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2D co-ordinate transformation based on a spike timing-dependent plasticity learning mechanism

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ABSTRACT

In order to plan accurate motor actions, the brain needs to build an integrated spatial representation associated with visual stimuli and haptic stimuli. Since visual stimuli are represented in retina-centered co-ordinates and haptic stimuli are represented in body-centered co-ordinates, co-ordinate transformations must occur between the retina-centered co-ordinates and body-centered co-ordinates. A spiking neural network (SNN) model, which is trained with spike-timing-dependent-plasticity (STDP), is proposed to perform a 2D co-ordinate transformation of the polar representation of an arm position to a Cartesian representation, to create a virtual image map of a haptic input. Through the visual pathway, a position signal corresponding to the haptic input is used to train the SNN with STDP synapses such that after learning the SNN can perform the co-ordinate transformation to generate a representation of the haptic input with the same co-ordinates as a visual image. The model can be applied to explain co-ordinate transformation in spiking neuron based systems. The principle can be used in artificial intelligent systems to process complex co-ordinate transformations represented by biological stimuli.

1. Introduction

The brain receives multiple sensory data from the surrounding environments where the different senses do not operate independently, but there are strong links between modalities (Taylor-Clarke, Kennett, & Haggard, 2004). Electrophysiological studies have shown that the somatosensory cortex (SI) neurons in monkeys respond not only to touch stimulus but also to other modalities. Strong links between vision and touch have been found in behavioural (Spence, Pavani, & Driver, 2000) and electrophysiological (Eimer & Driver, 2000) studies, and at the level of single neurons (Graziano & Gross, 1994). For example, neurons in the somatosensory cortex (SI) may respond to visual stimuli (Zhou & Fuster, 2000) and other modalities (Meftah, Shenasa, & Chapman, 2002). Neurons in a monkey's primary SI may fire both in response to a tactile stimulus and also in response to a visual stimulus (Zhou & Fuster, 2000).

A new interaction between vision and touch in human perception is proposed in Kennett, Taylor-Clarke, and Haggard (2001). These perceptions may particularly interact during fine manipulation tasks using the fingers under visual and sensory control (Johansson & Westling, 1987). Different sensors convey spatial information to the brain with different spatial coordinate frames. In order to plan accurate motor actions, the brain needs to build an integrated spatial representation. Therefore, cross-modal sensory integration and sensory-motor coordinate transformations must occur (Galati, Committeri, Sanes, & Pizzamiglio, 2001). Multimodal neurons using non-retinal body-centred reference frames are found in the posterior parietal and frontal cortices of monkeys (Colby & Goldberg, 1999; Gross & Graziano, 1995; Rizzolatti, Fogassi, & Gallese, 1997). Basis function networks with multidimensional attractors (Deneve, Latham, & Pouget, 2001) are proposed to simulate the cue integration and co-ordinate transformation properties that are observed in several multimodal cortical areas. Adaptive regulation of synaptic strengths within SI could explain modulation of touch by both vision (Taylor-Clarke, Kennett, & Haggard, 2002) and attention (Iriki, Tanaka, & Iwamura, 1996). Learned associations between visual and tactile stimuli may influence bimodal neurons.

Based on these concepts, a spiking neural network (SNN) model is proposed to perform the co-ordinate transformation required to convert a time-coded haptic input to a space-coded visual image. The SNN model contains STDP synapses from haptic intermediate neurons to the bimodal neurons. This paper is organized as follows. In Section 2, the SNN model is presented. The spiking neuron model and the STDP implementation is described in Section 3. The training approach is described in Section 4. After training, the strength of synapses between haptic intermediate neurons and bimodal neurons is obtained. A simplified model is provided in this paper to demonstrate that neural networks

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based on integrate-and-fire neurons with STDP are capable of performing 2D co-ordinate transformation. Finally, the implication for a biological system and applications in artificial intelligent systems are discussed in Section 5.

2. Task of 2D co-ordinate transformation

As illustrated in Fig. 1, a point on the touch area can be represented by arm angles or firing rates of X and Y neurons. The co-ordinates X and Y correspond to a pixel on the retina. This pixel is represented in retina-centered co-ordinates. Using the attention function, the brain can focus on the point (X, Y). If one uses the finger of the right hand to touch the point (X, Y) on Fig. 1, the associated haptic stimuli are transferred to the brain through the somatosensory pathway. These stimuli mainly include the information encoding the angles of arms. Suppose that the length of the arms is represented by L, and the angles are represented by Φ and θ. The co-ordinate transformation is given in the following expressions.

$$X = L[\cos(\theta) + \cos(\theta + \Phi)] \quad (1)$$

$$Y = L[\sin(\theta) + \sin(\theta + \Phi)]. \quad (2)$$

Mathematically, this is a very simple transformation. However, information in the brain is communicated via spike trains in various encoding schemes. A basic encoding scheme is a spatial encoding scheme such as spike trains from the retina neuron array. Suppose that co-ordinates X and Y are represented by a one-dimensional neuron layers where the number of neurons determine the resolution of the retina image (in this example 80 neurons are employed for each axis). The relationship between arm angles and the retina-centered co-ordinate neuron layers is shown in Fig. 1. For simplicity, assume that the retina image is an ideal geometrical image and then the retina-centred co-ordinate can be regarded as the Cartesian co-ordinates. The origins (reference points) of the Cartesian co-ordinates and the polar co-ordinates are set at the same point. Since a stimulus is represented by a bell-shaped distribution, the length of arms is set to correspond to 36 neurons. When the center of a stimulus is located at the ends of the neuron layers for example at neuron 76 or neuron 4, there are 4 neurons that can respond to the bell-shaped stimulus. As the length of two arms corresponds to 36 neurons, the circle with $R = 36$ shows the corresponding area that can be touched by the arms. The centre of the circle is at Xneuron 40 and Yneuron 40.

Suppose that angles θ and Φ are also represented by 1D layers of neurons and the number of neurons are set to 40 in these experiments. The task of the co-ordinate transformation is shown in Fig. 2. The inputs are represented by a bell-shaped distribution of Poisson spike trains for biological plausibility. For example, the stimuli for θ and Φ are illustrated in the top row in Fig. 2. The neuron with maximal firing rate corresponds to arm angles θ and Φ respectively. The key part of the SNN is the intermediate layer. This is a 2D neuron layer that receives signals from the θ and Φ neuron layers and provides outputs to output layers X and Y. Consider that the connections are STDP synapses and there are training signals injected into the output layers X and Y as shown in Fig. 2, such that it is possible to train the network to perform the co-ordinate transformation. During the training phase the mathematical results of Eqs. (1) and (2) are used as a training signal when the corresponding inputs are available.

3. Receptive fields in the SNN model

In a biological spiking neural network, neurons are usually connected to a specific neuron group, which is called a receptive field. In the proposed SNN model, different receptive fields are

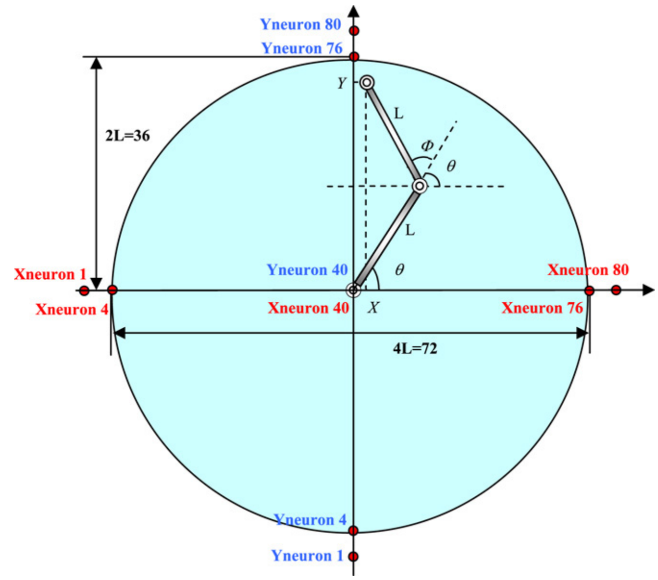

Fig. 1. Relationship between arm angles and retina-centered co-ordinate neurons.

represented in Fig. 3. Suppose that the X, Y neuron layers are bimodal neuron layers. Each neuron in these layers has a receptive field from the intermediate neuron layer, and also has a receptive field from training neuron layer as shown in Fig. 3. Initially, each neuron in the X, Y neuron layers is fully connected to the intermediate layer with a random strength. When θ and Φ stimuli and training signals are presented the network, the connection strength adapts to the input stimuli and training signals using the STDP rule. The weights connecting the training layer to X and Y layers are however set to a constant value within a restricted receptive field. In these experiments, the receptive field is set to 3 neurons. The connections from the θ and Φ input layers to the intermediate layer are also set to a fixed strength within the receptive fields shown in Fig. 3. Each neuron in a θ neuron layer is connected to the field x-RF by excitatory synapses, and connected to the outside of the x-RF field by inhibitory synapses. By analogy, each neuron in Φ neuron layer is connected to the field y-RF by excitatory synapses, and connected to outside of the y-RF field by inhibitory synapses. Therefore, the neurons within the cross-area of x-RF and y-RF will be activated by the spike train from both θ and Φ layers at same time. The other neurons will be inhibited by the inhibitory synapses. These neuron activities and the training signals are then used to train the synapses between the intermediate layer and X, Y neuron layers using the STDP rule.

4. Spiking neuron model and STDP implementation

The inspiration for this work is drawn from biology and the realization that spiking neurons represent the real neurons in the brain and STDP is a property found in real synapses. We have been trying to use these essential units and the properties to construct neural network model in neuronal circuit level, and investigate the learning mechanism of the network. For example, the spiking neurons are used to generate pre- and postsynaptic spikes in a precise time, and the STDP learning rule is implemented in the network to demonstrate a dynamic property. Each synapse follows an STDP learning rule to deal with each pair of spikes rather than a measure of average spike or firing rate.

4.1. Integrate-and-fire neuron model

The integrate-and-fire model is used for each neuron in the SNN. In a conductance based integrate-and-fire model, the