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MOTION LEARNING USING SPATIO-TEMPORAL NEURAL NETWORK

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ABSTRACT

Motion trajectory prediction is one of the key areas in behaviour and surveillance studies. Many related successful applications have been reported in the literature. However, most of the studies are based on sigmoidal neural networks in which some dynamic properties of the data are overlooked due to the absence of spatio-temporal encoding functionalities. Even though some sequential (motion) learning studies have been proposed using spatio-temporal neural networks, as in those sigmoidal neural networks, the approach used is mainly supervised learning. In such learning, it requires a target signal, in which this is not always available in some applications. For this study, motion learning using spatio-temporal neural network is proposed. The learning is based on reward-modulated spike-timing-dependent plasticity (STDP), whereby the learning weight adjustment provided by the standard STDP is modulated by the reinforcement. The implementation of reinforcement approach for motion trajectory can be regarded as a major contribution of this study. In this study, learning is implemented on a reward basis without the need for learning targets. The algorithm has shown good potential in learning motion trajectory particularly in noisy and dynamic settings. Furthermore, the learning uses generic neural network architecture, which makes learning adaptable for many applications.

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INTRODUCTION

Tracking objects or people is fundamental and essential in predicting the patterns of trajectory motion for behaviour modelling and surveillance. A number of studies have been reported on tracking human motion detection (Kratz & Nishino, 2012), prediction of lane trajectories (Tomar, Verma, & Tomar, 2010), ship trajectory (Xu, Liu, & Yang, 2011), movement of mobile users in cellular communication systems (Bhattacharya & Bhattacharya, 2011; Monreale, Pinelli, Trasarti, & Giannoti, 2009), and tourist movements (Xia, Zeephongsekul, & Packer, 2010). In most of the motion prediction applications, sigmoidal neural network (NN) with backpropagation (BP) was used to learn behavioural motion patterns.

A BP neural network (Rumelhart, Hinton, & Williams, 1986) consists of a set of connected neurons linked in a feedforward manner. There are basically three minimal layers namely input, hidden, and output layers. Depending on the problem complexity, a network can have more than one hidden layer. Learning is implemented via presenting a network with a set of input values and a target class (i.e. supervised learning), then the algorithm updates the weight strength between neurons based on the deviation between the presently produced output and desired output. The activity of a neuron is dependent on the activation function that computes the total weighted input signal based on a threshold value. A neuron will be activated if its activity passes the threshold; otherwise it will be deactivated.

The backpropagation neural network (BPNN) model is known as a sigmoidal neural net. Even though the sigmoidal NN models have been successfully used to solve problems in a number of tasks including motion classifications, the plausibility of these models with respect to biological neuron properties is minimal with several drawbacks. Furthermore, the complexity of a learning computation grows when learning with complex data (e.g. with spatio-temporal features) due to lack of functionalities for temporal coding. Hence, to overcome the problem in learning time-embedded data and with growing evidence on the importance of timing in neural activity from the neuroscience field, the field of NN has evolved to a third generation of NN.

Spatio-temporal neural networks or Spiking Neural Networks (SNNs) are the third generation of NN models. In comparison to sigmoidal neural network models, SNNs imitate more closely the biological neuron properties, have faster computation and are efficient for spatial temporal processing (Thorpe, Delorme, & Van Rullen, 2001; Van Rullen, Guyonneau, & Thorpe, 2005). In neuron communication, within a certain time interval, signals in the form of a spike pulse are propagated in the neuronal workspace. Thus, by exploiting the spiking behaviour as the core element of the model, SNN models simulate more closely the biological neural system. On the other hand, the computational complexity in the previous models that required a mass number of hidden units could be simplified with a single spiking neuron function. Hence, a small number of McCulloch-Pitts neural networks can also be computed by a small SNN (Maass, 1997). The dynamics of a neuronal circuit consisting of spiking neurons with spatio-temporal distribution of spikes have been of interest in most of the recent Artificial Neural Networks (ANN) models. Due to its powerful and realistic computational properties, SNN offers a range of applications including olfactory system (Ambard, Guo, Martinez, & Bermak, 2008), visual recognition (Hassanien, Abraham, & Grosan, 2009), speech processing (Glackin, McGinnity, Maguire & McDaid, 2010), robotics (Yanduo & Kun, 2009), and simulation of biological neural circuits (Brunel & Lavigne, 2009).

MOTION LEARNING IN SPATIO-TEMPORAL NEURAL NETWORK

Many studies of motion learning from the literature, have reported the use of neural network with backpropagation learning algorithm. Even though many studies have proven the success of NN with BP to predict motion, the spatial and temporal information from the data are treated independently. This could overlook some dynamic properties of the data due to the absence of spatio-temporal encoding functionalities in the sigmoidal neural net.

Realising the need for learning complex data on motion learning, many recent studies have shifted to spatio-temporal neural network. Some of the recent works on motion learning using spatio-temporal neural network include work by Zhang and Patras (2017). They proposed a deep spatio-temporal neural network (D-STN) to forecast long-term mobile traffic. From the experiments conducted with publicly available 60-day long traffic measurements collected in the city of Milan and the Trentino region, it demonstrated that the proposed D-STN provided up to 61% lower prediction errors as compared to the widely employed Autoregressive Integrated Moving Average (ARIMA) methods. Similarly, Paulun, Wendt, and Kasabov (2018) proposed using NeuCube for accurate recognition of moving objects. NeuCube convoluted a series of spikes and formed them into a brain-like spiking neural network. It integrated deep unsupervised learning, classification tasks and dynamic visual recognition. The method was successfully tested on the benchmark data with 92.90% classification accuracy. Furthermore, Yang, Wu, Huang, and Luo (2018) proposed a spiking neural network to classify human motion type via skeleton movements. Initially, the real time motion data were encoded into a series of spikes and the type of motion was represented by a spike time. Then for training, they used a two-layered spiking neural network using a gradient descent learning algorithm. The experimental results demonstrated that the proposed method achieved good learning precision and generalization.

In another application, Guo, Lin, Wöhrl, and Liao (2018) studied animal motion behaviour using spatio-temporal neural network based method. They used a spiking neural network to learn the trajectory of body centre for real ants locomotion compared with virtual ants. The findings showed that the simulated gait pattern, including joint trajectories, matched the experimental data collected from real ants walking in free mode. The model could also be beneficial in studying higher level behaviour of insects. In the implementation, a single neuron was used to simulate the neuron group activating the same muscle(s). This at some point overlooked some dynamic properties of spiking neurons and therefore the model was less practical for more complex problems.

In the studies mentioned, a supervised learning algorithm was mainly used to train a particular network to learn motion patterns. In these learning schemes, the aim of learning was to reduce the deviation value between the network output and desired output (learning target). However, the learning target was not always available for some applications and target encoding could become complex.

In this study, we propose a motion learning algorithm in spatio-temporal neural network. The contribution of this study can be attributed to the implementation of motion learning using a reinforcement approach. Unlike the supervised approaches, learning is established through a trial and error basis without the need for learning targets. In our approach, the algorithm is based on a modulated spike-time dependent plasticity (STDP), in which the standard STDP is modified by a reinforcement signal, known as the learning reward or penalty resulting from the network response.

METHODOLOGY

The core aim of this study is to propose a learning algorithm that can learn to bind a set of motion patterns in spatio-temporal manner to its desired network responses. As a case study, a neural network is trained to respond to a set of fish motion patterns. The fish motion data were chosen, as this research was a part of a fundamental research by the Ministry of Higher Education (MOHE) with the main aim of studying fish behaviour that could contribute to the field of remote sensing in developing technology beneficial to the fishery industry. Fish movement behaviour could also provide some indication on water quality. The methodology consisted of three main phases which are described as follows:

Phase 1: Design a Goal-Directed Spatio-Temporal Motion Pattern Learning Scheme

In this initial phase, a spatio-temporal motion pattern learning scheme was outlined at the macro level. The key outcome from this phase was a learning design that described the learning simulation protocols. For a more plausible and realistic learning strategy, the proposed learning scheme was inspired by a popular behavioural learning experiment by Erickson and Desimone (1999).

Phase 2: Encode Stimulus Input, Target Response and Motion Sequence

The purpose of this phase was to encode the neural input and output (response) and define a neural network simulation model and spiking properties. The fish dataset was obtained from fish4knowledge (Beyan & Fisher, 2012) in this study. Fish motion trajectory (*T*) is defined by the coordinates (*x* and *y*) in the fish bounding boxes in Figure 1. The *n* frame of the trajectories of any fish is defined by Equation 1.

$$T_i = \{(x_1, y_1), (x_2, y_2), \ldots (x_n, y_n)\}. \tag{1}$$

where *T* is the motion trajectory at time *i*, *x* and *y* are the coordinates in the fish bounding boxes and *n* is the number of frame.

An example of fish motion data for *Fish 1* and *Fish 2* are shown in Figure 1.

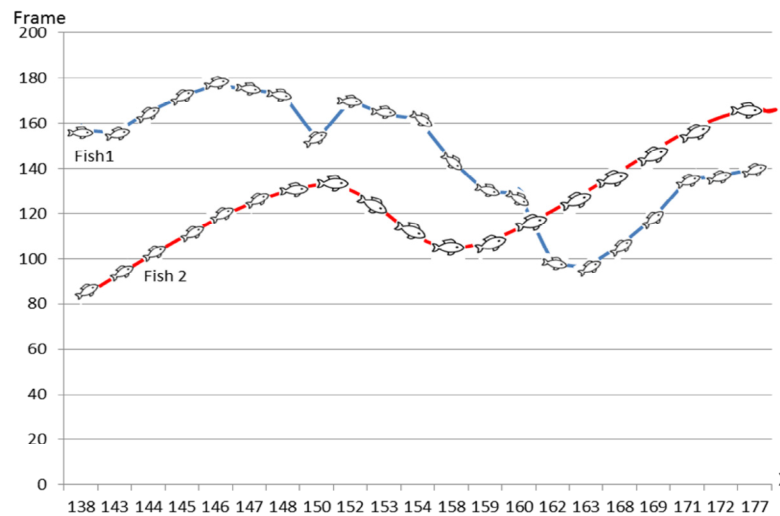

Figure 1. Motion trajectories for Fish 1 and Fish 2.

Phase 3: Develop Goal-Directed Motion Pattern Learning Algorithm via Modulated Spike-Time Dependent Plasticity (STDP)

The purpose of a learning algorithm is to update the strength of connections between neurons (i.e. information nodes) until convergence. The convergence state defines a stable association between input and target output neurons with strong connections. This learning algorithm was an extended version of Izhikevich (2007) for paired-associate learning task. The learning was primarily introduced to strengthen the association of stimulus-response. In our study, we investigated the performance of a modulated STDP for motion trajectory learning with a sequence of points. Moreover, we proposed a new reward policy (as in Table 1) for motion learning in a reinforcement learning paradigm.

From the standard STDP rule, weight changes are based on the variance (Dt) between the postsynaptic neuron (t_{post}) and the presynaptic neuron (t_{pre}) firing time. The firing time is captured from the last spike timing of presynaptic neurons of each fired neuron. The weight is fortified if the postsynaptic neuron fires after its presynaptic and weakened otherwise. The weight change is formulated as in Equation 2:

$$\mathrm{Dw}_{\mathrm{stdp}} = \{\mathrm{A}_{+}\mathrm{e}^{-\mathrm{Dt/t}+}, \mathrm{Dt} \geq 0; \mathrm{A}_{-}\mathrm{e}^{\mathrm{Dt/t}-}, \mathrm{Dt} < 0\} \tag{2}$$

where $Dt = t_{post} - t_{pre}$, parameters t_{+} (t_{-}) is the time constant (in ms), and A_{+} (A_{-}) denotes the highest change, Dw_{stdp}, when Dt is approaching 0.

The standard STDP alone only yields unsupervised learning. Therefore, in this phase, the standard STDP was modified to develop a goal-directed learning approach. For this purpose, we proposed a reward modulated STDP adapted from Izhikevich (2007) as presented by Equation 3.

$$\mathrm{Dw(t)} = [\mathrm{a} + \mathrm{r(t)}]\ \mathrm{z(t)} \tag{3}$$

The weight change Dw depends on a reinforcement signal $r(t)$, obtained from Table 1, and an admissibility trace $z(t)$, where $z_{ij}(t)$ is the STDP weighted sum of weight changes $Dw_{stdp.ij}$ of neuron i (i.e. presynaptic) to neuron j (i.e. postsynaptic). a represents a constant of synaptic weight increase. Hence, the learning supervisory signal will be based on the $r(t)$ value that modulates the $z(t)$. The novelty of our work can be ascribed to a reward policy that derives $r(t)$ (Table 1). The reward policy describes a learning scheme for a neural network in a reinforcement learning paradigm.

As described earlier, the number of fired neurons (spikes) in the response groups indicates a network response. From Table 1, it is assumed that R_A *and* R_B are the network responses in which R_A is the target response. If the number of spikes in the target neuronal response group is twice higher than the opponent neuronal group, a strong reward signal is given to the network. If the number of spikes is just slightly higher, only a weak reward is given to the network. Meanwhile, a negative reward (penalty) is given to the network if the target neuronal response group indicates lower activity with lower spikes than its opponent. The reward signal $r(t)$ could modulate the weight adjustments provided by the standard STDP, *z(t)*, that would eventually influence the weight connections during learning.

In this study, a motion is represented by a sequence of firings that indicates activation of certain spatially distributed neurons in the network. The biologically realistic learning algorithm with simple rules is the one of interest in this study. Furthermore, the algorithm should also be able to learn the association of a stimulus and a motion in a noisy setting with minimal assumptions on the dynamic properties of the network.

Table 1

Reward Policy

No. of spikes in the response group	Reward signal	
$F_A(dt) \geq 2F_B(dt)$	$r(t - 1) + 0.5$	strong +ve reward
$F_A(dt) < F_B(dt) < 2F_A(dt)$	$1 - F_j / F_i$	weak +ve reward
$F_A(dt) < F_B(dt)$	-0.1	-ve reward

Note: Let R_A be the target network response.

LEARNING SIMULATION EXPERIMENT

For learning simulation, fish trajectories were captured from 93 different videos with the specifications of 320x240 resolutions, and 5 frames per second. For this study, the *x* point values were normalised in which a motion point is an average value of *x* from three frames.

Prior to learning, for fish motion encoding, a recurrent spiking network was developed consisting of 1000 neurons with 800 excitatory (N_E) and 200 inhibitory (N_I) neurons. The spiking properties of the neurons followed the Izhikevich spiking model rule (Izhikevich, 2003; 2006). For connectivity, each N_E was connected to 100 neurons randomly. Each N_I was connected to 100 N_E neurons (Figure 2). The transmission time delays between neurons were set randomly from 1 to 20 ms.

Each motion point (S_n) (the input stimulus) was represented by a group of 50 excitatory neurons. For a learning simulation, there were seven stimulus groups ($S_0 – S_6$) to represent seven different points. An example of motion-target (T) set is as follows, $T = \{(S_4,S_2) \rightarrow R_A, (S_1,S_2) \rightarrow R_B, (S_5,S_3) \rightarrow R_A, (S_2,S_1) \rightarrow R_B\}$. The task of the neural network is to learn the association of motion trajectories and their target responses.

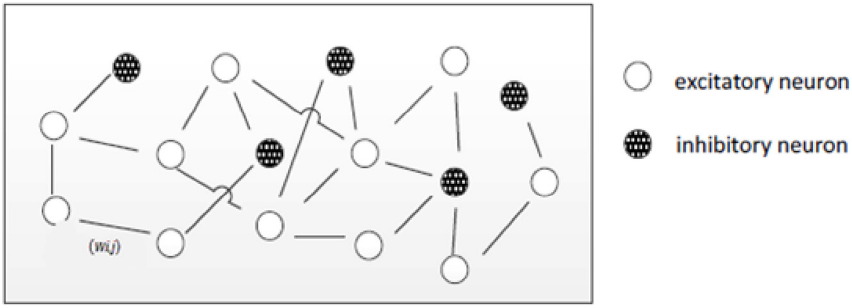

Figure 2. Spiking neural network (N_E = 80%, N_I= 20%).

Each target response (the network response) was represented by a group of 100 excitatory neurons. Each trajectory was associated to a network response. For each simulation, there were two responses namely R_A and R_B, represented by two excitatory neuron groups with 100 neurons each. The remaining excitatory neurons and the inhibitory neurons were known as non-selective neurons. The activity of the neurons contributed to the network dynamics. The inhibitory neurons were also non-selective to any stimulation and only acted as random network inhibition.

The proposed learning scheme was designed as follows:

1. At a particular simulated time, a neural network was presented with the first motion point.
2. Following the first point, the network was then presented with the second point of the motions. The number of motion trajectory points varied depending on the experiment tasks and settings. Each point was separated by 15 ms simulated time. The temporal delay was chosen from our initial experiment on the influence of temporal delays ranging from 10 to 20 ms. It was found that a 15 ms inter-stimulus interval (ISI) was the optimal delay in which the network response was influenced by the interaction between two associated points with no dominant stimulus in both that influence the response.
3. The number of spikes in the response group was then computed within the 20 ms after the onset of the second point. The winning response group was the one with the most active neurons. The network was then rewarded or penalised depending on the response. The learning protocol is depicted in Figure 3.
4. The network was rewarded if the response pointed to the correct match for a presented sequence, e.g. $(S_4, S_2, S_1) \rightarrow A$, of the fish motion trajectory.

5. The learning performance was measured as the average percentage of correct recalls from 10 different simulated networks and probe trials (testing).

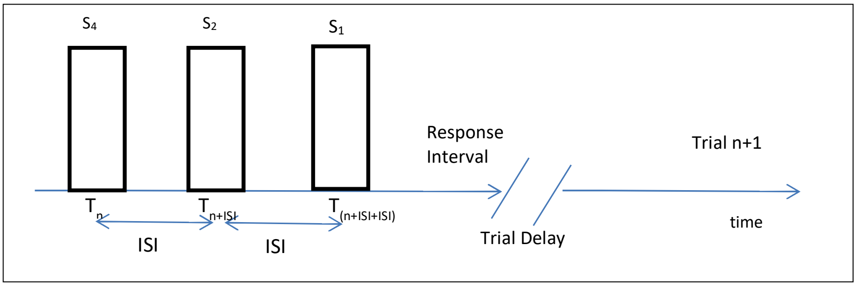

Figure 3. Motion learning protocol for a motion (S_4, S_2, S_1).

RESULTS AND DISCUSSION

The learning simulation experiments were run in C++ and MATLAB programming. The experiments were two-fold, in which the algorithm was tested with motion learning of 2-sequence and 3-sequence trajectory points. The *n*-sequence indicated the ability of network memory that could be trained and how well the network could associate a set of trajectory points of particular motions.

For each learning trial, a motion was selected and presented randomly to the network. The group of neurons representing the first point was initially activated followed by the following points after an inter-stimulus interval. After the last trajectory points, the number of spikes in the response group was then observed to compute the network response.

Motion Learning with 2-Sequence Points

In this section, we trained the network to associate a motion of two points with a target network response, e.g. (S_i, S_j) ® R_k. The network was trained with two conditions namely, motion with no repeating points and motion with repeating points. This was to investigate network confusion when presented with motion accompanied by different combinations of points that might have the same points with conflicting responses.

No repeating points

The aim of this experiment was to train the network with real fish motion trajectory for seq=2 (for no sequence with repeating points) association task.

If the network responded correctly in accordance to the presented fish motion trajectory, the network was rewarded. If the network responded incorrectly, it was penalized accordingly. The learning of seq=2 and the target network response for fish motion are performed using Equation 4.

$$Learning\ set = \{(S_2,S_1) \rightarrow R_A,\ (S_3,S_5) \rightarrow R_B,\ (S_4,S_2) \rightarrow R_A,\ (S_6,S_5) \rightarrow R_B\} \quad (4)$$

where S_i and Sj are the stimuli of neuronal groups i and j, respectively, R_A and R_B are the response groups A and B, respectively.

In the learning set, all pairs consisting of the unique combination of motion points S_n were exclusively trained to respond to R_A or R_B. At this point, the conditions in which $(S_i,S_j) \rightarrow R_A$ and $(S_j,S_i) \rightarrow R_B$ were avoided. This preliminary experiment was just to see how well the network learned the association with minimal confusion.

With the exclusive points in fish motion learning, the network performance was 80.43% and 85.57% for training and testing, respectively. Figure 4 shows the spike raster plot of the network activity during learning after a number of trials. The response neurons activated were significant to their target response from the start to the end of the simulation.

The network model had been trained to perform the fish motion sequence learning with a target response, R_A or R_B. Figure 5 illustrates the learning result for four learning motions $\{(S_2,S_1) \rightarrow A,\ (S_3,S_5) \rightarrow B,\ (S_4,S_2) \rightarrow A,\ (S_6,S_5) \rightarrow B\}$. This is to show that the network could successfully associate all pairs to their target responses.

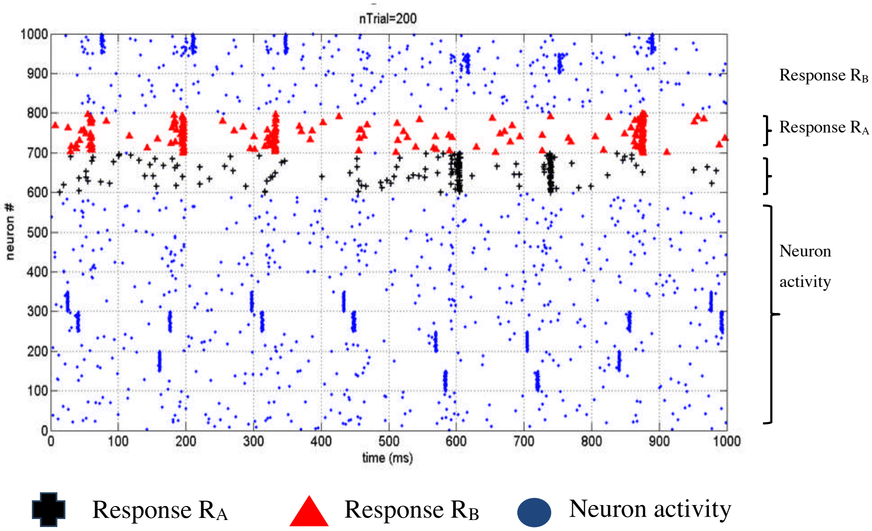

Figure 4. Spike raster plot of network activity during learning after 200 trials for 2- sequence points.

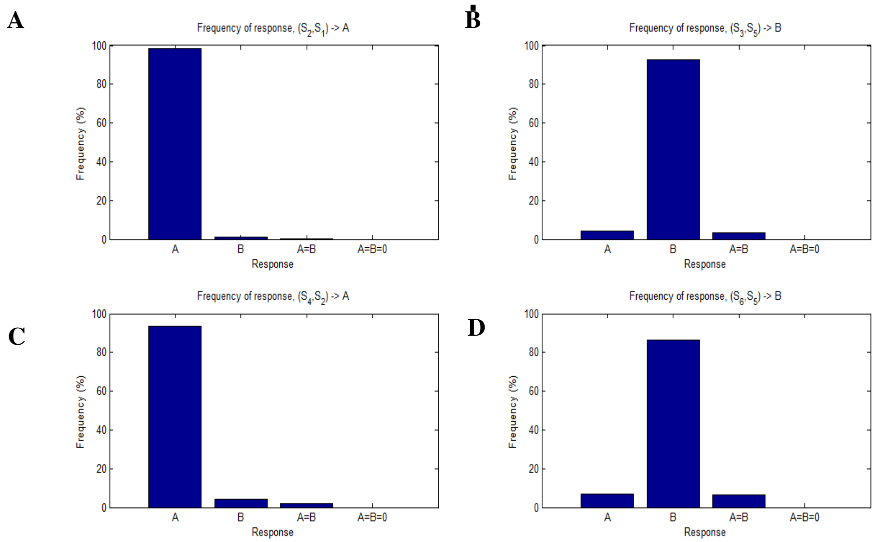

Figure 5. Learning result for four learning motions, $\{(S_2,S_1)\rightarrow R_A$, $(S_3,S_5)\rightarrow R_B$, $(S_4,S_2)\rightarrow R_A$,

$(S_6,S_5)\rightarrow R_B \})$ from one simulation

Learning with repeating points

The network was then trained with a set of fish motion with repeating points. In particular, they were motion consisting of $(S_i,S_j)\rightarrow R_A$ and $(S_j,S_i)\rightarrow R_B$. With such conditions, the network performance was observed if the network could successfully learn not just the association between S_i and S_j but also the sequence of $S_i...S_j$. The learning set was as follows as in Equation 5.

$$Learning\ set = \{(S_4,S_2)\rightarrow R_A,\ (S_1,S_2)\rightarrow R_B,\ (S_5,S_3)\rightarrow R_A,\ (S_2,S_1)\rightarrow R_B\} \quad (5)$$

where S_i and Sj are the stimuli of neuronal groups *i* and *j*, respectively, R_A and R_B are the response groups A and B, respectively.

The average performances (correct recall rates) for 10 different simulated networks were 69.87% and 65.15% for both training and testing, respectively. In comparison to the learning with no repeating points, the network performance decreased. This indicated that high competition or interference existed when the network was probed with motion having conflicting target responses (Figure 6).

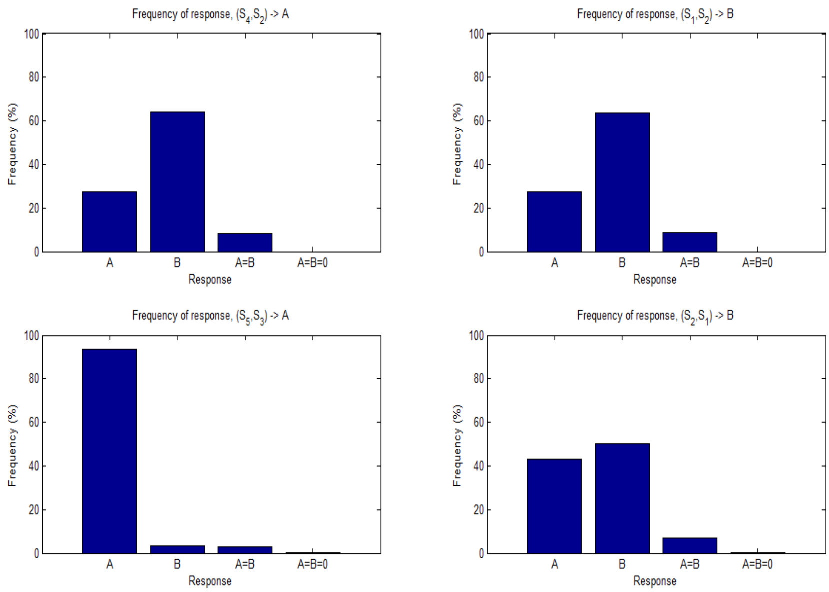

Figure 6. Learning result for four learning motions with repeating, $\{(S_4,S_2)\rightarrow R_A,$

$(S_1,S_2)\rightarrow R_B, (S_5,S_3)\rightarrow R_A, (S_2,S_1)\rightarrow R_B\}$ *from one simulation.*

Motion Learning with 3-Sequence Points

In the previous experiments, we trained the sequence with two points to train a network. The network only associated different stimulus groups with their target response, R_A or R_B. In the following experiments, this study investigated learning performance with three sequence learning. The goal was to train the network to discriminate motion with 3-sequence points using temporal sequence. From this experiment, we investigated the network ability to remember different motion in which each motion consisted of more than two points. The sequence learning for fish motion was performed as in Equation 6.

$$\textit{Learning set} = \{(S_4, S_2, S_1)\rightarrow R_A, (S_1,S_2,S_4)\rightarrow R_B, (S_5,S_3,S_2)\rightarrow R_A, (S_2,S_1,S_0)\rightarrow R_B\} \quad (6)$$

where S_i and Sj are the stimuli of neuronal groups i and j, respectively, R_A and R_B are the response groups A and B, respectively.

The average performances for correct recall rates for 10 different simulated networks were 68.94% and 69.1% for training and testing, respectively. From the experiment, by training the network consisting of motion with repeating points (e.g. $(S_4,S_2,S_1) \rightarrow R_A$ and $(S_1,S_2,S_4) \rightarrow R_B$), there was a positive impact on the performance of the network. Figure 7 illustrates the spike raster plot of network activity during learning after a number of trials.

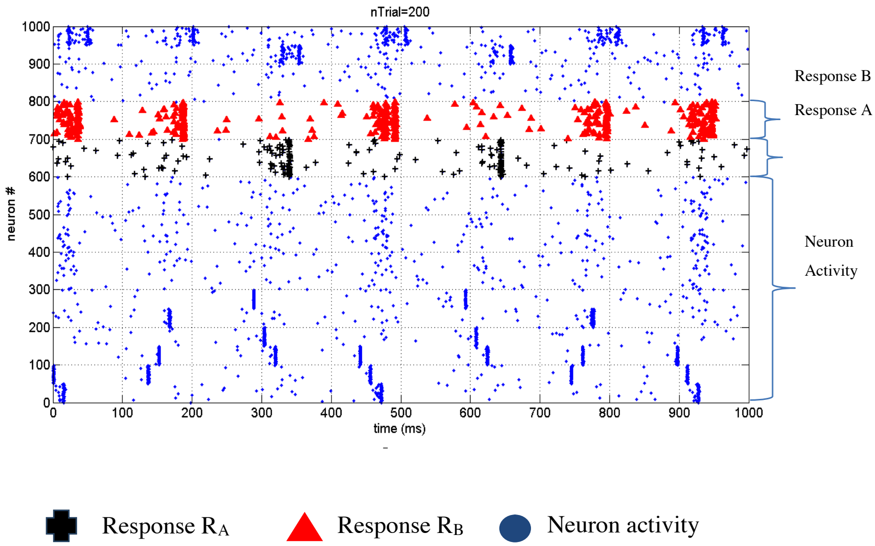

Figure 7. Spike raster plot of network activity during learning after a number of trials for 3- point motion learning

Figure 8 illustrates the four sequence learning for the fish motion trajectory from one simulation. The fair performance was achieved with one motion, namely $(S_4, S_2, {}_{S1}) \rightarrow R_A$, which showed incorrect recalls (Figure 8A) showing the evidence of high competition between $(S_1, S_2, S_4) \rightarrow R_B$.

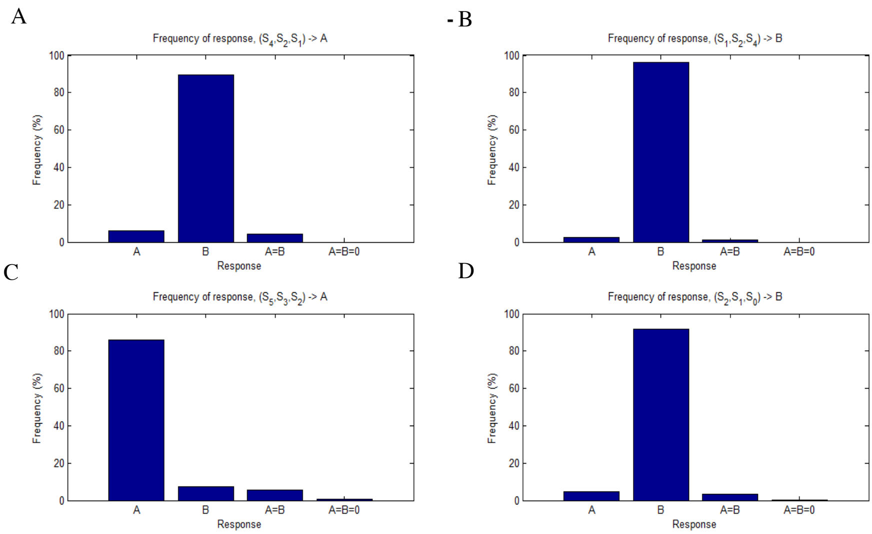

Figure 8. Learning result for four 3-point motion, $\{(S_4,S_{2,}S_1)\rightarrow R_A$, $(S_1,S_{2,}S_4)\rightarrow R_B$,

$(S_5,S_{3,}S_2)\rightarrow R_A$, $(S_2,S_{1,}S_0)\rightarrow R_B$ $\}$ from one simulation.

CONCLUSION

This study proposed motion trajectory learning using the reward modulated STDP in SNNs. Learning was experimented with real fish motion data obtained from fish4knowledge dataset. From the learning simulation experiments, it showed that the algorithm performed well in learning motion with no repeating points, in which there were no same points in a different sequence. In contrast, network confusion arose whenever learning consisted of repeating points. For future improvement, we think that the neural network requires a better network inhibition mechanism. With such a method, it could improve learning performance in a highly competitive environment.

We postulate that there is also a need to incorporate alternative stimulus encoding to increase memory capacity. In our approach, a stimulus was represented by a fixed group of excitatory neurons, and thus posed some limitations to our model for large-scale applications and especially for non-linear classification problems. A solution to this problem could be to implement a network with polychronous groups. Such a model would allow a neuron to be a member of multiple groups with different synaptic transmission delays, hence it could maximise memory capacity.

This study concerns the human learning paradigm (i.e. reward-based learning) and spatio-temporal neural network dynamics, under a framework of motion learning. The key advantages of our learning model can be credited to its biological realism and computational simplicity. In our approach, the network is trained to learn associations between a set of trajectories and their targets via a reinforcement approach that closely resembles human learning. In the proposed learning scheme, no particular learning targets are required. Unlike most related studies in motion learning using spiking neural networks, the widely used approaches are supervisory which require a set of spike trains as the learning targets. This also requires additional encoding to represent the desired network outputs/responses. Moreover, not all systems can easily be provided with such encoded target output.

In addition, from our proposed scheme, learning can be applied in a simple way based on the STDP rule that counts correlation in spike timings, and firing rate. Our model uses a generic architecture of neural networks with minimal assumption about the network dynamics. We have shown that learning can be implemented in a stochastic manner within a noisy setting. The network has rich dynamics resulting from sparse and recurrent connectivity, synaptic transmission delays and background activity.

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