Bayesian Recursive Algorithm for Width Estimation of Freespace for a Power Wheelchair Using Stereoscopic Cameras

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***Abstract* - This paper is concerned with the estimation of freespace based on a Bayesian recursive (BR) algorithm for an autonomous wheelchair using stereoscopic cameras by severely disabled people. A stereo disparity map processed from both the left and right camera images is constructed to generate a 3D point map through a geometric projection algorithm. This is then converted to a 2D distance map for the purpose of freespace estimation. The width of freespace is estimated using a BR algorithm based on uncertainty information and control data. Given the probabilities of this width computed, a possible movement decision is then made for the mobile wheelchair. Experimental results obtained in an indoor environment show the effectiveness of this estimation algorithm.**

I. INTRODUCTION

Power wheelchairs are necessary to provide mobility assistance for severely disabled people. However a conventional wheelchair in many cases is not sufficient to assist in their mobility. For this reason, certain wheelchairs are fitted with additional equipment, such as sensors, and given new, generally autonomous, capabilities such that they can be classified as smart wheelchairs, in order to enhance the independence and mobility of severely disabled people. In recent decades many significant algorithms, which utilise the additional equipment, have been developed to create these smart wheelchairs [1].

Cameras are one type of sensory equipment that can be mounted on robots and wheelchairs to obtain real-time information from the environment. This information is analysed and processed by advanced algorithms to produce necessary data and signals for the operation of the associated robots and smart wheelchairs [2, 3]. In particular, the left and right images acquired from stereoscopic cameras are matched to generate a disparity map using a Sum of Absolute Differences (SAD) algorithm [4]. This disparity map is used to produce a 3D point map, which is then applied a geometric projection algorithm to convert it to a 2D distance map [5-7]. These 2D distance maps can allow detection of obstacles and freespace distances necessary in the operation of robots and smart wheelchairs.

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The Bayesian method is useful in detecting freespace from sensor information for robots. For example, in a recent application, an autonomous exploration strategy for freespace detection based on mapping uses the Bayesian update theory [8]. A Bayesian filter algorithm with statistical tool is also applied to estimate locations based on uncertainty information from sensors. This Bayesian filter algorithm uses the Markov assumption and recursive process to compute the belief probability [9].

The BR algorithm is applied to estimate the width of freespace in a 2D distance map using measurements and control data from the wheelchair system. Firstly the previous probability is computed based on the prior probability and the control data. The second step of this algorithm is that the posterior probability using Bayesian rules is carried out based on the previous probability along with the measurement update. The process is recursively iterated in the next time step to choose the high belief probability. The average of the probabilities is to make a decision for the mobile wheelchair.

This paper is organised as follows. In Section 2, the problem of stereoscopic vision is introduced. In Section 3, a BR algorithm using Bayesian rules, control data and measured information is employed to estimate the width of freespace. Section 4 shows the experimental result, in which the width of freespace in a 2D distance map is estimated to make the decision. Finally Section 5 concludes the paper.

II. STEREOSCOPIC VISION

A. Stereo Disparity

The purpose of stereo vision is to perform range measurements based on the left and right images obtained from stereoscopic cameras. Basically, a correlation algorithm of the Sum of Absolution Differences (SAD) is implemented to establish the correspondence between image features in different views of the scene and then calculate the relative displacement between feature coordinates in each image to produce a disparity [5].

$$SAD = \min_{d=d_{\min}}^{d_{\max}} \sum_{i=-M}^{+M} \sum_{j=-M}^{+M} \left| I_R(x+i, y+j) - I_L(x+i+d, y+j) \right| \quad (1)$$

where the centre of a window of size *(2M+1)*x*(2M+1)* at the coordinates of the matching pixels *(i,j), (x,y)*, are pixel coordinates in one image. I_L and I_R are the intensity functions of the right and left images, and d_{min}, I_{max} are the minimum and maximum disparities. The disparity d_{min} of zero pixels often corresponds to an infinitely far away object and d_{max} denotes the closest position of an object.

B. Computation of a 2D Distance Map

Fig. 1: Left image

Fig. 2: Right image

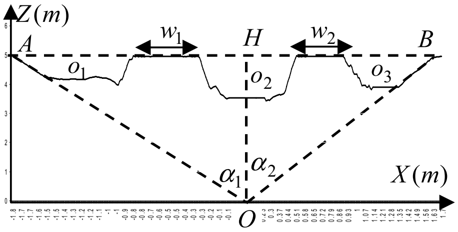

Fig. 3: 2D distance map

In this project, a Point Grey Research 'Bumblebee 2' stereoscopic camera system used to capture the left and right images as shown in Fig. 1 and Fig. 2 has two cameras which act like two "eyes". This camera system has a limited field of view, with the total range denoted here as α. This vision system produces a α_1 maximum angle to the left and a α_2 maximum angle to the right of the wheelchair due to the angle of the cameras system relative to the wheelchair. It means that the camera system can just see freespaces w_1, w_2 and obstacles o_1, o_2 and o_3 in the field of view *(AOB)* as shown in Fig. 3, in which Z is distance-axis, X is horizontal-axis and $OH=Z_{max}$ is the maximum visible distance of the cameras. The maximum range of Z-axis is *5000mm*, the 0.01 resolution of X-axis is from *-1800mm* to *1700mm* and the image resolution in this case is 320x640 in the 2D map.

Given the camera calibration, a stereo disparity map is processed to generate a 3D point cloud image based on sub-pixel interpolation for more accurate stereo depth extraction. From this 3D point image, four steps can be performed to convert this to a 2D distance map using geometric projection as follows:

- Step 1: n 3D points (x_i, y_j, z_k) are converted to n 3D points (X_i, Y_j, Z_k) on coordinates X, Y, Z.
- Step 2: Assume that a certain value X_i on the horizontal X-axis corresponds to many points (Y_j, Z_k). The minimum distance Z_{imin}, from an object to the wheelchair corresponding to a point X_i, is chosen.
- Step 3: In order to obtain a 2D distance map (X_i, Z_{imin}), all minimum distances Z_{imin} are computed as follows

$$Z_{i\min} = \min_{j=0}^{k} Z_{ij} \tag{2}$$

- Step 4: The width of freespace w is detected based on the maximum distance Z_{imax} as follows

$$w = \sum Z_{i\max} \tag{3}$$

III. FREESPACE ESTIMATION ALGORITHM

A. Bayesian Recursive Algorithm

The width of freespace in a 2D distance map is difficult to estimate due to noise information from the camera system. In order to solve this problem, Bayesian Recursive (BR) algorithm bases on measurements and control data of the wheelchair system to compute the conditional probability. The first step is that the algorithm requires the probability and the control *u(t)* to compute the probability over the width of freespace *w(t)* which is a state variable. The prior probability is expressed as follows

$$P_{pr}(w(t)) = \sum_{w(t-1)} P(w(t-1) \mid w(t-1), u(t)) P(w(t-1)) \tag{4}$$

in which *P(w(t-1))* and *P(w(t)|w(t-1),u(t-1))* are the previous probability and the conditional probability over the width *w(t-1)*.

The next step is that, the probability $P_{pr}(w_t)$ is used along with the conditional probability based on measurements z_t to make the posterior probability as follows

$$P_{po}(w(t)) = \frac{P(z(t) \mid w(t)) P_{pr}(w(t))}{\sum_{w(t)} P(z(t) \mid w(t)) P_{pr}(w(t))} \tag{5}$$

where Bayes theorem is utilised for the posterior probability $P_{po}(w(t))$ based on the measurement and $\Sigma P_{po}(w(t))=1$.

$P_{po}(w(t))$ will be the previous probability for the next time step to determine the previous probability $P_{pr}(w(t))$ based on the control in Eq. (4). This means that this algorithm is recursively carried out to compute the high belief probability for the dynamic system.

B. Decision Making

This algorithm is recursively iterated many times to produce the probabilities. The average of the probabilities is computed to make a decision for the wheelchair as follows

$$p_{av}(w) = \sum_{i=1}^{n} \frac{P_{po,n}(w(t))}{n} \tag{6}$$

where n is the amount of times.

The average probability is then compared to the threshold probability P_{th} that is carried out many times in the practical operation of the wheelchair. If $P_{av}(w)$ is greater than or equal to p_{th}, the mobile wheelchair can be decided to move.

IV. EXPERIMENTAL RESULTS

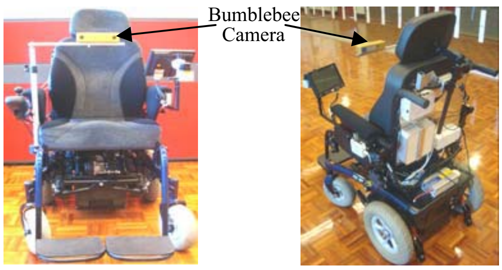

Fig. 4: Power wheelchair

The autonomous wheelchair has been fitted with the 'Bumblebee 2' camera system in the University Research Centre for Health Technologies as shown in Fig. 4.

Consider an actual width of a freespace w_a of an entry through a doorway or a corridor which is compared to the safe diameter d_s of a wheelchair. If w measured by the camera system is greater than or equal to d_s, the wheelchair can move through this freespace. If w is less than d_s, the wheelchair can not move through. In practice, w measured by the camera system can be less than, equal to or greater than w_a. This is very difficult to estimate. To solve this problem, BR algorithm is employed to estimate the width of freespace based on the conditional probabilities, control data and measurements. Two practical experiments implemented to estimate the width of freespace are shown below.

A. Experiment 1


Fig. 5: Left image


Fig. 6: Right image

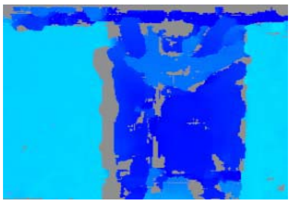
Fig. 7: Stereo disparity map

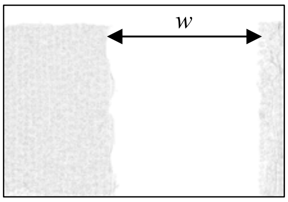

Fig. 8: 3D point map

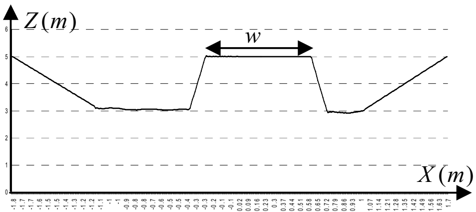

Fig. 9: 2D distance map

Fig. 5 and Fig. 6 show the left and right images with one freespace w. From these left and right images, the disparity and 3D point maps are constructed as shown in Fig. 7 and Fig. 8. A 2D map with a freespace w is shown in Fig. 9.

BR algorithm is utilised to estimate the width w of this freespace which is assigned as follows: if its measured width w is greater than or equal to the diameter d_s of the wheelchair, w is the freespace, called *"w=FS"* and the wheelchair can go through. If w is less than d_s, w is the obstacle, called *"w=OB"*, the wheelchair can't go through.

Assume that the actual width of freespace w_a is equal to the safe diameter d_s=*1000mm* of the wheelchair. However the measured width w of the freespace estimated by the camera system can be noisy. For this reason, BR algorithm is used to estimate this measured width w.

Initially, the equal prior probabilities are given as follows

$$P(w(0) = FS) = 0.5 \tag{7a}$$

$$P(w(0) = OB) = 0.5 \tag{7b}$$

Furthermore, the conditional probabilities corresponding to noise measurements and the width of freespace $w(t)$ at time t are carried out in fact by trial times

$$p(z(t) = FS \mid w(t) = FS) = 0.7 \tag{8a}$$

$$p(z(t) = OB \mid w(t) = FS) = 0.3 \tag{8b}$$

$$p(z(t) = FS \mid w(t) = OB) = 0.2 \tag{9a}$$

$$p(z(t) = OB \mid w(t) = OB) = 0.8 \tag{9b}$$

in which $z(t)=FS$, if $w(t)$ measured by the camera system is greater than or equal to *1000mm* and $z(t)=OB$, if $w(t)$ measured by the camera system is less than *1000mm*.

The conditional probabilities depend on the wheelchair control $u(t)=move$ and its previous state as follows

$$p(w(t) = FS \mid w(t-1) = FS, u(t) = move) = 0.8 \tag{10a}$$

$$p(w(t) = OB \mid w(t-1) = FS, u(t) = move) = 0.2 \tag{10b}$$

$$p(w(t) = FS \mid w(t-1) = OB, u(t) = move) = 0.9 \tag{11a}$$

$$p(w(t) = OB \mid w(t-1) = OB, u(t) = move) = 0.1 \tag{11b}$$

For similarity, the control case is u_t=*stop,* the conditional probabilities are determined as follows

$$p(w(t) = FS \mid w(t-1) = FS, u(t) = stop) = 0.1 \tag{12a}$$

$$p(w(t) = OB \mid w(t-1) = FS, u(t) = stop) = 0.9 \tag{12b}$$

$$p(w(t) = FS \mid w(t-1) = OB, u(t) = stop) = 0.1 \tag{13a}$$

$$p(w(t) = OB \mid w(t-1) = OB, u(t) = stop) = 0.9 \tag{13b}$$

In practice, relatively the error probabilities can occur as shown in Eqs. (10b), (11b), (12a) and (13a).

Firstly, the wheelchair takes on control action $u(1)=stop$ and the measurement $z(1)=FS$ at time t_1. From Eq. (4), the probabilities $P_{pr}(w(1))$ using the prior probability are computed for the width $w(1)$ as follows

$$P_{pr}(w(1) = FS) = \sum_{w(0)} P(w(1) \mid w(0), u(1)) P(w(0)) = 0.5 \tag{14a}$$

$$P_{pr}(w(1) = OB) = \sum_{w(0)} P(w(1) \mid w(0), u(1)) P(w(0)) = 0.5 \tag{14b}$$

Given the measurement $z(1)=FS$ and $P_{pr}(w(1))$, the posterior probabilities $P_{po}(w(1))$ using Eq. (5) are determined as follows

$$P_{po}(w(1) = FS) = \frac{P(z(1) = FS \mid w(1),) P_{pr}(w(1))}{\sum_{w(1)} P(z(1) = FS \mid w(1)) P_{pr}(w(1))} = 0.778 \tag{15a}$$

$$P_{po}(w(1) = OB) = \frac{P(z(1) = FS \mid w(1),) P_{pr}(w(1))}{\sum_{w(1)} P(z(1) = FS \mid w(1)) P_{pr}(w(1))} = 0.222 \tag{15b}$$

This BR algorithm is iterated for the next time step corresponding to $u(2)=move$ at time t_2, we obtain the probabilities using Eq. (4) as follows

$$P_{pr}(w(2) = FS) = 0.8778 \tag{16a}$$

$$P_{pr}(w(2) = OB) = 0.1222 \tag{16b}$$

As the measurement is still $z(2)=FS$, we have the posterior probabilities using Eq. (6) as follows

$$P_{po}(w(2) = FS) = 0.9617 \tag{17a}$$

$$P_{po}(w(2) = OB) = 0.0383 \tag{17b}$$

This process is recursively iterated ten times to produce the probabilities $P_{po}(w=FS)$, $P_{po}(w=OB)$ and the average probabilities, $P_{av}(w=FS)$, $P_{av}(w=OB)$ as shown in Table 1. If $P_{po}(w) \geq d_s$ then there is a freespace and if $P_{po}(w) < d_s$ there is an obstacle. In particular, the average probability $P_{av}(w=FS)=0.8821$ is greater than $P_{th}=0.8$, it means that the width w is the freespace and the wheelchair is possibly decided to go through.

Table 1: The estimated values of the width of one freespace

Times	$w(t)$	$P_{po}(w(t)=FS)$	$P_{po}(w(t)=OB)$
1	1020	0.7778	0.2222
2	1020	0.9617	0.0383
3	980	0.7640	0.2360
4	1020	0.9613	0.0387
5	1020	0.9679	0.0321
6	1000	0.9682	0.0318
7	970	0.7652	0.2348
8	990	0.7269	0.2731
9	1010	0.9600	0.0400
10	1020	0.9679	0.0321
Average probability P_{av}		**0.8821**	**0.1179**
Variance		**0.0115**	**0.0115**

B. *Experiment 2*

Fig. 10: Left image

Fig. 11: Right image

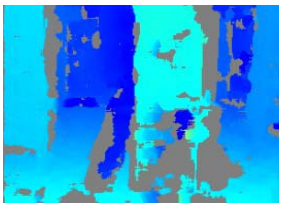

Fig. 12: Stereo disparity map

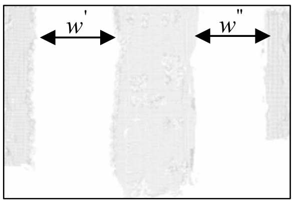

Fig. 13: 3D point map

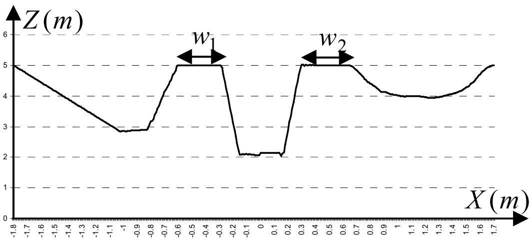

Fig. 14: 2D distance map

From the left and right images as shown in Fig. 10 and Fig. 11, the disparity and 3D point maps are shown in Fig. 12 and Fig. 13. From this 3D map, a 2D map with the widths of two freespaces w_1, w_2 is converted as shown in Fig. 14.

Assume that the actual widths of two freespaces w_{a1} and w_{a2} are equal to the safe diameter of the wheelchair d_s. This is difficult for the wheelchair to estimate and choose one of them to go through. For this reason, BR algorithm is used to find an optimal freespace and make the possible decision for the mobile wheelchair.

Consider the measured widths of two freespaces w_1 and w_2 as shown in Fig. 14. For similarity as *Experiment 1*, the high belief probabilities $P_{po}(w_1)$, $P_{po}(w_2)$ and their average probability are shown in Table 2.

In this Table 2, the average probability $P_{av}(w_1)$, which is greater than not only the average probability $P_{av}(w_2)$, but also the threshold probability P_{th}, results in this freespace w_1 being selected for the wheelchair to move through.

Table 2: The estimated values of the widths of two freespaces

Times	$w_1(t)$	$P_{po}(w_1(t)=FS)$	$w_2(t)$	$P_{po}(w_2(t)=FS)$
1	1010	0.7778	1020	0.7778
2	1000	0.9617	1010	0.9617
3	1020	0.9680	1020	0.9680
4	980	0.7652	1000	0.9682
5	1010	0.9613	1010	0.9682
6	1020	0.9680	1010	0.9682
7	1020	0.9682	1000	0.9682
8	990	0.7652	990	0.7652
9	1000	0.9613	980	0.7269
10	1010	0.9680	1020	0.9600
Average probability P_{av}		**0.9065**		**0.9032**
Variance		**0.0090**		**0.0104**

V. CONCLUSION

In this paper, stereoscopic vision, freespace detection in a 2D distance map and a BR algorithm are presented. The stereo disparity map is based on a combination of the left and right stereoscopic camera system images. From this disparity map, a 3D point map is computed based on a geometric projection approach. In addition, a 2D distance map is generated from this 3D map. Computation is performed on the 2D distance map to identify the presence of freespaces. For the freespace detection implementation for an autonomous wheelchair, a BR algorithm is applied to estimate the width of freespace. Experiment results on the wheelchair in a practical environment have illustrated the effectiveness of this estimation method.

REFERENCES

[1] R. C. Simpson, "Smart Wheelchairs: A Literature Review," *Journal of Rehabilitation Research & Dev*, vol. 42, no 4, pp. 423-436, 2005.

[2] P. Saeedi, P. D. Lawrence, and D. G. Lowe, "Vision-Based 3-D Trajectory Tracking for Unknown Environments," *IEEE Trans. on Robotics and Automation*, vol. 22, no. 1, pp. 119-136, 2006.

[3] Y. Adachi, K. Goto, Y. Matsnmoto, and T. Ogasawara, "Development of Control Assistant System for Robotic Wheelchair - Estimation of User's Behavior based on Measurements of Gaze and Environment," *Proceedings of the IEEE on Computational Intelligence in Robotics and Automation*, pp. 538-543, 2003.

[4] C. Watman, D. Austin, N. Barnest, G. Overett, and S. Thompson, "Fast Sum of Absolute Differences Visual Landmark Detector," *Proceedings of the 2004 IEEE International Conference on Robotics 8 Automation*, pp. 4827-4832, 2004.

[5] Thanh H. Nguyen, Jordan S. Nguyen, Duc M. Pham, and Hung T. Nguyen, "Real-Time Obstacle Detection for an Autonomous Wheelchair Using Stereoscopic Cameras," *The 29th Annual International Conf. of the IEEE EMBC*, pp. 4775 - 4778, 2007.

[6] G. N. Desouza and A. C. Kak, "Vision for Mobile Robot Navigation: A Survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 2, pp. 237-267, 2002.

[7] D. Murray and J. J. Little, "Using Real-Time Stereo Vision for Mobile Robot Navigation," *Auto. Robots*, vol. 8, pp. 161–171, 2000.

[8] Y. L. IP, A. B. Rad, and Y. K. Wong, "Autonomous Exploration and Mapping in An Unkown Environment," *Proceedings of the IEEE Third International Conference on Machine Learning and Cybernetics*, pp. 4194-4199, 2004.

[9] V. Fox, J. Hightower, L. Liao, D. Schulz, and G. Borriello, "Bayesian Filtering for Location Estimation," *IEEE Pervasive Computing*, vol. 2, no. 3, 2003.