Paper

Discrimination of Binary Isotrigon Textures by 1–D Oscillator Network of Cascade Arrangement

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Abstract. Experiments to discriminate isotrigon textures were performed by networks consisting of four 1–D oscillators in a cascade arrangement. The discrimination experiment by the 1–D oscillator network was similar to experiments done by humans. Is the experiment with the 1–D oscillator network the discrimination strategy was the minimum difference between the temporal development of the output oscillator and a reference data set consisting of previously sampled temporal development sequences of the output oscillator. The discrimination performance by the 1–D oscillator networks differed from that by human. These types of studies will yield what kind of texture discrimination strategies are used in human brain.

Key words: isotrigon, texture, 1–D oscillator, network, discrimination, performance, strategy.

1. Introduction

The 1–D oscillator used in the present study is a one dimensional mapping of cubic function with a parameter A, that determines the temporal development of the variable in recursively [1]. The mapping generates an oscillatory series of variable values so that we define a recursive difference equation using this mapping of the 1–D oscillator (one dimensional oscillator). We investigated small networks consisting of 3 or 4 1–D oscillators from the viewpoint of temporal behavior of each oscillator and found several interesting oscillations [2, 3, 4]. The previous work of our oscillator network studies introduced the subject of whether 1–D oscillator networks can recognize isotrigon texture patterns [5]. The previous study showed that the triangular network of 1–D oscillators can discriminate isotrigon textures generated by the Box glider [5]. The present paper reports how the one way network of cascade arrangement of 1–D oscillators responses the texture inputs of a 3×3 pixel domain that is moved from left to right and top to bottom across the presented texture. We did texture discrimination experiments using this cascade network of 4 oscillators. Experiments using the cascade network was similar to experiments in which task of human subjects was to discriminate isotrigon textures: that is whether the presented texture is even or odd, random or even, and random or odd [6, 7]. The discrimination of the cascade network was performed using the response activities of the output oscillator of the cascade network. In other words,

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the temporal pattern of response activity for the presented texture at a given instance was compared to texture response patterns of possible two type textures. This task performance is carried out on the computer using Basic program.

The study shown here is based on our studies of the discrimination of isotrigon textures by human [6, 7]. We have also developed isotrigon textures having multiple states that can be equated to multiple brightness levels [7, 8]. The originally binary versions were developed by Julesz et al [9] and Gilbert [10]. We have been investigating human performance of discriminating isotrigon texture classes from each other or from random textures [6, 7]. Our experiments on the human task of discriminating isotrigon textures has been performed binary textures [6] and ternary textures [7]. However, we only present here the performance of discriminating binary isotrigon textures by 1–D oscillator network in a cascade arrangement as the first step of discrimination experiments for isotrigon textures by 1–D oscillator networks.

In the next section, we describe the experimental situation using 1–D oscillator networks in a cascade arrangement, and the properties of elements of a 1–D oscillator and cascade oscillator network. Section 3 is devoted to showing examples of discrimination experiments by the 1–D oscillator network, and the performance of the discrimination task for the oscillator network using isotrigon textures generated by Box, Cross, Zigzag, Oblong, and Corner gliders. The task performance for Box glider textures is close to chance performance in the 1–D oscillator network of cascade arrangement. This result is quite different from the performance by human. The performance difference between human and 1–D oscillator network may be caused by the strategy, i.e. what kind of procedure is used on the Judgment of which texture is. This fact is discussed in the Section 4.

2. The Properties of 1–D Oscillator and Its Cascade Network

The 1–D oscillator used in the present study is of the N-type in which the temporal development of the variable is described by the following recurrence equation,

$$x(t+1) = -Ax(t)(x^2(t)-1)-x(t), \quad (1)$$

where A is a parameter that varies the oscillation mode. Note that the range of the parameter A is from 0 to 4. When the 1–D oscillator received input $I(t)$, the above equation (eq. (1)) was modified to a form that contained input term, namely,

$$x(t+1) = -Ax(t)(x^2(t)-1)-x(t)+\sigma I(t), \quad (2)$$

where σ means the effect factor of input to the 1–D oscillator. Fig. 1 shows an example of the response to an input at for A = 2.5. Fig. 1 also shows the example response of a P-type oscillator to the same input. The P-type oscillator is described by the same equation but with a changed sign of first and second terms of eq. (1) and eq. (2).

The 1–D oscillator network of a cascade arrangement is illustrated in Fig. 2. The cascade network consists of four 1–D oscillators with one-way information flow from the input

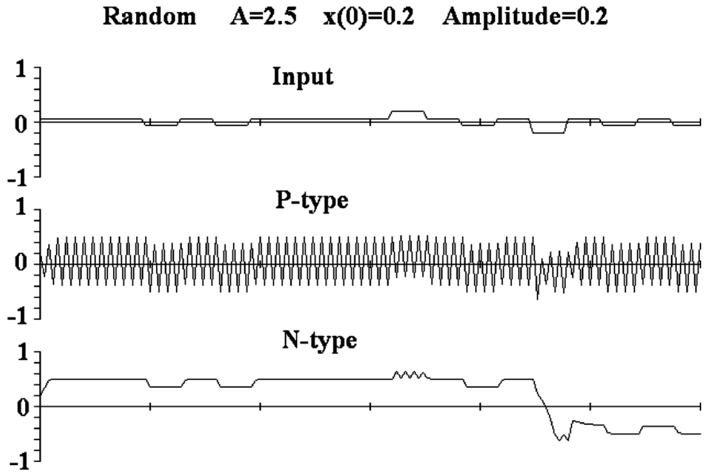

Fig. 1 The response of P and N type oscillators to an input time series. The bottom figure denotes the response of N-type oscillator to the input shown at the top figure. The N-type oscillator more closely imitates the temporal development of the input. The input was generated by a random texture.

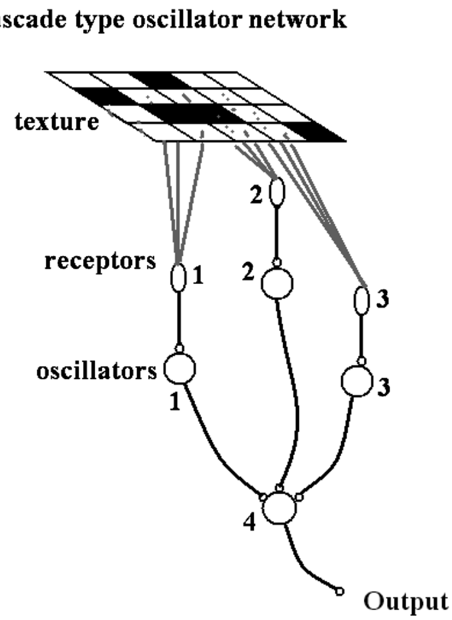

Fig. 2 A schematic of the 1–D oscillator network of cascade arrangement that was used in our texture discrimination experiments.

to the output. One of four oscillators is called output oscillator, given that it receives the output of the other three oscillators as its input. Three oscillators 1, 2, 3 are each fed by the output from its corresponding receptor, that in turn averages over the brightness of three pixels drawn from a succession of 3×3 pixel domains as illustrated in Fig. 2. The 3×3 domain is

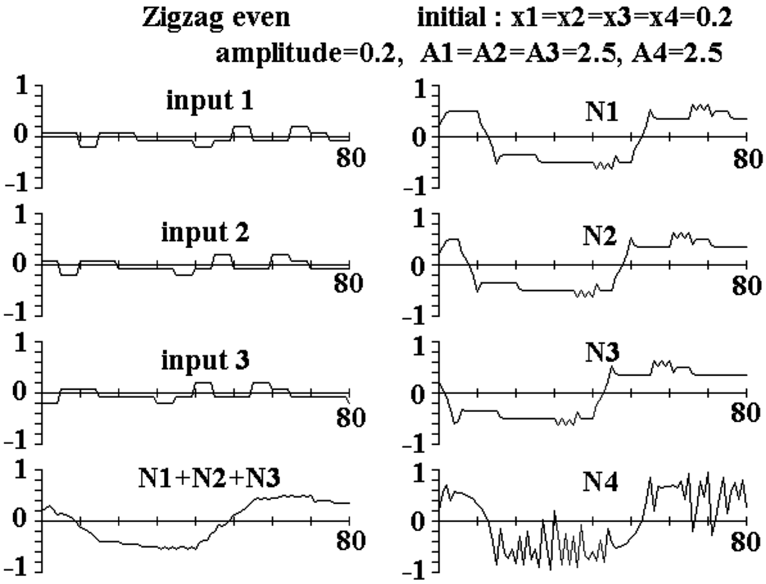

Fig. 3 A response of a cascade network of all N-type oscillators to an even Zigzag texture. The input to oscillator 4 (output oscillator) becomes smooth compared to the responses of oscillator 1, 2, and 3.

scanned across the texture presented in a given discrimination experiment. The situation of the experiment for discriminating textures is described with following set of equations (eqs. (3)–(5)),

$$x_4(t+1) = -Ax_4(t)(x_4^2(t)-1) - x_4(t) + \frac{1}{3}\sum_{j=1}^{3} x_j(t) \tag{3}$$

$$x_j(t+1) = -A_j x_j(t)(x_j^2(t)-1) - x_j(t) + \sigma_j R_j(t) \quad \text{for } j=1,2,3 \tag{4}$$

$$R_j(t) = \sum_{\langle k_1(j),\, k_2(j),\, k_3(j)\rangle_t} \Phi(T_{3\times 3}(t)) \tag{5}$$

where $T_{3\times 3}$ signifies 3×3 domain of the presented texture at the time t, and $\langle k_1(j), k_2(j), k_3(j)\rangle_t$ is the group of three pixels that are averaged by their governing receptor. Note that 3×3 domain scanned across the entire texture area. Thus, the three pixel group governed by the receptor varies in its time development. An example of response time behavior of the cascade network for even Zigzag texture is shown in Fig. 3.

3. Experiment of Discriminating Isotrigon Textures

The organization of experiments using 1–D oscillator networks followed those performed on human [5, 6]. The task of the experiment is to answer which class of texture presented is when a texture selected from one of two classes of textures is presented with equal probability. In general, the judgment of which class of texture is present depends on the criterion and methods that are embodied in the system to discriminate the textures. Here the temporal development of variable in the output oscillator (oscillator 4) was utilized to judge which class texture was present.

The isotriogon textures used in the present study were the so-called Box, Cross, Zigzag, Oblong, and Corners textures [5–7]. Examples of those texture classes are shown in Fig. 4. Each of isotrigon texture classes has even and odd types, which correspond to the positive and negative signs of triplet products of the recursion equation that generates them. Generally, the random textures are also isotrigon. There are therefore three classes of isotrigon textures, namely {random textures}, {even textures}, and {odd textures}. Examples of all three are shown in Fig. 4 for each glider type.

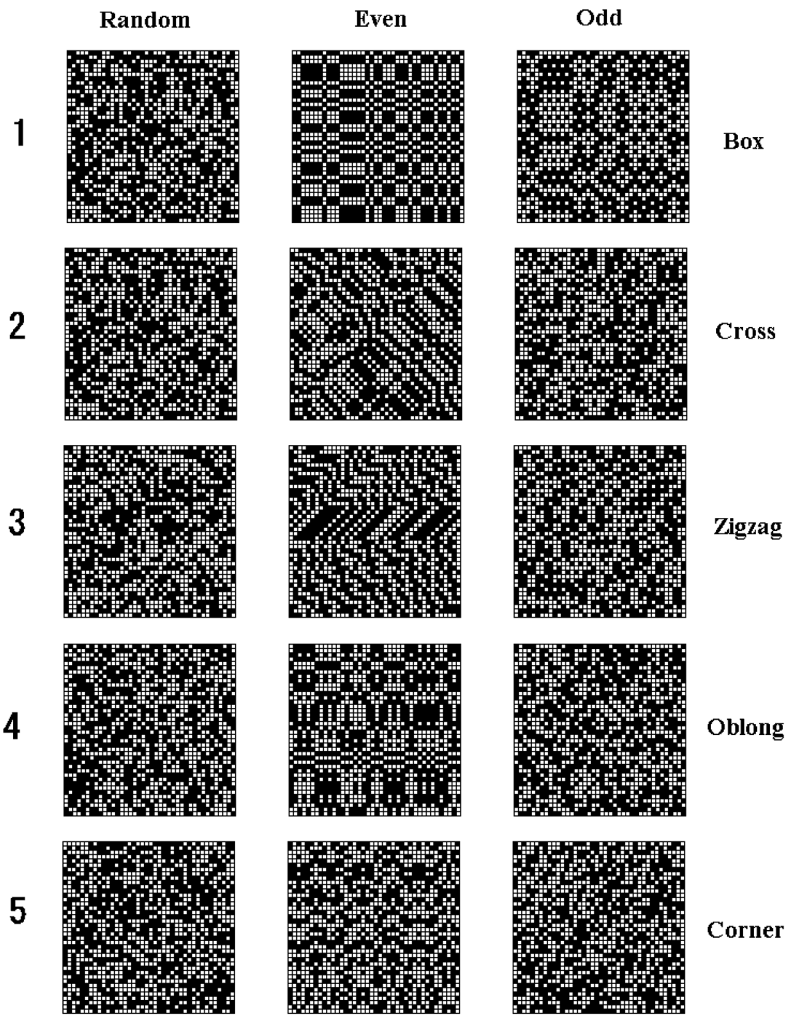

Fig. 4 Isotrigon textures using in the experiment of discriminating textures by a cascade network.

The experimental tasks of discriminating textures was formed for combinations of two classes chosen from the three texture classes, thus the tasks for the discrimination experiments were {Even *versus* Odd (EO), Random *versus* Even (RE), Random *versus* Odd (RO)}. Those tasks were done for each glider defined texture group. In the experiment, one of texture class pairs is selected with probability 1/2 (chance) and was presented as the stimulus to the 1–D oscillator network of cascade arrangement.

As seen from Fig. 3, each 1–D oscillator imitates the input temporal development so that some kind of quantity of the temporal development of oscillator 4 variable should be the criterion for discrimination. Two criteria were used in the present study of texture discrimination. Both criteria are organized from the difference between the time behavior $\{x_4(t)\,|\,0<t<80 \text{ iteration}\}$ for presented textures and a set of time behavior of $\{x_4(t)\,|\,0<t<80 \text{ iteration}\}$ of a learned reference data set, namely, $\{\{x_4(t)\,|\,0<t<80 \text{ iteration}\}_1, \{x_4(t)\,|\,0<t<80 \text{ iteration}\}_2, \cdots, \{x_4(t)\,|\,0<t<80 \text{ iteration}\}_m\}$ for the texture class specified. The quantity ''minimum difference'' for organizing a criterion is demoted by $DF_{\min}$ that is defined by follows,

$$DF_{\min} \equiv \min(\{\Delta_k^* \,|\, 1 \le k \le m\}),\ and \quad \Delta_k^* = \min(\{\Delta_\tau^k \,|\, -\gamma \le \tau \le \gamma\}) \tag{5}$$

thus using the difference Δ_τ^k between time behavior for presented texture and that for k-th data of already learned time behavior, i.e.,

$$\Delta_\tau^k = \frac{1}{T-\tau} \sum_{t=1}^{T-\tau} |x_4(t) - x_4^k(t+\tau)|. \tag{6}$$

The value of γ was taken to be 30 in these experiments. If the value of γ becomes smaller the value of DF becomes bigger. The value of DF may saturate for larger γ values. The number of data for learning temporal behavior for both classes is 10, i.e., $m=10$.

One criterion used in the present study was that small differences betweenand $DF_{\min}^{texture1}$ and $DF_{\min}^{texture2}$ implies the correct texture class. Notice that upper suffix implies the texture class to be compared with the presented texture. If $DF_{\min}^{texture1} < DF_{\min}^{texture2}$ then the presented texture is taken to be a class 1 texture. This criterion is simple and principled in the statistical sense. But this criterion yields poor discrimination of the Box glider texture group compared to human performance [6]. Fig. 5 shows an example of the experiment of discriminating texture. Each task of {EO, RE, RO} completed for 3 texture sizes {32×32, 16×16, 8×8 pixels}. In each examination, 16 repeats of texture presentations were carried out. This methodology was very similar to that used in our human experiments [6]. Fig. 5 illustrates and example of a correct discrimination for a odd texture of the Box glider group. The texture size used in that particular was 32×32. This size of even Box texture is quite easily recognized by the human brain, The performances using this criterion for tasks {EO, RE, RO} are shown in Figs 6 to 8. The criterion described here is referred to as small DF_1–DF_2.

Since the criterion small DF_1–DF_2 yields performance at less than chance performance for almost tasks of five glider groups, we should take another criterion that attends to one of

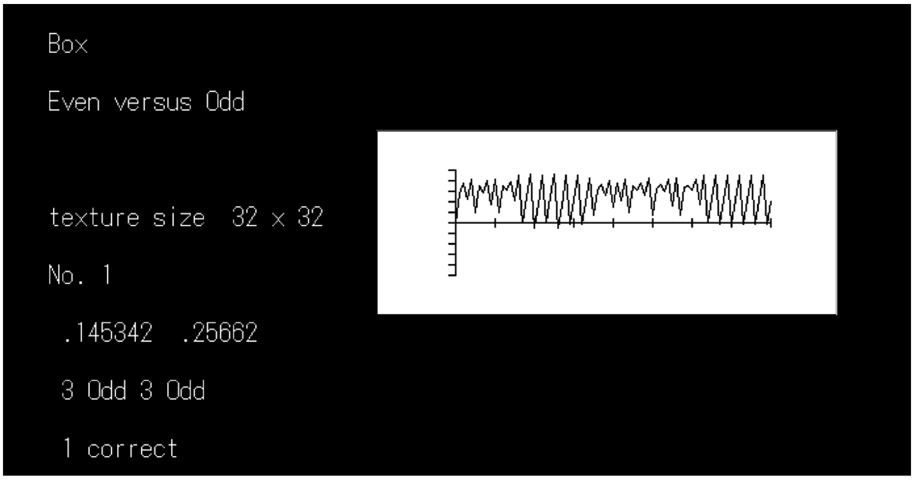

Fig. 5 An example of an experiment for discriminating isotrigon textures. The task shown in the figure is to discriminate even versus odd examples of the Box glider texture groups.

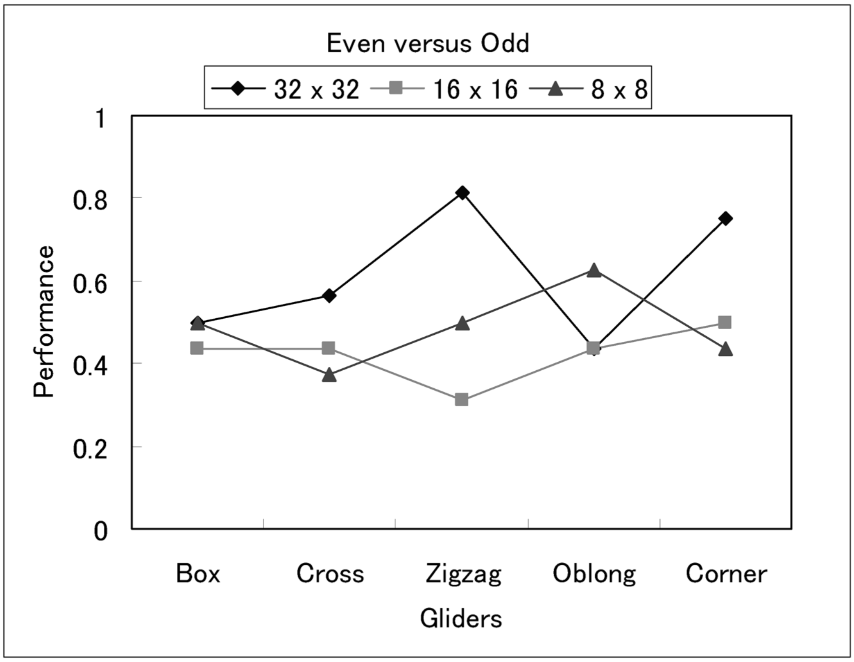

Fig. 6 Performance by the cascaded 1–D oscillator network for the task even versus odd.

the two DFs. In this case if DF is less than a value then it is a texture of the attended class. The criterion to pay attention to texture class is referred to here as *one side attending*. This criterion requires a parameter provides a cut-off value for DFs for the attended texture class. The value of cut off is taken the value 0.5. A summary of performance is shown from Fig. 9 to Fig. 11 for the tasks EO, RE, and RO, respectively.

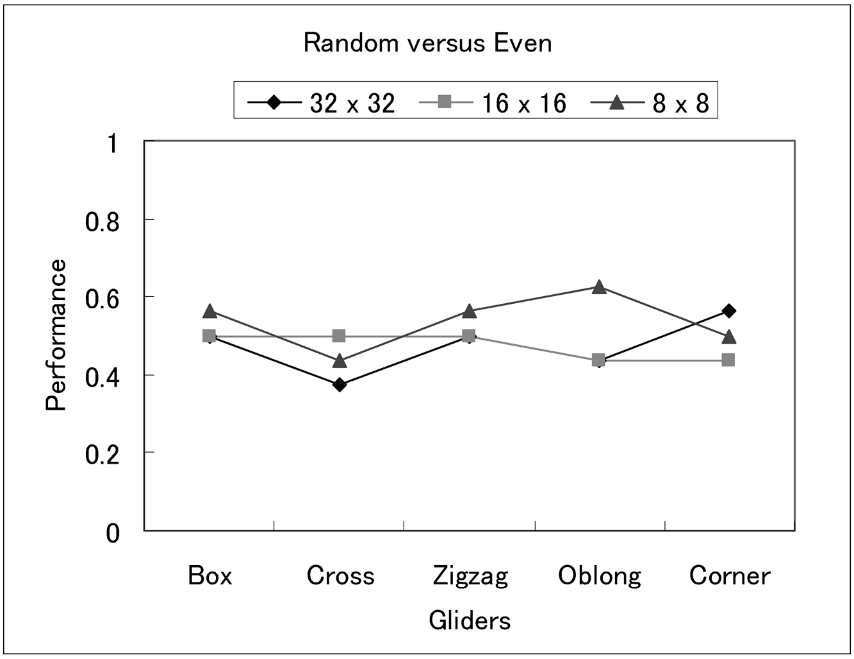

Fig. 7 Performance by the cascaded 1–D oscillator network for the task random *versus* even.

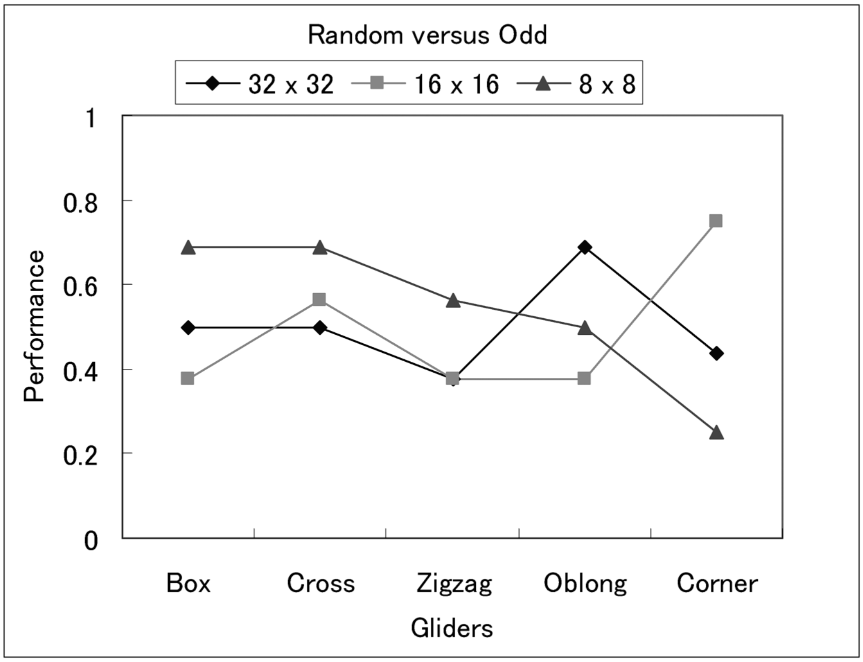

Fig. 8 Performance by the cascaded 1–D oscillator network for the task random *versus* odd.

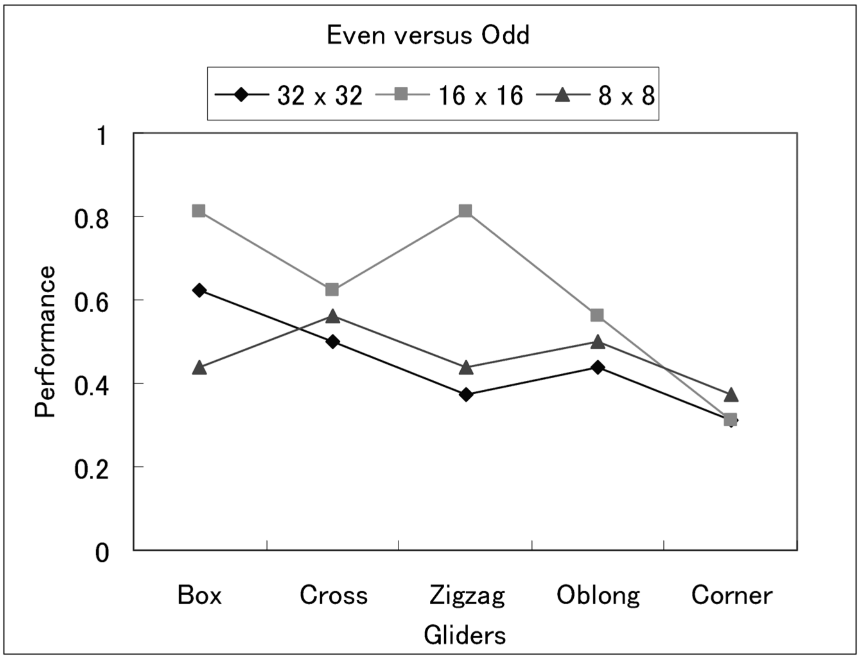

Fig. 9 Performance by the 1−D oscillator network using criterion of one side attending for the EO task.

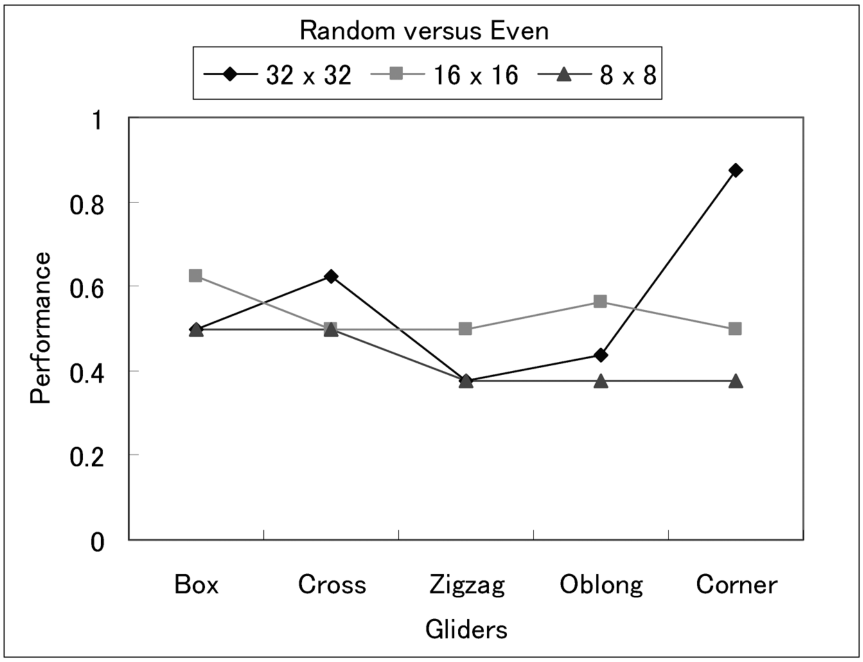

Fig. 10 Performance by the 1−D oscillator network using criterion of one side attending for the RE task.

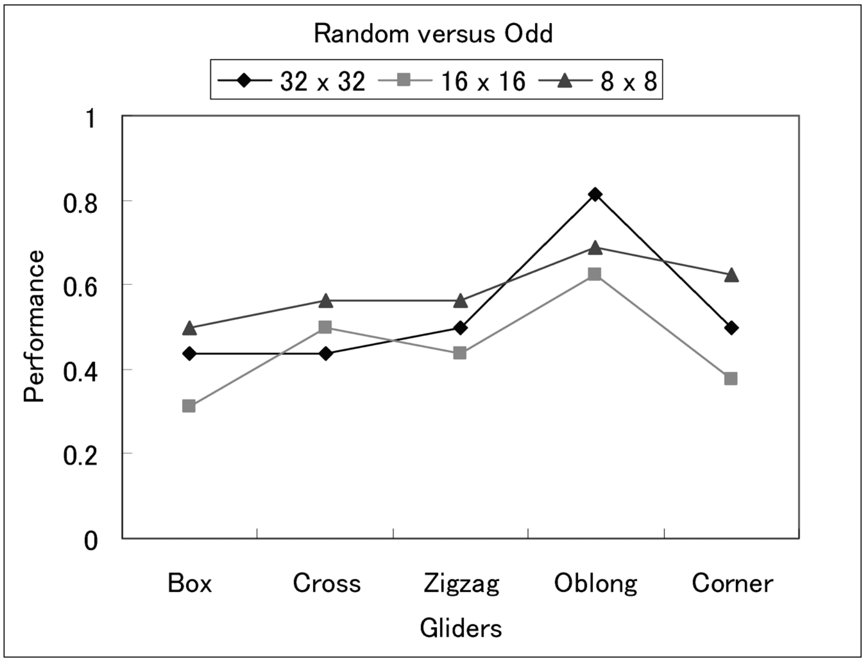

Fig. 11 Performance by the 1–D oscillator network using criterion of one side attending for the RO task.

The criterion of one side attending improved the performance of the EO task, but this criterion produced chance performance for the RE and RO tasks. In the case of the RO task, the smaller texture size 8×8 gave the best performance. The cascade oscillator network shows better performance of texture discrimination for RE task of Corner one at the texture size 32×32. For the RO task, Oblong shows relatively better performance compared to the performance of other type textures.

4. Discussion

We had carried out the experiment on how humans discriminate isotrigon textures [6, 7]. Thus we can know what kinds of differences exist between human and cascade oscillator network discrimination since we used the same binary isotrigon texture types, discriminations and texture sizes as in our human studies. The performances of texture discrimination tasks by humans are shown in Fig. 12. As seen from Fig. 12, it is easily known that human can better discrimination of some textures.

In the previous sections, we equated the correct answer ratio to performance. The performance using the criterion of smaller DF_1–DF_2 was poor so that we used another criterion called one side attending. One side attending of textures worked a little bit better, but the criterion of one side attending was also not better than human performance. In the present

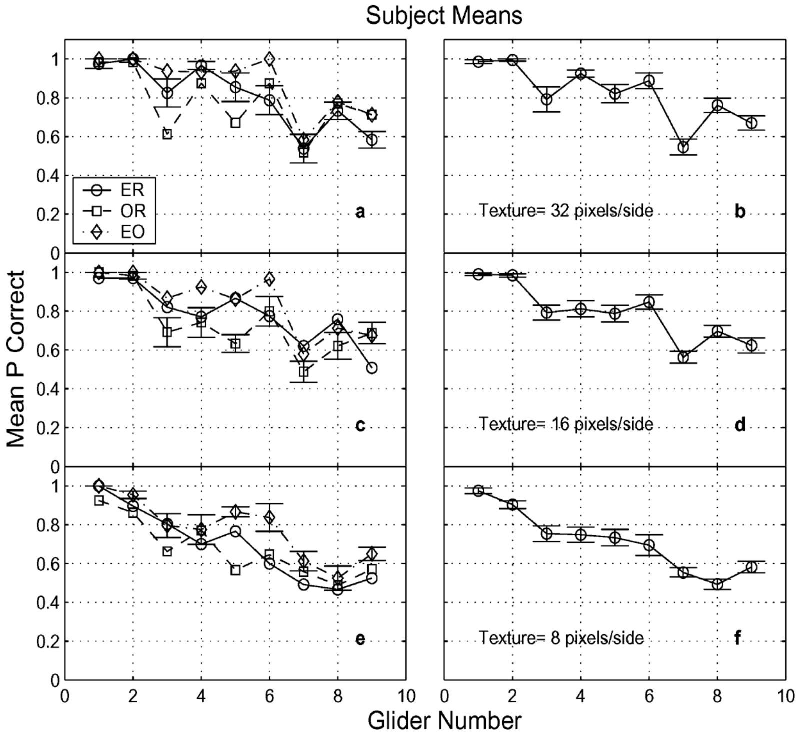

Fig. 12 Average psychometric functions for the mean probability of correct discrimination from 5 subjects for ER, OR, EO. Integers along the abscissa mean the gliders 1: Box, 2: Triangle, 3: Cross, 4: Zigzag, 5: Oblong, 6: Tee, 7: Wye, 8: Foot, 9: El. Vertical is equivalent to mean performances. (see ref. [6]). The three rows correspond to decreasing texture size: 32×32, 16×16 and 8×8.

paper we examine only the quantity of the value difference between two time series in each time in the averaged sense. If we use another criterion to discriminate the textures, another performance for texture discrimination will be obtained. There are many kinds of criterion. Here we examined only one kind of criterion. The criterion of one side attending of texture class is a possible strategy in humans. However, humans probably use several strategies at the same time and select the one of them for a given instance, based on the experience of individuals. This kind of procedure can be taken considering criterion for the discrimination experiments account into, but it is not easily implemented on a computer.

These types of computer simulations will give some knowledge about what kind of strategy or criterions humans employ when discriminating materials. This becomes a subject to search the human abilities as progressed in the human brains.

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