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Human Tracking with Variable Prediction Steps based on Kullback-Leibler Divergence

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Abstract: This paper deals with a path planning problem for tracking humans in order to obtain detail information about human behavior and characteristics. In our method, path planning is performed based on Kullback-Leibler (KL) divergence between the predicted distribution of all human positions and the intensity of field of view of agents. The number of prediction steps is determined according to the consistency of the prediction. Experimental results show that when prediction of human movement is accurate, the long-term prediction is useful for the path planning. On the other hand, when prediction is inaccurate, long-term prediction might not be useful. Our path planning method works well even under changing circumstances by changing the number of the prediction length.

Keywords: path planning, human tracking, variable term prediction

I. INTRODUCTION

Visual surveillance methods have been intensively studied in order to ensure a security because it provides less stress to a tracked human, and most of these researches focus on improving the quality of position estimation by image processing technique [1] [2]. For a surveillance system, however, detail information such as human behavior and their characteristics are also important. Since high resolution images are necessary to obtain such information, visual sensors must be in close range to human. Mobile agents with visual sensors can be one of solutions to achieve this. In this research, we focus on a path planning for mobile agents to acquire detail information of tracked humans.

The human tracking system is often developed using a Kalman filter or a particle filter. Since these researches have only used one-step prediction of the human movement, the planned paths tend to be myopic one. In order to overcome this problem, it is useful to plan the path based on longer-term predictions in the future. Real-Time A* (RTA*) is a search algorithm for semi-optimal path planning, but it can be applied to a problem with given start and goal point. However, it was shown that long-term prediction make the performance of path planning improved.

Although an accurate prediction of human position improves performance of human tracking [3] [4], accurate long-term predictions are not always possible . For instance, long-term prediction becomes accurate if every humans move to a certain direction (Imagine a station at the morning and evening rush hours). In contrast, it becomes inaccurate if every human moves their own way like in a shopping moll or at an intersection without signals. When humans arrived at a cross over point, the prediction may become difficult because humans might interact with each other and therefore human movements might become complicated. As mentioned above, the accuracy of prediction varies with the situation, such as the day, the time and the location. In this research, we proposed a path planning method with varying prediction length according to changes in the environment to realize effective human tracking system.

II. HUMAN TRACKING TASK

In this research, the number of humans who independently walk in a surveillance area and the number of agents who track humans for obtaining humans' detail information were denoted by N_h and N_c. We assume that the position and velocity of each human can be measured by sensors embedded in the environment. This assumption would be satisfied by employing a recent research technique for human position tracking system using sensors embedded in the environment [5][6](See Fig.1). We also assume that no occlusions between humans and agents occur.

A set of planned paths of agents is evaluated based on following equation :

$$D = \frac{1}{N_t} \frac{1}{\sum_t N_{h\_in}(t)} \sum_t \sum_{i \in I(t)} \min_j ||\bar{\boldsymbol{\mu}}_{h\ i}(t) \quad \bar{\boldsymbol{\mu}}_{c\ j}(t)|| \quad (1)$$

where N_t is the number of time steps of the path planning task, $I(t)$ and $N_{h\_in}(t)$ are the set the of indexes of humans who exist in the surveillance area at time t and its element count. $\bar{\boldsymbol{\mu}}_{h\ i}$ and $\bar{\boldsymbol{\mu}}_{c\ j}$ are the position of the i-th human and the position of the j-th agent. Hereinafter $\min_j ||\bar{\boldsymbol{\mu}}_{h\ i}(t) \quad \bar{\boldsymbol{\mu}}_{c\ j}(t)||$ is called nearest neighbor distance (NND).

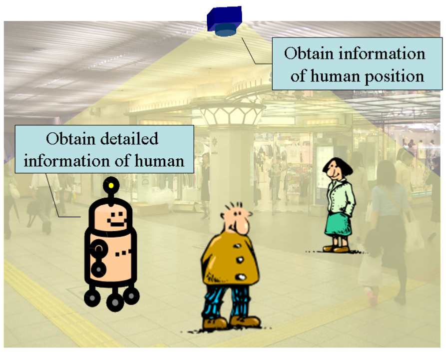

Fig. 1: Human tracking problem.

III. PATH PLANNING PROCEDURE

The predicted position of the i-th human at time $t +$ is approximated by a Gaussian whose center is $\boldsymbol{\mu}_{h\ i}(t + \ ; t)$

where t denotes the time to make the prediction. That is, the probability of the i-th human existing at $\boldsymbol{x}$ at time $t+$ is defined as:

$$H_i(\boldsymbol{x} \quad t+ \quad ;t) = \frac{1}{2 \quad \sigma_h^2} \exp\left\{ \frac{||\boldsymbol{x} \quad \boldsymbol{\mu}_{h\ i}(t+ \quad ;t)||^2}{2\sigma_h^2} \right\} \quad (2)$$

where $\sigma_{h\ i}$ is its variance.

The closer cameras are to a subject, the more detail information of the human can be obtained. In this research, we assume the distance between the camera and the human corresponds the amount of information of human behavior to be obtained, and the intensity of field of view (FOV) of the j-th camera is defined by a Gauss function :

$$C_j(\boldsymbol{\mu}_{c\ j}) = \frac{1}{2 \quad \sigma_c^2} \exp\left\{ \frac{||\boldsymbol{x} \quad \boldsymbol{\mu}_{c\ j}||^2}{2\sigma_c^2} \right\} \quad (3)$$

where $\boldsymbol{\mu}_{c\ j}$ is the position of the agent j and σ_c is size of FOV of cameras.

The predicted distribution of all humans' positions of all humans and the intensity of FOV of cameras at time $t+$ are calculated as follows :

$$H(t+ \quad ;t) = \sum_{i=1}^{N_{h\_in}} H_i(\boldsymbol{\mu}_{h\ i}(t+ \quad ;t) \quad \sigma_{h\ i}) \quad (4)$$

$$C(t+ \quad ;t) = \sum_{j=1}^{N_c} C_j(\boldsymbol{\mu}_{c\ j}(t+ \quad ;t) \quad \sigma_c) \quad (5)$$

In our method, the path is determined based on the Kullback-Leibler (KL) divergence between H and C, and the path which minimizes the KL divergence is obtained by a gradient method.

1 . Path Planning

The KL divergence between H and C at time $t+$ is calculated as :

$$KL(H(t+ \quad ;t) \quad C(t+ \quad ;t)) = \int_{\infty}^{\infty} H(t+ \quad ;t) \log \frac{H(t+ \quad ;t)}{C(t+ \quad ;t)} d\boldsymbol{x} \quad (6)$$

We assume that the KL divergence at each time step is independent to the one at another time step and the multi step KL divergence can be calculated by the sum of single step KLs :

$$F(t) = \sum_{=1}^{T} \quad (t+ \quad ;t) KL(H(t+ \quad ;t) \quad C(t+ \quad ;t)) \quad (7)$$

where is the weighting factor. By using movements of agents at every time steps $\boldsymbol{d} \equiv [\boldsymbol{d}(t+1;t)^\top \cdots \boldsymbol{d}(t+ \quad ;t)^\top]^\top$, $\boldsymbol{\mu}_c(t+ \quad ;t)$ can be calculated as:

$$\boldsymbol{\mu}_c(t+ \quad ;t) = \bar{\boldsymbol{\mu}}_c(t) + \sum_{n=1} \boldsymbol{d}(t+n;t) \quad (8)$$

where $\boldsymbol{d}(t+n;t)$ is planned movements of agents at time $t+n$.

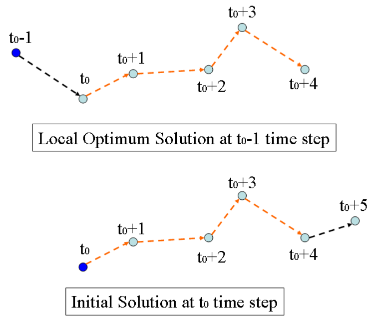

Fig. 2: Example of solutions. Orange dashed lines indicate the path which is able to be reused as initial solution at $t = t_0 + 1$ time step.

Since the maximum velocity of each agent is limited to V_{max}, the traveling distance for each agent is truncated when it becomes longer than V_{max} in the process of optimization based on the gradient method. That is, if $||\mathbf{d}^{(k+1)}(t+n;t)|| > V_{max} \quad n = 1 \ 2 \ \cdots \ T$, then $\mathbf{d}^{(k+1)}(t+n;t) := \frac{V_{max}}{||\mathbf{d}^{(k+1)}(t+n;t)||} \quad \mathbf{d}^{(k+1)}(t+n;t)$.

2 . Prediction Model of Human Motion

In order to calculate the prediction at each time step (equation (7)), a model of humans movement is necessary. For the simplicity, the motion of human is assumed to follow a fixed rule given in advance, for example, we use uniform linear motion, circular motion or zig-zag motion in our experiments. The performance of the prediction model would have large effect to the performance of human tracking [7], however, we focus on the number of the prediction steps in this research. If the predicted motion model is uniform linear motion model, the predicted position of human at time $t+$ can be calculated as :

$$\boldsymbol{\mu}_h(t+ \quad ;t) = N(\bar{\boldsymbol{\mu}}_h(t) + \bar{\boldsymbol{v}}_h(t) \qquad \sigma_h) \quad (9)$$

where $\bar{\boldsymbol{\mu}}_h(t)$ and $\bar{\boldsymbol{v}}_h(t)$ are the position and the velocity of human at current time t.

3 . Generating an Initial Solution

Since the number of iterations in the gradient method depends on the distance between the initial solution and the suboptimal solution, it seems to be better that the initial solution is generated near by the optimal solution. In our method, the initial solution is generated as $\boldsymbol{d}^{(0)}(t+ \quad ;t) = \bar{\boldsymbol{d}}(t+ \quad ;t \quad 1)$, where $\bar{\boldsymbol{d}}(t+ \quad ;t \quad 1)$ is the obtained solution at the previous time step. That is, the orange part of the path in Fig.2 is reused. Movements which were not dealt in the optimization at the previous time step are initialized to 0.

If the prediction is accurate, the longer prediction length makes the performance better but computational cost also becomes higher, because the dimensionality of $\boldsymbol{d}$ becomes large (curse of dimensionality). However, when the optimal solution at current time step is similar to that of the previous time step, the number of iterations would be reduced much, even if the prediction steps becomes large.

4 . Prediction Steps

Although path planning using accurate long-term prediction would be efficient, one using inaccurate long-term prediction might decrease performance of tracking in some

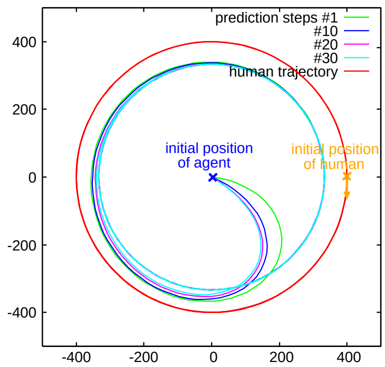

Fig. 3: Trajectories of human and agent in case of uniform circular motion

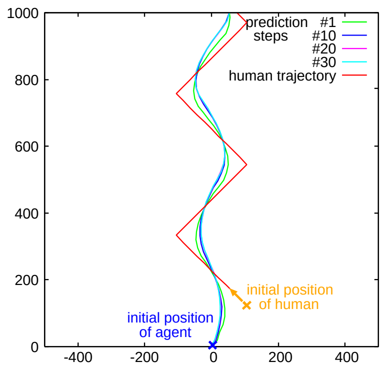

Fig. 4: Trajectories of human and agent in case of uniform zigzag movement

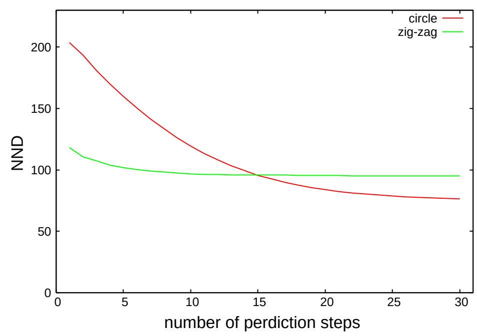

Fig. 5: NND between human and agent of each prediction step under static environment (refer to Fig. 3 and Fig. 4).

case. In our planning method, the number of prediction steps T is determined based on accuracy of the prediction. The probability that human moves following the prediction model until time $t +$ is calculated as:

$$P(t + \ ; t) = \prod (1 \quad (t + \ )) \tag{10}$$

where is the probability of human taking a motion different from the prediction model.

The weighting factor $(t + \ ; t)$ in equation (7) is calculated based on $P(t + \ ; t)$ as:

$$(t + \ ; t) = (1 \quad (t)) \quad (t + \quad 1; t \quad 1) \tag{11}$$

where, $(t+1; t) = 1$. When the $(t+ \ ; t)$ becomes below a certain threshold, KL divergences after time $t+$ $(\ > \ )$ are not used in the path planning procedure.

IV . SIMULATION EXPERIMENT

We conducted simulation experiments in a static environment where human movements do not change and those in a dynamic environment where human movements sometimes change. In these simulations, both the number of humans and that of agents are one.

1 . Tracking in Static Environments

In this case, the path planning was done by constant-term predictions $T = 1 \sim 30$. The length of each simulation was 200 time steps and the human motion models used in experiments are a circular motion model (Fig.3) and a zigzag motion model (turn $\pm 90°$ every ten time steps)(Fig.4). The velocity of the human is 1 2 times faster than that of the agent.

Fig.3 and Fig.4 show the trajectories of the human and the agent. Red lines in the figures indicate the trajectory of the human and other lines show trajectories of the agents which are planned with constant prediction steps (T = 1 10 20 30). Fig.5 show NND between the human and the agent whose path planning was done with each prediction steps. According to Fig.3, 4 and 5, the longer-term prediction improve performance of the human tracking.

2 . Tracking in Dynamic Environment

The simulation experiment are conducted in the case of using zig-zag motion model with dynamically changing probability of human turning $\pm 90°$ (Fig. 6). The total time step in this simulation was 200 and the probability of the turning are 0 3 at time step $t = 1 \sim 50$ $101 \sim 150$ (Mode1) and 0 05 at time step $t = 51 \sim 100$ $151 \sim 200$ (Mode 2). The ratio of velocity are same to the previous simulation. In this method, the uniform linear motion model is used as the motion prediction model. Ten sets of simulated human motion data are generated from this model. Fig. 6 shows an example of human trajectory in this case. Using these data sets, following three methods are compared.

Constant : The number of the prediction steps is constant ($T = 1 \sim 30$).

Variable : The number of the prediction steps is variable (proposed method)

Optimal : All human positions in the future was given in advance and used to calculate the path (upper bound).

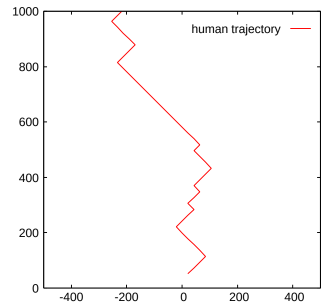

Fig. 6: Typical trajectory of human (unsteady zigzag movement)

A . Estimating probability of turning

In our method under the dynamic environment, the accuracy of prediction of human motion was calculated based on the probability of human turning. An online moving average of the turning probability of was used as , and was updated as:

$$(t) = 0\ 7 \quad (t \quad 1) + 0\ 3 \quad (t) \tag{12}$$

$$(t) = \begin{cases} 0 & \text{(go forward)} \\ 1 & \text{(turn)} \end{cases} \tag{13}$$

B . Experimental results

Lines in Fig.7 shows the ten steps' moving average of the NND by each method. The comparison between *Constant*

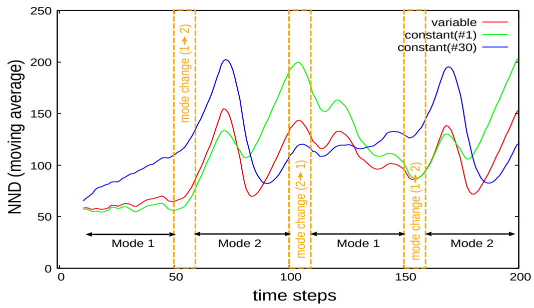

Fig. 7: Ten steps moving average of NND.

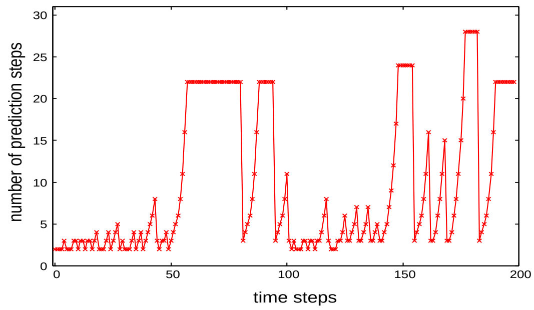

Fig. 8: Prediction steps of each time steps.

($T = 1$) and *Constant* ($T = 30$) bear out that when the prediction was accurate (Mode 2), the path planning method with a long-term prediction (*Constant* ($T = 30$)) is efficient, on the other hand, when the prediction was inaccurate, the method with a short-term prediction (*Constant* ($T = 1$)) is efficient. The behavior by the *Variable* was similar to that of *Constant* ($T = 1$) during Mode 1 and was similar to that of *Constant* ($T = 30$) during Mode 2. Fig.8 shows the number of prediction steps of each time step. According to Fig.7 and 8, the number of prediction steps in *Variable* can be changed adequately based on the accuracy of the prediction.

Fig.9 shows the average NNDs of humans and agents against each data set (data ID = 1 $\sim$ 10). In Fig.9, the value for *Constant* shows the best value among NNDs by *Constant* with different prediction steps. The result of *Variable* was always better than that of *Constant*. Fig.10 shows an average NND of human and agents of *Constant* of each number of prediction steps. Red crosses indicate values for each dataset, and blue points indicate the average taken over ten data set. Green crosses plotted on the left side of the graph indicate average NND by *Variable*. The performance of *Variable* was better than that of *Constant*.

V. CONCLUSIONS

In this paper, we proposed a path planning method where the path planning was done based on the long-term prediction of human positions. In this method, the number of the prediction steps is varied according to the accuracy of the prediction because subsequent predictions would be similar (consistent) when the prediction is accurate. In a static situation, the performance of the human tracking becomes better by increasing the number of the prediction steps. On the other hand, in a dynamic situation, it is not necessarily the case that the long term prediction improve performance of the human tracking. In our method, the number of the prediction steps is adjusted according to the current situation, and the performance of the human tracking can be kept high in a changing environment.

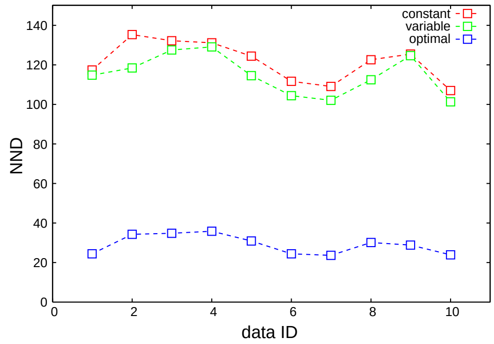

Fig. 9: NND between human and agent of each data set under dynamic environment.

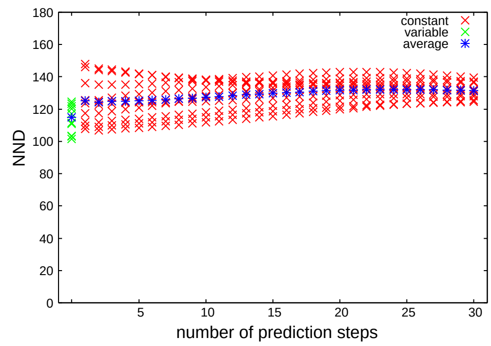

Fig. 10: NND between human and agent of each prediction step under dynamic environment.

VI. ACKNOWLEDGMENTS

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