A WIRELESS SENSOR NETWORKS PLATFORM FOR MODELLING SPACE PERCEPTION DURING SACCADIC EYE-MOVEMENTS[*]

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Abstract: Gaze shifts pose serious problems to the human visual system, causing transient spatial distortions. We simulate these distortions by assuming an undersampling of spatial information. We propose that such process helps maintaining stable space representations across sensors shifts, a strategy that may be useful also for wireless sensor networks.

Keywords: visual perception, saccadic eye-movements, wireless sensor networks.

1. INTRODUCTION

Very frequently, three times a second on average, we make rapid eye movements called saccades. The resulting sequences of gaze shifts have a specific aim: directing the fovea (the highest resolution part of the retina) on interesting visual objects or events. This strategy can be considered as an optimal one, as it permits to analyze the whole visual scene at a very high resolution: a resolution which is available only at fovea. But eye movements pose a strong challenge to the visual system: at each gaze shift our retinae transmit radically different images to the brain (like an unsteady video-camera). How does the visual system keep perception stable across eye movements, despite the continuous displacement of retinal images? How does it integrate information collected from successive fixations, making a coherent representation of the visual scene out of a sequence of spatially uncorrelated snapshots?

Similar challenges are faced by any system endowed with mobile sensors, or even more generally any system which deploys its resources serially over space. An example is given by wireless sensors networks – monitoring systems composed of a multitude of sensors connected reciprocally and with a collector via wireless technology. In these systems, due to energetic requirements, most nodes composing the network remain usually inactive, and only a small fraction of them is activated upon request. Thus, similarly to the eyes glancing at sequential locations, sensor nodes can be turned on and off to monitor events in disparate locations at different times. As for eye movements, this strategy is cost-effective, but poses serious challenges to the system. The latter must be able to attribute the incoming information to the appropriate sensor node, and therefore to the right spatial location. Furthermore, it must maintain synchrony in the stream of information from the various nodes, and overcome transmission bottlenecks.

Psychophysical research offers a possibility to gain insight on these mechanisms. It has been reported that human observers, when localizing objects briefly displayed at the time of a saccade, systematically make errors [1-3]. To account for this phenomenon, it was proposed that the visual system accesses some information about the impending gaze shift (like timing and trajectory of eye movements, as suggested by neurophysiological findings [4, 5]), and adjusts the correspondence between retinal activity and external space accordingly [6, 7].

In this view, localization errors would merely result from asynchronies between the recalibration process and the actual gaze shift. However, the pattern of localization errors observed at the time of saccades can be more complex than predicted from such simple model. Recent experiments demonstrated that saccades cause an overall distortion of the perceived space, possibly involving a transient change of spatial metrics [8]. Building on the analogy between the visual system and wireless sensors networks, here we propose that the re-calibration of the coordinate system process is also associated with an undersampling of spatial localization information, and this later process will help minimizing the discrepancy between spatial representations before and after the sensor shift.

In the present paper, we report crucial psychophysical findings about space perception at the time of saccades (Section 2). An analytical model, based on the undersampling of visual space will be presented in section 3 together with the simulation of the psychophysical data. Finally, section 4 briefly reviews the characteristics of wireless sensors networks, and describes the experimental platform developed to implement the model.

2. PSYCHOPHYSICAL RESULTS

The errors made by human subjects when localizing objects at the time of saccades offers the possibility to understand the computational mechanisms subtending space

constancy – more specifically, the mechanisms involved in maintaining visual stability across saccades.

Objects that remain continually visible before and after a saccade (as most objects of our visual world do) are obviously perceived veridically. However, as first revealed by Matin & Pearce and by Mateef [2, 3], visual stimuli presented briefly around the onset of a saccade are systematically mislocalized.

In these pioneering studies, errors were found to occur for stimuli flashed during but also before the actual onset of the eye movement, with mislocalizations appearing in a very narrow time-window of some *50* ms before and after its onset. The maximum error amounted to about half the amplitude of the eye movement, and was observed for stimuli displayed just at the time of the saccade onset. The magnitude of errors decreased as the delay between the stimulus presentation and the saccadic onset increased. Most importantly, errors were only observed in the direction of the eye movement. Errors caused by saccades were therefore believed to take the form of a shift in the direction of the eye movement, homogeneous across the whole visual field.

More recent studies [8-10] suggested that this pattern of result were peculiar for specific eccentricity and the phenomena determining the localization errors are more complex than a simple anticipatory translation of the coordinate system. Indeed, the amplitude and even the direction of mislocalizations were found to vary across the visual field. The resulting distribution of perceived position can be described as a compression of visual space around the ending point of the eye movement, i.e. the saccadic target.
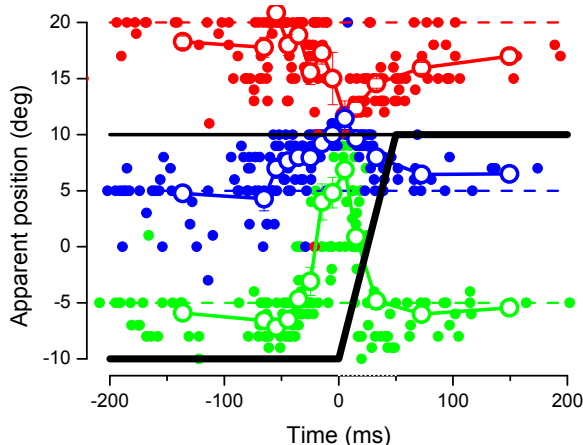

Figure 1. Sample curves of mislocalization. The perceived location of stimuli is plotted against the time relative to the saccadic onset of their brief presentation. A typical eye-trace is shown by the black solid curve; the horizontal black line indicates the position of the saccadic target. Different colors refer to the different positions tested (veridical positions are indicated by the dashed colored lines). Dots are single-trial localization responses; hollow symbols report the average localization (and standard errors) at each delay from the saccade onset.

The typical pattern of mislocalization curves is shown in Figure 1, where stimuli appearing on one side of the saccadic target (the closest side, given the direction of the

eye movement) are mislocalized in the direction of the saccade, but stimuli presented beyond the saccadic target are shifted in the opposite direction [8]. These errors are most evident along the trajectory of the eye movement, and are far less prominent along the orthogonal path [10].

Previous work has shown that the mislocalization occurs only when the observer is actively moving his eyes; a rapid displacement of the whole visual image, similar in all aspects to the one caused by saccades, is not sufficient to produce the effect – indeed, some mislocalization does occur under conditions of "simulated saccades", but it takes the form of a uniform shift of perceived positions in the direction of the saccade, whose maximum value equals the amplitude of the image displacement [9].

Thus, at the time of saccades, stimuli are mislocalized along the trajectory of the eye movement and compressed towards the saccadic target, so that the relative distances among stimuli are consistently underestimated [9]. The latter observation strongly suggests that not only perceived position, but also the metrics of perceived space is altered by saccades.

One plausible consequence of this could be that the ability to discriminate among different locations is impaired during rapid gaze shifts. A recent study tested directly this prediction, and provided support for it [11]. Spatial discrimination, or the precision of localization, was measured by asking subjects to compare the positions of two brief stimuli presented sequentially. During steady fixation, relative positions were found to be discriminated reliably even for stimuli that were just one degree of visual angle apart. However, at the time of saccades, the comparison became nearly ten times less precise. Stimuli needed to be separated by as much as 10 degrees not to be seen in overlap.

Taken together, these results indicate that strong distortions of visual space perception occur during saccades and suggest that the distortions might be the by-product of the perceptual mechanisms that mediate space constancy.

Localization errors at the time of saccades were initially believed to result from some inaccuracy in this process of spatial remapping. This hypothesis can account for a localization bias that uniformly affects all positions in the visual field. By no means, an incorrect shift of the origin of the coordinate system can produce a distortion of the relative distances among spatial positions.

The observed compression of visual space cannot be easily account by a compensation of the impending retinal shift using an inaccurate eye-position information [6, 7]. Here we aim at identifying a perceptual mechanism that plausibly can accounts for the compression of relative distances

3. MODEL

The visual information is initially encoded within a gaze-centred spatial representation, where positions are labelled with respect to the centre of the retina (and therefore the

centre of gaze). The transformation from this gaze-dependent to a gaze-invariant coordinate system probably occurs at a later stage of visual processing. Such transformation can be performed by taking the vectorial sum of gaze-centred coordinates and the current position of the eyes, i.e. by shifting the origin of the gaze-centred representation along the trajectory of each gaze shift. There is evidence that the visual system can access the eye-position information and this may be used to compensate for the displacement of retinal images caused by rapid gaze-shifts.

Spatial compression may result from a change in the metrics of spatial representations. More specifically, we propose that saccadic gaze shifts trigger a strong, albeit transient, expansion of the spatial units used to represent visual information. The expansion is such that the two positions corresponding to the centre of gaze before and after the saccade are transiently represented within a single spatial unit. This process would provide an important contribute to perceptual stability because, during a narrow time-window around the execution of the eye movement, the same spatial unit would represent the same object, irrespectively of the displacement of its retinal image, and independently from any spatial updating that corrects for it.

Recent neurophysiological findings support the idea that receptive fields of visual neurons change dramatically at the time of saccades. Visual processing proceeds through multiple stages, with different properties of neuronal receptive fields. At low-level stages, receptive fields are anchored to retinal coordinates, and always represent veridically retinal eccentricity. Such accurate spatial information represents the input to higher level stages, where receptive fields can change their location and dimension depending of the programmed eye movement, [12, 13]. Our hypothesis entails that, at the time of saccades, receptive fields in high-level visual areas expand, leading to erroneous estimates of the relative locations of visual stimuli.

Note that the present model deals only with relative distances of stimuli, not with their absolute position

3. 1. Analytical formulation

We assume that, at the time of a saccade, spatial metrics change expanding along the trajectory of the eye movement (given the purpose of this deformation, there is no need to assume that units expand also in other directions, e.g. orthogonal to the gaze shift). At the moment the eye movement begins, the expansion is so large that a single unit receptive field covers both the pre-saccadic retinal position and the post-saccadic retinal position of the stimulus. The expansion is not performed all at once, but proceeds trough an iterative process; given that the iteration takes time, the process needs to start before the actual onset of the gaze shift. The expansion rate is assumed to be constant; the duration of the iterative process therefore scales with saccadic amplitude. After the eye movement, spatial representations revert to their original form and the spatial receptive fields return to their normal dimension. Also this process proceeds progressively; it is completed by the time the eyes achieve the next steady fixation.

Distances in the system are calculated by looking at the activity over a map which contains several spatial units. In conditions of steady fixation two stimuli at a given physical distance elicit an activity in two separate spatial units and, in between them, several distinct and inactive units lie. The more the distance, the more the number of distinct and inactive units comprised between the two active ones. The system exploits this rule to estimate the distance between two visual stimuli.

When receptive fields elongate, the number of distinct and inactive units comprised between the two points of the map decreases. If the system still applied the law whereby a "small" number of inactive units corresponds to a small distance, then, in conditions of elongated receptive fields, the system would be mistaken and consider the given physical distance as less than usual.

While it is not possible to define unequivocally a transducing factor for converting physical distances into representational distances, it is possible to define by how much spatial representations are distorted during receptive fields changes (*scale*). This value is inversely related to the dimension of representational units, but is directly proportional to represented distances.

The evolution of the scaling factor is given in Eq. 1. Before the iterative process begins, the scaling factor is set to a constant value ($scale_0$); at each iterative step, the current value of the scaling factor ($scale_{t-1}$) is reduced by a small quantity ($scale_{step}$).

$$scale_t = scale_{t-1} - scale_{step} \qquad \text{(Eq. 1)}$$

During steady fixation, perceived distances ($dist_0$) are estimated as the physical distance *stimdist* between two stimuli *S1* and *S2* (more appropriately, the physical distance between the retinal images of the two stimuli) multiplied by the usual scaling factor $scale_0$. Just before and during a saccade, perceived distances are compressed, following the reduction of the scaling factor $scale_t$ (see Eq. 2)

$$dist_t = stimdist(S1, S2) * scale_t \qquad \text{(Eq. 2)}$$

Thus, for example, the perceived distance between the fixation point and the saccadic target progressively decreases before the onset of the saccade, until it reaches a value close to zero. However, the evolution rate (i.e. $scale_{step}$) is set to ensure that the iterations stop before the zero limit is reached, avoiding that metric information is completely lost. When the saccade begins, spatial units progressively get back to their usual dimension, and perceived distances gradually return veridical.

3. 2. Simulation results

In order to validate the model we performed a series of simulations based on a Matlab® code, testing its ability to predict psychophysical results. To this end, we replicated the typical experimental conditions, where a spot of light serving as the saccadic target (ST) is continually presented and a stimulus (*stim*) is briefly flashed. Following Eq. 2, the model computes the distance between the stimulus and the saccadic target for various presentation times.

Simulations were performed for different saccadic amplitudes and with different position of the stimuli. Figure 2 shows the results from one set of simulations that reproduced the conditions of the experiment reported in Figure 1. Conventions are the same as in Figure 1, except that the y-axis here reports the perceived distance of the stimuli from the saccadic target, not their apparent positions. This is because, as mentioned earlier, our model does not deal with relative distances between stimuli; it does not estimate their locations, as this would require further processing stages, where spatial representations are recoded from a gaze-centred to a gaze-invariant frame of reference.
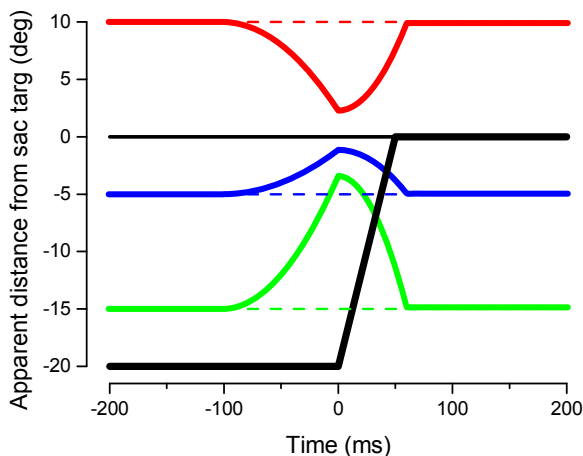

Figure 2. Sample curves of mislocalization. Predictions of the model. Same conventions as in Figure 1, except that the ordinate reports the perceived distance of each stimulus from the saccadic target, not its perceived location .

In agreement with psychophysical results, stimuli appearing on both sides of the saccadic target are mislocalized towards it. A compression of the internal system metric, caused by an expansion of representational units receptive field, is able to reproduce the pattern of localization errors made by human subjects at the time of saccades.

The model is also able to predict another crucial psychophysical finding, namely that spatial discrimination is impaired peri-saccadically. Given that the spatial receptive fields expands, stimuli that are usually separated by several receptive fields become represented within a single receptive field; therefore their position becomes virtually indistinguishable. Interestingly, the model assumes an expansion of the representational receptive field of a factor

of about 10, which fits with the ten-fold reduction of localization precision observed psychophysically.

Because receptive fields are assumed to expand only along the direction of the saccade, no compression is expected to occur in the orthogonal direction.

3. 3. Notes to the model

The model represents one of the possible formalizations of our hypothesis – that the peri-saccadic compression of visual space results from an undersampling of spatial information. The key feature of such architecture is the recursive expansion of spatial receptive field. Units are iteratively augmented by a constant value; when the iteration is stopped, a single receptive field covers both the starting and the ending point of the saccade. Thus, the amount of expansion is assumed to be a function of the represented distance between the fixation point and the saccadic target – this also implies that factors affecting the perceived location of the saccadic target relative to the fixation spot should modulate the amount of spatial compression, as recent results suggest to be the case [14]. Such recursive process may be regarded as a robust strategy to estimate the discrepancy between the pre-saccadic and the post-saccadic views of a scene: it avoids that any error or delay of the information abut eye position (most probably provided to the visual system, see above) undermines perceptual stability.

The recursive features of our model may enable also to predict that only stimuli presented briefly can be mislocalized, not stimuli that remain continually visible across the saccade. At each iteration, the expansion of the spatial receptive field is function of its dimension at the previous step. The recursive process maintains a memory trace of the dimension of spatial units. If the whole evolution is stored, the system would be able to compensate for the distortions transiently produced in spatial maps, leading to accurate localization. For brief stimuli, however, only a fragment of the evolution might be available; as a consequence, distortions could not be compensated and localization would be erroneous. Moreover, even in the absence of such compensation, the recursive would assign to a steady stimulus the average of the spatial estimates over its duration, dramatically reducing the localization error.

4. WIRELESS SENSORS NETWORK

A wireless sensors network is a network composed of a large number of physically small, low cost, low power sensors that provide ubiquitous sensing and computing capabilities [15]. The sensor nodes are normally battery powered, and they send wirelessly the acquired samples to the network coordinator (sink), which in turn transfers all data to a central unit for further analysis. The low cost, the simplicity of implementation and the independence from any kind of infrastructure pose the wireless sensor networks as a very attractive solution in a wide variety of application areas, including geophysical monitoring, precision agriculture, habitat monitoring, military systems, business processes and transportation [16]. However, the fact that the

wireless sensor nodes are powered by batteries implies that they need to save as much energy as possible. For this reason the sensor nodes are normally in sleep mode, and activate their sensing and transmission circuits only periodically or when a particular event occurs [18, 19]. This behavior requires that the nodes perform clock synchronization among each other [20, 21]. The complexity of the synchronization algorithms and the duty cycle of the nodes activation are application dependent. In the case of the object tracking, for instance, wireless sensor networks must be able to follow the objects at the object's velocity and this may require a very high duty cycle. Moreover, a lack of synchronization among the sensors and the sink can generate delays in the data transmission leading mislocalization or even loss of the object trajectory [17]. A solution that can mitigate these effects, while keeping power consumption low, can be the following:

- Anticipating the object movement: the sink activates the sensors in the region where the object is suppose to go while deactivates gradually the sensors in the previous region

- Performing a spatial down-sampling: during the previous process the sink activates only some sensors that are in between the two regions so that accidental changes in the object trajectory are monitored and consequent countermeasures are taken.

Interestingly, the combination of these two processes – anticipation and spatial down-sampling – is likely to produce a pattern of spatial distortions like those affecting localization judgments at the time of saccadic eye movements.

4. 1. Experimental test-bed

In order to validate our reasoning and test the analogy between networks of visual neurons and networks of wireless sensors, we developed a test-bed based on a wireless sensors network that we plan to use to implement the model presented above, simulating the localization of peri-saccadic stimuli.

The test-bed was projected as modular, so as to be adaptable to different levels of complexity. At the current stage of development, it comprises the following components.

- Two wireless sensors and an array of LEDs. The two sensor nodes sense light intensity levels and therefore represent the eyes. The array of LEDs lies on a plane in front of the two sensors and serves as stimulus generator. The system is hosted within a dark chamber (that prevents the sensors from recording ambient light). For this reason all the elements (the sensors and the stimulus generators) are fixed.

- One further wireless node which collects data from the two sensors, and transfers them to a central unit.

- A central unit that analyzes data from the sensors.

- A control unit which is responsible for the stimuli presentation (for economy, the control processes have been implemented in the central unit mentioned above).

The system is able to perform two tasks that should enable us to simulate psychophysical experiments on peri-saccadic spatial localization – it is able to localize a stimulus in conditions of simulated steady fixation, and it can mimic a gaze shift.

4.1.1 Localization during steady fixation

Figure 3 presents a geometrical illustration of our system; the stimulus array (P_1, P_2, … P_i, …, P_N), the sensors position (S) and the projection of the sensors on the stimulus plane (S_x) are shown.

The system estimates the location of any stimulus from the pattern of light captured by the two sensors. It is initialized by setting the maximum value of light intensity that can be sensed. When sensors receive such a maximum amount of light from one LED, the system deduces that they are pointed towards that LED – and therefore that LED is considered to be the fixation point. In the same way, the location of any other stimulus can be defined based on light intensity, because the amount of light sensed decreases geometrically with the distance from the sensors.

Thus, in this system, the distance between the stimulus plane and the sensors, together with the amount of light sensed defines univocally the distance of any LED from the fixation point.
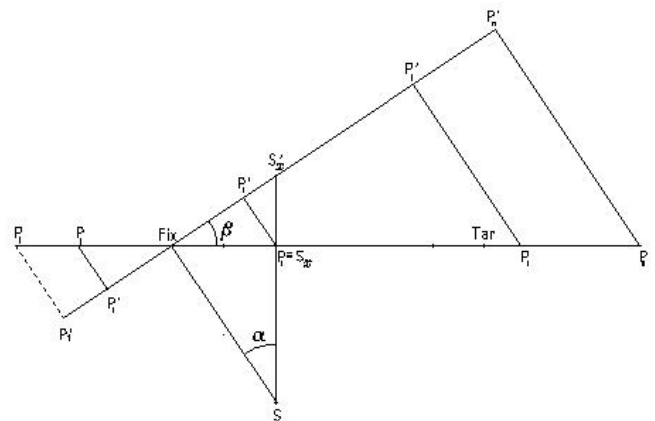

Figure 3 Illustration of a virtual rotation of the stimulus plane

In our set up, both the sensors and the LEDs array are fixed and real sensors shifts cannot take place; still, it is possible to simulate different gaze directions by varying the correspondence between the amounts of light sensed and the location of the stimuli relative to the sensors. For our purposes, changing gaze direction equals rotating the plane containing the LEDs; the concept of this virtual rotation is illustrated in Figure 3 where both the initial stimulus plane and one emulating a different gaze direction (P'_1, P'_2, … P'_i, …, P'_N) are shown.

For a certain gaze direction (and virtual rotation) the light received by a sensor from a single light source is computed from the original amount of light emitted, following equation 3.

$$L_i^{/} = \frac{L_i * D_i^2}{d_i^2} \qquad \text{(Eq 3)}$$

where:

- L_i is the light value acquired by the sensor,

- D_i is the distance between the sensor and the light source in the initial stimulus plane $\overline{SP_i}$

- d_i is the distance between the sensor and the light source in the rotated stimulus plane $\overline{SP_i^{/}}$, which is computed by Pitagora's theorem (eq. 6)

$$d_i = \sqrt{\overline{SFix}^2 + \overline{FixP_i^{/}}^2} \qquad \text{(Eq 4)}$$

where $\overline{SFix}$ (the distance between the sensor and the point which is fixated), is known and $\overline{FixP_i^{/}}$ (the distance between the point which is fixated and the light source in the rotated plane), can be calculated by:

$$\overline{FixP_x^{/}} = \cos(\alpha) * \overline{FixP_i} \qquad \text{(Eq 5)}$$

and alpha (the rotation angle) is

$$\alpha = \arctan\left(\frac{\overline{FixS_x}}{SS_x}\right) = \beta = \arctan\left(\frac{\overline{S_x^{/}S_x}}{\overline{FixS_x}}\right) \qquad \text{(Eq 6)}$$

Applying Eq. 3 allows to calculate the whole pattern of light across the stimulus array (FixSet) when the sensor is supposed to look at the generic point Fix. However, the computation of the new light values for every stimulus gives a non-monotone function which has a maximum in correspondence of the point which is fixated and decreases on both sides of it. One simple way how to avoid this problem is by taking a simple function of both the actual and the original patterns of light. For this reason, to localize correctly a stimulus we construct the reference frame as:

$$\text{Re}\,f = \{FixSet(i) - ZeroSet(i)\}_{i=1\cdots n} \qquad \text{(Eq 7)}$$

where *ZeroSet(i)* is the light pattern without the virtual rotation of the axis. Such a difference permits to calculate the full mapping of the light source locations given a certain gaze direction, thus acts as a reference frame.

4.1.2 Localization during gaze shift

During a learning phase, a reference frame is stored for all stimuli positions and for different (simulated) gaze directions. Hence, changing the reference frame means mimicking eye movements. This represents the critical condition to enable the platform to support the implementation of our model, and ultimately to allow it localizing transient stimuli presented at the time of simulated gaze shifts.

5. CONCLUSIONS

Keeping spatial representations stable in spite of sensors shift represents a problem for the biological visual system, as well as for other artificial system that deploy sensing resources serially over space – e.g. wireless sensors networks. We propose that undersampling spatial information just before and during a sensors shift can be a solution to this problem – although other processes may contribute.

We show that assuming a transient spatial undersampling allows to predict the errors made by the human visual system when localizing objects briefly displayed at the time of rapid saccadic gaze shifts.

In order to demonstrate the generality of our model, we aim at implementing it on an artificial monitoring system, based on wireless sensors networks. The system has been developed so as to simulate a gaze shift; at the current stage of development, it is able to define the position of objects presented within its field of view, while sensors are in stead-fixation state. Once our model will be implemented on the system, we expect it to maintain stable representations of those objects also across simulated gaze shifts. As a pay-off for representational stability, localization errors are expected, similarly to localization error perceived by the human visual system.

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