for this book comprise a cross-section of topics that reflect a variety of perspectives and disciplinary backgrounds. Besides the introduction of new achievements in video surveillance, this book also presents some good overviews of the state-of-the-art technologies as well as some interesting advanced topics related to video surveillance. Summing up the wide range of issues presented in the book, it can be addressed to a quite broad audience, including both academic researchers and practitioners in halls of industries interested in scheduling theory and its applications. I believe this book can provide a clear picture of the current research status in the area of video surveillance and can also encourage the development of new achievements in this field.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Kunio Takaya (2011). Real-time Stereo Disparity Map for Continuous Distance Sensing Applications - A Method of Sparse Correspondence, Video Surveillance, Prof. Weiyao Lin (Ed.), ISBN: 978-953-307-436-8, InTech, Available from: <http://www.intechopen.com/books/video-surveillance/real-time-stereo-disparity-map-for-continuous-distance-sensing-applications-a-method-of-sparse-corre>

INTECH
open science | open minds

InTech Europe

University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China

Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

© 2011 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the [Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License](#), which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.

IntechOpen

IntechOpen