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RESEARCH ARTICLE

Visual estimation of travel distance during walking

Markus Lappe · Harald Frenz

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Abstract The optic flow generated in the eyes during self-motion provides an important control signal for direction and speed of self-motion, and can be used to track the distance that has been traveled. The use of vision for these behavioral tasks can be studied in isolation in virtual reality setups, in which self-motion is merely simulated, and in which the visual motion can be controlled independently of other sensory cues. In such experiments it was found that the estimation of the travel distance of a simulated movement shows characteristic errors, sometimes overestimating and sometimes underestimating the true travel distance. These errors can be explained by a leaky path integration model. To test whether this model also holds for actual self-motion in the real world we studied walking distance perception in an open field with tasks similar to those previously used in virtual environments. We show that similar errors occur in the estimation of travel distance in the real world as in virtual environment, and that they are consistent with the leaky integration model.

Introduction

Orientation and navigation in space are supported by the interaction of several sensory and motor signals. Among them are vestibular and proprioceptive cues, stride length, step frequency, and motor efference copy signals, as well as visual input, which is used to control locomotor direction, obstacle avoidance, balance, and speed. The central question of our work in the SFB 509 Neurovision in Bochum was how the visual system uses optic flow for the control of self-motion. Work on the visual estimation of heading, the integration of optic flow with oculomotor and binocular cues, and the adaptation of visual motion processing on the characteristics of locomotion in the natural environment combined experimental studies with computational modeling of the supporting perceptual mechanisms (for overviews see Lappe et al. 1999; Lappe 2000; Lappe and Hoffmann 2000; Calow and Lappe 2008).

Over the last years, a particular focus has been the estimation of travel distance from optic flow. 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 (Bremmer and Lappe 1999; Peruch et al. 1997; Riecke et al. 2002). To isolate visual motion from other sensory cues, we have performed distance estimation experiments in virtual environments with simulated observer movement through different scenes. We have first used a discrimination paradigm in which subjects were presented with two successive visually simulated self motions in a simple planar environment, and afterwards had to discriminate which motion went a longer distance (Bremmer and Lappe 1999; Frenz et al. 2003). The reason for using this paradigm was that optic flow by itself is ambiguous with respect to distance information since the speeds in the optic flow scale with distance and observer speed. Therefore, only combinations of speed and distance, such as time-to-contact, can be calculated directly from visual motion (Lee 1980). However, in the discrimination paradigm, if both

M. Lappe (✉) · H. Frenz
Psychological Institute II and Otto Creutzfeldt Center
for Cognitive and Behavioral Neuroscience,
Westf. Wilhelms-University, 48149 Münster, Germany
e-mail: mlappe@uni-muenster.de

H. Frenz
e-mail: frenzh@uni-muenster.de

motions are simulated in the same virtual environment, discrimination is unambiguously possible because it requires only the comparison of motion signals. Human observers were very accurate in this task (Bremmer and Lappe 1999). Subsequent work showed that discrimination of travel distances is not based directly on the speeds of visual motion but is rather based on an estimate of observer speed that is derived from the combination of the speeds of the optic flow with environmental layout (Frenz et al. 2003). This was shown by varying environmental layout (distance above ground, viewing distance in simulated fog, angle of view to the ground plane) between the motion simulations. When subjects were aware of the simulation changes they could perceptually compensate and were still able to perform the discrimination.

These discrimination experiments showed that human subjects were quite good at comparing the distances of two sequentially presented movement intervals, even when the two movements differed in speed, duration, scene visibility, or environmental layout. However, a different picture appeared when subjects had to indicate travel distance of a single movement by adjusting the size of a static distance interval within the virtual scene (Lappe et al. 2005; Frenz and Lappe 2005). In these experiments, subjects first saw a simulated forward movement over a ground plane. After the movement stopped, a target line on the ground appeared which the subjects had to adjust to match the travel distance of the previous movement. Unlike the discrimination task, which can be solved by using a comparison of ego-speed and duration of the two movements, the target adjustment task requires the build-up of a true metric representation of distance from the visual motion experience. Although subjects could do this task consistently, i.e., they gave consistent responses over multiple trials, their responses fell systematically short of the true travel distance (Frenz and Lappe 2005). This underestimation occurred for different types of displays [projection screen, stereographic projection, or a fully immersive virtual environment (Frenz et al. 2007)] and different perceptual reports [visual interval adjustment, verbal report, blind folded walking (Frenz and Lappe 2005)]. It was also not due to the general compression of distance often observed in virtual scenes (Frenz and Lappe 2006; Knapp and Loomis 2004; Thompson et al. 2004).

We observed the underestimation of travel distance in experiments in which subjects first experienced a simulated self-motion through a virtual scene and afterwards had to indicate the travel distance of the movement by adjusting a target in the now stationary scene. However, while results of this target adjustment task consistently gave an underestimation of the perceived travel distance, results from a seemingly very similar task indicated an overestimation of perceived travel distance. In a study by Redlick et al. (2001), subjects first saw a target at a particular distance in a virtual scene. Then the target was taken away and a simulated forward movement began. 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. Thus, in the move-to-target task of Redlick et al. (2001) subjects usually overestimated the travel distance while in the adjust-target task of Frenz and Lappe (2005) subjects usually underestimated the travel distance. A collaborative effort with the lab of Laurence Harris at York University, however, showed that both results could be replicated with a leaky integrator model of distance perception (Lappe et al. 2007).

Leaky path integration

Path integration is a theory of distance estimation during self movement (Mittelstaedt and Mittelstaedt 1973; Maurer and Seguinot 1995; Mittelstaedt and Mittelstaedt 2001; Loomis et al. 1999; Glasauer et al. 2007). It assumes that the moving individual tracks the amount of space covered by the movement by integrating the changes of position that occur 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 of Lappe et al. (2007) proposes that a state variable, such as the current distance from the starting point, is incremented with each step by an amount proportional to the step size, but that it is subsequently slightly reduced in proportion to its current value. Thus, the state variable is continuously incremented according the movement but has a tendency to decay by itself. The model has two parameters: a leak rate α and a gain k. The leak rate describes how much the integrated distance value decays over the length of the movement. The gain describes how much distance a particular small movement (a single step, for instance) adds to the integrated distance value. This can be formalized by the following differential equation:

$$\frac{dp}{dx} = -\alpha p + k, \qquad (1)$$

where p is the current perceptual position (i.e., the state variable), 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. 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. The gain k, thus, influences the distance with which each individual step enters the integration. If $k = 1$ the visual motion is transformed perfectly into the instantaneous travel distance. If $k < 1$ the transformation underestimates the current step. If $k > 1$ the size of the current step is overestimated. The leak rate α influences how much of the integration is lost over a longer movement. For a true distance x the integrated distance $p(x)$ then is:

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

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 (Frenz and Lappe 2005; Frenz et al. 2007).

The seemingly conflicting results of (Redlick et al. 2001) can be explained with the leaky integration model by considering the necessities of the move-to-target task (Lappe et al. 2007). 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 (see also Mittelstaedt and Glasauer (1991) for a related proposal for path integration over time). The state variable is decremented in every step proportional to the length of the step size and the gain k. 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 Lappe et al. (2007) as

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

The leaky integrator 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. This was confirmed in experiments in which the same subjects had to complete both tasks in the same virtual environment (Lappe et al. 2007). 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 $\alpha = 0.0076$. The leak rate α was greater than 0 in all subjects, indicating that the leakage was a common finding. The gain was lower than 1 in some subjects, indicating a general underestimation of each step size, or greater than 1 in other subjects, indicating a general overestimation of each step size. In the latter case, the underestimation over longer distances was solely due to the leakage, which takes a progressively larger influence as the movement distance gets longer.

In the experiments reported in the following we compare those results to a real world situation in which subjects actually walked within a real environment, using two tasks that were as similar as possible to the conditions run previously in the virtual environment.

Methods

We performed the experiments on a large open field (130 × 100 m) 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 × 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° 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. Each distance was measured five times for each subject resulting in 25 trials per condition. The order of trials was randomized. The two conditions were tested in different blocks.

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.

Results

For each reference distance, task, and subject we calculated the actual and the perceived travel distance. In the adjust-target condition, the actual travel distance was the distance that the subject walked, i.e., one of the set of five distances used (8, 12, 16, 24, and 32 m). The perceived travel distance was the distance to the target (experimenter) that the subject adjusted afterwards. In the move-to-target condition, the actual travel distance was the distance that the subject actually walked before he/she stopped to indicate that the target was reached. The perceived travel distance was the distance to the target that was shown initially, i.e., one of the five distances used (8, 12, 16, 24, and 32 m).

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. The leaky integrator model was fitted to the data to estimate the leakage and gain factor. The fit was done simultaneously to both data sets to obtain a single set of parameters (k, α) for both conditions.

Figure 1 shows the results for the pooled data of all subjects. Red data points indicate the mean data obtained in the adjust-target condition, blue data points the means in the move-to-target condition. Error bars denote standard deviations. In the move-to-target condition error bars are vertical because the dependent variable, the travel distance to the target is plotted on the x axis. Like in the previously obtained results in the virtual environments, distances were underestimated in the adjust-target condition and overestimated in the move-to target condition. For example, in the adjust-target condition (red data points) an actual walking distance of 32 m was estimated at only 28 m in terms of a static distance. In the move-to-target condition, in contrast, an average actual walking distance of 26 m was perceived as equivalent to an initial static target distance of 32 m (blue data points). The differences between the two conditions were subjected to a paired t test. For each tested distance, the difference between the test distance and the reported distance were calculated for each subject. Overestimation was calculated as a positive value, underestimation as a negative value. Bonferoni-corrected paired t tests were run for each test distance. The differences between the two conditions were highly significant ($P < 0.001$) for the 24 m and the 32 m measurements, but not for the distances between 8 and 16 m. This is consistent with the leaky integrator model which predicts that the differences between the two condition should become more pronounced as the base distance increases. We therefore proceeded to fit the data with the leaky integrator model.

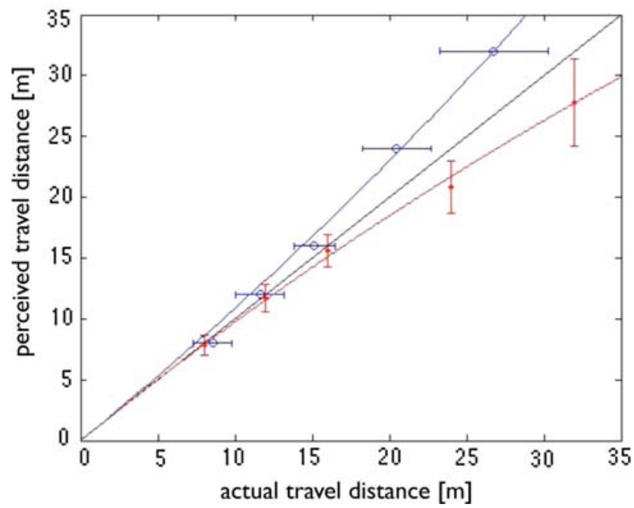

Fig. 1 Perceived versus actual travel distance in the adjust-target (*red*) and the move-to-target (*blue*) conditions. Data point are means over subjects for a particular tested distance. *Error bars* denote standard deviations. *Blue and red lines* are fits of the leaky integrator model

Both data sets were well fitted by the leaky integrator model with a leak rate of $\alpha = 0.011$ and gain $k = 1.029$. The fit is illustrated by the red and blue lines in Fig. 1. These values are close to the values of $\alpha = 0.079$ and gain $k = 0.98$ that best fitted the data from the virtual environment experiment (Lappe et al. 2007).

Figure 2 shows the results for all individual subjects. The parameters of the best fitting leaky integrator model for each subject are given in Table 1. Nine of the ten subjects showed an underestimation in the adjust-target condition and an overestimation in the move-to-target condition. The remaining subject showed perfect estimation in both conditions. With the exception of subject J2 all individual subject data could be well fitted with the leaky integrator model, even though the amount of over- and underestimation varied between subjects. The best fitting values for the leak rate α varied between individuals from 0 to 0.024. Individual values for the gain k ranged from 0.96 to 1.066. Four of the ten subjects had a gain slightly smaller than 1, six subjetcs had a gain slightly larger than 1. Individual gain smaller or larger than 1 had also been observed in the previous virtual reality experiments. However, compared to the virtual environment study, the gain in the real walking experiments was on average higher and less variable between subjects. A reason for this may be that 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.

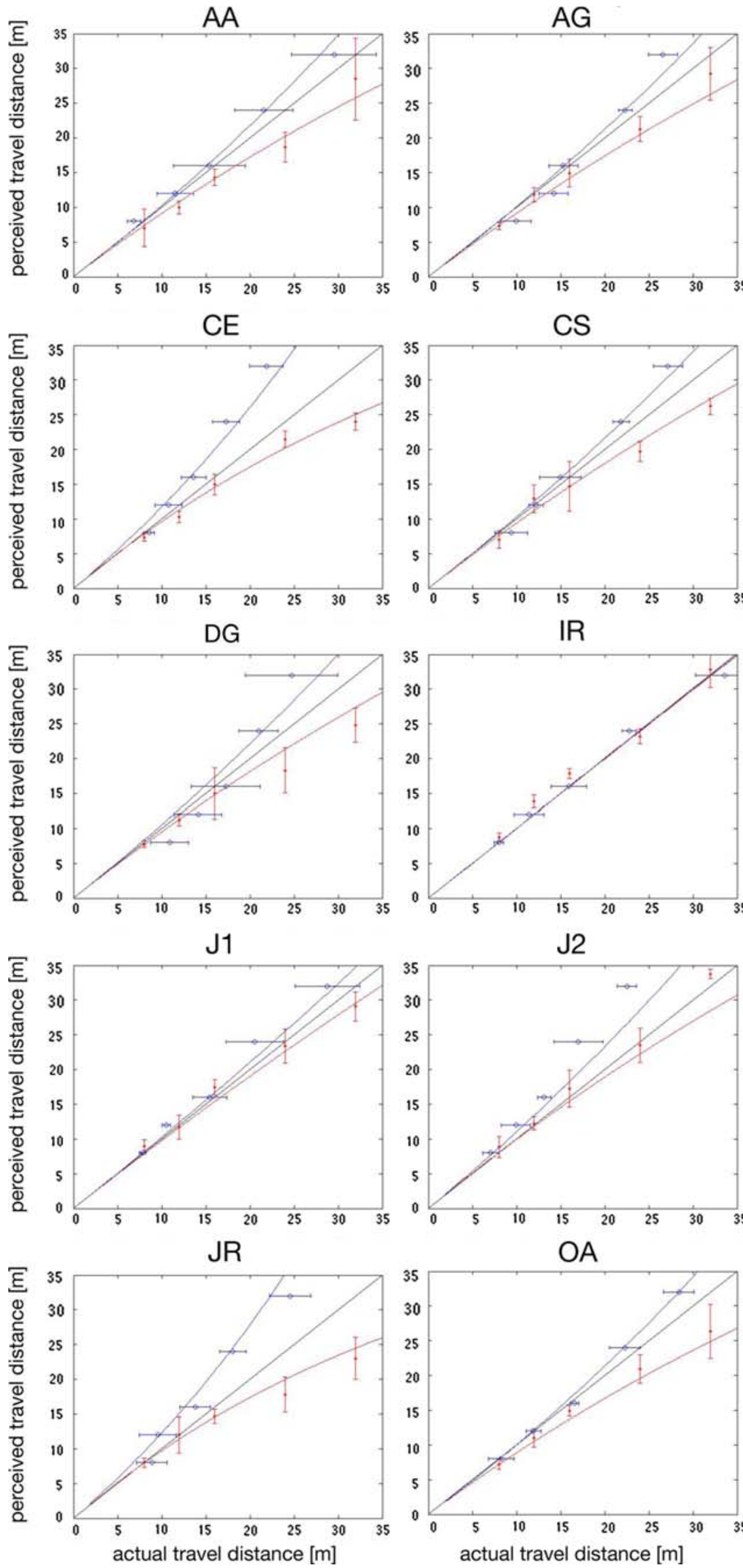

Fig. 2 Perceived versus actual travel distance in the adjust-target (*red*) and the move-to-target (*blue*) conditions for all individual subjects. The blue and red lines are the fits of the leaky integrator model to the individual subject data. Best fitting values for leak α and gain k in each case can be found in Table 1

Table 1 Estimated values for the gain k and the leak rate α for the individual subjects

	AA	AG	CE	CS	DG	IR	J1	J2	JR	OA
Gain	0.97	0.96	1.07	0.99	1.03	1.0	1.0	1.05	1.09	0.94
Leak	0.012	0.01	0.021	0.010	0.018	0.000	0.005	0.011	0.024	0.012

Discussion

We measured perceived travel distance for walking in an open field with two tasks that were previously used for travel distance estimation in virtual environments. Consistent with previous data, travel distance was underestimated in the adjust-target condition, in which an unknown traversed distance had to be indicated by adjusting the size of a static distance interval, and overestimated in the move-to-target condition, in which the distance to a static target had to be reproduced by walking.

For comparing perceptual estimates of travel distance with static distances to visual targets it is important to avoid that subjects use a location on the ground for their task behavior rather than an estimate of distance. For instance, if one were to show a target in the move-to-target condition and ask a subject to walk towards that target, the subject might remember the location of the target and simply walk to that location guided by landmarks that surround the target. One would expect subjects to be quite accurate in such a task since they can continuously monitor the target location. To avoid this, and to focus the subjects on the use of distance rather than location, we asked our subjects to inspect the target and register its distance, then turn by 180° and walk the just seen distance. The 180° turn, therefore, was necessary to avoid confounds with a continuously visible location. It is unlikely that the turn itself influenced the outcome of the experiment very much since the previous virtual reality experiment gave quite similar results and did not include a turn. In the virtual reality experiment the monitoring of target location and surrounding landmarks was obfuscated by randomly flickering the color of the elements that made up the virtual scene.

The results of the travel distance estimation in this and in the previous study were predicted by the leaky integrator model of Lappe et al. (2007). 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.

The leaky integrator model for travel distance perception has two parameters: a leak rate α and a gain k. 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. Our experiments have shown that both α and k vary between individuals. However, while α should have a fixed value for a particular individual, the gain k is likely to 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. Sun et al. (2004) studied travel distance perception in walking tasks with different cue combinations (static vision, vision and locomotion, blindfolded walking) and found that errors in distance estimation varied depending on the cues available and the combination of conditions. Their results are compatible with different gains used for different sensory cues. In particular, differences in gain between vision and idiothetic locomotor signals might explain why blindfolded walking to a remembered target seems to be more accurate than sighted walking to a remembered target. Blindfolded walking to a remembered target is quite accurate over distances up to 21 m (Rieser et al. 1990; Loomis et al. 1992). In contrast, our subjects stopped short of the target distance. This indicates that the presence of vision and optic flow during walking led to an overestimation of the travel distance in moving towards a target. This difference between sighted and blindfolded walking points to a difference in gain k for visual and idiothetic information. If the gain for idiothetic information is smaller than the gain for visual information then the removal of visual input and the reliance on idiothetic information during blindfolded walking would result in higher accuracy during blindfolded than during sighted walking to a remembered target. The alternative possibility that perceived static distance errors (undershooting) that happen to match the underperceived walked distances lead to accurate performance is unlikely. Evidence against this possibility comes from other forms of action, like pointing while walking on oblique paths with eyes closed (Fukusima et al. 1997) and bean bag throwing (Sahm et al. 2005).

While each sensory modality that may be used to gauge travel distance might have a different gain k associated with it, the leak rate α should be independent from the sensory modality that is used to gauge travel distance, since α describes a property of the integrator and not of the input signal. A comparison of our data from the real walking experiment with the data from the previous virtual environment experiment 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. This is consistent with the prediction that the leak rate should not depend very much on the cues that are used to estimate the distance of a step, whereas the gain should depend on the cues available.

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References

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

Calow D, Lappe M (2008) Efficient encoding of natural optic flow. Network Comput Neural Syst 19(3):183–212

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

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

Frenz H, Lappe M (2006) Visual distance estmation in static compared to moving virtual scenes. Span J Psychol 9(2):321–331

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

Fukusima SS, Loomis JM, DaSilva JA (1997) Visual perception of egocentric distance as assessed by triangulation. J Exp Psychol Hum Percept Perform 23(1):86–100

Glasauer S, Schneider E, Grasso R, Ivanenko YP (2007) Space-time relativity in self-motion reproduction. J Neurophysiol 97(1):451–461

Knapp JM, Loomis JM (2004) Limited field of view of head-mounted displays is not the cause of distance underestimation in virtual environments. Presence 13(5):572–577

Lappe M (2000) Computational mechanisms for optic flow analysis in primate cortex. In Lappe M (ed) Neuronal processing of optic flow volume 44 of International Review of Neurobiology. Academic Press, London, pp 235–268

Lappe M, Bremmer F, van den Berg AV (1999) Perception of self-motion from visual flow. Trends Cogn Sci 3(9):329–336

Lappe M, Frenz H, Bührmann T, and Kolesnik M (2005) Virtual odometry from visual flow. In: Rogowitz BE, Pappas TN, Daly SJ (eds) Human vision and electronic imaging X volume 5666. Proceedings of the SPIE/IS&T conference on human vision and electronic imaging, vol X, pp 493–502

Lappe M, Hoffmann K-P (2000) Optic flow and eye movements. In: Lappe M (ed) International reviev of neurobiology volume 44 neuronal processing of optic flow. Academic Press, New York, pp 29–47

Lappe M, Jenkin M, Harris LR (2007) Travel distance estimation from visual motion by leaky path integration. Exp Brain Res 180:35–48

Lee DN (1980) The optic flow field: the foundation of vision. Philos Trans R Soc Lond B Biol Sci 290:169–179

Loomis JM, Da Silva JA, Fujita N, Fukusima SS (1992) Visual space perception and visually directed action. J Exp Psychol Hum Percept Perform 18(4):906–921

Loomis JM, Klatzky RL, Golledge RG, Philbeck JW (1999) Human navigation by path integration. In Golledge RG (ed) Wayfinding: cognitive mapping and other spatial processes. Johns Hopkins, Baltimore, pp 125–151

Maurer R, Seguinot V (1995) What is modelling for? A critical review of the models of path integration. J Theor Biol 175:457–475

Mittelstaedt H, Mittelstaedt ML (1973) Mechanismen der Orientierung ohne richtende Außenreize. Fort Zool 21:46–58

Mittelstaedt M, Mittelstaedt H (2001) Ideothetic navigation in humans: estimation of path length. Exp Brain Res 139:318–332

Mittelstaedt ML and Glasauer S (1991) Idiothetic navigation in gerbils and humans. Zool Jb Physiol 95(3/4):427–435

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

Redlick FP, Jenkin M, Harris LR (2001) Humans can use optic flow to estimate distance of travel. Vis Res 41:213–219

Riecke BE, van Veen HAHC, Bülthoff HH (2002) Visual homing is possible without landmarks: a path integration study in virtual reality. Presence 11:443–473

Rieser JJ, Ashmead DH, Talor CR, Youngquist GA (1990) Visual perception and the guidance of locomotion without vision to previously seen targets. Perception 19(5):675–689

Sahm CS, Creem-Regehr SH, Thompson WB, Willemsen P (2005) Throwing versus walking an indicators of distance perception in similar real and virtual environments. ACM Trans Appl Percept 2(1):35–45

Sun H-J, Campos JL, Chan GSW (2004) Multisensory integration in the estimation of relative path length. Exp Brain Res 154(2):246–254

Thompson WB, Willemsen P, Gooch AA, Creem-Regehr SH, Loomis JM, Beall AC (2004) Does the quality of the computer graphics matter when judging distances in visually immersive environments? Presence 13(5):560–571