Journal of Algorithms and Computation

journal homepage: http://jac.ut.ac.ir

C. elegans Neural Network Analysis

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ABSTRACT

Artificial neural networks that have been so popular in recent years, are inspired from biological neural networks in the nature. The aim of this work is to study the properties of biological neural networks to find out what is actually happening in these networks. To do so, we study on Caenrohibditis elegans neural network, which is the simplest and the only biological neural network that is fully mapped. We implemented the sub-circuit of C.elegans neural network that is associated with the sensation of aversive stimuli which results in forward and backward locomotion, and we found out that some of its neurons are ineffective in developing considered outputs. However, removing these neurons together has considerable effect on these outputs.

ARTICLE INFO

Article history:
Research paper
Received 20, September 2022
Received in revised form 11, November 2022
Accepted 06, December 2022
Available online 30, December 2022

artificial neural network, C.elegans, biological neural network, complex network

AMS subject Classification: 05C78.

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1 Introduction

Artificial neural networks, known as ANN, have been so popular in recent years due to their extensive applications in many fields such as pattern recognition, pattern prediction, classification, and clustering [1]. The main idea of these networks is inspired from biological neural networks in the nature, except that, in ANNs, in order to avoid complexity, the minimal set of biological concepts are used [32].
Thus, it is so helpful to study the features of biological neural networks in the nature, in order to apply these features on ANNs.
The aim of this paper is to study on the properties of biological neural networks to find out what is actually happening in these networks, and how these experiments could be applied in artificial neural networks. The simplest and the only biological neural network that is fully mapped, is Caenrohabditis elegans (C.elegans) neural network [19].
While studying this biological neural network, we recognize that its structure is different from common structures that are defined for ANNs. Thus, we were motivated to study this biological neural network, identify its properties, and evaluate the effect of these properties on ANNs.
ANNs are a type of networks, in which, nodes represent artificial neurons, and each link is a model for synapse that transmits signals among neurons. The signal in ANNs is modeled by a real number, and the output signal of each neuron is computed by a non-linear function that is applied on the sum of inputs. Typically, each link in the ANN has a special weight that is proportional to its strength. In the standard forms of ANNs, the neurons are grouped into layers. The first layer is the input layer which receives the input signal, and after processing, transmits it to the next layer. Finally, the last layer transmits the output signal as the output of network.
Many studies have been done to evaluate the effect of different network topologies on the ANN's efficiency so far. In some of these studies such as [8] and [17], considering the standard structure of an artificial neural network, as special topology of complex neural network has been applied on it. In some other researches such as [31] the concepts of complex network, for example the property of randomness is applied on the neural networks.
The structure of this paper is as follows: In part II, we review some related works that have been done in this field, in part III, we represent some information about C.elegans neural network, and extract some of its main structural features, in part IV, we represent the datasets that we have used in order to implement C.elegans neural network, in part V, we describe our hypothesis and results, and in part VI we represent our conclusion.

2 Related Works

One of the first attempts for applying the concepts of complex networks on ANNs was in [24], which the efficiency of Hopfield neural network with asymmetric weight updating was studied in different topologies such as regular lattice, random network, small world network, and scale-free network. They showed that, with the same number of nodes, neural networks with random structure have better efficiency compared to neural networks with other topologies. Moreover, according to the latest studies, the pattern of neurons connectivity is some animal's brain such as C.elegans worm is not fully random, but follows small world structure [5]. Thus, in [24] they concluded that neural networks with small world topology and a balanced number of shortcut links have a higher efficiency, as, in these networks, the cost of neuron connectivity is less than neural networks with random topology.

In [5], a Hopfield neural network was simulated with scale-free topology, in which, each new neuron was connected to only m other neurons. In this case, although for small values of m, the quality of retrieving data is reduced, for the values of m that are grate enough, the neural network has suitable efficiency.

In [22], they proved that, the more the neural network topology is close to random structure and the less the network clustering coefficient is, the higher stability and quality of data retrieving occurs. Thus, adding random components and shortcut links to the neural network can improve its efficiency.

In [7], using Watts-Strogatz rewiring algorithm, a feedforward neural network with small world topology was represented. After applying this neural network on the dataset, its efficiency was computed, and the result was that with the same number of nodes and layers, feedforward neural network with small world topology shows higher efficiency than feedforward neural network with standard structure.

Inspired by the brain structure of living organisms, in [34] ANNs were implemented with sparse structure. The result was that neural networks with fully regular structure had weak efficiency in data retrieval, while random neural network could retrieve data with grate efficiency. Moreover, in [34] they concluded that a combination of random and regular connections yields to the best result.

In [31], inspired by this fact that neurons are not fully connected in the neural network of living organisms [13], the concept of StochasticNet was represented. According to [31], a StochasticNet is a deep neural network defined with random graph concepts, in which the neural connections are formed randomly and followed by a probability distribution pattern. Using this approach, neural connections in a deep neural network can be formed in a way that the efficiency will be increased, and it results to a neural network that the number of its connections is much less than a standard deep neural network with the same number of neurons, while it is as accurate as a standard deep neural network.

In order to analyze and predict the traffic data, in [16] a new type of LSTM neural network called RCLSTM is represented, in which, unlike LSTM, the neural connections are in random structure. Thus, due to the sparsity property in RCLSTM most of the potential links are removed, which leads to the reduction of learning parameters and computational cost.

In [29] a decentralized version of Evolution Strategy algorithm called NetES was represented to study the effect of random, small world, scale-free, and fully connected topologies on the efficiency. The results show that ANNs with random topology not only act better than others but they also have higher efficiency even with 1/3 number of neurons com-

pared to fully connected topologies.
In [9] Feedforward neural networks with small-world topology (SW-FFANNs) with another network constructing method called Newman-Watts (NW) were explored, and their classification performance was compared with WS and conventional FFANN. According to the proposed method in [9], Newman-Watts SW-FANN network is obtained by adding extra shortcuts to regular FANN. In [150] they claimed that WS and NW small-world structures have better performance than the conventional FFANN. Moreover, they claimed that NW-FFANN outperforms the WS-FFANN. Thus, by applying these neural network structure on PIDD dataset, they concluded that the NW structure shows the best performance in the diagnosis of the diabetes. In order to evaluate the classification performance of each structure, they calculated metrics such as the learning error, accuracy, sensitivity, and specificity. The results of [9] show that in WN-FFANN there is 2% improvement of accuracy while for sensitivity and specificity the results in WN-FANN structure are the same as in WSFANN structure.
In [18] they explored [24], in which different complex structures have been compared. In this work, which is one of the pioneering works of applying SFs on Hopfield associative memory along with other structures such as random, SW, FC networks. In [18], they claimed that the performance of SFs is the same as the performance of random structures even with a large amount of stored patterns. In addition, among all structures comparing in this paper, they reported that SFs are the most efficient in partial recognition of patterns due to their highly connected hubs. It is also showed that removing the neurons with low connectivity does not affect the performance.
Scale-free ANNs are investigated in [28], in which the focus is on hybrid networks and the role of power-law exponents has not been considered. The most important point in these complex systems based ANN studies is that the more the ANNs become similar to biological networks, which shows SW and SF properties, the more improves their performance. Consequently, it is inferred that high clustering coefficient, low mean path length, and power-law degree distribution play a key role in optimizing ANNs structure in order to obtain high-quality performance.
Extensive evaluations were done on the architectures corresponding to different types of random graphs in [17], and the effect of different structural and numerical properties of graphs were studied on the accuracy of neural networks. The result was that none of these traditional graphs alone has the best efficiency. Thus, a new structure was represented which had the best efficiency compared to classic structures.
Sparse neural networks (SNN), in which layers are not fully connected to each other have received much attention by researchers and have achieved many improvements [11, 39,33, 35].
In [25] a novel study on deep neural networks (DNN) sparsity was started which considered hybrid structures containing both scale-free and small-world characteristics. In [25], they aim to explore the main components of deep learning which are Restricted Boltzmann Machines (RBM) and Gaussian RBMs (GBMs) using complex network concepts and from topological point of view.
In [26], they proposed another type of sparsity which is implemented in multi-layer per-

ceptron (MLP) and Boltzmann Machine. That is a FFANN learning a supervised manner with two types of supervised and unsupervised learning. To generate a sparse ANN, a new algorithm is proposed in [26] in which the network evolves from ER topology containing two successive layers of neurons towards a BA topology using a Drawinian evolutionary approach while training that is dubbed sparse evolutionary training (SET) method which is based on natural evolutionary process in complex systems.

In [27], previous method of ANN evolution by SET from ER random graph into scale-free structure was expanded, and the application of the SET procedure on convolutional neural networks (CNN) was investigated. By evaluating metrics such as accuracy, P-value, and log-probability it was inferred that CNN networks outperform their fully connected and non-evolutionary counterparts.

In [23], an investigate is done on the generation of locomotory behavior in C.elegans brain with focus on neuronal and muscular activity patterns that control forward locomotion. To do so, the neuronal network of C.elegans is mapped as a multilayer neuronal network. The neurons of locomotory subnetwork is predicted in [23] by logistic regression analysis, the dynamics in this subnetwork is studied, and using a harmonic wave model the forward locomotion of C.elegans is predicted. Furthermore, for a coordinated locomotory behavior in this subnetwork, the significance of a certain neuron is determined by making its activity silent while analyzing the synchronicity.

In [21] inspired by C.elegans neural network, novel recurrent neural networks are designed for robotic control. The authors used the neurons communication property of C.elegans neural network, by which the neurons communicate through a nonlinear time-varying synaptic links established among them. As a result, the network can show complex behaviors with small number of neurons. In order to generate sequential robotic tasks, in [21], neuron-pair communication motifs are identified as design operators and used to configure compact neuronal network structure. The topology of neural networks represented in [21] resembles C.elegans neural network in which the topology is hierarchical from sensory neurons through recurrently wired interneurons to motor neurons. This property enables the networks map the environmental observations to motor actions. These recurrent neural networks are configured by a search-based algorithm in a supervised-learning scheme, and their performance is evaluated in controlling mobile and arm robots and compared to other artificial neural network-based control agents.

In [6] a suit of unified web-based Graphical User Interfaces is represented and their underlying methods and technologies are considered. Using a worm locomotion and neural activity viewer, the framework presented in [6] enables users to graphically visualize the simulation results. Furthermore, by this framework users can graphically create neuron and network models, and behavioral experiments. This framework is generated using a novel XML-based behavioral experiment definition encoding format, which is a NeuroML XML-based model generation along with network configuration description language.

In [36] a method was proposed to visualize the connections in C.elegans neural network, and using the structure of this neural network, its statistical and topological properties such as degree distribution, synapse multiplicity, and small world properties were computed. In addition, the neurons playing a key role in processing information are identified

using linear systems theory, and neuron activities in response to sensory inputs are studied. Finally, the interactions between chemical synapse networks and gap junctions were analyzed.
A control framework for C.elegans neural network was represented in [38] according to which, it can be predicted that which neurons of C.elegans neural network are involved in its locomotion behaviors. According to [38], it is predicted that 12 neural classes are required to control motor neurons in C.elegans neural network. The aim of [38] was to predict that which neurons play a vital role in response to gentle touch, in a way that removing these neurons causes reduction in the number of controllable muscles.
Although C.elegans neural network is accurately mapped, its excitatory or inhibitory property of its synapses is yet unknown [20]. To address this problem, in [20] a recurrent model of C.elegans neural network is represented, which can simulate known behaviors of C.elegans. This approach is used to study neural sub-circuits involved in aversive stimuli with escape response. Thus, a study on stimuli-response behaviors of C.eleganse was done in [20] and the results were collected into a dataset used in a recurrent neural network, in which all the connections are the same as C.elegans neural network, but the excitatory or inhibitory property of connections is determined randomly.

3 C.elegans Worm

C.elegans worm is a tiny living organism found in all over the world. The length of its newly hatched larvae is about 0.25mm and the adult is about 1mm long. Since its body structure is transparent, all cellular details are observable. Using electron micrographs, researchers have reconstructed this worm's neural network, which is the most complete neural network wiring diagram [38].
Researchers have studied different types of simple and complex behaviors of C.elegans including chemotaxis, thermotaxis, multiple responses to touch, nourishment, and associative and non-associative learning [2]. In other words, C.elegans reacts to sensory stimuli by regulated behaviors [14]. These behaviors are as follows:

- It will react to chemical attractant or repellant [4].
- It will avoid environments with high osmolarity [14].
- It will actively retain itself in an optimal temperature [12].
- In the case of gentle touch, it will react by receding [3].

C.elegans also experiences time periods in which it is in resting state that is like sleeping in mammalians [30].
C.elegans neural network includes 302 neurons and the majority of these neurons are located in head, tail, and ventral parts of its body [14]. These neurons are grouped into three categories [38]:

1. 1. Sensory neurons: This category forms the input neurons of neural network. All the input stimuli into the neural network is received by the neurons in this group.

2. Interneurons: Sensory neurons transmit their output signals into the interneurons to be processed. Neurons in this category act as hidden layer in ANN.

3. 1. Motor neurons: Neurons in this category receive the output signals from interneurons, and after processing, transmit the output signal of neural network to the muscular cells. In other words, neurons of this category are the output neurons of neural network.

In C.elegans neural network, each neuron has a unique combination of properties such as morphology, connections, and location resulting in a unique label for each neuron. Neurons that differ only in location are put in the same class. There are 118 classes of neurons in this network, and the number of neurons in each class varies from 1 to 13 [14]. Neurons in C.elegans neural network are connected through about 6400 chemical synapses and 900 gap junctions. Also, output neurons of this network, transmit output signals to muscular cells through 1500 links connecting motor neurons to muscular cells [19]. Fig. 1. shows C.elegans neural network.

Figure 1: C.elegans neural network [38]. Each label specifies the corresponding neuron name. Blue nodes represent sensory neurons, orange nodes represent interneurons, yellow nodes represent motor neurons, and purple nodes represent muscular cells.

In Fig. 1., There are 4 groups of nodes represented in 4 colors: Blue nodes represent sensory neurons, which is the input of neural network, orange nodes represent interneurons, which the signals received from sensory neurons, yellow nodes are motor neurons, which receive signals from interneurons, process it, and produce the output signals of the neural network. Finally, purple nodes represent muscular cells that receive the output of motor neurons. Also, the name of each neuron is specified by its label. Moreover, as it is shown in Figure1, there are some nodes such as AVAL and AVAR, which are the hubs of network. Some parts of layer structure of this neural network are shown in Figure 2.

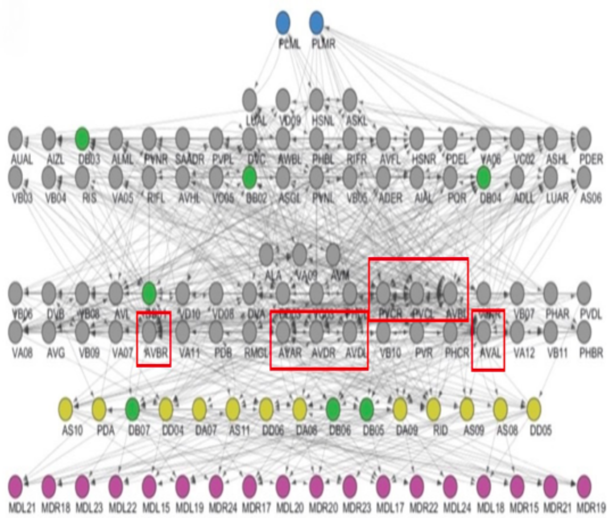

Figure 2: A fragment of layer structure of C.elegans neural network adopted from [38]

In Fig. 2., sensory neurons PLML and PLMR, that are represent in blue, receive gentle touch stimuli, and transmit the input signals into interneurons such as PVC, AVB, AVD, and AVA [14]. The functionalities of these neurons are described as follows [14]:

- AVA and AVD neurons regulate backward locomotion in response to gentle touch. The output signals of these neurons are received by DA motor neurons including DA01, DA02, DA03, DA04, DA05, DA06, DA07, DA08, DA09
- PVC and AVB neurons regulate forward locomotion in response to gentle touch. The output signals of these neurons are received by DB motor neurons including DB01, DB02, DB03, DB04, DB05, DB06, represented in green color in Fig. 2.

The nodes in the last layer in Fig. 2., that are shown in purple, represent muscular cells, that receive locomotion signals from motor neurons [14].
As it was mentioned earlier, there are some properties in C.elegans neural network, which are not seen in standard ANNs. Some of these properties are shown in Fig. 3.
In Fig. 3., blue nodes are sensory neurons PLML and PLMR, that as the input layer of neural network, receive gentle touch stimuli signals. Purple nodes are muscular cells that receive the output signals of neural network. Yellow nodes represent neurons that are in the neighborhood of muscular cells, and green nodes are DD class of motor neurons including DD01, DD02, DD03, DD04, DD05, and DD06.
Structural properties observed in Fig. 3. Are as follows:

- Links that are highlighted in pink color, are two samples of back link, observed in this neural network. The first one connects neuron VA07 in the third layer, to the

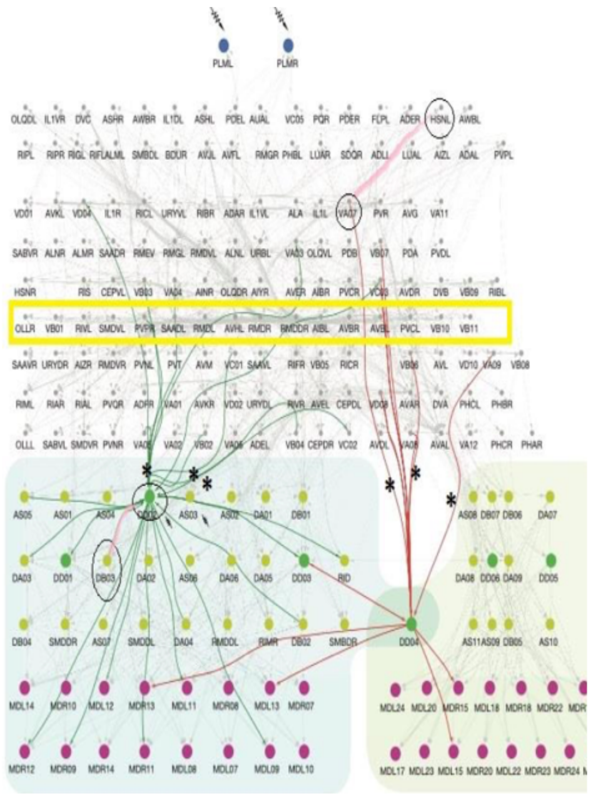

Figure 3: A representation of some properties in C.elegans neural network (Adopted from [38])

neuron HSNL in the second layer. And the second one, connects neuron CB03 in the 12th layer, to the DD04 in the 11th layer.

– Links specified in the yellow frame, are samples of intralayer links in the neural network.

– Links specified by *, are samples of shortcut links, that connect neurons in two non-consecutive layers.

– Also, by observing this neural network, we realize that this neural network is not fully connected. For example, there is no link connecting neurons PHAR in 10th layer and DA07 in 11th layer.

4 Dataset

In this work, in order to study C.elegans neural network, we have used some resources that are described as follows.

4.1 WormAtlas Dataset

WormAtals website [14] includes a database representing all the information of behavioral features and anatomical structure of C.elegans. dataset that WormAtlas represents about C.elegans neural network includes:

- Information about neurons: neuron name, neuron type, neuron location, etc.
- Information about neuron connectivity in C.elegans neural network: In this part, the type of synapse and the number of synapse connecting each two individual neurons are represented.

4.2 WormWiring Dataset

In WormWiring website [15], C.elegans neural network data is represented along with some tools to visualize and analyze these data. WormWiring dataset includes:

- C.elegans neural network adjacency matrix: Each entry of this matrix represents the number of synapses connecting neurons of corresponding row and column.
- Synapses in C.elegans neural network: In this part of dataset, a list of all synapses in C.elegans neural network is represented along with their features.
- Neuron names and neuron types
- C.elegans adjacency matrix along with neuron classes
- Diagrams of C.elegans neural network

5 Our Proposed Method

In this section, we focus on a sub-circuit of C.elegans neural network that is associated with the sensation of aversive stimuli which results in forward and backward locomotion. Out of total 302 neurons and about 6400 chemical synapses, there are 125 neurons and about 950 links involved in this sub-circuit [20]. This sub-circuit is shown in Fig. 4.
In Fig .4., triangle nodes represent sensory neurons that receive input signals, hexagonal nodes represent for interneurons, and circle nodes represent motor neurons which result in forward or backward locomotion
In order to study the features of this network, we implemented this network using adjacency matrix and synapse weights reported in [14]. Also, we used information reported in [20], [10], [14], and [15] to determine the polarity of synapses.
We considered sensory neurons ASHL, ASHR, PVDL, and PVDR, among which activation of ASHL and ASHR causes DA and VA motor neurons to be activated that results in backward locomotion. On the other hand, activation of PVDL and PVDR causes DB and VB motor neurons to be activated which results in forward locomotion [14].

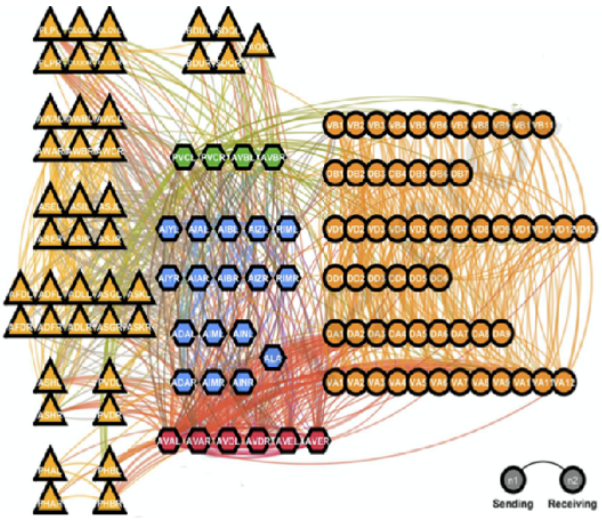

Figure 4: The sub-circuit of aversive stimuli in C.elegans neural network [20]

We use McCulloch-Pitts model [37] to describe the dynamics of neural network. According to this approach, the state of neural network is described by the vector described as follows [20]:

$$\sigma = \{\sigma_1, \sigma_2, ..., \sigma_n\} \tag{1}$$

Where n is the number of neurons in the network, and each element σ_i is a binary number that represents the activation of corresponding neuron. In other words, if $\sigma_i = 1$, it means that neuron 'i' in the network is activated, and conversely, if $\sigma_i = 0$, it means that neuron 'i' is inactivated.

In order to determine the next state of the neural network, we need adjacency matrix of chemical synapses weights JC, and the matrix of synapse sign S in addition to vector. The next state of the neural network is computed by Eqn. (2) [20].

$$\sigma_i(t + \Delta t) = \theta(\Sigma_{j=1}^{K} \sigma_j(t).JC_{ji}.S_{ji} - \tau) \tag{2}$$

Where θ is the Heaviside step function with threshold , and K is the number of input neighbors of neuron 'i'. That is, if the sum of signals entering a neuron is greater than , it will be activated.

In the first step, we compute the output result for each sensory neuron ASHL, ASHR, PVDL, and PVDR. To do so, we first make all neurons inactivated except the single considering input sensory neuron, for example ASHL. Then, for each neuron in the network we compute its activation using Equation 2. We repeat the computation step for several times until it reaches a stable state in the neural network. We consider the state of motor neurons activation as the output signal called MS, which is described in Eqn. (3):

$$MS_{input\_neuron} = \{\sigma_1, \sigma_2, ..., \sigma_m\} \tag{3}$$

Where m is the number of motor neurons in the neural network, σ_i represents motor neuron 'i' activation, and input_neuron is the sensory neuron for which we aim to compute output signal. Thus, for each single of these sensory neurons we have a set MS that indicates the state of motor neurons as an output. We consider the result outputs as follows:

- MS_{ASHL}: Indicates the state of motor neurons in the case that the only sensory neuron activated is ASHL.
- MS_{ASHR}: Indicates the state of motor neurons in the case that the only sensory neuron activated is ASHR.
- MS_{PVDL}: Indicates the state of motor neurons in the case that the only sensory neuron activated is PVDL.
- MS_{PVDR}: Indicates the state of motor neurons in the case that the only sensory neuron activated is PVDR.

After determining these output sets, we try to examine the role of neurons in this network for sensory neurons ASHL, ASHR, PVDL, and PVDR as input. To do so, we make some hypothesis:

Hypothesis 1. There are neurons in this neural network, whose existence is neutral in terms of affecting the considered output when the input neuron is ASHL/R or PVDL/R.

In order to test Hypothesis 1, we first remove each single neuron from the network, activate the sensory neuron and measure the similarity of resulted output and the standard output. For example, with the ASHL sensory neuron activated, each time, we remove a single neuron and measure the similarity of the resulted motor neurons state with the MS_{ASHL} (MS_{ASHL} is the state of motor neurons when ASHL is activated and neither of neurons is removed) using Jaccard similarity. The less the similarity is, the more important is the role of the removed neuron. The output similarity for each neuron z and input sensory neuron x is computed as it is shown in Eqn. (4):

$$Output\_Sim_{x,z} = Jac(MS_x, MS_{x/z}) \tag{4}$$

where Jac is Jaccard similarity function, MS_x represents the state of motor neurons in the case that the only sensory neuron activated is neuron x, and $MS_{x/z}$ represents the state of motor neurons in the case that the only sensory neuron activated is x, and neuron z is removed from the network.

For each neuron z and input neuron x, we define a metric called $importance_{x,z}$ that is computed by Eqn. (5):

$$importance_{x,z} = 1 - Output\_Sim_{x,z} \tag{5}$$

Where $Output\_Sim_{x,z}$ is defined by Eqn. (4)

In our network, for each neuron z, and each sensory input neuron x, where $x \in \{ASHL, ASHR, PVDL, I$
we compute $importance_{x,z}$. The results are shown in Table 1.

Table 1: The $Importance_{x,z}$ for $x \in \{ASHL, ASHR, PVDL, PVDR\}$. Background color of each cell denotes the rate of importance for corresponding neuron.

Input	Removed Neuron	$Importance_{input,removed\_neuron}$
ASHL	AVAL	0.439
	AVAR	0.273
	ADFL	0.037
	AWBL	0.037
	ADLL	0.037
	AVBR	0.037
	AIAL	0.037
	AIBL	0.037
	AIBR	0.036
	ADAL	0.037
ASHR	AVAL	0.410
	AVAR	0.313
	AIBR	0.038
	RIML	0.038
	AVER	0.038
PVDL	PVDR	0.806
	PVCL	0.550
	PVCR	0.812
PVDR	PVCL	0.778
	PVCR	0.778

For all other neurons y that are not in Removed Neurons in Table 1, the $Importance_{x,y}$ is equal to 0. Thus, we could infer that Removed Neurons reported in Table 1 might play a key role for each sensory neuron.
On the other hand, for neurons y whose removal resulted in the $Importance_{x,y}$ of 0 or close to 0, we could infer that in the case of removing them singly, these neurons could be neutral. However, in the case of removing multiple neurons we could not certainly claim that they are neutral. Thus, we make Hypothesis 2:

Hypothesis 2. There are some neurons in this neural network that are redundant.

In order to test Hypothesis 2, we remove all neurons whose removal resulted in Importance equal to 0 in the last step. So, in this case, the presented neurons in the network consist of ASHL, ASHR, PVDL, PVDR, AVAL, AVAR, PVCL, PVCR, ADFL, AWBL, ADLL, AVBR, AIAL, AIBL, AIBR, ADAL, RIML, RIMR, and AVER, along with motor neurons. The corresponding network is shown in Fig 5.

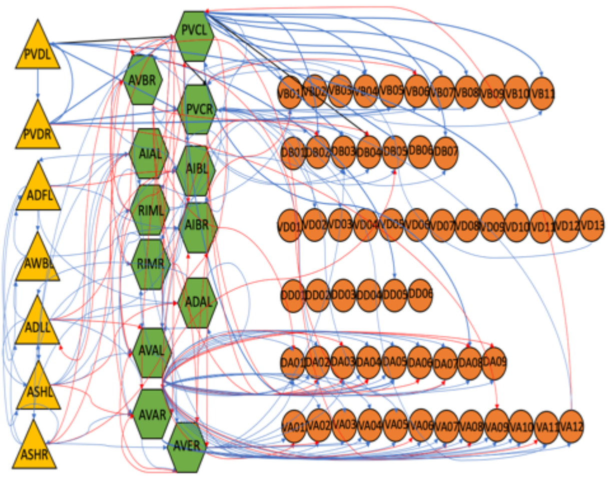

Figure 5: The neural network after removing neurons with importance equal to 0 in Table1. Yellow triangle nodes represent input sensory neurons, green hexagonal nodes represent interneurons, and circle nodes represent motor neurons. Blue links represent excitatory connections, and red links represent inhibitory connections. In this figure, the connections among motor neurons are not shown.

Then, for each single sensory neuron activation, we measure the similarity of resulted motor neurons state and the standard MS. Table 2 shows the results:

Table 2: The similarity between standard MS and motor neurons state after removing all neutral neurons

Input	**Similarity**
ASHL	0.719
ASHR	0.194
PVDL	1
PVDR	1

As it is shown in Table 2, for input sensory neurons ASHL and ASHR, although there are some neurons that their single removal does not affect the result, if we remove these

neutral neurons together, the result will seriously be affected. So, these neurons could be redundant for each other.
On the other hand, for neurons PVDL and PVDR, even if we remove all those neutral neurons together, it won't have any effect on the result. Thus, for PVDL and PVDR, these neurons are neutral not only in the case of single removal, but also in the case that all of them be removed together.
In the next step, we want to find the minimal set of neurons whose existence in the network results the suitable outputs for input neurons PVDL and PVDR. In order to do that, for each input neuron, we remove neurons used in **Hypothesis2** (ASHL, ASHR, PVDL/PVDR, AVAL, AVAR, PVCL, PVCR, ADFL, AWBL, ADLL, AVBR, AIAL, AIBR, ADAL, RIML, RIMR, and AVER) one by one, and for each neuron removal we measure the $Importance_{PVDL,removed\_neuron}$.
Considering neuron PVDL as input, for each removed neuron $Importance_{PVDL,removed\_neuron}$ is shown in Table 3.

Table 3: . The measured $Importance_{PVDL,removed\_neuron}$ for each neuron removal

Removed Neuron	$Importance_{PVDL,removed\_neuron}$
ASHL	0
ASHR	0
PVDR	0.2
AVAL	0
AVAR	0
PVCL	0.7
PVCR	1
ADFL	0
AWBL	0
ADLL	0
AVBR	0
AIAL	0
AIBR	0
ADAL	0
RIML	0
RIMR	0
AVER	0

The rows highlighted in Table 3., represent important neurons whose removal causes similarity decrease. For other neurons, the similarity is 1 when they are removed, so their importance is equal to 0. Thus, for PVDL as input neuron, the minimal set is PVDR, PVCL, PVCR. Fig 6 shows the sub-circuit corresponding to PVDL minimal set.
In Fig 6, input sensory neurons PVDL and PVDR are represented by yellow triangles, in-

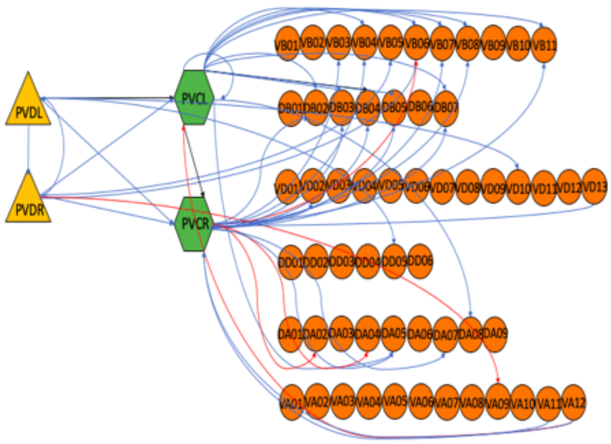

Figure 6: The sub-circuit corresponding to PVDL minimal set. Yellow triangle nodes represent input neurons PVDL and PVDR, green hexagonal nodes represent interneurons PVCL and PVCL, and circle nodes represent motor neurons. Blue links represent excitatory connections, and red links represent inhibitory connections. In this figure, the connections among motor neurons are not shown.

terneurons PVCL and PVDR are represented by green hexagonal, and motor neurons are represented by orange circles. Also, in this sub-circuit inhibitory connections are shown in red links, and excitatory connections are shown in blue links.
Considering input neuron PVDR as input, for each removed neuron $Importance_{PVDR,removed\_neuron}$ is shown in Table 4.
As it is shown in Table 4., The importance of neurons PVCL and PVCR is equal to 1. On the other hand, removing other neurons doesn't change the similarity, meaning that their importance is equal to 0. Thus, for PVDR as input neuron, the minimal set is PVCL, PVCR. Fig 7 shows the sub-circuit corresponding to PVDL minimal set.
In Fig 7., input sensory neuron PVDR is represented by yellow triangle, interneurons PVCL and PVDR are represented by green hexagonal, and motor neurons are represented by orange circles. Also, in this sub-circuit inhibitory connections are shown in red links, and excitatory connections are shown in blue links.

6 Conclusion

In this paper, we studied the structure of the sub-circuit of C.elegans neural network that is associated with the sensation of aversive stimuli which results in forward and backward locomotion to understand the role of neurons in C.elegans locomotion.
We also defined a metric called Importance for each neuron, by which it is possible to measure the effect of removing each neuron on the output of motor neurons. By implemented this system and creating the corresponding network, we found out that some of its neurons are ineffective in developing considered outputs. However, removing these

Table 4: . The measured $Importance_{PVDR,removed\_neuron}$ for each neuron removal

Removed Neuron	$Importance_{PVDR,removed\_neuron}$
ASHL	0
ASHR	0
PVDL	0
AVAL	0
AVAR	0
PVCL	1
PVCR	1
ADFL	0
AWBL	0
ADLL	0
AVBR	0
AIAL	0
AIBR	0
ADAL	0
RIML	0
RIMR	0
AVER	0

neurons together causes a decrease in C.elegans locomotion efficiency, which supports this hypothesis that some neurons in this network are redundant and they are possibly in common with each other in their tasks. Finally, for input sensory neurons PVDL and PVDR we found the minimal set of neurons whose existence in the network results the suitable outputs.

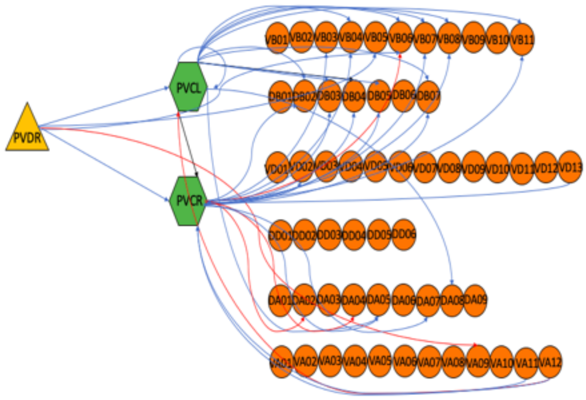

Figure 7: The sub-circuit corresponding to PVDR minimal set. Yellow triangle node represents input neuron PVDR, green hexagonal nodes represent interneurons PVCL and PVCL, and circle nodes represent motor neurons. Blue links represent excitatory connections, and red links represent inhibitory connections. In this figure, the connections among motor neurons are not shown.

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