Adaptive Co-ordinate Transformation Based on a Spike Timing-Dependent Plasticity Learning Paradigm

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Abstract. A spiking neural network (SNN) model trained with spiking-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 in order to create a virtual image map of a haptic input. The position of the haptic input is used to train the SNN using STDP 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. This principle can be applied to complex co-ordinate transformations in artificial intelligent systems to process biological stimuli.

1 Introduction

The brain receives multiple sensory data from environments where the different senses do not operate independently, but there are strong links between modalities [1]. 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 [2] and electrophysiological [3] studies, and at the level of single neurons [4]. For example, neurons in the somatosensory cortex (SI) may respond to visual stimuli [5] and other modalities [6]. Neurons in monkey primary SI may fire both in response to a tactile stimulus and also in response to a visual stimulus [5].

A new interaction between vision and touch in human perception is proposed in [7]. These perceptions may particularly interact during fine manipulation tasks using the fingers under visual and sensory control [8]. 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 [9]. Multimodal neurons using non-retinal bodycentred reference frames are found in the posterior parietal and frontal cortices of monkeys [10-12]. Basis function networks with multidimensional attractors [13] 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

L. Wang, K. Chen, and Y.S. Ong (Eds.): ICNC 2005, LNCS 3610, pp. 420 – 428, 2005.

SI could explain modulation of touch by both vision [14] and attention [15]. 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. In Section 2, the SNN model is presented. The spiking neuron model and 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 based on integrate-and-fire neurons with STDP are capable of performing 2D co-ordinate transformation. The implication for a biological system and applications in artificial intelligent systems are discussed in Section 5.

2 Spiking Neural Network Model for Co-ordinate Transformation

In order to simulate location related neurons in the somatosensory cortex (SI), suppose that x' and y' are single layers of bimodal neurons that represent the Cartesian co-ordinates of the output. A point (X, Y) at the touch area can provide both visual and haptic stimuli that reach x' and y' bimodal neuron layers through a visual pathway and a haptic pathway respectively. Fig.1 shows a simplified SNN model for building associations between visual and haptic stimuli. When a finger touches a point in the touch area, visual attention focuses on the point and the retinal neurons corresponding to this point are activated. These neurons provide the training stimulus to x' and y' bimodal neuron layers through the visual pathway. When the finger touches the point, the arms activate the corresponding neurons in θ and Φ neuron layers. These stimuli are fed into haptic pathway. Actually, θ and Φ are based on bodycentred co-ordinates, which are polar co-ordinates. The neurons in θ and Φ layers transfer haptic location signals to the intermediate layer, and then this intermediate layer transfers the bodycentred co-ordinate to the integrated co-ordinate x' and y' neuron layers. In the SNN model, x' and y' bimodal neurons have a receptive field corresponding to the vertical and horizontal lines on the retinal neuron layer respectively, and receive haptic stimuli from all the intermediate neurons through STDP synapses. These STDP synapses make it possible to learn and transform bodycentred co-ordinate (θ, Φ) to co-ordinate (x', y'). The co-ordinate (x', y') can be regarded as integrated co-ordinates in the brain. For simplicity, the synapse strength from retinal neuron layer to (x', y') neurons is fixed. Under this situation, co-ordinate (x', y') is actually the retina-centred co-ordinate. The transformation is equivalent to transformation from a haptic bodycentred co-ordinate to a retina-centred co-ordinate. Each neuron in the θ and Φ layers is connected to an intermediate layer within a vertical field and a horizontal field with fixed synapse strength respectively, as shown in Fig.1.

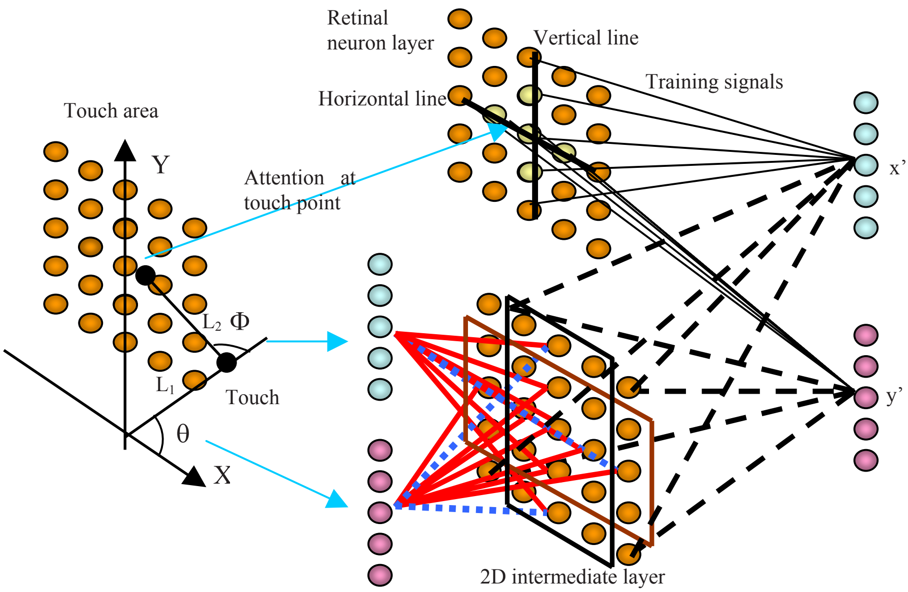


Fig. 1. A SNN model for 2D co-ordinate transformation. (X,Y) is co-ordinate for touch area. (a) Visual pathway: the retinal neuron layer is represented by 2D layer with 40X40 neurons that are connected to x' and y' neuron layer with a fixed weights. (b) Haptic pathway: L1 and L2 are arms. θ and Φ are arm angles represented by a 1D neuron layer respectively. Each θ neuron is connected to the neurons within a corresponding vertical rectangle in the 2D intermediate layer. Each Φ neuron is connected to the neurons within a corresponding horizontal rectangle in the 2D intermediate layer. The neurons in the intermediate layer are fully connected to the x' and y' neuron layers with STDP synapses. These connections are adapted in response to the attention visual stimulus and haptic stimulus under STDP rules.

3 Spiking Neuron Model and STDP Implementation

3.1 Integrate-and-Fire Neuron Model

The integrate-and-fire model is applied to each neuron in the SNN. In a conductance based integrate-and-fire model, the membrane potential $v(t)$ is governed by the following equations [16], [17], [18], [19].

$$c_m \frac{dv(t)}{dt} = g_l(E_l - v(t)) + \sum_j \frac{w^j g_s^j(t)}{A_s}(E_s - v(t)) \tag{1}$$

where c_m is the specific membrane capacitance, E_l is the membrane reversal potential, E_s is the reversal potential ($s \in \{i,e\}$, i and e indicate inhibitory and excitatory synapses respectively), w^j is a weight for synapse j, and A_s is the membrane surface area connected to a synapse. If the membrane potential v exceeds the threshold voltage, v_{th}, v

is reset to v_{reset} for a time τ_{ref} and an action potential event is generated. Fig. 2 shows that a neuron receives spike trains from three afferent neurons.

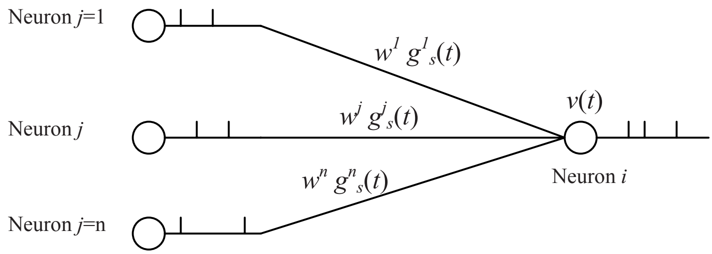


Fig. 2. Conductance based synapses connections in a SNN

The valuable $g^j_s(t)$ is the conductance of synapse j. When an action potential reaches the synapse at t_{ap}, the conductance is increased by the following expression.

$$g_s^j(t_{ap}+t_{delay}^j+dt)=g_s^j(t_{ap}+t_{delay}^j)+q_s \tag{2}$$

Otherwise, the conductance decays as illustrated in the following equation.

$$\frac{g_s^j(t)}{dt}=-\frac{1}{\tau_s}g_s^j(t) \tag{3}$$

where q_s is the peak conductance. Neuron i integrates the currents from afferent synapses and increases the membrane potential according to Equation (1). In our simulation, the parameters are set as follows. t^j_{delay}=0. v_{th} =-54 mv. v_{reset} =-70 mv. Ee= 0 mv. Ei=-75 mv. q_{e_max}=0.01 µs. q_{i_max}=0.01 µs. q_e=0.002 µs. q_i=0.002 µs. El=-70 mv. g_l =1.0 µs/mm^2. c_m=10 nF/mm^2. τ_e=3 ms. τ_i=10 ms. A_e=0.028953 mm^2. A_i=0.014103 mm^2.

3.2 STDP Implementation Approach

In order to perform STDP learning in the SNN, the implementation approach in [20],[21] is applied. Each synapse in an SNN is characterized by a peak conductance q_s (the peak value of the synaptic conductance following a single presynaptic action potential) that is constrained to lie between 0 and a maximum value q_{s_max}. Every pair of pre- and postsynaptic spikes can potentially modify the value of q_s, and the changes due to each spike pair are continually summed to determine how q_s changes over time. The simplifying assumption is that the modifications produced by individual spike pairs combine linearly.

A presynaptic spike occurring at time t_{pre} and a postsynaptic spike at time t_{post} modify the corresponding synaptic conductance by

$$q_s \rightarrow q_s + q_{s\_max} F(\Delta t) \tag{4}$$

where $\Delta t = t_{post} - t_{pre}$ and

$$F(\Delta t) = \begin{cases} A_+ \exp(\Delta t / \tau_+), & if \quad \Delta t > 0 \\ -A_- \exp(\Delta t / \tau_-), & if \quad \Delta t \le 0 \end{cases} \tag{5}$$

The time constants τ_+ and τ_- determine the ranges of pre- to postsynaptic spike intervals over which synaptic strengthening and weakening are significant, and A_+ and $A\_$ determine the maximum amount of synaptic modification in each case. The experimental results indicate a value of τ_+ in the range of tens of milliseconds (about 20 ms). The parameters for STDP are set as follows.

$$q_{s\_max} = 0.01, \ A_+ = 0.01, \ A_- = 0.005, \ \tau_+ = 20 \text{ ms}, \ \tau_- = 100 \text{ ms}.$$

The function $F(\Delta t)$ for synaptic modification is shown in. Fig. 3.

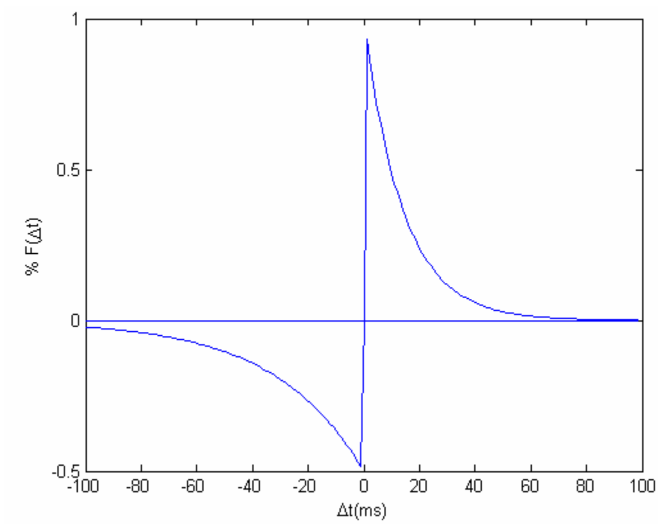
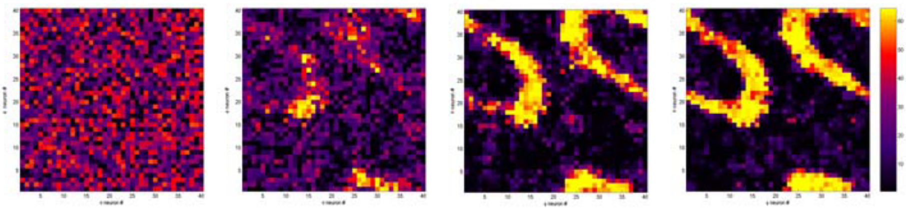


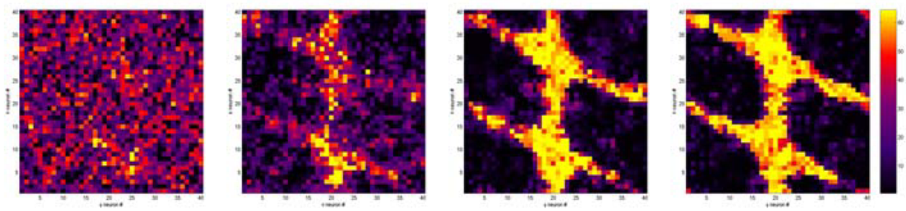
Fig. 3. Synaptic modification

4 Learning and Simulation Results

This network can be trained using an unsupervised approach. When a finger touches a point in the touch area, the haptic stimulus triggers (θ, Φ) stimuli that are fed into the haptic pathway. At the same time, the visual attention focuses on the tip of the finger and this position signal is transferred to (x', y') neuron layer through the visual pathway. The STDP synapses between intermediate layer and (x', y') neuron layer are trained under STDP rules. The finger randomly touches different points for a Poisson distribution period with a mean of 20ms. The STDP synapses from the intermediate layer to (x’, y’) neurons can adapt synapse strength in response to the stimulus and form a weight distribution for association between haptic and visual training stimuli. By repeating the finger touching within the whole touch area randomly, the weight distribution is adapted in response to the haptic and visual stimuli and reaches a stable state after 800s training time. The weight distribution is shown in Fig. 4. The stimuli are represented by Poissonian spike trains whose firing rate is drawn from a Gaussian distribution. The centre of the stimulus corresponds to the finger position within the touch area.



A. Weight distribution of STDP synapse from intermediate layer neurons to y’-Neuron 29.



B. Weight distribution of STDP synapse from intermediate layer neurons to y’-Neuron 40.

Fig. 4. Change of weight distribution during STDP learning. During the learning process, the weight distribution is recorded each 100s time interval. The distributions at moment 0, 100, 400, and 800s are shown in row A for y’-neuron 29 and row B for y’-neuron 40. Colour yellow indicates maximal weights.

In our experiments, 40 neurons are employed to encode θ and Φ layers respectively. 1600 neurons are applied to the 2D intermediate layer and training layer respectively. 80 neurons are applied to x’ and y’ layers respectively. After training, (x’, y’) neurons can respond to both visual and haptic stimuli. When the visual pathway is blocked, (x’, y’) neurons respond only to haptic stimulus at the correct position, i.e. (θ, Φ) layers and the intermediate layer can perform a co-ordinate transformation from the bodycentred co-ordinate (θ, Φ) to co-ordinate (x’, y’). If two Poisson procedure spike trains with bell-shaped distributions are fed into the (θ, Φ) layers respectively, the responses of (x’, y’) neurons, representing the result of the co-ordinate transformation, are shown in Fig.5.

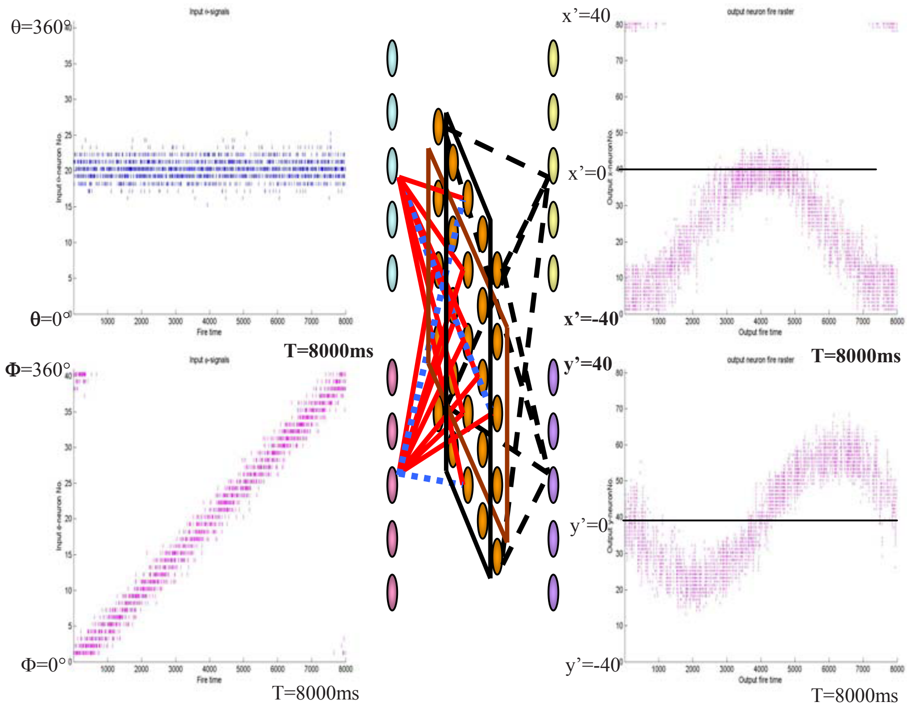


Fig. 5. Co-ordinate transformation from bodycentred co-ordinate (θ, Φ) to co-ordinate (x', y'). One Poisson spike train stays at θ = 180° for 8000ms. Another Poisson spike train stays for 200ms in sequent positions at Φ=0°, 9°, 18° , …360°. The changes of (θ, Φ) correspond to the finger moving along a circle with radius *L*. The output x' = L (Sin(θ) – Cos(Φ)), y'=L(Cos(θ) + Sin(Φ)).

5 Conclusion

In the presented SNN model, the network is trained by the arm angles of the haptic stimuli position fed to the input layer, and a position signal, which is regarded as a supervising signal, fed to the output layer via the visual pathway. The strength of the synapses between the intermediate layer and output layer is trained under the STDP learning paradigm. A firing rate encoding scheme is applied in the network. The input stimulus is represented by Poissonian spike trains whose rates are drawn from a two-dimensional Gaussian distribution at the input layer and a one-dimensional Gaussian distribution at the output layer. The conceived network is able to perform a 2D coordinate transformation by learning the Cartesian coordinates (x, y) from the angular positions of the haptic stimulus. The network is more robust and provides better noise immunity than classical neural networks as even if some of the neurons do not work, the network can still perform the transformation function. The model can provide a biologically plausible approach for designing artificial intelligent systems.

Acknowledgement

The authors gratefully acknowledge the valuable discussions on 1D co-ordinate transformation model with Dr. Andrew Davison and Dr. Yves Frégnac from UNIC (Unité de Neurosciences Intégratives et Computationnelles, Centre National de la Recherche Scientifique, France). The authors also acknowledge the financial and technical contribution of the SenseMaker project (IST-2001-34712), which is funded by the EC under the FET life like perception initiative.

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