A Human-Following Robot Using Human Skeleton and Pedestrian Dead Reckoning

Yuan-Ting Fu, Chih-Ming Hsu*, and Yu-Fan Wu

***Abstract*— This paper proposes an online correction of pedestrian step length parameter estimation and the ability to continuously following the mechanism for following robot losing target in the view of image field. Use the smartphone placed in the user's trouser pocket to estimate the posture information of the leg movement, and the Kinect camera tracks the position of the target skeleton, it could make the slope parameter of the user step length estimated in real time. In the case about the robot losing target, the Inertial Measurement Unit of the mobile phone carried by the user is used to estimate the posture information of the current pedestrian dead reckoning. We can use the mechanism of the trajectory reduction to control the movement of the robot to the pedestrian dead reckoning. The location of the track could be successfully recovered the original follow-up target, and continued to follow.**

I. Introduction

As early as the 20th century, humans have gradually begun research in the field of robotics. Robots replace human in various fields. Human-Following is one of key components in many computer vision applications. There are some challenges of Human-Following. In order to achieve continuous tracking of the target position, it is necessary to design algorithms to solve the problems. Our research in this paper is using the concept of human skeleton and pitch angle as the basic framework, using pitch angle to calculate the pose of the followed target, and recover the trajectory from missing following. Robot can find the missing target and follow it. In addition, we using the Kinect camera to measure human moving. The experimental results show that our proposed method is better than the statistical regression model. Finally, the experimental results also prove that online parameter correction can effectively reduce the error of step size estimation.

II. Related Works

A. Human-Following

For the Human-Following, the most of used sensors are radar, LiDAR and RGB-D camera. Radar [1][3][5][8][10] is a type of high accuracy sensor. Radar sensor offer the distance and angle for every observed points. However radar sensor performs low accuracy when occur occlude or observe the calf of human. K.Koide [1] used LiDAR scanning calf to follow human. P.Nikdel[3] fused the LiDAR scanning to calf and SLAM(Simultaneous localization and mapping) algorithm to get the pose of robot to estimate the velocity and orientation of target. RGB-D camera[1-4][6][7][9] is commonly used for Human-Following robot, camera offers sufficient image information, but RBG image data is constrained and affected by problems arising from occlusions or illumination. M.Gupta[4] proposed a robust method to extract the object feature to follow the target stably.。E.Babaians [6] designed the region of interesting to detect the skeleton of human, and tracking the target in RGB-D image. ChenB.X [9] fused the stereo vision and convolutional neural network to estimate the distance from target to camera.

B. Missing Target

Generally, robots can detect target from image sensor information and keep following in a distance range. However, there are many challenges on human-following scenario. Most of recent methods easily lose track of human when facing unexpected situations such as when human turns at a corner sharply with high speed, or due to occlusion by another human, and limitation of sensors. As a result, a recovery mechanism is necessary in order to assist robot predict the future of human position, navigate and search the environment until the human is relocated. M.Ota[2] presents following continuation function for human following robot losing target at corner. This method is using logarithmic function to model the trajectory of human. The each of distance error between predict position and measure position was less than 0.65meters. R.Tasaki[8] put an IMU sensor on the ankle to reference the orientation information when missing the target. M.D.Hoang[10] propose a moving target localization method that directly measures or indirectly estimates the position of the robot's following target.

C. Pedestrian Dead Reckoning

Pedestrian dead reckoning (PDR) is usually used for localization in indoor environment. . According to the existing indoor positioning technology, the PDR algorithm typically uses an inertial measurement unit (IMU) sensor as a cost-effective choice.

Step detection is import for PDR algorithm. The purpose of step detection is to recognize the target is moving or not. We can measurement the peak value of step when the pedestrian is walking. Different signal feature like norm of the acceleration [11], vertical acceleration [12] and analysis of frequency [13]. To avoid noise of the signal, the signal pre-processing and ramp detection is necessary. The most common step detection method is to use IMU to detect and estimate the number of moving steps. The disadvantage of the above feature detection is that the signal is easily affected by

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pedestrian walking speed, and it is more difficult to estimate the number of steps. [14][15] solve the problem is accumulation of positioning errors due to the drift caused by the noise in the sensors. The method is to detect a ramp, the slope of the terrain on which the user is walking, and the change in height sensed when moving forward, are estimated from the IMU. [16][17] proposed method based on the opening angle of the leg or pitch angle to estimate the step length and to detect steps for PDR navigation systems, the advantage of this type method do not require the use of additional sensors, such as barometers, or additional information, such as maps. [18] proposed a step length model for evaluating the distance travelled by a pedestrian holding an IMU in a hand, The proposed step length model for smart phone users combines the user's step frequency, the user's height and a set of three variables. [19][20] using the value of acceleration to determine the pedestrian's heading. [21] aims at developing a robust step detection algorithm for indoor navigation applications, and assume the user is handling the phone in front of him. [22] proposed for robust step detection irrespective of step mode and device pose in smartphone. They designed adaptive thresholds to validate peak and valley candidates in magnitude and temporal direction to select the correct of peaks or valleys.

III. The Proposed Method

A. Framework of Algorithm

Fig. 1 shows the whole system structure combining skeleton tracking and PDR. The left hand side is the overall architecture for tracking the target. The right hand side is the structure of pedestrian dead reckoning. The distance of the target position is provided to the PDR for online correction step length formula for parameter correction. Integrating human skeleton tracking and PDR to estimate the position of the target in the real environment. When the target exceeds the detectable human skeleton field of view, it means that the robot has lost the target. Using the last vanishing point of the Kinect camera to control the robot to move to the vanishing point.

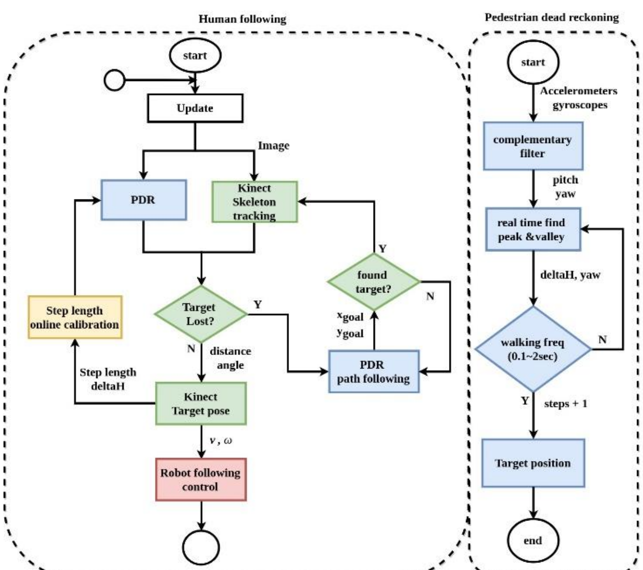

Figure 1. Framework of algorithm

B. Target Following

To follow the path based on the recorded movement position of the target. In order to reduce the possibility of hitting an obstacle, the point-to-point control method is used. The robot is controlled in a 2D plane when the target disappears. The position of the robot in the world coordinate $O(x_R, y_R)$, the target point (x_{goal}, y_{goal}) is the position of pedestrian dead position estimation. θ_R is the heading angle(pitch) of the robot, the black arrow is the moving distance between the target and the robot. The black imaginary circle is the tolerance distance between the robot and the target point. Using point-to-point control to keep the robot following up the target. During the movement, the linear velocity v of the robot will be controlled. For the relationship between the robot position and the target distance, it can be defined as equation (1). Where v is the linear velocity of the robot , k_p is the gain equal to 0.5 in our scenario. The angular velocity ω of the control robot uses the angle relative to the coordinates of the robot. The relationship between the orientation angle of the robot and the angle between the target point can be defined as equation (2). Among them, ω is the angular velocity of the robot, and k_p is equal to 4. The linear velocity and angular velocity calculated by equations (1) and (2) are used to control the robot to move to the target point position.

$$v = k_p \times \sqrt{(x_{goal} - x_R)^2 + (y_{goal} - y_R)^2} \tag{1}$$

$$\omega = k_p \times \tan^{-1}\left(\frac{y_{goal} - y_R}{x_{goal} - x_R}\right) - \theta_R \tag{2}$$

C. Pedestrian Dead Reckoning Estimation

The fusion of the acceleration and gyroscope signals is obtained for better orientation estimation, the output heading angle(pitch) is fused by the filter based on quaternion [23]. This is the reason why we need is the heading angle (pitch) to detect the leg swing angle (yaw) estimation. To measure the yaw and pitch, through searching the peaks and valleys in real time. When the smartphone is swinging in the pocket, the completion of a number of steps will be composed of a peak-valley signal θ_{valley} and a peak signal θ_{peak}. If the user keeps standing, the pitch angle is horizontal. Fig. 2 shows the swing of the pitch angle signal. The horizontal axis is the sampling time, and the vertical axis is the estimated pitch angle. The figure represents the pitch angle result of walking for eight steps, and the blue line represents for the signal of the pitch angle estimation, the red triangle mark is the maximum estimated pitch angle, the blue square is the minimum estimated pitch angle, and the green dot is the false peak value that does not meet the condition setting.

We use [17] proposed a linear regression model based on the pitch angle. The step-length linear model can be defined as equation(3). Where d_h is the estimated step length, a and b are the slope parameters and bias of the linear model. In addition, using a constant slope parameter will be affected by factors such as the user's height and other conditions, also cause some accumulated errors, the accuracy is reduced.

$$d_h = a \times (\theta_{peak} - \theta_{valley}) + b \tag{3}$$

According to the position of the sensor, select the measured signal characteristics as in equation (3), extract the step features from the signal content, and identify the correlation between each step to estimate the step length and estimate the position of the user. The estimation model was defined as equation(4), where X_{k-1} and Y_{k-1} are the positions of the x and y axes at the last k time, and X_k and Y_k are the position at time k, d_h is the estimated step length of the pedestrian in equation(3), and ψ_h is the heading angle of the pedestrian.

$$X_k = X_{k-1} + d_h \cdot cos(\psi_h),\ Y_k = Y_{k-1} + d_h \cdot sin(\psi_h) \quad (5)$$

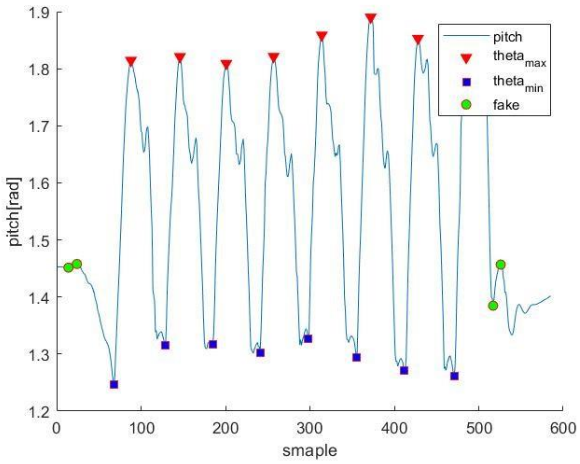

Figure 2. The signal of pitch

D. Step length online calibration

Due to the step length parameter are different for each person, because the height and weight of each person are different, so that the slope parameters estimated in the step length are slightly different. We combined the human skeleton distance observed from camera and the PDR estimation method, to find the distance changes from last time to current time. The magnitude of the pitch angle measured by the IMU is regarded as the actual swing situation in the pocket position, which can be defined as equation(6). Where d_k is the distance difference between the Kinect camera at the previous time and the current time, a_i, b_i are the slope parameters estimated by the linear model at time i, and $\Delta\theta_H$ is the magnitude of the estimated pitch angle. The least square error and the amplitude of the pitch angle can be defined as equation(7). Where ${d_k}^{Kincet}$ is the distance difference measured by the Kinect camera, and ${d_h}^{PDR}$ is the step length of the PDR estimation. Using the least square method to find the smallest slope parameters a, b at time k.

$$d_k^{kinect} = a_i \times \Delta\theta_H + b_i \quad (6)$$

$$\min_{a\,\cdot\,b} \sum_{k=1}^{n} \left| {d_k}^{Kincet} - {d_k}^{PDR} \right| \quad (7)$$

IV. Experiment

Here are three parts of experiment, (a) Missing target (b) PDR estimation (c) Calibration.

A. Missing Target

Fig.3 shows the situation of missing target at left corner, and Fig.4 is the trajectory of Fig.3. The robot is stationary , and the user starts to move away from the robot. When the distance of robot and user is 5 meters, the skeleton of user cannot be detected from (a) to (d) in Fig.3. The position estimated by the PDR allows the robot to continue tracking the target and find the target at approximately coordinate at (x,y) is (8.1,-1.7) from (e) to (k) in Fig.3.

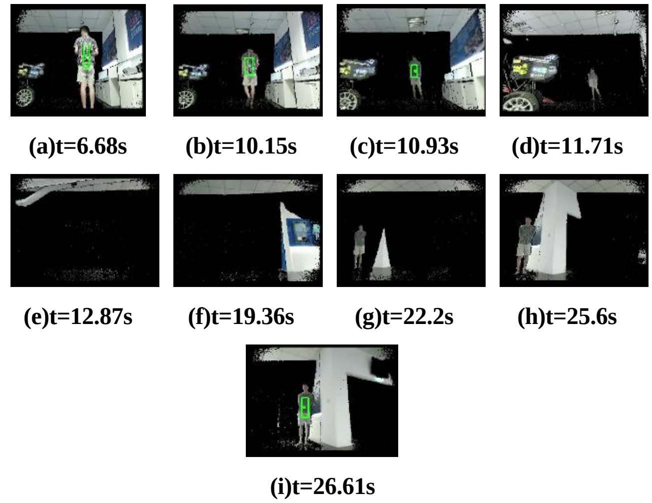

Figure 3. The situation of missing target at left corner

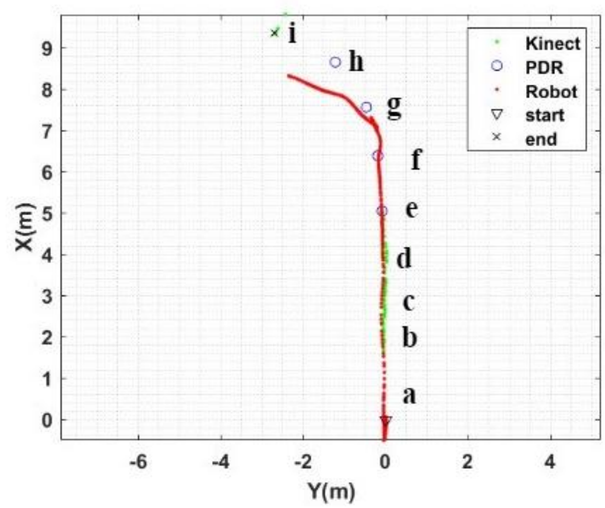

Figure 4. Trajectory of left corner

B. PDR Estimation

The trajectory of user is shown in Fig.5, the X and Y axis are the position of the x component and y component. The black point is obstacle from LiDAR observation such as walls and stairs. The red point is the user position from step length estimation. The blue point is the user position from LiDAR observation. Affected by the placement of the mobile phone in the pocket, there will be an error in the pitch angle. In addition, each step length and walking speed of person are affected by height, so we need to calibrate the step length of each users.

C. Calibration

Table 1 shows the results of the online calibration of step length parameter. The direction of each walking is forward movement. There are five experimental samples, a and b are the slope parameters and distance. The error is the total distance error. From five sets of experimental results, the errors of after calibration are all smaller than before calibration.

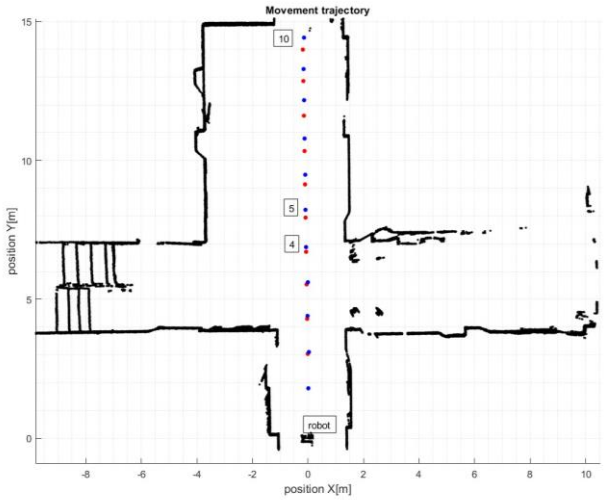

Figure 5. Trajectory of the user

TABLE I. THE RESULT OF CALIBRATION

	Before calibration			After calibration		
step	**a**	**b**	**error(m)**	**a**	**b**	**error(m)**
7	0.0214	0.3251	0.261	0.0275	0.325	**0.043**
10	0.0214	0.3349	1.477	0.0243	0.274	**0.047**
13	0.0214	0.3106	2.569	0.0234	0.31	**0.001**
15	0.0214	0.3702	1.543	0.0249	0.319	**0.015**
17	0.0214	0.3416	2.929	0.0239	0.274	**0.284**

V. CONCLUSION

This paper proposed based on inertial measurement with smart phone in user's pocket to estimate the step length and heading angle of the user. When the user moves beyond the camera's FOV and the robot cannot keep up with the target, the pedestrian navigation will estimate the trajectory of user. In addition, for the linear model estimation of step length, we proposed an online calibration method to correct the step length, which combines the movement of skeleton and trajectory to follow the target. We used the least squares to optimize the pitch of PDR estimation, and provides the online correction of the step length formula parameter to find the slope parameter of step length.

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