

Cost Based Estimation of Intended Locomotion Targets Using Human Locomotion Models

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Abstract

This paper presents a novel approach to estimate a person's intended locomotion target. This estimation is based on models of human locomotion and the finding that locomotion is planned such that the movement minimizes a certain cost function. Using such a cost function, we calculate the expected costs for a path trajectory to a number of possible targets, and make an estimation of a person's intended target based on changes in these expected costs in relation to the cost of the path up to this point.

CR Categories: I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Virtual reality H.1.2 [Models and Principles]: User/Machine Systems—Human factors;

Keywords: path prediction, optimal control, walking, path models

1 Introduction

In Virtual Reality, real walking can be used for navigating in virtual worlds. To do so, a user is wearing a head mounted display while a tracking system captures his head position to adjust the view of the displayed virtual environment accordingly. While this is already an advantage over CAVE systems, the area is still limited by the size of the tracked space. To overcome this limitation, Razzaque et al. proposed redirected walking [Razzaque et al. 2001]. This technique exploits the visual dominance in human perception and uses a mismatch between the movement in the real and the virtual world to compress the user's motions and therefore allows visiting a virtual environment that is significantly larger than the tracked area.

Nescher et al. [Nescher et al. 2014] demonstrated the performance of a controller using Optimal Control. It redirects the user in such a way that the mismatch and disturbance of the user is minimized. While this works well if the user's future path is known, any user decision decreases the performance, because there is no knowledge about his upcoming decisions.

This paper proposes an approach that, given a set of predefined targets, gives an estimation of the user's intention to walk towards a certain goal.

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2 Related Work

Some approaches exist for target estimation in VR. Nescher et al. [Nescher and Kunz 2013] presented a prediction based on head tracking data. While extrapolation of the current position based on the walking velocity seems to be a good approach for estimating the walking direction, tests revealed that the biomechanical principles of walking cause a tracked point on the head to oscillate around the actual path trajectory. Thus, Nescher et al. introduced a double exponential smoother to reduce oscillations while also keeping the latency low. Although the approach was demonstrated for two targets next to each other, it is not easily extendible to scenarios with a large angular difference between the possible targets.

Research showed that human movements follow certain optimality criteria, e.g. by Flash and Hogan for arm movements [Flash and Hogan 1985], which was later confirmed for locomotion paths by Hicheur et al. [Hicheur et al. 2005] and Mombauer et al. [Mombauer et al. 2010]. They showed that the path of a person towards a target is optimal with respect to a certain cost function. While different cost functions were presented, the general pattern is an optimization towards a short path while also trying to keep the path smooth.

These models optimize a path with a given cost function, trying to find the path with the lowest cost. In the case of Mombauer et al. the function (1) is used, where ψ is the angle between the current facing direction and the direction to the target and T the overall time.

$$J(\mathcal{P}) = T + 1.2 \int_0^T \dot{a}_{forw}^2 dt + 1.7 \int_0^T \dot{a}_{rot}^2 dt + 5.2 \int_0^T \psi^2 dt \quad (1)$$

The following approach is given for a situation in which a person has full knowledge of the environment, sees all targets and the decision for one target is made in advance and is not changed.

3 Target estimation

Assuming that a person has chosen a target T and has planned an optimal path $\mathcal{P}_M(s_0, s_T)$, he will follow that path towards T . Because of the principles of the cost function, the cost for the remaining path must decrease if he moves along the optimal path. For a person's current state s_c and the path $\mathcal{P}(s_0, s_c)$ he walked, $J(\mathcal{P}_M(s_0, s_T))$ should be equal to $J(\mathcal{P}(s_0, s_c)) + J(\mathcal{P}_M(s_c, s_T))$, assuming that T is the intended target. Assuming that the model fits, this unexpected additional cost J_{loss} must be caused by deviation from the initially planned optimal path $\mathcal{P}_M(s_0, s_T)$ as defined in equation (2).

$$J_{loss} = J(\mathcal{P}(s_0, s_c)) + J(\mathcal{P}_M(s_c, s_T)) - J(\mathcal{P}_M(s_0, s_T)) \quad (2)$$

When the person starts walking towards a target, J_{loss} will change depending on how well he or she is following the optimal path. Since only one of the targets can be the intended one, J_{loss} will develop differently for different targets, making one with the smallest loss the most likely target.

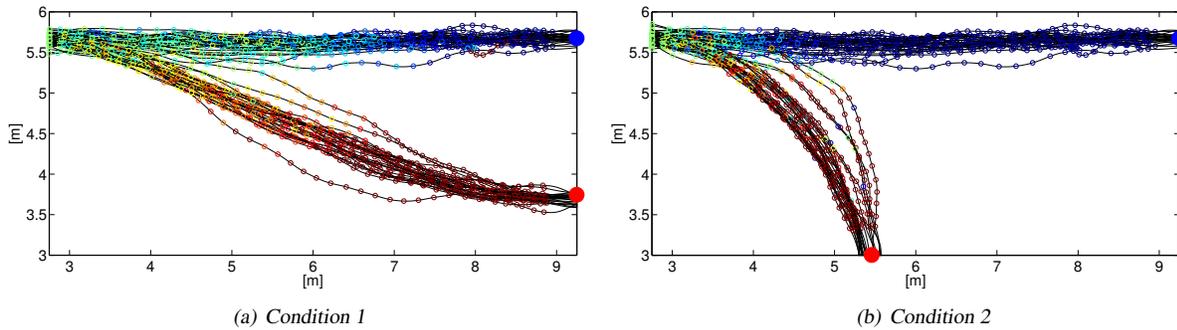


Figure 1: All recorded paths of conditions 1 and 2. The big circles represent the targets T_1 (blue) and T_2 (red), the small circles represent target estimations at this position and the color represents the estimated target. The color code corresponds to $J_{loss}(T_1) - J_{loss}(T_2)$

4 Experiment

In order to validate this, a user study was conducted using a VR simulator that consists of an Intersense IS-1200 6-DOF tracking system mounted on top of an Oculus Rift DK1 head mounted display¹. The measured position of the user’s head controlled the viewpoint in the virtual environment.

The participants were asked to walk through a series of virtual rooms each with an exit at a different position. The recorded paths were then assigned to two conditions. Condition 1 had two exits side by side, similar to the setup used in [Nescher and Kunz 2013]. In the second condition, one exit was on the opposite wall, while the other one was on the right hand side. In this scenario, the targets are further apart and the target’s orientation is different.

12 participants (10 male, 2 female) were recruited among students and institute staff to participate in the experiment. The median age was 25 (standard deviation 9 years), the average height was 1.73m. 72 paths were recorded.

5 Results

Using Mombaur’s cost function, J_{loss} was calculated along the recorded paths and for all the targets after every 25th position measurement. For modeling the paths the model proposed by Arechavaleta et al. [Arechavaleta et al. 2006] was used. Figure 1 shows the difference of J_{loss} for the two targets at certain positions along the path, the difference itself is color coded. Figure 2 illustrates this for a single path from condition 1. It can be seen that the J_{loss} indeed increases less for the correct target. Using a function to map the cost difference to a binary decision or a probability, this can be used as an estimation of a person’s locomotion goal. If we would use a difference of 0.3 as a threshold, the correct decision would - in average - be reached after 20% of the of the path.

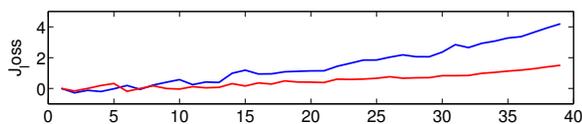


Figure 2: Difference between J_{loss} for the correct target (red) and the incorrect target (blue)

¹www.oculusvr.com

6 Conclusion

The proposed approach uses the development of a path’s cost and the already traveled path. The performance was demonstrated for two model situation. The advantage of this approach is that it is independent of the underlying path model and cost function. Given more advanced models, the estimator automatically works for more complex situations such as stationary or mobile obstacles.

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