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Walking Human Avoidance and Detection from A Mobile Robot using 3D Depth Flow

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Abstract

This paper shows walking human avoidance and detection behavior of a mobile robot using 3D Depth Flow. we propose 3D Depth Flow, that is able to measure 3D motion vector of every pixels between two time sequential images. First, a definition of 3D Depth Flow and a simple 3D Depth Flow calculation method are denoted. Then an implementation of real-time 3D Depth Flow Generation system using standard PC, and experimental results are denoted. Finally, as an application, walking human detection and avoidance task using a mobile robot in real environments is shown.

1 Introduction

The purpose of this research is to realize the robot which behaves in human walking environments. Recently, several real-time depth map generation systems have been proposed [1–4], and we implemented it on some mobile robots (quadrupled robot and wheel type humanoid robot) [5, 6]. These robots were able to avoid static obstacles in indoor or outdoor environments. However, to realize the robot which behaves in human walking environments, where obstacles are moving, requires 3D motion information of an environment in order to cancel its own motion and/or to distinguish mobile deformable target from the back ground. There are several researches which solve this problem with an assumption of the target [7, 8].

In order to solve this problem with no assumptions, we proposed 3D Depth Flow [9], which is able to percept three-dimensional structure and motion information. 3D Depth Flow is calculated by combining two time sequential depth images and optical flow, thus 3D Depth Flow can be calculated in real-time with real-time depth map generation system and real-time optical flow generation system. Similar concept is simultaneously proposed as 3D Scene Flow [10].

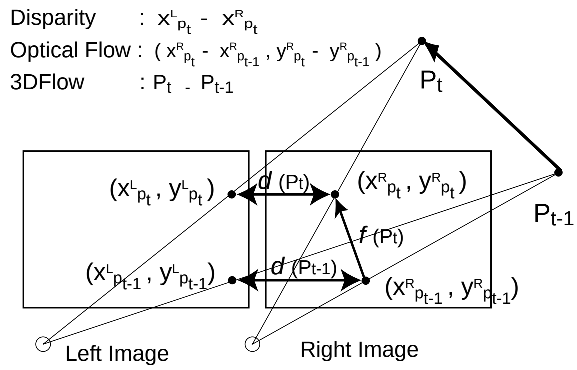

Figure 1: 3D Depth Flow, which is able to percept three-dimensional structure and motion information, is calculated by combining two time sequential depth images and optical flow. Optical flow is used for finding a corresponding points between two depth images.

This paper proposes a 3D Depth Flow generation system which measures 3D motion vector of every pixels between two time sequential images. First, definition of 3D Depth Flow, and simple method in order to calculate 3D Depth Flow are denoted. Then implementation of real-time 3D Depth Flow Generation system using only PC, and experimental results are denoted. Finally, as an application, walking human detection or avoidance task using mobile robot is denoted.

2 3D Depth Flow

2.1 Definition of 3D Depth Flow

We will present a definition of 3D Depth Flow which is able to percept three-dimensional structure and motion information of an environment. Following this paper, we assume that an epipolar line along stereo cameras is horizontal. In this situation, a moving point P_t in time t is projected to the right camera screen as $(x^R_{p_t}, y^R_{p_t})$, and P_t is also projected to the left camera screen as $(x^L_{p_t}, y^L_{p_t})$. A moving point P_{t-1} in time $t-1$ is also projected to the camera screens as $(x^R_{p_{t-1}}, y^R_{p_{t-1}})$, $(x^L_{p_{t-1}}, y^L_{p_{t-1}})$ respectively (see Figure 1).

Disparity $d(p)$ of designated point $d(P_t)$ is represented as follows:

$$d(p) = (x^R_{p_t} - x^L_{p_t}) \tag{1}$$

Thus, calculating disparity is to find corresponding points between a right camera image and a left camera image.

Optical flow is defined as a projection of three dimensional motion in a scene to the (two dimensional) image plane. Thus Optical flow $f(P_t)$ is calculated as follows:

$$f(P_t) = \begin{pmatrix} x^R_{p_t} - x^R_{p_{t-1}} \\ y^R_{p_t} - y^R_{p_{t-1}} \end{pmatrix} \tag{2}$$

Therefore, optical flow is obtained by finding corresponding points between two sequential images.

We define 3D Depth Flow as follows. 3D Depth Flow is composed of disparity $d(P_t)$ of a point P_t in time t and three dimensional motion vector $mv(P_t)$ of a point P_t between time t and $t-1$:

$$\begin{aligned} d(P_t) &= (x^R_{p_t} - y^L_{p_t}) \\ mv(P_t) &= \begin{pmatrix} x^R_{p_t} - x^R_{p_{t-1}} \\ y^R_{p_t} - y^R_{p_{t-1}} \\ d(P_t) - d(P_{t-1}) \end{pmatrix} \end{aligned} \tag{3}$$

2.2 Simple 3D Depth Flow Calculation Method

We propose the simple 3D Depth Flow calculation method by combining two time sequential depth images and optical flow between these images, since the first two elements of $mv(P_t)$ of Equation 3 is as same as optical flow. Hence, 3D Depth Flow is able to calculated as follows:

1. In order to obtain $d(P_t)$, search the point $(x^L_{p_t}, y^L_{p_t})$ in the left image which corresponds to the point $(x^R_{p_t}, y^R_{p_t})$ in the right image.
2. Calculate optical flow by finding the point $(x^R_{p_{t-1}}, y^R_{p_{t-1}})$ in the previous image which corresponds to the $(x^R_{p_t}, y^R_{p_t})$.
3. Then, find the point $(x^L_{p_{t-1}}, y^L_{p_{t-1}})$ in the left image which corresponds to the point $(x^R_{p_{t-1}}, y^R_{p_{t-1}})$ using disparity $d(P_{t-1})$.
4. Lastly, obtain 3D Depth Flow: $d(P_t), (x^R_{p_t} - x^R_{p_{t-1}}, y^R_{p_t} - y^R_{p_{t-1}}, d(P_t) - d(P_{t-1}))^T$

3 Real-time 3D Depth Flow Generation System

For robotics applications, real-time and robustness are important features. We developed PC-based real-time 3D Depth Flow generation system. The advantage of using PC as a vision system is 1) Current CPU is as fast as hardware system due to high frequency clock cycle and SIMD-based multimedia instruction set suit visual processing. 2) Software approach enables us to implement complex algorithms such as reliability evaluation.

3.1 1D & 2D Recursive Correlation Technique

To generate 3D Depth Flow in real-time, it is necessary to generate both depth image and optical flow in real-time. Some researchers have developed real-time stereo vision system using the recursive correlation technique [2, 11]. The recursive correlation technique eliminate redundancy in correspondence calculation and reduce a computation time. We expand this technique to two dimensional in order to generate optical flow in real-time [12].

3.1.1 1D Recursive Correlation Calculation

Correspondence calculation of every pixel from one image to another is required to generate depth map. In this paper, we assumed that a epipolar line is horizontal, thus no horizontal disparity occurs for a correspondent two image region.

Introducing recursive correlation technique, total computational order is known to be changed from $O(N^2W^2D)$ to $O(N^2D)$ by reducing a redundancy, where N is the size of input images, and W is the window size of correlation, and D is the maximum disparity size.

Table 1: Calculation Time : a) Correlation, b) Recursive Correlation Method, c) Cache Optimal Correlation, d) Adopt MMX Instructions

	PentiumIII-500MHz			
	Disparity Map Generation		Flow Generation	
	WithCC	WithoutCC	WithCC	WithoutCC
a)	5,332.7	2,594.5	1,928.7	903.5
b)	66.5	51.2	78.3	63.6
c)	41.9	34.0	40.9	31.5
d)	32.6	23.6	25.4	18.6

(unit:msec)
(N=128, W=15, D=20 in Disparity Map Generation and, N=64, W=16, D=8 in Optical Flow Generation)
CC:Consistency Checking

3.1.2 2D Recursive Correlation Calculation

So far, since 2D optical flow generation requires high computation performance, thus many hardware approaches have been proposed to generate 2D optical flow in real-time [13–16]. These hardwares enable to calculate fast 2D optical flow. However, we enhanced one dimensional recursive correlation algorithm to two dimensions in order to calculate optical flow. This approach has two advantages, one is no special hardware required, and the other is consistency checking method or other method can be easily adopted in order to omit occluded or mismatched region. In 2D Recursive Correlation, total computational order is changed from $O(N^2W^2D^2)$ to $O(N^2D^2)$ by reducing a redundancy.

3.2 Reliable 3D Depth Flow Generation

Fundamentally, stereo matching suffers from occlusions or mismatches. To generate reliable depth map, we apply "Consistency Checking Method" [17, 18].

To apply this method to 3D Depth Flow generation, we calculate consistency checking between two depth image and optical flow image. This checks spatio-temporal consistency.

3.3 System Evaluation

Our 3D Depth Flow generation system runs on standard PC hardware with dual Pentium III processors at 500 MHz and Linux(kernel 2.2.13). Video capture card which uses BT 848 chip is installed. This card is connected to PCI bus and is able to transfer a captured image to the main memory of CPU at video rate(30 Hz). Table 1 shows the calculation time of our 3D Depth Flow generation system.

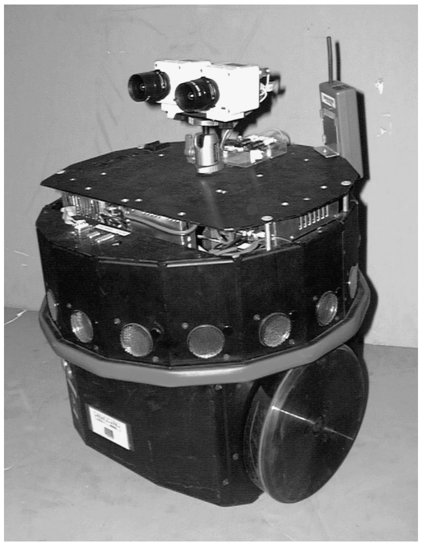

Figure 2: Figure of mobile robot with PC-based vision system

4 Applications of 3D Depth Flow

3D Depth Flow would be useful in a number of applications, especially a robot which behaves in human walking environments. In this paper, we show two example behaviors using a mobile robot. One is walking human avoidance, and the other is walking human detection from a running robot.

4.1 Mobile Robot with PC-based Vision System

We developed a mobile robot that embed PC-based vision system as shown in Figure 2 . The robot is composed of a mobile robot base(Scout-II of Nomadic Inc.), stereo cameras and PC-based vision system.

We installed PC system for visual processing in the robot body. The PC has Pentium III at 500 MHz, 128[MB] memory, 1.5[GB] Hard disk and radio wave LAN. We utilize two video capture cards with BT848, witch is connected to right and left cameras respectively(see Figure 3).

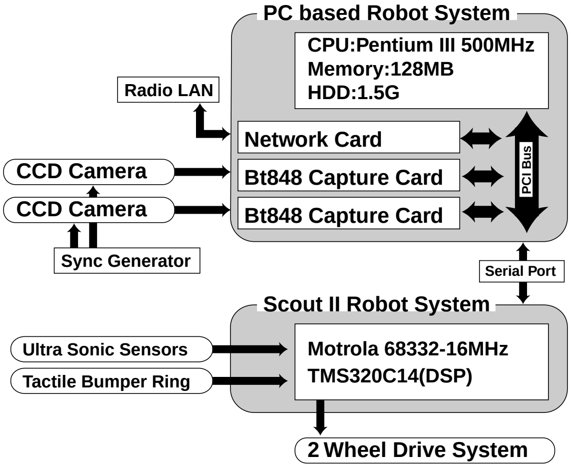

Figure 3: Hardware components of vision-based mobile robot system: The system is composed of a mobile robot(Scout II) and PC based vision system. The vision system determines a motion of the mobile robot from visual information, and sends commands to Scout II through the serial connection.

4.2 Walking Human Avoidance based on Potential Field using 3D Depth Flow

Walking human avoidance is an important behavior for the mobile robot in human walking environments. To achieve this behavior, a moving obstacles avoidance function is required. However, previous researches on moving obstacle avoidance are theory, which assume ideal sensors [19, 20].

We proposed the method of moving obstacles avoidance based on 3D Depth Flow using Potential Field. Our proposed method has the advantage that 1)It does not require ideal sensors. It works on a real robot, a real sensor and a real environment. 2)Any a priori knowledge about environments or human is required, 3)This method is able to apply to both manipulators and mobile robots.

4.2.1 Potential Field using 3D Depth Flow

This section describes a method to calculate potential field using 3D Depth Flow. Let $d(x, y)$ to be disparity at image coordinate x, y and three dimensional motion vector at x, y is $mv(x, y) = (mx_{x,y}, my_{x,y}, md_{x,y})$. The repulsive force at voxel x, y, d is as following:

$$P_O(x, y, z) = \sum \frac{1}{1 + dist(x + mx_{x,y}, y + my_{x,y}, d(x, y) + md_{x,y})}$$

where $dist(x, y, d)$ denotes the distance between the camera and the object, that is:

$$dist(x, y, d) = \sqrt{\alpha x^2 + \beta y^2 + \gamma d^2}$$

4.2.2 Motion control based on potential field

To control motion of the robot, the gradient of potential field at present the robot position is utilized. The robot moves toward the orientation of the gradient.

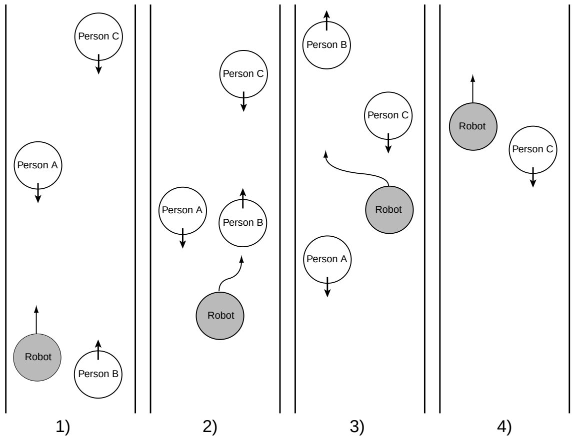

Figure 4: A situation of an experiment

4.2.3 Walking Human Avoidance Experiment

We had the experiment at the environment with three walking human. Figure 4 illustrates movement of each person and the robot. Figure 5 shows the sequence of the experiment.

4.3 Walking Human Detection from A Running Robot using 3D Depth Flow

In human walking environments, the robot is required to detect walking human while the robot is running. To achieve this task, we proposed the method using “Relative 3D Depth Flow”.

First, we calculate “Relative 3D Depth Flow” by canceling Ego-Motion of a robot from 3D Depth Flow. Several methods to obtain ego-motion of a robot are conceivable. We calculate ego-motion using a internal dead-reconing sensor.

Walking human regions in the image are detected as follows. Large three-dimensional motion vector regions in Relative 3D Depth Flow are walking human regions. Figure 6 shows the result of the walking human detection experiment in the real-world.

5 Conclusion

In this paper, the walking human avoidance and detection from a running robot under complex environment using 3D Depth Flow is denoted.

At first, we proposed 3D Depth Flow, the method to percept three-dimensional structure and motion of environments. Then we denoted the implementation of real-time 3D Depth Flow generation system.

We also show an experiment which the robot avoids several walking human and the robot is able to detect walking human while the robot is moving.

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Figure 5: An experiment of moving obstacles avoidance while a robot is running.

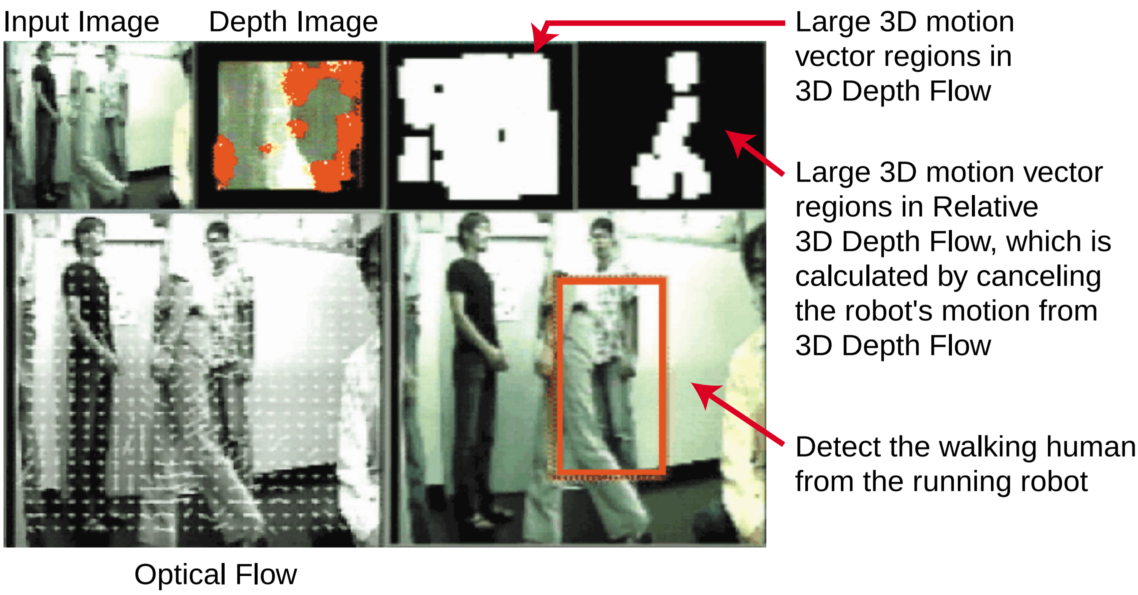

Figure 6: An experiment of walking human detection from a running robot using 3D Depth Flow