Travel distance estimation from leaky path integration in virtual and real environments

Markus Lappe*
Psychological Institute II
Westf. Wilhelms-University
48149 Münster, Germany

Harald Frenz†
Psychological Institute II
Westf. Wilhelms-University
48149 Münster, Germany

ABSTRACT

The estimation of the travel distance of a simulated movement in virtual environments shows characteristic errors. These errors may be explained by leaky path integration. We show that similar errors occur also in the estimation of travel distance in the real world, and that they are consistent with the leaky integration model. Thus, errors in travel distance estimation are not induced by factors of the virtual environment but by properties of perception.

Index Terms: H1.2 [Models and Prinicples]: User/Machine Systems—Human Factors; I3.m [Computer Graphics]: Miscellaneous—Perception

1 INTRODUCTION

Spatial orientation and navigation is supported by the interaction of visual, proprioceptive, auditory, and vestibular signals, as well as efference copy signals from motor commands. Virtual environments can be used to study this interaction – and the contribution of individual senses – by manipulating the presence of or the relationships between these signals. We are particularly interested in the role of vision in the estimation of the travel distance of a movement, for instance a walk. Forward movement, such as walking, induces visual motion in the eye of the walker. This visual motion provides cues about direction, speed, and duration of the walk, which can be integrated to achieve a measure of the distance traveled [1, 15, 18].

To isolate visual motion from other sensory cues, we have previously performed distance estimation experiments in virtual environments with simulated observer movement through different scenes. We found that human subjects were quite good at discriminating the distances of two sequentially presented movement intervals, even when the two movements differed in speed, duration, scene visibility, or environmental layout [1, 3]. However, substantial errors were made when travel distance of a single movement had to be indicated by adjusting the size of a static distance interval within the virtual scene [4]. Unlike the discrimination task, which can be solved by using a comparison of speed and duration of the two movements, the target adjustment task requires the build-up of a true representation of distance based on the visual motion experience. Results showed that subjects could do this task consistently (i.e. reliable over multiple trials and correlated with the true distance) but not accurately with respect to magnitude, i.e., they systematically underestimated the travel distance [4]. This underestimation occurred for different types of displays (projection screen, stereographic projection, or a fully-immersive virtual environment [6]) and different perceptual reports (visual interval adjustment, verbal report, blindfolded walking [4]). It was also not due to the general compression of distance often observed in real [11, 2, 9] and virtual scenes [5, 7, 16, 20], since over the range of distances that were used in the above studies the perception of static distances in our virtual environment was quite accurate.

*e-mail: mlappe@uni-muenster.de
†e-mail:frenzh@uni-muenster.de

However, while results of the target adjustment task consistently gave an underestimation of the perceived travel distance, results from a seemingly similar task indicated an overestimation of perceived travel distance [17]. In that study, subjects briefly saw a target at a particular distance before a simulated forward movement. The task was to indicate the point in time at which the target's position was reached. Subjects in this task typically responded too early, indicating that they felt they had reached the target before they had actually traversed the whole distance. Based on experiments comparing both tasks in the same subjects, [8] formulated a leaky integrator model of distance perception from visual motion which replicated both results.

2 LEAKY PATH INTEGRATION

Path integration [10, 12, 13, 14] assumes that the moving individual tracks the amount of space covered by the movement by integrating the changes of position over the course of the movement. Misrepresentation of the length of the movement may arise if the integration of the new position uses a misrepresentation of the momentary position change (which would essentially be an error in gain) or if the integration is leaky. The leaky path integration model assumes that a state variable, such as the current distance from the starting point, is incremented with each step by the distance of the step with a gain factor k, but that it is subsequently slightly reduced in proportion to a leak factor α. Thus, the state variable is continuously incremented according to the movement but has a tendency to decay by itself. This can be formalized by the following differential equation:

$$\frac{dp}{dx} = -\alpha p + k, \tag{1}$$

where dx is the change of position of the subject along the trajectory of the movement, α is the rate of decay of the integrator, and k is the gain of the sensory (visual) input. If k=1 the visual motion is transformed perfectly into the instantaneous travel distance. In this equation, in each step dx, the state variable p is reduced proportional to its current value (due to the leak) and incremented by the distance given by the gain k of the step. For a true distance x the integrated distance $p(x)$ then is:

$$p(x) = \frac{k}{\alpha}(1 - e^{-\alpha x}). \tag{2}$$

If the leak rate α is large, then the perceived distance p of an extended movement is smaller than the true distance x, consistent with the results of [4, 6]).

The seemingly conflicting results of [17] can be explained with the leaky integration model by considering the necessities of the move-to-target task [8]. That task began with a static representation of a target in a given distance D_0. Then the target was extinguished and a movement towards the now invisible target was simulated. Participants pressed a button when they felt that they had arrived at the target position. This task can be simulated in the leaky integrator model by assuming that the state variable is the distance to the target, which has to be nulled by the movement. The state variable is decremented in every step proportional to the length of the step size. Moreover, leakage occurs with every spatial step and is proportional to the current value of the state variable according to the leak rate, α. Thus, two processes lead to a reduction of the perceived distance to the target: the decrement according to the forward movement and the leakage of the integrator. Therefore, with ongoing movement the distance to the target becomes overproportionally smaller because of the leakage. The point of perceived distance zero is then reached early. Mathematically, this point is given by

$$p_{hit}(D_0) = \frac{1}{\alpha}[\ln(D_0 + \frac{k}{\alpha}) - \ln(\frac{k}{\alpha})] \quad (3)$$

[8].

3 Travel distance estimation in virtual and real environments

The leaky integration model explains both the underestimation in the adjust-target condition and the overestimation in the move-to-target condition with the same mechanism and the same set of parameters [8]. In experiments in a fully immersive virtual environment subjects experienced motion through a virtual hallway, and either had to estimate the length of the travel path by adjusting a post-motion target, or had to terminate the movement when they felt that they had reached a specified distance. Although the travel distance was underestimated in the first condition and overestimated in the second, the leaky integration model predicted both results with the same values of the gain k and leak rate α. The best fit to both data sets indicated that $k = 0.98$ and $\alpha = 0.0076$. Values for individual subjects ranged between 0.002 and 0.015 for α and between 0.79 and 1.25 for k. Thus, the leak rate was always positive, indicating a decline in all subjects, while the gain could be lower than 1, indicating a general underestimation of distance, or greater than 1, indicating a general overestimation of distance. In the latter case, the underestimation over longer distances was solely due to the leakage.

To compare those results to real world situation in which subjects actually walked within a real environment we conducted similar experiments in a large open field (130 by 100 meters) devoid of visual landmarks. Each trial started in the middle of this field. In the move-to-target condition, an experimenter placed a pole (2 m x 4.5 cm) painted with bright orange lacquer in a certain distance from the subject. The subject was asked to estimate and memorize the distance to the target. The subject could view the target as long as desired. The subject then turned around 180 deg and started walking, guided by a second experimenter, until the subject thought he/she had covered the same distance as the reference distance. The walking distance was then measured with a tape measure. At the end of the trial the subject went back to the starting position to start the next trial.

In the adjust-target condition the subject walked a certain distance guided by an experimenter. The distance was not known to the subject. The experimenter stopped the subject when the predetermined distance was reached. The experimenter then walked further on until the subject indicated verbally that the experimenter had now reached the same distance as the one that the subject had previously walked. The distance between the experimenter and the subjects was then measured with a tape measure. After the trial both subject and experimenter returned to the starting position.

Five different distances (8, 12, 16, 24, and 32 m) were used in a block design. Ten subjects (eight female, two male) participated. All subjects were students of the department and received course credit for their participation. All subjects had normal or corrected to normal vision.

We measured perceived distance in both condition for five different reference distances (8, 12, 16, 24, and 32 m) in a blocked design. Means and standard deviation were determined for each tested distance. This was done for the single subjects results as well as for the pooled data of all subjects. Afterwards, we fitted the leaky integrator model to the data to estimate the leakage and gain factor for both experiments. The fit was done simultaneously to the data from both conditions to obtain a single set of parameters (k, α) for both conditions.

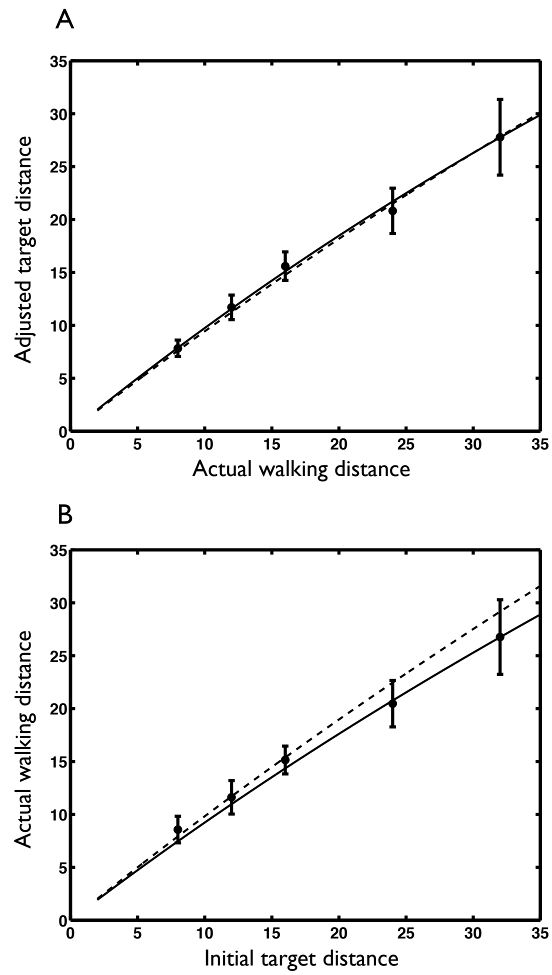

Figure 1: Results of the travel distance estimation experiment together predictions of the leaky integrator model. A: adjust-target condition. B: move to target condition.

Results were very similar to the results previously obtained in the VE. Distances were underestimated in the adjust-target condition and overestimated in the move-to target condition. Both data sets were well fitted by the leaky integrator model. The average leak rate was $\alpha = 0.011$, quite similar to the value found in VE ($\alpha = 0.0076$). Values of individual subjects ranged between 0 and 0.024. The average gain was $k = 1.029$, with individual values ranging from 0.96 to 1.066. Compared to the values obtained in the virtual environment, the gain was higher and more consistent between subjects.

Figure 1 shows the data together with the fits of the leaky integrator model. Figure 1A shows the results in the adjust-target condition. The distance in which the target was placed is plotted as a function of the distance that was actually travelled. The target distance is usually lower than the actual travel distance, i.e. the travel distance is underestimated. The continuous line gives the best fit of the leaky integrator model to the data. Figure 1B shows the results in the move-to-target condition. In this plot, the x-axis is the distance in which the initially viewed target was placed. The y-axis gives the the distance that was actually travelled until the subject indicated that the target distance was reached. The actual walking distance is usually lower than the initial target distance, i.e. the travel distance is underestimated. The continuous line gives the best fit of the leaky integrator model to the data. The leak rate and gain of the leaky integrator model are the same in both panels because the model was fitted to both data sets simultaneously. For comparison, the dashed lines in the two panels shows the predictions of the leaky integrator model that was fitted to the data from the prior VE experiment [8]. Although that experiment used a different environment, purely simulated self-motion, and different subjects the parameters of the model fit the real walking data very well.

The two parameters of the leaky integrator model for distance perception relate to different parts of the integration procedure. The leak rate describes how much the integrated distance value from the start decays over the length of the movement. The gain describes how much distance a particular movement (a single step, for instance) adds to the integrated distance value. Therefore, α should have a fixed value for a particular individual since the leak acts only on the actual state variable, whereas the gain k might depend on the particular sensory signals that are available to estimate movement length. Specifically, there might be separate gains for the visual input, for the vestibular input, for the proprioceptive input, etc. Consistent with this, distance errors in walking tasks with different combinations of available information (static vision, vision and locomotion, blindfolded walking) varied depending on the cues available and the combination of conditions [19]. Likewise, a comparison between real walking experiments and virtual environment experiments showed that the leak rates were similar in both cases while the gains were higher and less variable between subjects in the real walking case. Since subjects in the real world experiment actually walked, and therefore had proprioceptive, vestibular and motor information available in addition to vision, this information might help to achieve a greater consistency between the movement of a single step and its perceived distance.

4 Conclusion

Estimation of travel distance can be modeled as leaky path integration. According to this model, a perceptual state variable accounts for the current distance from the starting point or the remaining distance to the goal, depending on the task to be completed. As the travel progresses, the state variable is incremented (when counting from the start) or decremented (when counting towards the goal) with a particular gain for each step. The gain depends on the sensory information that is available for the current movement. Moreover, the state variable has a tendency to decline over the movement, which corresponds to the leakage of the integrator. The combination of gain, leakage, and task results in distances appearing over- or underestimated. The model works well in explaining data from virtual environments and from real walking in the natural environment. Thus, estimation errors previously observed in virtual environments do not result from inefficiencies of the simulation or unnaturalness of the graphical display but rather are inherent in the perceptual mechanism of travel distance estimation.

Acknowledgements

The authors wish to thank Irina Kaltwasser and Philipp Hintze for their help in data collection. M.L. is supported by the German Science Foundation DFG LA-952/3, the German Federal Ministry of Education and Research project Visuo-spatial Cognition, and the EC Projects Drivsco and Eyeshots.

References

[1] F. Bremmer and M. Lappe. The use of optical velocities for distance discrimination and reproduction during visually simulated self-motion. *Exp. Brain Res.*, 127(1):33–42, 1999.

[2] J. M. Foley. Binocular distance perception. *Psychol. Rev.*, 87(5):411–434, 1980.

[3] H. Frenz, F. Bremmer, and M. Lappe. Discrimination of travel distances from 'situated' optic flow. *Vis. Res.*, 43(20):2173–2183, 2003.

[4] H. Frenz and M. Lappe. Absolute travel distances from optic flow. *Vis. Res.*, 45(13):1679–1692, 2005.

[5] H. Frenz and M. Lappe. Visual distance estmation in static compared to moving virtual scenes. *Span. J. Psych.*, 9(2):321–331, 2006.

[6] H. Frenz, M. Lappe, M. Kolesnik, and T. Bührmann. Estimation of travel distance from visual motion in virtual environments. *ACM Trans. Appl. Percept.*, 3(4):419–428, 2007.

[7] J. M. Knapp and J. M. Loomis. Limited field of view of head-mounted displays is not the cause of distance underestimation in virtual environments. *Presence*, 13(5):572–577, 2004.

[8] M. Lappe, M. Jenkin, and L. R. Harris. Travel distance estimation from visual motion by leaky path integration. *Exp. Brain Res.*, 180:35–48, 2007.

[9] J. M. Loomis, J. A. Da Silva, N. Fujita, and S. S. Fukusima. Visual space perception and visually directed action. *J. Exp. Psychol.: Hum. Percept. Perform.*, 18(4):906–21, 1992.

[10] J. M. Loomis, R. L. Klatzky, R. G. Golledge, and J. W. Philbeck. Human navigation by path integration. In R. G. Golledge, editor, *Wayfinding: Cognitive mapping and other spatial processes*, pages 125–151. Baltimore: Johns Hopkins, 1999.

[11] R. K. Luneburg. The metric of binocular visual space. *J. Opt. Soc. Am.*, 40(10):627–642, 1950.

[12] R. Maurer and V. Seguinot. What is modellimg for? a critical review of the models of path integration. *J. Theor. Biol.*, 175:457–475, 1995.

[13] H. Mittelstaedt and M. L. Mittelstaedt. Mechanismen der Orientierung ohne richtende Außenreize. *Fort. Zool.*, 21:46–58, 1973.

[14] M. Mittelstaedt and H. Mittelstaedt. Ideothetic navigation in humans: estimation of path length. *Exp. Brain Res.*, 139:318–332, 2001.

[15] P. Peruch, M. May, and F. Wartenberg. Homing in virtual environments: Effects of field of view and path layout. *Perception*, 26(3):301–311, 1997.

[16] J. M. Plumert, J. K. Kearney, and J. F. Cremer. Distance perception in real and virtual environments. In *ACM Int. Conference Proceedings Series*, volume 73, pages 27–34, 2004.

[17] F. P. Redlick, M. Jenkin, and L. R. Harris. Humans can use optic flow to estimate distance of travel. *Vis. Res.*, 41:213 – 219, 2001.

[18] B. E. Riecke, H. A. H. C. van Veen, and H. H. Bülthoff. Visual homing is possible without landmarks: A path integration study in virtual reality. *Presence*, 11:443–473, 2002.

[19] H.-J. Sun, J. L. Campos, and G. S. W. Chan. Multisensory integration in the estimation of relative path length. *Exp. Brain Res.*, 154(2):246–254, 2004.

[20] W. B. Thompson, P. Willemsen, A. A. Gooch, S. H. Creem-Regehr, J. M. Loomis, and A. C. Beall. Does the quality of the computer graphics matter when judging distances in visually immersive environments? *Presence*, 13(5):560–571, 2004.