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Sensory Integration for Space Perception Based on Scalar Learning Rule

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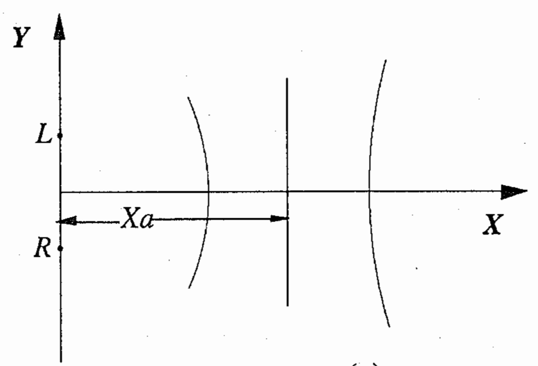
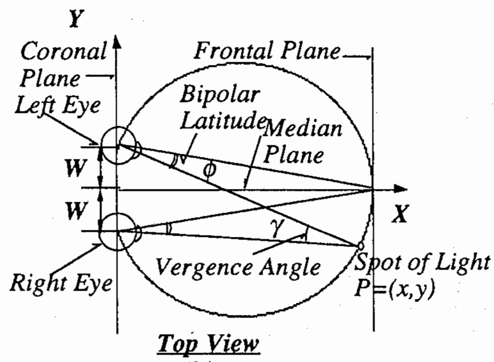
Abstract: From a psychophysical viewpoint, the human sensory space does not completely coincide with physical space. The purpose of this study is to clarify why such a human perceptional space does not completely coincide with a physical one. Toward this end, we propose a learning rule and a neural network model using it. We call the learning rule Scalar Learning Rule and name the model Independent Scalar Learning Elements Summation Model (ISLES Model). The space discordance phenomena reflected in the model are similar to human ones reported in many psychophysical experiments. Therefore, the neural network model can be a good approximation to the physiological process of human space perceptions.

1. Introduction

From a psychophysical viewpoint, the human visual space does not completely coincide with physical space. Even in the darkness, humans can perceive the location of spots of light and the distance between them with binocular vision. In such a situation, the subjective straight line to the objective point becomes the reference. However, the subjective straight line is found as a certain physical curve which is, in general, not straight in the physical sense. This interesting observation is well known as Helmholtz's horopter [1]. A horopter curve is a subjective frontal plane. Figure 1(a) shows a top-view of some typical Helmholtz's horopter curves. In the figure, L and R are the left and right eyeball positions of the observer, respectively. The shape of the horopter curve depends on the distance from the observer. At a certain distance, it is practically straight. At closer distances, the horopter curves are concave to the observer, while at greater distances they are convex [2].



(a)



(b)

Figure 1: Helmholtz's horopter and the human oculomoter system

Such phenomena were known not only in visual space, but also in haptic space [3]. Moreover, in some sensory integration process, such space discordance phenomena are also known. Foe example, in visual control of reaching movement without visual feedback of the limb position, when a subject feels subjectively that a reaching position of his limb coincides with the position of the visual target corresponding with it, in general, the reaching position does not physically coincide with the position of the visual target [4].

The purpose of this study is to clarify why a such human perceptional space does not completely coincide with a physical one. Toward this end, we propose a learning rule and a neural network model using it.

2. Scalar Learning Rule

When a human subject gazes at a spot of light, the location and orientation of the eyeballs are identified by the sensory signals of the vergence angle γ and the bipolar latitude ϕ (Figure 1(b)). In a process of human visual space perception, a transformation is required to map γ and ϕ to the physical world orthogonal coordinates x and y that describe planes and lines. Mathematically, one such transformation is :

$$x = \frac{W}{\sin\gamma}(\cos\gamma + \cos 2\phi) = X(\gamma, \phi)$$

$$y = \frac{W}{\sin\gamma}\sin 2\phi = Y(\gamma, \phi) \qquad \text{...(1)}$$

A plane and a straight line are also abstract concepts acquired developmentally rather than through innate sensings. Therefore, the transformation should be obtained from some learning mechanism involving a visual space perception process. Suppose the human learning mechanism could learn completely such transformation, the human sensory space would coincide with physical one. However, a subjective straight line of a human operator differ from a physical one. Therefore, it seems that the human learning mechanism cannot completely learn such transformations. Then, what kind of mechanism generates the characteristics for human visual space?

The incompleteness should be mostly made of physiological factors of neural networks of human brains because everyone has the same tendency. We propose here an assumption of the physiological learning rule that the physiological learning mechanism cannot propagate error signals backward to any layer but the last (output) one. It is such a basic and natural constraint from a physiological viewpoint that such learning mechanisms are really found in a human brain [5]. In this case, the training signal for learning is not a vector but a scalar signal because only one scalar signal is made from a scalar evaluating function. We call this learning rule the Scalar Learning Rule.

3. Independent Scalar Learning Elements Summations Model

We now propose a model, called the Independent Scalar Learning Elements Summations Model (hereafter ISLES Model), for scalar learning rule (see Figure 2).

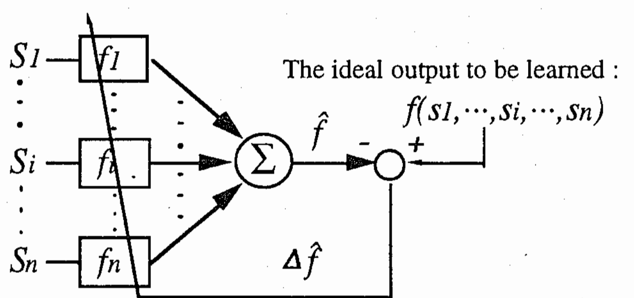


Figure 2: Independent Scalar Learning Elements Summations Model

When the model has n independent input signals, it has n independent scalar learning elements $\hat{f}_1(s_1)$~$\hat{f}_n(s_n)$ and only one summation unit for an output $\hat{f}$:

$$\hat{f}(s_1, s_2, \cdots, s_i, \cdots, s_n) = \sum_{i=1}^{n} \hat{f}_i(s_i) + C \qquad , \text{...(2)}$$

and where each of $\hat{f}_1(s_1)$~$\hat{f}_n(s_n)$ is a nonlinear continuous scalar function acquired with learning. Each scalar function of $\hat{f}_1(s_1)$~$\hat{f}_n(s_n)$ is made to learn its output with the error signal $\Delta\hat{f}$:

$$\Delta\hat{f}_i = \Delta\hat{f} \equiv f - \hat{f} \qquad ...(3)$$

, where $f(s_1,...,s_i,...,s_n)$ is a training function to be learned.
These scalar learning function can be implemented by some kinds of neural network models with the constraint mentioned above [6,7,8]. If the neural network model's learning method is like Perceptron or a method of steepest decent, after sufficient learning times, each function of $\hat{f}_1(s_1)$~$\hat{f}_n(s_n)$ converges to each expectation as follows,

$$\lim_{t\to\infty} \hat{f}_i(x) = E_{s_i=x}(\, f(s_1,s_2,\cdots,s_i,\cdots,s_n)\,) + C \qquad ...(4)$$

because each of $\hat{f}_1(s_1)$~$\hat{f}_n(s_n)$ is dependent on only each of s_1~s_n which is independent of other inputs. In the ISLES model, input signals are "isled" with each other until they are summed up in the output layer. Therefore, while this model cannot completely learn all mathematical functions, it can make some differences from ideal ones. When the differences are similar to human ones reported in many psychophysical experiments, the neural network model can be considered as a good approximation to the physiological process of human space perceptions.

4. Helmholtz's Horopter by ISLES Model

We have proposed the ISLES model for application to some psychophysical phenomena in human space perception. Although these phenomena have been studied mathematically from a psychological viewpoint [2,9,10], the physiological neural network generationg these phenomena are not clearly ubderstood as yet. ISLES model is a physiologically natural model, and the model can represent each of those phenomena as a developmentally learning result with each space perception cue as the training signal of the model. Helmholtz's horopter is a subjective straight line as mentioned above. Therefore neural networks of human brain must have learned such transformations from the angles γ and ϕ to a subjective orthogonal coordinate system, which does not completely coincide with a physically correct one. In order to learn a frontal plane, the training function is not necessarily the $X(\gamma, \phi)$ of (1), but necessarily invariant on the frontal plane. From one of our works, it was known that ISLES model could represent the shape of human horopter as its learning result with a training function of a depth cueing function $f_h(\gamma, \phi)$,

$$f_h(\gamma, \phi) = \gamma - \arcsin(\sin\alpha \cos 2\phi) + C$$
$$\left(\sin\alpha = \frac{W}{\sqrt{\tilde{x}^2 + W^2}} : \tilde{x} \text{ is the depth of the frontal plane.}\right) \qquad ...(5)$$

whose value was equivalent to a half of γ on the point of interaction of the median plane and the frontal plane including the gaze point [11]. In this case, the value of $f_h(\gamma, \phi)$ is the invariant to represent a subjective frontal plane in the human visual space perception process. The horopter curves are represented by the ISLES model as shown in Figure 3.Their shapes are so similar to human ones that the ISLES model is a good approximation of the physiological process for human visual space perceptions.

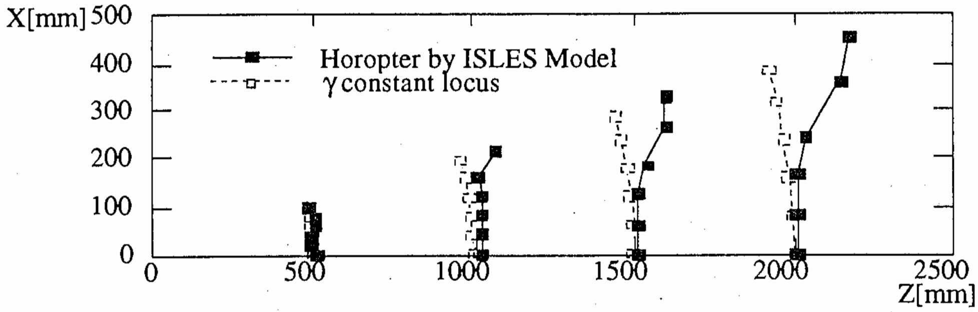


Figure 3: The Horopter represented by ISLES Model

5. Concluding Remark

In this paper, we proposed Scalar Learning Rule and ISLES Model. In the experiments of Helmholtz's horopter, the space discordance phenomena by the model were similar to human ones. In the studies of visual depth perception, the individual constants K and σ in Luneburg's visual space model are generally known as the significant constants to represent the characteristics of visual space perception of a human subject. ISLES model suggests further that the individual constants is defined by the distribution of the points where the human subject has been learning his subjective visual orthogonal coordinates developmentally.

Like the horopter, ISLES model can also represent the space discordance phenomena of parallel/distance alley, haptic subjective straight lines, and visual control of reaching movement without vision of the limb [12,13]. Therefore, the neural network model can be a good approximation to the physiological process for human space perceptions.

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