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多層パルスニューラルネットによる非定常な同期発火モデル

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脳が視覚刺激を統合して一つのパターンとして認識する際，知覚に関与する広い範囲の機能部位でガンマ振動が増大して発火が同期するが，この同期現象は数 100 ミリ秒の単位で非定常にゆらいでいる．本研究では離散的なスパイクを発生する多層パルスニューロンを用いてこの現象をモデル化する．本モデルは三層のニューロンから成り，各層はそれぞれ線分の傾きを表現する線分カラム層，フィードバックの同期入力を検出するコインシデンスデテクター層，図形特徴を表現する自己組織化層から成る．生理学的構造に従い，コインシデンスデテクター層は自己組織化層より全投射型のフィードバック入力を受けている．本研究はこのような簡約された多層ネットワークで同期による特徴統合が実現でき，非周期性や過渡性の性質を持つ皮質の同期現象を再現できることを示した．

Synchronized Spiking Neural System for Recognition of Basic Figures

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Our model is based on the idea that synchronous firing of the gamma band governs visual cues in the visual cortex. This synchrony is unstable and fluctuates on hundreds millisecond scale. We employed spike response neuron model in order to simulate this phenomenon. The system consists of three layers: the lower layer is Edge layer which simulates column neurons of the primary visual cortex. The higher layer is Feature linking layer which is composed of several oscillatory coupled neurons. These neurons respectively correspond to different figures. The middle layer is Coincidence detector layer. This layer receives feedback signal from the higher layer. Synchrony between neuron is amplified via the feedback connection. Experimental result shows that the model recognized simple figure and exhibited the properties such as weak-locked status without periodicities.

Introduction

The complex "spatio-temporal spike pattern" is broadly considered as a key role of neuronal coding in visual cortex and other cortical areas. This idea began dominant since collective oscillatory behavior was observed in the visual cortex of cat and monkey[1].

Stocker proposed non-linear coupled oscillator model for scene segmentation[2], and Shimizu showed flexible figure recognition model by using oscillatory neuron[3]. MAGIC[4] is a linking phase model for figure recognition. Despite these study, it is still unsolved issue which of concepts (spike, oscillation, or other ensemble behaviors) is sufficiently suited for emulating higher visual area which applies to the natural scene recognition.

In the inferior temporal area, the existence of the column neuron is well-known. This column neuron selectively responds to a certain object composed of simple features such as circle, triangle, stripe, and the combination of them. Despite the several physiologically studies in this area, how brain represents feature units and how brain realizes size invariant, shift invariant, and deformation invariant recognition is still under debate.

Correlation theory, one of the approaches to model the brain function, has been intensively studied by Malsburg[5], Abeles[6], and others. According to these studies, synchronous firing are accompanied by the oscillatory firing. Based on experimental data, Sillito[7] shows the phenomenon that two LGN neurons evoked synchronous firing when the concatenate bar was projected onto the neurons. Since LGN neuron maintains no lateral connection between neighbor neurons, the coherence is evoked by a feedback signal from V1. Cutting this feedback connection, the correlation of two neurons is diminished. Dinse et al.[8] investigated the temporal structure of receptive fields in the primate visual cortex and found unsteady changes of firing on a time scale of 10-30ms They allow us to address that the recognition model should be correlation based and correlate state should change in short time range in order to realize heuristic object recognition in real scenes. Pulse neural network seems to be suited for this purpose.

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2 Spike response model

The formulation of the spike neuron model employing in our study follows the literature [9]. A single neuron i can generate a spike which is mathematically defined as: $S_i(t) \in \{0,1\}$. The wave length of a spike is defined as 1 time step. Spikes are transmitted via axon. Thus the signal arrives at the synapse after some axonal delay. Spike signal evokes excitatory or inhibitory postsynaptic potential (EPSP or IPSP) which are formulated as exponential functions shown in Fig.1.

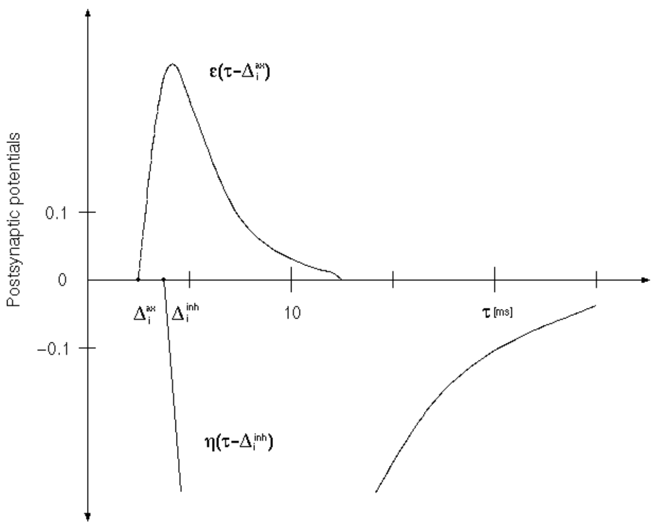

Fig.1 Excitatory(EPSP) and inhibitory(IPSP) postsynaptic potential. Neuron fires at τ =0. Taken from[9].

The firing dynamics of neuron i is defined by the probability of firing during one time step. It is a function of membrane potential $h_i(t)$:

$P_f[S_i(t+\Delta t)=1 \mid h_i(t)] = (1/2)(1+\tanh[b(h_i(t)-q)])$,

where β is a parameter of internal noise of the neuron and θ is a threshold. The membrane potential $h_i(t)$ consists of three components:

$h_i(t) = h_i^{syn}(t) + h_i^{ext}(t) + h_i^{ref}(t)$,

where $h_i^{syn}(t)$ denotes the total input from other neurons, $h_i^{ext}(t)$ represents external potential, and $h_i^{ref}(t)$ denotes the refractoriness of the neuron. The expression $h_i^{ref}(t)$ is given as

$$h_i^{ref}(t) = \begin{cases} -R & if \quad t_F \le t \le t_F + t_{ref}, \\ 0 & otherwise \end{cases}$$

where $R >> 1$ and it prevents the neuron from firing during a time t_{ref} after the firing at $t = t_F$.

To put it simply, the pulse neuron model mentioned above is summarized that the neuron converts the input potential which exceeds the threshold into the frequency of pulse train. The frequency of neuron i increases monotonously with the high input potential it receives.

A single spike neuron can realize varied functions by modulating some parameters, which are axonal delay, time constant, and synaptic efficacy. If the neuron which has only one input synaptic connection and its time constant of decay of EPSP is greater than that of refractory period, the neuron can integrate potential induced by the spikes from one pre-synapse (Temporal addition). Another typical neuron is characterized as a *coincidence detector*, which is utilized later, the time decay of which is modulated to very short. This neuron fires only when it receives signals simultaneously from several connected neurons (Spatial addition).

3. System architecture of correlation based figure recognition model

Zeki et. al.[10] addressed that the feed-forward connection from V2 to higher cortical area is selectively linking onto the small domain called *patch* which is a functional unit of the cortical area, such as color selectivity, movement extraction, etc. Contrarily, the feedback connection starting from the higher layer neuron ends in the lower "all" patches. This type of neural connection structure is found in many regions of the cortex. Thus this inter-cortical feedback connection would implicate the roll of the synthesis of multiple features processed in different patches. With considering above structure, we modeled the figure recognition system (Fig. 2, 3)

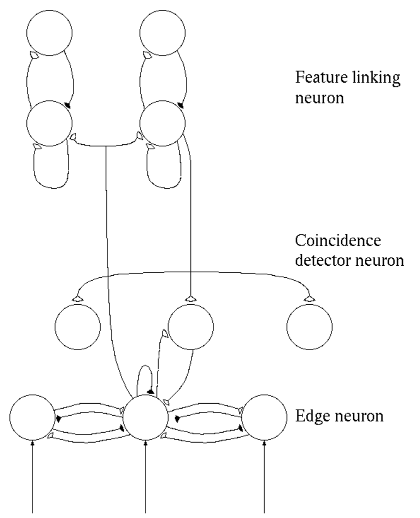

Fig.2 Schematic diagram of the model's circuitry. Open (filled) triangles indicate excitatory (inhibitory) synapses.

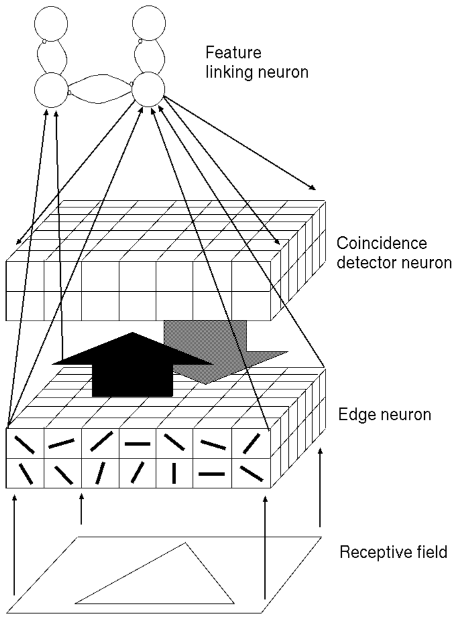

Fig.3 Entire diagram of the model.

Edge layer, which simulates column neuron, is composed of 7x7 retinal fields. A retinal field includes 8 spiking neurons, each of which corresponds to preferred direction respectively. Edge layer neuron poses the lateral inhibitory and excitatory connection which attains a preference of continuous segments.
Feature linking layer is composed of several feature linking neurons, each of which is a couple oscillatory neuron and respectively corresponds to a peculiar figure such as triangle and square. The synaptic weights of the linking neurons had been previously trained by Hebbian learning rule. Feature linking neurons inhibit each other. Once the neuron fires, the feedback signal is sent to the coincident detector neurons. This feedback from feature linking neuron to edge neuron is constant and homogeneous in all range of the edge layer neurons.

The coincident detector neuron is an adjunct of edge neuron, which receives spikes from both the feature linking neuron and the edge neuron. The coincident detector neuron is firing only when the neuron receives pulses from the linking neuron and edge neuron coincidentally.
The details of a process of emerging synchronous firing is as bellows:
(1) When input image is given to the receptive field, the corresponding edge neurons are stimulated, and begin to fire with a peculiar frequency and amplitude. Local neighbor neurons link to each other by inhibitory or excitatory connections. Due to the link, the edge layer neurons prefer to detect a smooth line.
(2) Once a moderate quantity of spikes stimulates the feature linking neuron within sufficient timing, the feature linking neuron promptly feedback the responses to the coincident detector neurons. Since the coincident detector neuron amplifies the synchronous stimuli loop over two layers, a neuron which represent the feature but is not stimulated frequently is also excited gradually, thus a neuron group is bound by synchronous firing.
(3) Since each Feature linking neuron exclusively fires, besides the edge layer neuron fires changeable within short time scale, the collective activity of the synchronous firings has no periodicity. The neuron group frequently alters states, such as weak locking, periodic firing, and no-locking.

4. Simulation results and Conclusions

We trained the feature linking neurons by using Hebbian learning rule. Linking neuron is composed of two neurons. One learned a data set of triangle figures and another learned square figures. The number of all the given training patterns is 40. A simulation result is shown in Fig.4. In this experiment, the given input image(Fig.4.I) contains overlapped a square and a triangle. Fig.4.II is a few selected states of firing edge neurons and Fig.4.III is time course of spike event. They show that the activities of two linking neurons were independent (precisely saying, they have a negative correlation due to the mutual inhibitory connection as shown in Fig.4.IV(b).) and that the linking neuron was binding features and was forming a group within a short-range time scale. Thus, the edge neuron corresponding triangle or square recurred to the states of bound and disbanded as shown in Fg.II.

Fig.4.IV(a) shows auto-correlograms of the square linking neuron and the triangle linking neuron respectively. The time range for computing auto-correlogram is between 0 and 2500 time step, which is equivalent to about 1.2 sec real time. One can observe that the strength of the auto-correlation rapidly diminishes as with shifting from the peak of correlation. This means that the collective activity of feature linking group is neither periodically nor alternately. This result agrees with Abeles' experimental report which supports that the strength of auto-correlation of neural action in the cortex of behaving animal diminishes rapidly after 2-3 cycles.

Fig. 5 shows the effectiveness of the feedback connection. Without feedback connection, Edge neurons cannot reach coherent state.
Despite the simplicity of feedback connection, the

model showed that it can interpret simple figures by neural coherence activity and that two temporally linking groups can overlap in the same receptive field firing with random frequencies.

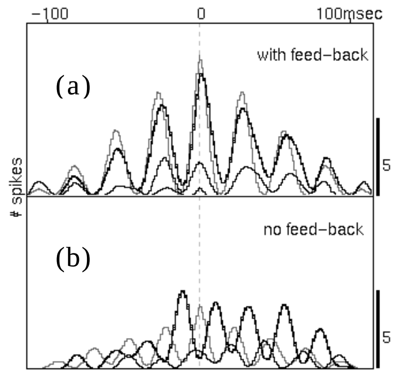

Fig. 5 Cross-correlogram. We chose several active neurons from edge neurons and computed the cross-correlation among them. Omitting feedback connections of neuron in (b). (a) shows the steady coherence but did not any in (b).

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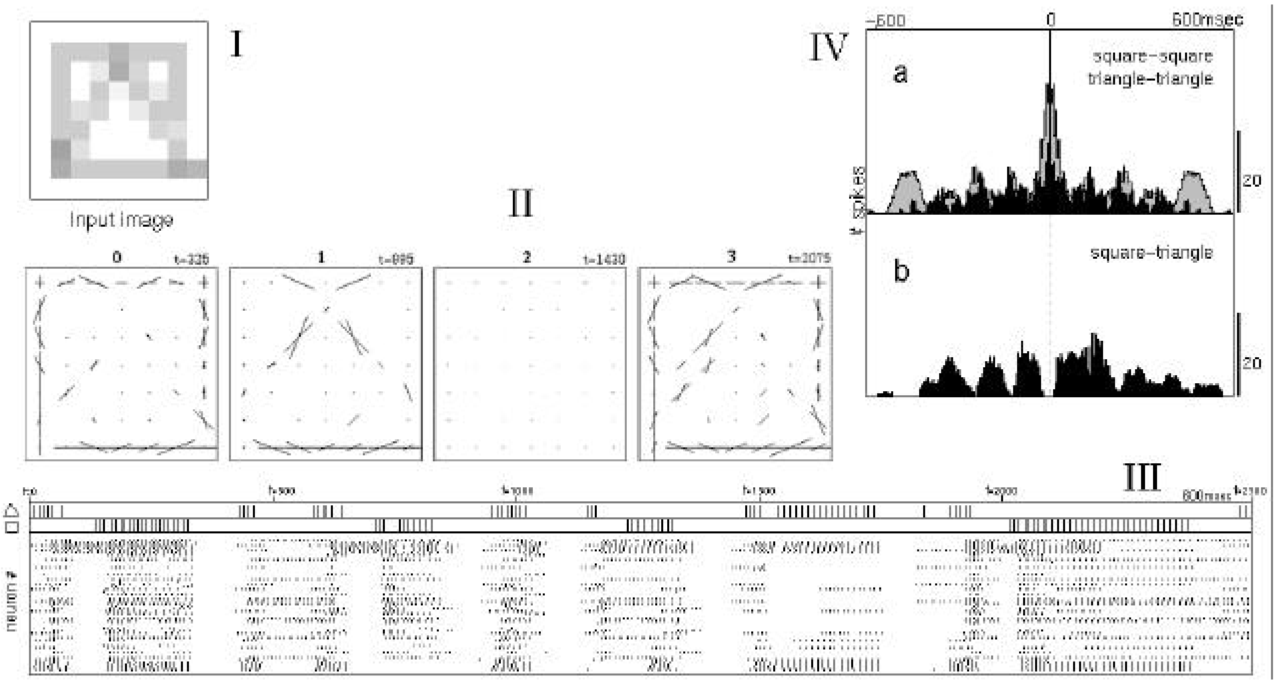

Fig. 4 Simulation result. (I) Input image. (II) The states of edge layer. This lock-in state neuron group show variety: square shape(0), triangle(1), none(2), and overlap of two(3). (III) Time course of firing pattern t=0-2500. First and second row is linking neuron. (IV)(a) Auto-correlogram computed for the square linking neuron (filled gray bar) and triangle linking neuron (black) in the range of t=0-2500. (b) Cross-correlogram of triangle neuron versus square neuron. It exhibits negative correlation.