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Scene Memory of Mobile Robot based on Competitively Growing Neural Network using Temporal Coding

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Abstract

This paper describes the saliency-based scene memory model of a mobile robot in which objects in salient spots are quickly learned and recognized based on the competitively growing neural network using temporal coding. This neural network represents objects using latency-based temporal coding and grows size and recognizability through self-organized learning with growth. In this model, objects in saliency-based attended spots are sequentially encoded to be invariant with respect to position and size by this neural network and their positions and sizes are encoded simultaneously. Through experiments using a Khepera robot equipped with a camera, it is shown that quick self-organized learning and glance recognition of objects in scenes are well performed by our model.

Keywords: scene memory, saliency, self-organized learning, recognition, competitive neural network, temporal coding, mobile robot

1 Introduction

Latent scene learning can be useful for a mobile robot wandering around a real world to make route plans in any future task execution. In the human visual system, spatially circumscribed regions of the visual field are selected based on saliency-based attention as well as volition-controlled attention before further processing. The former is rapid, bottom-up and task-independent attention and the latter is slow, top-down and task-dependent attention [1]. The saliency-based attention is considered to play a major role to latent scene learning. Under this attention, it is known that a human can learn scenes in almost one shot and also recognize them at a glance. We have been building the saliency-based scene memory model based on the competitively growing neural network using temporal coding, that is named the COGNET (COmpetitively Growing NEural network using Temporal coding), and verified its effectiveness by using a simulated robot [2, 3]. In the COGNET, objects are internally represented using latency-based temporal coding. This network enables fast self-organized learning of objects based on recruiting neurons, dismissing neurons and similarity-based sorting of neurons. It also enables glance recognition of objects by only using their distinctive features based on this temporal coding. In this paper, we discuss performance of our model, especially fast self-organized learnability and glance recognizability, in a real world through experiments using a Khepera robot equipped with a camera.

This paper is organized as follows. In section 2, requirements for robotic scene memory and a model of saliency-based scene memory are outlined. In section 3, the COGNET is described in detail. In section 4, learning performance and recognition performance of a Khepera robot equipped with a camera are evaluated.

2 Scene Memory of a Mobile Robot

2.1 Robotic Scene Memory:Requirements

It is necessary for a mobile robot in a real world to latently learn salient objects in scenes and to make use of their memory for route planning in future task execution. To this necessity, we have specified the following functional requirements for the scene memory system of a mobile robot:

1. Salient objects in a scene are learned in almost one shot and to be invariant with respect to their position and size.

2. Object memories are systematically clustered based on their similarity and enhanced in accordance with increase of objects to be stored.

3. A scene memory is constituted by a set of triplets each of which consists of a salient object, its position and its size.

4. It is possible to recall an intended object, recognize it in an actual scene at a glance and identify the scene with a pattern of objects in a scene memory.

2.2 A Model of Scene Memory

A model of saliency-based scene memory is shown in figure 1. It consists of the attention phase and the memory phase. In the attention phase, contrast and opponent color channels of red, green, blue and yellow are computed at each pixel of a scene image [1]. Then the saliency map is produced to represent saliency at every pixel of the image by combining contrast and opponent color channels [4]. Next, connected object regions are segmented using a grow-and-merge method on the saliency map and their bounding boxes are extracted as attended spots. Three or less attended spots are extracted. In the memory phase, attended spots are processed in the order of decreasing saliency at a certain interval. This interval of time corresponds to an interval at which the focus of attention jumps from one attended spot to the next. In this phase, the COGNET encodes an object in each attended spot to be invariant with respect to position and size, and the position and the size of the attended spot is encoded at the same time. These correspond to visual processing in the ventral or "what" visual pathway and the dorsal or "where" visual pathway respectively.

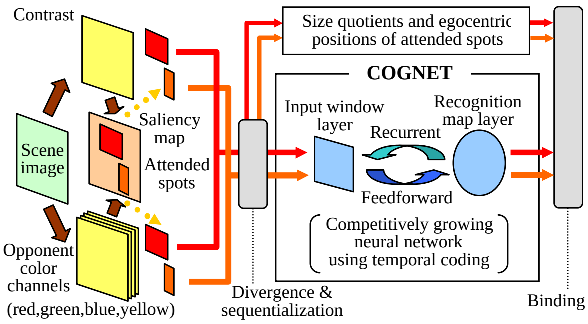


Figure 1: A model of saliency-based scene memory

The COGNET consists of the input window layer and the recognition map layer. The input window layer consists of $l_w \times l_w \times 5$ neurons that receive normalized values of contrast and four opponent colors at $l_w \times l_w$ sections in height and width on an attended spot. The recognition map layer is a competitively growing layer where neurons can be arranged in a two-dimensional lattice. An object in an attended spot is encoded by the winner neuron in the recognition map layer. The input window layer and the recognition map layer have the entire reciprocal connection by feedforward and recurrent synapses. Objects in attended spots are memorized in these synapses by the fast self-organized learning. Neural dynamics is controlled by a discrete-time clock. In this network, it is possible to recognize an object in an attended spot when it is given to neurons in the input window layer, and it is also possible to recall a mental image of an object when a neuron in the recognition map layer is stimulated. Meanwhile, the position of an object is expressed by the center coordinate of its bounding attended spot in the egocentric coordinate system whose origin is the center of a scene image. The size of an object is expressed by the size quotient $q = \frac{l_s}{l_w}$ where l_s is the larger of height and width of the attended spot. The size quotient represents relative distance of the same object in different views or relative size of different objects in a view.

Finally, consecutive processing results of attended spots in a scene are bound together and a scene memory is given by a set of triplets each of which consists of the winner neuron, the center coordinate and the size quotient for each attended spot. We call this triplet an attended spot code and a set of triplets a scene code.

3 Competitively Growing Neural Network using Temporal Coding

3.1 Latency-based Temporal Coding

In neural network models, information is internally represented in the form of a rate code or a temporal code. Several temporal coding schemes have been proposed [5]. In the COGNET, latency from trigger such as pulse transmission or stimulation to a neuron until firing is used as a temporal code to encode information.

Each neuron in the input window layer converts an input value into a latent period so that the larger the input value is, the shorter the latent period is. As a result, a spatial pattern of input strength that codes an object is converted into a spatiotemporal pattern of pulse transmissions, and the object is internally represented by the pattern. A neuron in the input window layer is formulated as follows. When an external excitatory input or recurrent pulse transmission is given to a neuron n_i at time t, membrane potential $p_i(t)$ of n_i is computed by

$$p_i(t) = \sum_j (w_{ij}^R \times \delta_{ij}(t)) + ext_i(t) - ip_i(t) \quad (1)$$

where w_{ij}^R is recurrent synaptic efficacy from a neuron n_j in the recognition map layer, $\delta_{ij}(t)$ is a function which takes the value 1 if a pulse is transmitted from a neuron n_j at time t and 0 otherwise, $ext_i(t)$ is an external excitatory input, and $ip_i(t)$ is an inhibitory input. The output function $o_i(p)$ of the neuron n_i returns latency until firing as a function of membrane potential p when $p \geq 0$ and is given by

$$o_i(p) = \lambda \times \max(1 - p, 0) \quad (2)$$

where λ is a constant called the validity term of latency and takes the value 255. According to these equations, the neuron n_i fires at time $t + o_i(p)$ so long as there is no strong inhibition.

In neurons in the recognition map layer, membrane potential is computed based on a spatiotemporal pattern of pulse arrival, that is, a pattern of latency from pulse arrival until the competition time. For a neuron n_i in the recognition map layer, membrane potential $p_i(t)$ at time t is computed by

$$p_i(t) = \sum_j ep_{ij}(t) + ext_i(t) - ip_i(t) \tag{3}$$

$$ep_{ij}(t) = w_{ij}^F \times \frac{kp_{ij}(t)}{N_i^P(t)} \tag{4}$$

where $ext_i(t)$ is an external excitatory input, $ip_i(t)$ is an inhibitory input, w_{ij}^F is feedforward synaptic efficacy from a neuron n_j in the input window layer, $kp_{ij}(t)$ is a kernel function, and $N_i^P(t)$ is a normalization function. These two functions are given by

$$kp_{ij}(t) = \begin{cases} t - t_{ij}^a & \cdots \quad 0 \le t - t_{ij}^a \le \lambda \\ 0 & \cdots \quad otherwise \end{cases} \tag{5}$$

$$N_i^P(t) = \sqrt{\sum_j kp_{ij}(t)^2} \tag{6}$$

where t_{ij}^a is a recent time of pulse arrival from a neuron n_j in the input window layer and λ is the validity term of latency. The $kp_{ij}(t)$ encodes latency from pulse arrival. Firing in the recognition map layer is determined through competition among neurons using $\{p_i(t_c)\}$ at a competition time t_c. The competition time is controlled by the pre-competition inhibition imposed on neurons in the recognition map layer. The pre-competition inhibition continues in default for a period of λ to suppress firing by any pulse arrival from the input window layer.

3.2 Self-organized Learning with Growth

For a spatiotemporal pattern of pulse transmissions caused by an external input to neurons in the input window layer, membrane potentials of neurons in the recognition map layer are computed at the competition time. Then, if the maximum membrane potential of them is above a threshold, that is called the threshold of discrimination, a neuron that takes the maximum membrane potential is selected as the winner neuron. Otherwise, a new neuron is recruited as the winner neuron, whose synaptic efficacy is initialized so that it takes the maximum membrane potential to the spatiotemporal pattern of pulse arrival. Suppose t_{ij}^a to be a pulse arrival time from a neuron n_j in the input window layer to a recruit neuron n_i and t_c be a competition time. Then, feedforward synaptic efficiency w_{ij}^F from n_j to n_i and recurrent synaptic efficiency w_{ji}^R from n_i to n_j are chosen by

$$w_{ij}^F = \frac{kp_{ij}(t_c)}{N_i^P(t_c)} \tag{7}$$

$$w_{ji}^R = \frac{kp_{ij}(t_c)}{\lambda} \tag{8}$$

where

$$kp_{ij}(t) = \begin{cases} t - t_{ij}^a & \cdots \quad 0 \le t - t_{ij}^a \le \lambda \\ 0 & \cdots \quad otherwise \end{cases} \tag{9}$$

$$N_i^P(t) = \sqrt{\sum_j kp_{ij}(t)^2} \tag{10}$$

and λ is the validity term of latency. According to these equations and (3) (4) (5) (6), membrane potential of the recruit neuron is 1. Since the maximum membrane potential is 1 when there is no external input, it is clear that the recruit neuron becomes the winner neuron.

The winner neuron fires at the competition time t_c. Let n_s be the winner neuron. Then every neuron n_k whose membrane potential is above a threshold, that is called the threshold of neighborhood, is selected as a neighbor neuron of n_s and fires with a lag proportional to difference of membrane potential between n_k and n_s. That is, n_k fires at $t_c + lag(n_s, n_k, t_c)$ which is given by

$$lag(n_s, n_k, t_c) = \gamma \times (p_s(t_c) - p_k(t_c)) \tag{11}$$

where γ is a constant called the upper limit of firing lag at competition.

The winner neuron and its neighbor neurons modulate their synaptic efficacy just after firing so that they may become easy to fire for the same pattern of pulse arrival. That is, synaptic modulation is performed for the winner neuron so as to memorize an object that is encoded by the pulse pattern, and for neighbor neurons so as to bring their memory close to the one of the winner neuron. Synaptic efficacy w_{sj}^F of the winner neuron n_s is modulated according to the following rule at the competition time t_c:

$$w_{sj}^F \leftarrow \frac{w_{sj}^F + \Delta w_{sj}^F}{N_s^W} \tag{12}$$

where

$$\Delta w_{sj}^F = \alpha \times \left(\frac{kp_{sj}(t_c)}{N_s^P(t_c)} - w_{sj}^F\right) \tag{13}$$

$$N_s^W = \sqrt{\sum_j (w_{sj}^F + \Delta w_{sj}^F)^2}. \tag{14}$$

In these equations, α is a modulation rate, $kp_{sj}(t_c)$ and $N_s^P(t_c)$ are values given by equations (5) and (6) respectively, and N_s^W is a normalization factor. On the other hand, synaptic efficacy w_{kj}^F of each neighbor neuron n_k whose firing lag $u_k = lag(n_s, n_k, t_c)$ is modulated according to the following rule:

$$w_{kj}^F \leftarrow \frac{w_{kj}^F + \Delta w_{kj}^F(u_k)}{N_k^W} \tag{15}$$

where

$$\Delta w_{kj}^F(u) = \alpha \times \left(\frac{kp_{kj}(t_c)}{N_k^P(t_c)} - w_{kj}^F\right) \times G(u) \tag{16}$$

$$N_k^W = \sqrt{\sum_j (w_{kj}^F + \Delta w_{kj}^F(u_k))^2}. \tag{17}$$

In these equations, α, $kp_{kj}(t_c)$, $N_k^P(t_c)$ and N_k^W are the same as above, and $G(u)$ is the Gaussian function which gives a decrease rate of modulation due to the firing lag. Let σ be a specified standard deviation of firing lags. Then $G(u)$ is given by

$$G(u) = \exp(-\frac{u^2}{2\sigma^2}). \quad (18)$$

When a neighbor neuron k becomes exceedingly similar to the winner neuron s as a result of synaptic modulation, that is, $\sum_j (w^F_{sj} \times w^F_{kj}) \geq \kappa$ where κ is called a threshold of reidentification, the neighbor neuron is dismissed from the recognition map layer by identifying it with the winner neuron. This enables dissolving redundant encoding of an object by some fluctuation.

This competitive growth and learning achieves similarity-based clustering of attended object images to neurons in the recognition map layer. In addition, in order to achieve topology preservation among clusters in the sense of the self-organizing map [6], the sorting of neighbor neurons is performed in descending order of their membrane potentials [2] so as to bring more similar neighbors closer to the winner neuron on a two-dimensional lattice of the recognition map layer.

3.3 Reciprocal Learning

Recurrent synaptic efficacy is modulated based on pulse transmissions from the winner neuron and its neighbor neurons and the second and the same external input to the input window layer. In this process, the post-competition inhibition is imposed on the input window layer just after the competition time to counterbalance excitation caused by these transmissions. It continues for a period γ followed by the pulse conduction time. The second external input after the post-competition inhibition causes neurons fire with the same latent period as for the first input according to the equations (1)(2). Just after firing, synaptic efficacy of neurons in the input window layer is modulated dependent on firing latency and the distribution of recurrent pulse arrival time. Let t_0 be the second external input time. For a neuron n_j in the input window layer, let t_j be the firing time, t^a_{js} be the pulse arrival time from the winner neuron n_s, and t^a_{jk} be the pulse arrival time from a neighbor neuron n_k in the recognition map layer. Then synaptic efficacy w^R_{ji} from a neuron n_i, which is n_s or n_k, to n_j is modulated as follows:

$$w^R_{ji} \leftarrow w^R_{ji} + \Delta w^R_{ji} \quad (19)$$

where

$$\Delta w^R_{ji} = \alpha \times (\frac{\lambda - (t_j - t_0)}{\lambda} - w^R_{ji}) \times G(t^a_{ji} - t^a_{js}). \quad (20)$$

In this rule, α is a modulation rate, λ is the validity term of latency, and $G(u)$ is the Gaussian function which gives a decrease rate of modulation due to the lag of pulse arrival from n_i against pulse arrival from n_s. Let σ be a specified standard deviation of firing lags. Then $G(u)$ is given by

$$G(u) = \begin{cases} \exp(-\frac{u^2}{2\sigma^2}) & \cdots \quad u \geq 0 \\ 0 & \cdots \quad u < 0 \end{cases}. \quad (21)$$

According to this rule, each recurrent synaptic efficacy w^R_{ji} is modulated to be similar with corresponding feed-forward synaptic efficacy w^F_{ij}, that is, w^R_{ji} is modulated to be a constant times w^F_{ij}. As a result, symmetrical synaptic efficacy is acquired in reciprocal connection.

3.4 Recognition and Recall

In recognition, if winner neurons in the recognition map layer are the same for the first and the second external input to the input window layer, it is judged that an object is steadily encoded and recognized by the neuron. By the way, the glance object recognition is considered to be achieved based on quickly capturing partial information that represents distinctive features of objects. In the COGNET, this can be realized by shortening the length of the pre-competition inhibition period at recognition, which is in default set to λ. Then the winner neuron is selected at the competition time brought forward by using only early pulse arrivals that encode large contrast or opponent color values.

The recall of an object is performed by stimulating a neuron in the recognition map layer. Since symmetrical synaptic efficacy has been acquired in reciprocal connection, membrane potential on neurons in the input window layer caused by this stimulus-driven pulse transmission generates spatiotemporal pulse transmission to the recognition map layer that represents mental image of an object. In this process, if the winner neuron is the same as the stimulated neuron, which is in general satisfied by the symmetry in the reciprocal connection, it is judged that an object is recalled.

4 Experimental Results

4.1 An Experimental World

Figure 2 shows an experimental world, a Khepera robot, which is connected to an external computer, and an example of a saliency map and attended spots computed on a color camera image of 320×240 pixels in width and height. A robot slowly moves right-handed in the world not to bump against a wall based on reactive rules using six infrared sensors, where two in the front and two each on both sides, and processes a scene image about once a second.

Main parameter values used in experiments are as follows. The l_w of the input window layer is 12. In the recognition map layer, no neuron is arranged initially but neurons are recruited at learning. The threshold of discrimination and the threshold of reidentification are 0.9 and the threshold of neighborhood is 0.6. The upper limit of firing lag at competition is 16. The modulation

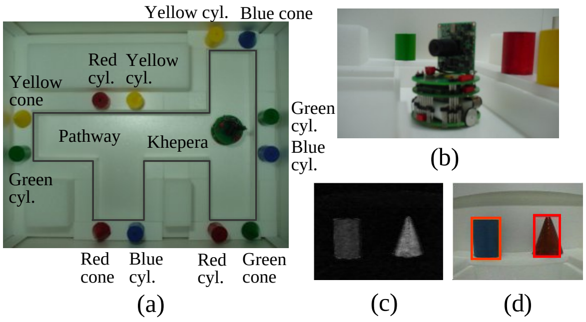


Figure 2: (a)An experimental world. A total of 12 objects, which are two each of red, blue, green and yellow cylinders and one each of red, blue, green and yellow cones, are arranged as landmarks. (b)A Khepera robot. (c)A saliency map. (d)Attended spots.

rate of synaptic efficacy is 0.1. The standard deviation σ of the Gaussian function is 1.6.

In experiments, a robot moves one lap in the experimental world while learning scenes, then moves another lap while recognizing scenes and recording scene codes without learning. After that, he/she repeatedly searches for a target scene that is picked out every 15 codes from the recorded scene code sequence.

4.2 Learning Performance

As for self-organized learning, one-shot object learning performance and fast self-organization performance in the recognition map layer were evaluated, and also discriminative and invariant object learning performance was evaluated.

Figure 3(a) shows a series of concordance between attended object images and winner neurons for them and a series of the number of neurons as the number of attended spots increases at learning. The concordance is given by $\sum_j (w^F_{sj} \times ext_j)/\sqrt{\sum_j (ext_j)^2}$, where w^F_{sj} is a feedforward synaptic efficacy between the winner neuron s and a neuron j in the input window layer and ext_j is an input image element to the neuron j. Since the concordance always takes high values that are almost larger than the threshold of discrimination, we can conclude that attended objects were learned quickly.

Figure 3(b) shows series of the degree of self-organization in the recognition map layer, the number of neighbors and the number of neurons as the number of scenes increases at learning. The degree of self-organization is obtained as the Kendall's rank correlation coefficient between the similarity distance and the Manhattan distance for all neuron pairs on a two-dimensional lattice. The similarity distance of each neuron pair is calculated as the cosine of the angle between synaptic efficacy vectors, which is defined by $\sum_k (w^F_{ik} \times w^F_{jk})$ where w^F_{ik} and w^F_{jk} are feedforward synaptic efficacy for a pair of neurons i and j. A dotted line in the figure shows the critical value of a positive correlation at the significance level (right-sided probability) of 0.5%. We can observe that the degree of self-organization is quickly recovered though it sometimes falls when a neuron is recruited especially in the first stage. It is also observed that significant and steady self-organization is achieved as the number of neurons increases in response to increase of the object variety.

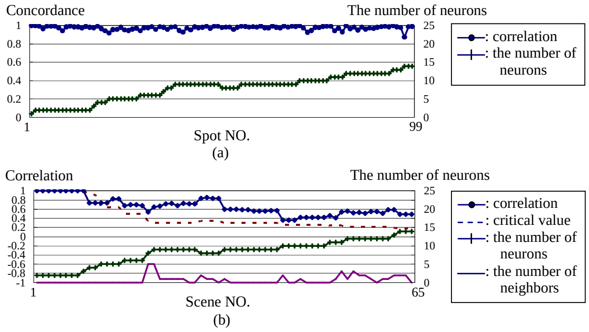
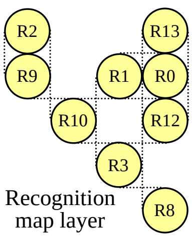


Figure 3: (a)One-shot learning performance. (b)Fast self-organization performance.

Figure 4 shows an example of object encoding in the recognition map layer and discriminative and invariant rates of object recognition after learning. For each neuron, a class of objects is the one that occupies the maximum number of objects encoded to it. The discriminative rate expresses the ratio of the number of objects in the class to the number of all objects encoded to the neuron. The invariant rate expresses the ratio of the number of objects in the class encoded to the neuron to the number of objects in the class encoded to all neurons. By repeating experiments, it was confirmed that discriminative and invariant object recognition with respect to position and size was achieved with a high probability.



ID	Class of objects encoded	Discriminative rate	Invariant rate
R0	Red cyl.	100%	100%
R1	Yellow cyl.	100%	100%
R2	Blue cyl.	100%	100%
R3	Green cyl.	100%	100%
R8	Green cone	100%	100%
R9	Blue cone	100%	100%
R10	Red cyl. and yellow cyl. in front	100%	100%
R12	Yellow cone	100%	100%
R13	Red cone	100%	100%

Figure 4: An example of discriminative and invariant object learning performance.

4.3 Recognition Performance

As for recognition, target scene recognition performance and glance object recognition performance were evaluated. In target scene search, the success or failure is determined by whether a robot can steadily recall target objects and find an actual scene whose code satisfies the following condition. For each attended spot code in it, there exists an attended spot code in a given target scene code which satisfies: (1) both winner neuron are the same, (2) distance between both center coordinates is less than or equal to 80 pixels, and (3) the ratio of larger to smaller size quotient is less than or equal to 2.0. Table 1 shows an example of target scene codes and scene codes found in their successful search. Steady recall of target scenes and their searches succeeded in this example. By repeating experiments, it was confirmed that target scene search succeeded almost perfectly, which meant that positions and sizes of objects were encoded suitably enough for scene recognition.

Table 1: A result of target scene search.

NO.	Target scene code	Scene code found
1	$R2,(59,-16),5.75$ $R3,(-56,-16),5.75$	$R2,(72,-16),5.75$ $R3,(-43,-16),5.75$
2	$R3,(112,-13),7.83$	$R3,(114,-13),7.0$
3	$R10,(114,4),5.75$	$R10,(102,-13),5.33$
4	$R0,(119,7),7.83$	$R0,(132,-6),5.75$
5	$R3,(-13,-16),5.75$ $R12,(97,-16),5.75$	$R3,(-1,-18),6.17$ $R12,(109,-11),5.75$
6	$R2,(-51,-16),5.75$ $R13,(59,-16),5.75$	$R2,(-33,-16),5.75$ $R13,(79,-16),5.75$

As for the glance recognizability, it is tested whether recognition succeeds for 96 object images that a robot paid attention in the experimental world when the length of the pre-competition inhibition period is shortened. Figure 5(a) shows the mean, standard deviation and distribution of the lower limit for success of the glance recognition when the length of the pre-competition inhibition period is gradually shortened. Figure 5(b) shows those against the number of effective pulse transmissions, that is pulse arrivals before the competition time, which is decreased by shortening the length of the pre-competition inhibition period. The mean of the lower limit length of the pre-competition inhibition period for success is 165.3, which is about two thirds of the default length 255. Also the mean of the lower limit number of effective pulse transmissions for success is 33.5, which is 4.7% of 720 that is the number of pulse transmissions in case the length of the pre-competition inhibition period is 255. Figure 6 shows the success rate of the glance recognition for the length of the pre-competition inhibition period and the number of effective pulse transmissions. We can observe that a high recognition success rate is achieved using only a small number of early pulse arrivals, that encode large contrast or opponent color values, by bringing the competition time forward.

5 Conclusions

We have evaluated the scene memory system of a mobile robot, especially the self-organized learnability and the glance recognizability of salient scenes, through experiments using a Khepera robot equipped with a camera. As for learnability, it was confirmed

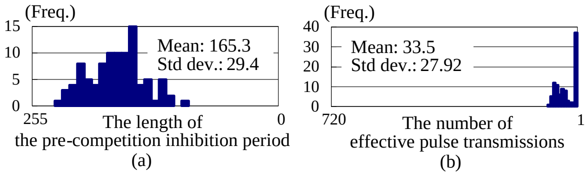


Figure 5: The lower limit for success of the glance recognition. Data are summed up every 8 interval.

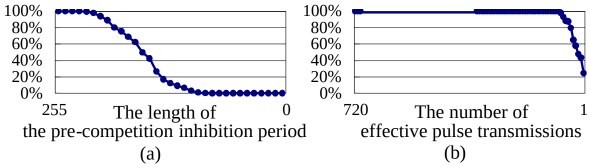


Figure 6: The success rate of the glance recognition. Data are summed up every 8 interval.

that quick one-shot object learning and fast self-organization of object memory structure were performed, and discriminative and invariant object recognition with respect to position and size was achieved. As for recognizability, it was confirmed that scenes were encoded by the scene code suitably enough for scene recognition. It was also confirmed that glance object recognition was achieved using only early pulse arrivals which encoded distinctive feature of objects. We can conclude from these results that the scene memory system based on the COGNET is effective from a point of view of specified requirements.

References

[1] Itti, L., Koch, C. and Nieber, E., “A Model of Saliency-based Visual Attention for Rapid Scene Analysis”, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 20(11), pp.1254-1259 (1998).

[2] Atsumi, M., “Saliency-based Scene recognition based on Growing Competitive Neural Network”, *Proc. 2003 IEEE Int. Conf. on Systems, Man & Cybernetics*, pp.2863-2870 (2003).

[3] Atsumi, M., “Scene Learning and Glance Recognizability based on Competitively Growing Spiking Neural Network”, *Proc. 2004 IEEE Int. Joint Conf. on Neural Networks*, pp.2859-2864 (2004).

[4] Breazeal, C. and Scassellati, B., “A Context-dependent Attention System for a Social Robot”, *Proc. of 16th Int. Joint Conf. on Artificial Intelligence*, pp.1146-1151 (1999).

[5] Thorpe, S., Delorme, A. and Rullen, R. V., “Spike-based Strategies for Rapid Processing”, *Neural Networks*, 14, pp.715-725 (2001).

[6] Kohonen, T., “Self-Organizing Maps”, Springer-Verlag, 1995.