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Fish Motion Encoding in Learning with Spiking Neural Network

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Abstract

In this study, we propose a neural encoding method for fish motion learning using spiking neural network. The network is trained to associate a particular motion to its target response using our initially developed reward-based learning algorithm. For the encoding purposes, we use a recurrent neural network with sparse and random connection consisting of 1000 spiking neurons. Each point in a motion is represented by a group of neurons, in which a sequence of group stimulations forms a motion trajectory. The sequence is associated to a target response, represented by a group of response neurons. For this study, there are two groups of competing response neurons. In each learning trial, the sequence is activated and the network is rewarded or penalised depending on the winning response. The learning follows a simple and natural protocol implemented in a noisy and dynamic setting. Based on the experiment findings, the encoding method of fish motion trajectory seems feasible to be coupled with the reward based learning shown by the sequence recognition performance. Moreover, this is among the pioneer studies that implement motion trajectory learning using spiking neural network in a reward-based paradigm.

Keywords*:* motion trajectory, spiking neural network, fish motion learning, reward-based learning.

1 Introduction

Motion trajectory is a track of moving object that follows through a space over time. Predicting the motion trajectory implies forecasting the moving object to meet the movement data such as time, location, speed, acceleration and position for control, capture or observation purpose (Payeur, Le-Huy, & Gosselin, 1995). Fish motion trajectory analysis has been studied for different solutions, for example anomalous fish trajectories (Beyan & Fisher, 2013; Spmapinato & Palazzo, 2012), water quality(Ma, Tsai, & Liu, 2010), and normal fish trajectories and electric fish (Fujita, 2012). The study of fish behaviour is a fundamental research area in marine biology to understand various environmental effects such as water quality, pollution, climate change and fish behavior (Beyan & Fisher, 2012).

For learning the fish motion patterns, sigmoidal neural network (NN) with Backpropagation (BP) learning algorithm has been a popular technique used in which a set up network is trained with a set of motions in classifying each motion into a particular class of behaviour. Even though, many studies have proven the success of NN with BP in predicting motions, learning the spatial and temporal features of the motions is complex and challenging. This is due to the absence of spatio-temporal encoding functionalities in the sigmoidal neural net. Thus learning requires an additional mechanism that sometimes may involve massive computation.

Realising the needs to learning of complex data, in this study we propose a spiking neural network for fish motion learning. The new class of computational models uses time as a resource for coding information, computationally more powerful than the conventional models. For a complex data learning which requires hundreds of hidden units on a sigmoidal neural net could be computed by a single neuron in an SNN. In comparison to the conventional McCulloch Pitts-based models, SNNs have more advantages for biological reasonable values of its function parameters, and they also boast off fast and efficient computation where the timing of the input signals carries important information (Bi & Poo, 1998; Yu, Tang, Tan, & Yu, 2014). However, information encoding is a major challenge as the tradeoff for its realism. SNN is complex and dynamic depending on the choice of spiking model, network topology, and spike coding. Hence, there are a number of SNN models emerged today with variety of computational complexity and plausibility levels.

For this study, we propose a fish motion encoding and learning using a spiking neural network using real fish motion data obtained from fish4Knowledge (Beyan & Fisher, 2012). The motion trajectories in this dataset are classified into normal and abnormal trajectories. In particular, the spiking neural network is used to learn normal fish trajectories that hold usual behaviour of fish. The contribution of this study can be attributed to the approaches implemented to encode the feature of the spatio-temporal properties of fish motion using firing rate and spike timings and to train the network for sequence learning in a reward-based paradigm.

2 Background

The advent of technology in electrophysiological and neuroimaging studies to delineate activity in brain have allowed better investigations, recordings and simulations of brain activity projecting the structural and functional behaviour of it. Looking closely into the brain, it consists of a large number of neurons. These neurons form connections with each other to compose a network and interact among them by receiving stimuli (input) or triggering actions (output).

The cortical neuronal network is composed of pyramidal cells (80%) and interneurons (20%) (Abeles, 1991) . Each neuron receives excitatory synaptic contacts from pyramidal cells and inhibitory contacts from interneurons. In most parts of the brain, neuron connectivity is found to be sparse e.g., (Capaday et al., 2009; Grillner, Markram, De Schutter, Silberberg, & LeBeau, 2005)Pyramidal cells send connections to other pyramidal cells through AMPA (*α-amino-3-hydroxy-5-methyl-4-isoxazolepropionic acid*) and NMDA (*N-methyl-D-aspartic acid*) synapses. Interneurons send GABAergic (*gamma-aminobutyric acid*) connections to pyramidal cells and other interneurons. AMPA and NMDA receptors play a vital role in the mediation of excitatory synaptic transmissions, meanwhile GABA is the inhibitory neurotransmitter in the brain. These connections send to the network all the information (stimuli) received from the lower levels of the brain, and interactions between cortico-cortical subpopulations. An example of a cortical model as proposed by Brunel and Wang (2001) is shown in Fig. 1.

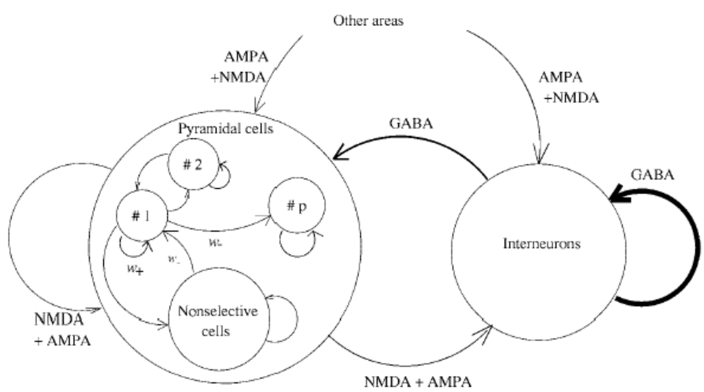

Fig.1: Cortical network model.

Pyramidal cells send connections to other pyramidal cells through AMPA and NMDA synapses. Interneurons send GABAergic connections to pyramidal cells and other interneurons. Both receive excitatory connections from other cortical areas. Pyramidal cells can be functionally divided in several groups according to their selectivity properties, e.g. group #n is selective to object #n, etc., reproduced from (Brunel & Wang, 2001).

Neurons transmit information by emitting sequences of spikes in various temporal patterns. Therefore, in neural encoding, timing of action potentials conveys essential information (e.g., Bi & Poo, 1998; Thorpe, Delorme, & Van Rullen, 2001). Neural encoding involves measuring and characterising how stimulus signals are represented by stereotyped action potentials in mapping the stimulus to a response.

In general, there are two paradigms of coding schemes namely firing rates and temporal codes. Firing rate has been a standard measurement for neural encoding for many years. Firing rate can be viewed in three different notions as follows (Gerstner & Kistler, 2002; Vogels, Rajan, & Abbott, 2005):

a) Rate as a spike count (average over time) – firing rate at time t during a trial is measured by counting all the spikes that occur between times t and $t+\Delta t$, for some interval Δt defined by the experimenter, and dividing this count by Δt. For some sensible averages of spike occurrences, typical values for Δt can be 100 ms or 500 ms.
b) *Rate as spike density (average over trials)* – firing rate is defined as the averaged number of spikes occurring between t and $t+\Delta t$ over multiple trials.
c) *Rate as a population activity (average over several neurons)* – firing rate is the summation of the number of spikes for the whole population, that occur between times t and $t+\Delta t$, for a small value of Δt.

Without also to deny the role of firing rates in neural coding, there is growing evidence from behavioural experiments suggesting that essential information could also be found in the precise timing of spikes. Some studies suggest the significance of spike timing in neural encoding. The concept of temporal coding arises when the precision of spike timing provides most of the information in neural processing. Some well-known strategies of temporal coding are time-to-first-spike coding, phase coding, latency coding, rank order coding, synchrony scheme and polychrony scheme (e.g., Borst & Theunissen, 1999; Christopher deCharms, Blake, & Merzenich, 1998; Gabbiani & Midtgaard, 2001; Gerstner & Kistler, 2002; Izhikevich, 2006; Liu, Tzonev, Rebrik, & Miller, 2001).

For information encoding in a spiking neural network, it is well-advised to count for time measurement either using firing rate (within a time window) or precise timing. Until now, there is no clear evidence that could lead us to determine the most realistic spike encoding (i.e. firing rate or precise timing) since both have been proven to convey computational significance on how the real neuronal system encodes a certain information. It is also unknown if different parts of the brain may execute different encoding strategies. Hence, in this study it is tempting to explore the integration of firing rate and precise timing encoding schemes. As neurons work collaboratively to perform a cognitive function (Bloom, 2005; Purves & Pacala, 2008), we anticipate that the neuronal activity may result from the interaction between the process at local synapses and global network activity.

3 Methodology

In this section we describe the methodology for encoding of fish motion and learning the fish motion trajectory. Initially, we develop a recurrent spiking neural network, and then we encode the fish motion data to represent a particular fish motion sequence in the neural network. The encoding transforms a fish motion into a group of spiking neurons. For brevity, each point (*S*) in a motion is represented by a group of spiking neurons. Hence, a sequence of $x_0 \rightarrow x_1 \rightarrow x_2$ is represented by 3 neuronal groups $S_0 \rightarrow S_1 \rightarrow S_2$. Each sequence is assigned a target response that is represented by a group spiking neurons (*R*). The encoded network is then trained with a reward based approach. The network is trained to associate a motion sequence to a target response.

3.1 Fish Dataset

In this study, the fish dataset is obtained from fish4knowledge (Beyan & Fisher, 2012). Fish motion trajectory (*T*) is defined by the coordinate (*x* and *y*) in the fish bounding boxes. The *n* frame of the trajectories of any fish is defined by $T_i= \{(x_1, y_1),(x_2, y_2),\ldots(x_n, y_n)\}$.

For the experiment reported in this paper, we only encode the information on *x* points. An example of fish motion data for *fish1* and *fish2* is shown in Fig. 2. The fish trajectories are captured from 93 different videos with the specifications of 320x240 resolutions, and 5 frames per second.

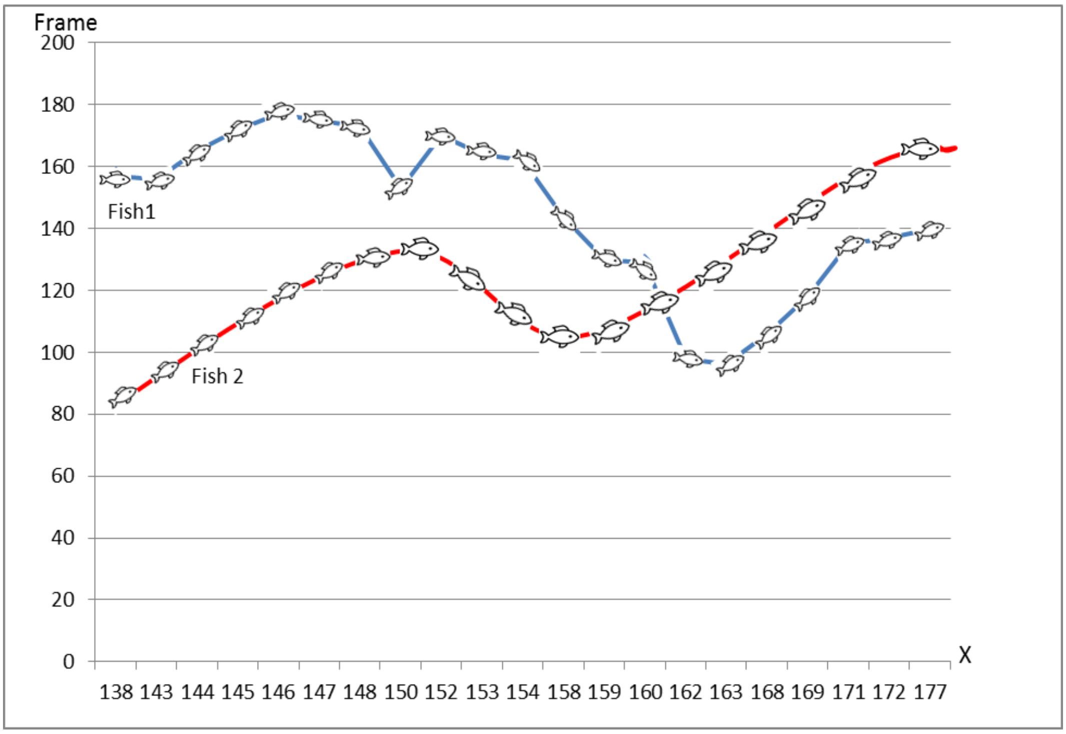

Fig. 2. Motion trajectories for *fish1* and *fish2* (Jemili & Mohd Soid, 2017)

The motion trajectory data is stored in a Matlab file. The file contains 3102 structures, each of which corresponds to one fish trajectory. There are 3043 normal and 59 rare trajectories. For this study, we selected 100 trajectories classified as "normal" (Jemili & Mohd Soid, 2017). The normal behaviour applied when the fish was noted to have been swimming freely. The abnormal fish trajectory applied in any of the following conditions including fish stopping inside the coral for a long time, fish biting the coral, fish diving immediately and fish turning.

3.2 Neural Encoding

To encode a fish motion, we develop a recurrent spiking network consisting of 1000 neurons with 800 excitatory (N_E) and 200 inhibitory (N_I) neurons. Each excitatory neuron is randomly connected to 100 neurons. Each inhibitory neuron is connected to 100 excitatory neurons (Fig.3). The connection weight delays are between 1 to 20 ms.

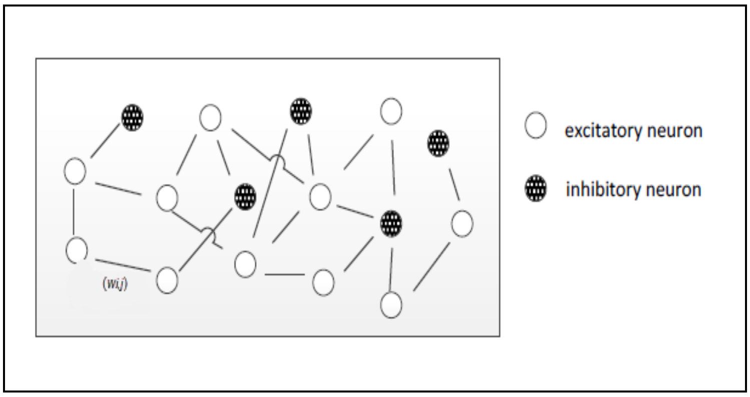

Fig. 3. Spiking Neural Network (N_E = 80%, N_I= 20%)

The neural encoding focuses on converting the dataset into the form of spike. The encoding method retains the information of the original dataset to assist the learning process later (Yu et al., 2014). Encoding is generating the spiking pattern from the input stimuli. The binary information has to be converted into the temporal pattern of the discrete spiking pattern. The fish bounding box has 4 points *x*, *y*, *h* and *w*. Nonetheless, this study only uses the position of *x*. The neural encoding steps of fish motion are described as follows:

i. Normalise the value of *x* points

In this study the *x* point values are normalised in which a motion point is an average value of *x* from three frames. An example of the normalised *x* values can be found in Table 1. From the dataset, the values for *x* points are in between 2 to 306. Table 2 shows the point of *x* as a motion of the fish and the time window (frame).

Table 1: Average value of *x* for fish dataset

Frame	*x*	Averaged *x*
138	157	-
143	156	-
144	165	159
145	172	-
146	177	-
147	175	175
148	173	-
150	153	-
152	170	165

Table 2: Motion trajectory data of normalised *x*

Trajectory	#1	#2	#3
1	165	136	126
2	159	175	165
3	203	107	53
4	27	46	60
5	82	115	201
6	183	193	184
7	17	62	74
8	61	56	49
9	22	41	67
10	20	17	22
11	129	117	81
12	265	182	116
13	108	187	146
14	102	53	28

ii. Encode the stimulus input, target response and sequence learning

For the experiment reported in this paper, each *x* point represents a stimulus input in which the stimulus input is a group of neurons in the same group. From the 800 excitatory neurons described earlier, each point is represented by 50 excitatory neurons. Each target response is represented by a group of 100 excitatory neurons. For our learning simulation there are seven stimulus groups ($S_0 – S_6$) to represent seven different points. The point (stimulus input) encoding is shown in Table 3.

Table 3: Stimulus input

Point (stimulus input)	# neuron
S_0	1-50
S_1	51-100
S_2	101-150
S_3	151-200
S_4	201-250
S_5	251-300
S_6	301-350

For the output neurons, each trajectory is associated to a network response. For our simulation, there are two responses represented by two excitatory neuron groups with 100 neurons each. The encoding for the target response shown in Table 4:

Table 4: Target response

Response	# neuron
R_A	600-700
R_B	701-800

An example of the neural network activity is shown in the spike raster plot in Fig. 4. The network consists of 1000 with 800 excitatory neurons (neurons #1 - #800) and 200 inhibitory neurons (#neurons #800 - #1000). There are seven groups of excitatory neurons to represent seven *x* points (Table 3). Thus, each point is represented by a group of excitatory neurons. There are two target network responses namely, R_A and R_B that each target is represented by 100 excitatory neurons (Table 4). The remaining excitatory neurons and the inhibitory are known as the non-selective neurons. The activity of the neurons contributes to the network dynamics. The inhibitory neurons are also non-selective to any stimulation and only act as the random network inhibition.

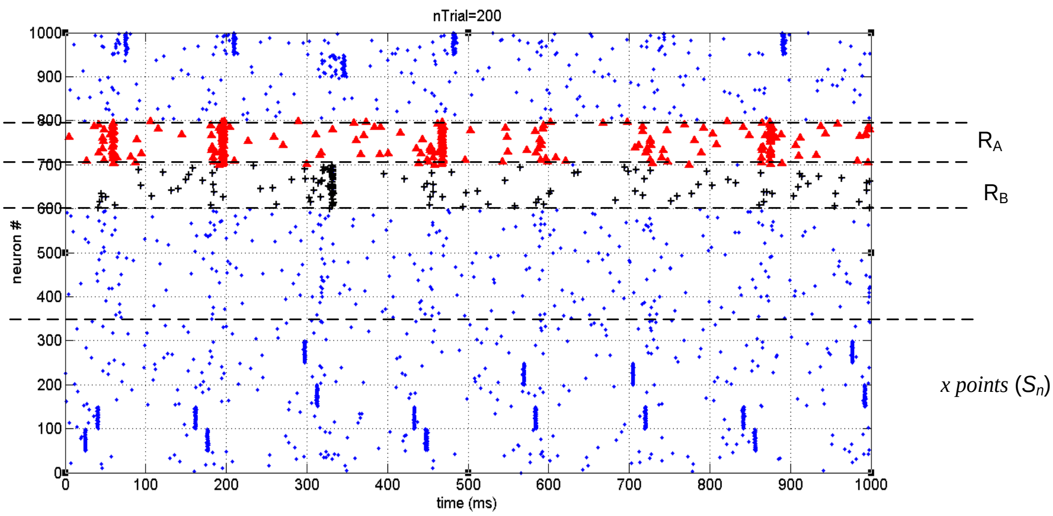

Fig. 4. An example of neural network activity in a spike raster plot

The neural network is trained to associate a motion trajectory to a target response. An example of motion-target (T) set is as follows:

$$T = \{(S_4,S_2) \rightarrow R_A,\ (S_1,S_2) \rightarrow R_B\ ,\ (S_5,S_3) \rightarrow R_A\ ,\ (S_2,S_1) \rightarrow R_B\ \}$$

iii. Encode the network activity

In our approach, the network response is measured based on the spike rate in the response groups. After a motion is presented to the network, the number of spikes in each response groups is counted within a 20-minute time interval. As learning progresses, the activities of neurons in the associated groups are synchronised.

3.3 Learning Fish Motion

For training the network described in the earlier section, we implement the learning scheme as proposed in (Yusoff & Grüning, 2012). The task of learning is to associate a sequence of points (i.e. motion trajectory) to a target response. Every learning trial runs for 20 minutes simulated time. The algorithm is as follows:

1. Simulation starts
2. While time <= 20 min. simulated time
3. Stimulate a network with background activity
   - apply a 1-ms pulse of 20 pA current to a randomly selected excitatory neuron if time > 100 ms,
4. For each trial, present a sequence, e.g. $(S_i,S_j)\rightarrow R_k$, to the network
   - select randomly a sequence, e.g. a two-point sequence, $S_0 \rightarrow S_1$, and set its target response, e.g. R_A
   - at t_n: stimulate all 50 neurons within each stimulus group of the *first point*, S_i with 1-ms super threshold current (20 pA)
   - at $t_{n+inter\text{-}stimulus\ interval}$: stimulate all 50 neurons within each stimulus group of the second point, S_j with 1-ms super threshold current (20 pA)
   - at t = onset of the last point, in a 20-ms time window of the response interval, count the number of spikes (F) fired by neurons in the response groups, R_A and R_B.
5. Calculate the reward signal, *r*, with the reward policy Θ(F) as follows (Table 5) :

Table 5: Reward policy

Num. of spikes in the response group	Reward signal	
$F_A(\delta t) \geq 2F_B(\delta t)$	$r(t-1)+0.5$	strong +ve reward
$F_A(\delta t) < F_B(\delta t) < 2F_A(\delta t)$	$1-F_j/F_i$	weak +ve reward
$F_A(\delta t) < F_B(\delta t)$	-0.1	-ve reward

6. For every 10-ms time step,

- compute the sum of weight changes, Δw_{stdp}, based on the spike time dependent plasticity (STDP) function

Definition 2.1 Weight changes
$\Delta w_{stdp} = \{A_+ e^{-\Delta t/\tau+}, \text{ if } \Delta t \geq 0; A_- e^{\Delta t/\tau-}, \text{ if } \Delta t < 0\}$

The change of weight depends on the difference Δt between the firing time of postsynaptic and that of the presynaptic.

- compute the weight change of all excitatory neurons based on the reward signal, r, obtained from the reward policy Θ(F) and α is an activity-independent increase of synaptic weight.

Definition 2.2 Synaptic Weight

$$\Delta w(t) = [\alpha + r(t)] \sum \Delta w_{stdp}$$

Definition 2.3 Update the weights, w

$$w(t+1) = w(t) + \Delta w(t)$$

7. End of trial (the next trial proceeds with a delay of 100 ms after the offset of each response interval)

4 Results and Discussions

All learning simulation is implemented in C++ and Matlab is used to analyse the experiment results. To see the performance of learning, we trained a network to provide a target response when stimulated with a sequence. We observed the performance of learning with 3-point sequences.

In the following experiments, this study investigated the learning performance with sequences of 3 trajectory points. The aim of the experiment was to train the network with the real fish motion trajectory for sequence learning task with different points without any repeating point. The sequence learning sets and their response for fish motion are shown in Table 6.

Table 6. Sequence learning sets

Sequence stimulus	X_1	X_2	X_3	Response
(S_4,S_2,S_1)	203	107	53	R_A
(S_1,S_2,S_4)	82	115	201	R_B
(S_5,S_3,S_2)	265	182	116	R_A
(S_2,S_1,S_0)	102	53	28	R_B

For learning, the group of neurons that represent the first point was first stimulated by applying 20-pA pulse current. This followed by stimulation of the same strength of current to the second point and later to the third point. Each point is separated by 15 ms simulated time. The temporal delay was chosen based on our preliminary experiment on the effect of temporal delays from 10-20 ms. It has been found that 15 ms inter-stimulus interval (ISI) is the optimal delay in which the network response is influenced by the interaction between two associated points with no dominant stimulus among both that influences the response. The numbers of spikes in the response group were then computed within the 20 ms after the onset of the third point. The response group with the most active neurons is the winner. The network was then rewarded or penalized depending on the response. The learning protocol is depicted in Fig. 5.

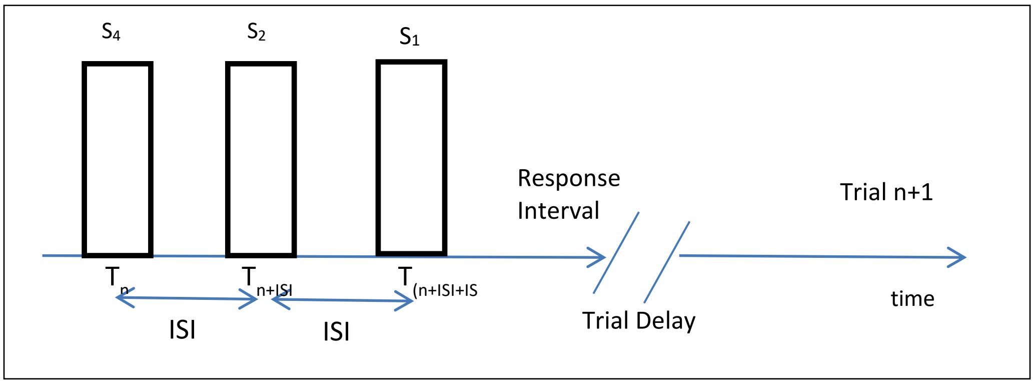

Fig. 5. Fish motion learning protocol

The network was rewarded if the response pointed to the correct match for sequence learning, e.g. $(S_4,S_2,S_1)\rightarrow A$, of the fish motion trajectory motion. The average performances for correct recall rates for 10 different simulated networks were 68.94 and 69.1 for training and testing, respectively.

5 Conclusion

In this paper, we introduce the encoding of fish motion trajectory using a recurrent spiking neural network. The real data of fish motion obtained from fish4knowledge (Beyan & Fisher, 2012) has been used in the learning simulation. Using a population of 1000 neurons with properties of Izhikevich spiking neuron model, we simulated association learning of fish motion trajectories and their target response. The learning protocol is followed from (Yusoff & Grüning, 2012). The learning is simple and plausible using a reward-based approach inspired from a neurophysiological study by (Erickson & Desimone, 1999).

Based on the experiment findings, the encoding method of fish motion trajectory seems feasible to be coupled with the reward based learning that is based on modulated spike-time dependent plasticity (STDP). However the performance of learning could be improved especially for leaning with more complex pattern of motion trajectories. From our findings there seems a significant effect when a motion trajectory consists of repeating points (the findings are not discussed in this paper). Nevertheless, this could be regarded as among the pioneer studies that implement motion trajectory learning using spiking neural network in a reward-based paradigm.

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