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Visuo-motor interaction in the estimation of distance: athletes vs. no-athletes.

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Abstract— **To build a representation of the space surrounding us with an appropriate perceptual precision, our brain has to obtain the distance information from a variety of cues that are present in the scene. But these data are affected in some way by our self-motion perception. Using an indirect method of distance estimation, we investigated the effect of the visuo-motor interactions on the perception of distance in two groups of observers, one of athletes and other of no-athletes. The results showed a difference between the distances obtained in static and dynamic conditions and also in the magnitude of the absolute errors of each group. The data were modeled and interpreted in terms of the Bayesian framework of perceptual inference.**

Keywords— **distance perception, space compression, after effect, Bayesian inference, sport.**

I. INTRODUCTION

The perception of the space is one of the most relevant problems that we have to solve in our daily lives. This is so because such information is crucial for our interaction with the environment. The achievement of an appropriate representation of the three-dimensional space, from the two-dimensional images projected onto the retina, is a great challenge for the visual system. Such a representation is known as 'visual space', and it is constructed from the physical configuration of the space and the available cognitive information [1]. The invariance and the coherence of this space allow to achieve an appropriate "perceptual precision", i.e. capacity of discrimination. The "perceptual accuracy", less relevant than precision, indicates the correspondence between the visual and the physical variables [2]. Although such correspondence is linear for small distances, systematic distortions appear for larger distances, which leads to characterize the visual space as anisotropic [3], since perceived dimensions depend on direction and orientation. This has hindered the mathematical definition of the geometry of the visual space. The main models are those that are based on a modified Euclidean geometry [4], or those that are based on a space of Riemannian curvature [5,6]. However, more recently, approaches combining Euclidean and hyperbolic geometries [7] as other contextually variables (or "affine") [8] have been proposed. Some authors, are skeptical about considering a specific geometry [9,10]. A different approach was proposed by Yang and Purves [11], who express the idiosyncratic relation with the physical space, from a statistical analysis of the geometry of the visual scenes, supporting the idea that such relation arises as a result of an optimal processing of visual information.

To build the visual space, our brain has to obtain the distance information from a variety of cues that are present in the scene [12]. It can be noted that almost all the research in distance perception has been performed with static observers. This simplification is based on the idea that much of the visually guided motor behavior (e.g. grasping an object) is performed from an approximately static position [13]. However, it is a fact that we and the world around us move all the time. The optic flow and the proprioceptive and vestibular systems inform about the spatiotemporal relationship between us and the environment. Much of the time, such information is consistent and allows us to perform correctly by estimating the distances with an acceptable perceptual precision. An evidence of the relationship that exists between the visual and motor systems is the visual after-effect that appears after a run on a treadmill, even in a short period of time [14]. This effect is evidenced in the fact that observers systematically overestimate the distance. This overestimation would arise from the need to compensate the estimated distance during egomotion due to, during the visual processing time, the position of the observer changes in vdt, being v the observer's speed and dt the visual processing time. Therefore, the estimated distance in dynamic conditions can be expressed as $D_{dyn} = D_{sta} - vdt$, where D_{sta} is the estimated distance in static conditions. According to Durgin [2], the perceived speed during egomotion is $v_p = v_v - v_m$, where the subindexes *p*, *v*, and *m* indicate perceived, visual and motor, respectively. Hence, if we consider that the visual component during the after-effect is negative, and that the motor component is zero, then $D_{dyn} = D_{sta} + v_v dt$. Therefore, the model predicts that a distance estimate performed while running on a treadmill ($v_v = 0 \; y \; v_m > 0$) will be larger than that estimated in static conditions.

In this study, we propose to investigate the effect of the visuo-motor interactions on the perception of distance in two groups of observers that perform activities with different visual spaces. One of the groups consists of athletes that perform their activities in large fields (soccer and rugby union), and the other group consists of undergraduate students with no systematic experience in sport.

The results will be interpreted in terms of the Bayesian framework of perceptual inference.

II. Methods

We quantified the perception of distance of two groups of observers, athletes and no-athletes, in two experimental conditions on an open grassy sun-lighted field. In one of them, the observer performed the task standing still on the observation position over the treadmill and, in the other condition, running on it at a specified velocity.

We used an indirect method of distance estimation that consisted in showing a target (1.65m white stake) located at the distance to be estimated and ask the observer to equate that distance with one in the frontal plane such is shown in Figure 1. The observer had to indicate to an assistant who had a mark similar to the target, how much she/he had to move to equate the distance of observation of the target.

Firstly, we performed the experiment in static condition. The distances were 12, 18, 24, and 32 m. Secondly, these same distances were estimated while running on a treadmill at a speed of 8 km/h (2.2 m/s). In this situation, the observer run during 2 minutes without seeing the target before performing the task (the view of the target was blocked during motion adaptation). Each distance was estimated 5 times by each observer, for each experimental condition. The order was randomized.

To perform the experiment we used a PROTEUS, model MTM-5600 treadmill with speed selector.

15 athletes and 15 no-athletes, selected without regard to sex, participated in this experiment. All of them had normal or corrected-to-normal vision and signed an Informed Consent. The experimental protocol followed the tenets of the Declaration of Helsinski.

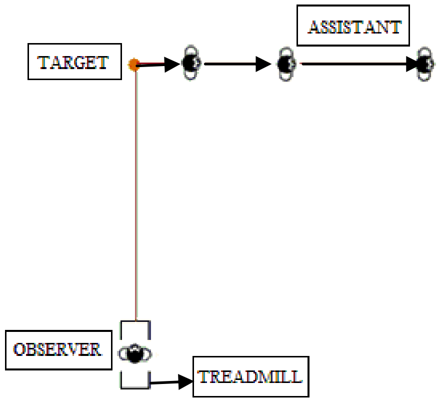

Fig. 1: Experimental layout.

III. Results

The Figure 2 shows the absolute error in the distance estimation, calculated as the difference between the physical and the estimated value, for athletes and no-athletes, and for the two experimental conditions.

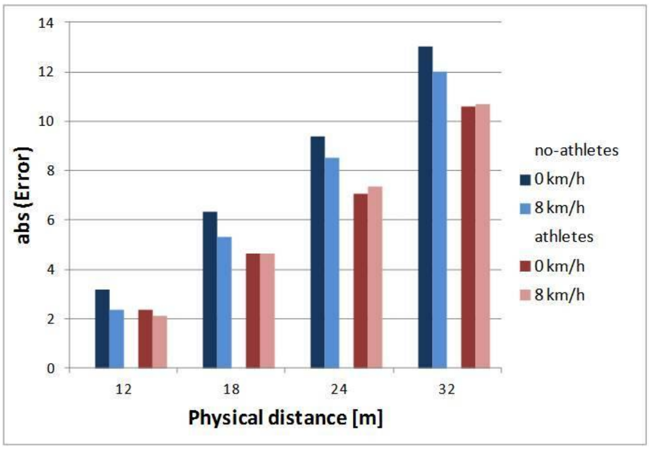

Fig. 2: Absolute error as a function of distance for the athletes (red) and the no-athletes (blue), for the two experimental conditions.

Firstly, it can be observed the typical compression of the space reported in previous studies [15]. This is a systematic underestimation of the physical distance. Secondly, the results show the predicted difference between the distances obtained in static and dynamic conditions. Consistently with such prediction, this difference is independent from distance and, in average, is $\Delta D = 0.94m$. If we consider that the speed was $v = 2.2\,m/s$ (8 km/h), we can calculate the processing time as $dt = 0.42s$, which is in the order of the times involved in perceptual processes. It is interesting to note that this difference does not appear in the group of athletes.

IV. Bayesian Model

It is well known that skilled perception is an important determinant of performance in sports that are characterized by a complex and rapidly changing environment [16]. In this context, we can formulate different hypothesis about why athletes are less inaccurate than the no-athletes. We first discuss why observers tend to underestimate the distance when external references are removed (as generally occur in the open field). Yang and Purves [11] proposed that this, among other errors in the perception of space, result from an optimal behavior of the system. We refer to an optimal behavior to that in which the estimations of the physical environment are not independent from it but, such estimations are affected by the expectations that the environment produces through the *a priori* knowledge of its statistics. Because, from the point of view of an observer, the distribution of distances of a natural environment presents a maximum of occurrence for very low values (close to one meter) and decays monotonically as the distance increases [11], the observers tend to bias their estimations to smaller values. This idea can be formalized by using the Bayes theorem that states:

$$P(D|m)P(m) = P(m|D)P(D) \quad (1)$$

where $P(D)$ is the *a priori* probability of distance in the environment, and $P(m|D)$ is the probability to obtain a visual measurement m given the physical distance D, and it is known as the *likelihood function*, and represents the state of the (visual) system. $P(m)$ is the probability to obtain a measurement m, and it is considered as uniform, and $P(D|m)$ represents the *a posteriori* probability, i.e. the probability of a distance given a measurement m. Therefore, if we know $P(D)$, we can model $P(m|D)$ to obtain the *a posteriori* probability and thus, an estimation of the perceived (inferred) distance (see Figure 3).

We propose to model the *likelihood* function as a Gaussian whose standard deviation represents the internal noise of the system. Therefore we have:

$$P(m|D) = \frac{1}{\propto} exp\left[\frac{-(D-m)^2}{2\sigma^2}\right] \quad (2)$$

where α is a normalization constant, and σ is the noise. We compute the estimated distance as the value of distance corresponding to the maximum of the *a posteriori* probability.

The model has only one free parameter, which is the internal noise σ that is modeled as the sum of an additive component and a multiplicative component such that:

$$\sigma = \varepsilon + \rho \cdot m \quad (3)$$

The figure 4 shows the perceived distance in static condition as a function of the physical distance, for athletes (red) and no-athletes (blue), and the model fittings. The physical distance is shown in solid line. The fittings were obtained for noise values of ε=5.8 and ρ=0.53 for the athletes and ε=5.8 and ρ=0.63 for the no-athletes.

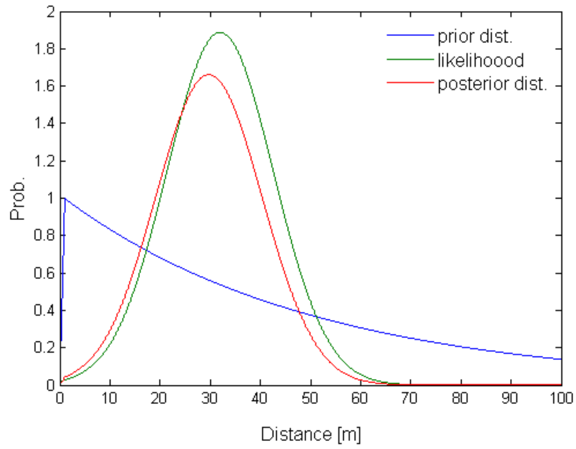

Fig. 3: Prior, posterior and likelihood distributions.

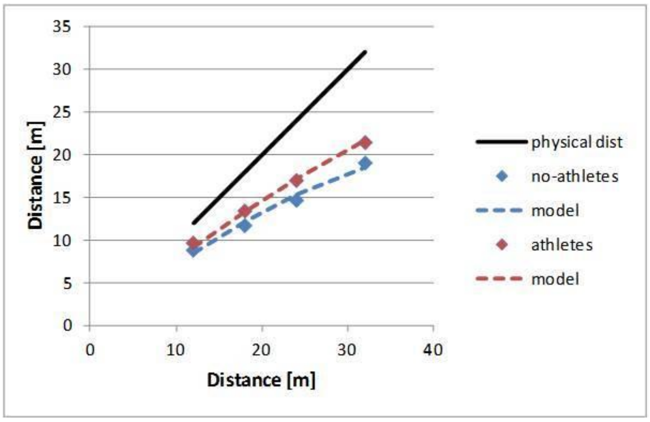

Fig. 4: Model fittings.

V. CONCLUSSION

The perceptual distance estimation, under conditions of proprioceptive movement, showed a similar compression of frontal visual space to that found in other previous works using different psychophysical methodologies and static conditions [17]. In the case of the non-athletes, we found differences between the estimates in dynamic and static conditions. Interestingly, this difference does not appear in the group of athletes, which would suggest a different perceptual strategy to that of the no-athletes. Other significant result is that the athletes present smaller errors that the no-athletes (Figure 2) and this difference increased when increasing distance.

Probably, the constant practice of athletes allows them to assimilate typical environment conditions (for example of the open field) and some characteristics of the task [18] allowing to reduce the influence of propioceptive information, and given more weight to the visual information for these kind of distance estimations. Hence, because when they are running on the treadmill the visual component of speed is zero as well as in the static condition, the difference between the two conditions does not appear.

If we suppose that the visual space is generated by the visual system using a probabilistic strategy, to explain the perceptual phenomenology we will inevitably require to know the statistical properties of the different environments as perceived by the observers. As stated by Yang [19] this approach also assume that perceived distances are not a simple mapping of physical distances; on the contrary, apparent distance will always be determined by the way all the available information at that moment affects the probability distributions of the range of the possible sources of any physical point in the scene. A broad hypothesis of this theoretical framework is that the response properties of visual cortex neurons, meaning the patterns of activity elicited by visual stimuli, are all determined by the probability distributions of the visual stimuli. In this conception, neurons do not detect or encode features, but by virtue of their activity levels, act as estimators of the probability distributions of the variables underlying any given stimulus.

The proposed model, based on Bayesian inference, allowed to represent perceptual features (errors) of both types of observers (athletes and non-athletes) when estimating distances under proprioceptive movement. This means that, according to the model, the results reflect that the athletes perform these estimations with a smaller internal noise than the no-athletes. This is reasonable since many activities of the ball-based sports (passes, interceptive actions, etc.) and their success depend on these estimations.

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