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An Inherent Fog Network: Brain-Spinal Cord-Nerve Networks

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ABSTRACT The spinal cord plays a key role for big data processing in the central nervous system, which is composed of the brain and spinal cord. A close look to the spinal cord reveals that the main functions of fog nodes such as communication, computation, and storage capability define what spinal cord does in the central nervous system. Based on this analogy, a new network architecture is described dubbed *brain-spinal cord-nerve* network that bears a striking resemblance to *cloud-fog-thing* network architecture under consideration for 5G networks. A stochastic geometry analysis is performed for this network to specify the optimum number of special neurons at the spinal cord responsible for learning. Additionally, to provide an alternative model for some fundamental motor skills in our daily life such as driving, swimming, dancing, and the *brain-spinal cord-nerve* network is modeled as a coded cache. These findings can be quite useful for neuroscientists who may want to apply the fog network model to the central nervous system with the ultimate aim of treating serious central nervous system diseases. Lastly, a novel coded caching structure is developed for fog networks inspired by the central nervous system.

INDEX TERMS Fog networking, spinal cord, brain, stochastic geometry, caching.

I. INTRODUCTION

One of the most challenging aspects in the Internet of Things (IoT) applications over fifth generation (5G) wireless networks is big data processing due to a very large number of nodes. Although it may be questionable whether such large-scale networks can successfully process the massive amount of data, a network within our body is capable of such heavy data processing. The central nervous system, which is composed of the brain and spinal cord, does a vast amount of data processing including many tasks such as breathing, controlling involuntary movements, interpreting information coming from our eyes, ears, nose, internal organs, etc. Indeed, the way of handling the data coming from millions of neurons inside the central nervous system may be quite inspiring as a model for the large-scale IoT/5G wireless networks. In this regard, observing the network structure of the central nervous system may shape our understanding of how it can be possible to process such a heterogeneous, enormous amount of data in large-scale data networks.

The synergistic combination of the brain and spinal cord in the central nervous system basically processes big data. Specifically, the global centralization and the large-scale data processing capability of the brain, and the widely deployed, e.g., from the medulla to the lumbar region of the vertebral column, and the location-aware nature of the spinal cord that is closer to the peripheral nerves ensure efficient data processing. Interestingly, this structure has astonishing similarities with the network architecture based on the integration of cloud and fog networking proposed by Cisco a few years ago [1]. According to this proposal, the interplay of cloud and fog networking processes big data where some portion of data is locally processed in the fog nodes and the rest is globally processed in the cloud.

Heretofore, the conceptual definition of fog networking and its relation to cloud computing has been discussed in [1] and [2]. Specifically, the integration of cloud and fog nodes have been considered in big data processing for different use cases including smart traffic lines, smart grid [1], smart pipeline monitoring [3], smart building control [4], content delivery to vehicular networks [5], and augmented reality and real time video analytics [6]. However, the authors are not aware of any studies that provide an analogy between cloud and fog nodes with the central nervous system. In this paper, the potential success of *cloud-fog-thing* hierarchical networking is emphasized for large-scale data processing by observing the same architecture in the central nervous system that has been used for centuries, dubbed a *brain-spinal cord-nerve* network.

The analogy between the *cloud-fog-thing* network and *brain-spinal cord-nerve* network is reciprocal so that each party can benefit from each other. By this is meant that the central nervous system may be better modeled via the basic notions and tools used in the *cloud-fog-thing* network architecture to help treating serious central nervous system diseases more efficiently such as addictions, depression, trauma, stroke, etc. Similarly, novel network protocols/algorithms can be developed for IoT/5G wireless networks inspired by the *brain-spinal cord-nerve* network.

The main contributions of this paper are as follows. The central nervous system is modeled in terms of cloud and fog networking so that brain is treated as a cloud and the neurons at the spinal cord that are responsible for learning where the plasticity[1] occurs are considered as fog nodes. Note that plasticity refers to a change in the internal parameters of neurons in time through practice, and ensures learning [7]. Then, the relation between the optimum number of these neurons that have plasticity and the peripheral neurons is found using molecular communication [8] and stochastic geometry [9]. Notice that neurons can be considered as points, and the central nervous system has a network structure that can be accurately modeled by a Poisson Point Process (PPP) because of the very large number of neurons [9]. Lastly, coded caching [10]–[12] is proposed to model the acquaintance and maintenance of motor skills in the spinal cord such as driving, swimming, dancing, etc. This model can further shed light to neuroscientists for their future studies. A novel coded caching scheme is proposed for future 5G networks inspired by the interrelations between brain and spinal cord as well.

The paper is organized as follows. The *brain-spinal cord-nerve* network model is presented in Section II. A stochastic geometry analysis of finding the optimum number of neurons in the spinal cord responsible for learning with numerical results is given in Section III. The relation between motor skills and caching is explained in detail in Section IV, and the paper ends with the concluding remarks in Section V.

II. BRAIN-SPINAL CORD-NERVE NETWORK MODEL

The combination of fog and cloud networking has attracted considerable attention as an architecture that has the capacity to manage the big data expected within 5G networks since the seminal paper of Cisco [1]. The basic idea is to process some portion of data in the fog nodes and convey the remaining data to the cloud, which yields the *cloud-fog-thing* hierarchical network topology [1]–[6]. In this topology, the striking features of fog networking, namely widely deployed fog nodes with computing and storage resources, location and content awareness and proximity to end devices, are associated with global centralization and large-scale data management capability of cloud networks.

To emphasize the potential success of this architecture, a similar network topology in the central nervous system named $brain - spinalcord - nerve$ network that successfully processes the big data is worth studying. By analogy, the brain

[1] Plasticity is the ability of neurons to strengthen or weaken the signal over time in response to increases or decreases in their activity.

TABLE 1. The analogy between brain-spinal cord-nerve and cloud-fog-thing hierarchical networks.

Brain-Spinal Cord-Nerve Network	*Cloud-Fog-Thing* Network
Brain	Cloud
Spinal Cord	Fog networking
Nerves	Things
Stimulus	User demands
Corticospinal tract	Fronthaul
Motor skills	Files

represents the functions of a cloud, the spinal cord behaves similarly to the fog network, and nerves, which are the peripheral neurons, denote things or end devices activated in response to stimulus and users' demands, respectively. Additionally, the fronthaul network between the fog nodes and the cloud is denoted as the corticospinal tract, which is the pathway between the brain and the spinal cord. In this paper, the motor skills that are acquired through practice and stored in the spinal cord are modeled as learning popular files and storing them at fog nodes. Table 1 summarizes these analogies.

Although it can be straightforward to express the similarities between the cloud and the brain, or things and nerves, it is not trivial to specify the relation between fog networking and the spinal cord. There are, however, astonishing similarities. Indeed, the spinal cord ensures the basic features of a fog node such as communication, computation and storage capability, and are explained as follows:

- Communication capability: The spinal cord lies between the brain and peripheral nerves. This means that the spinal cord relays the data to the brain coming from the peripheral nerves. Similarly, the information in the brain is transmitted to the peripheral nerves through the spinal cord. Specifically, the spinal cord includes 31 pairs of spinal nerves, each of which has one $posterior(dorsal)$ and one $anterior(ventral)$ horn [7]. The peripheral nerves transmit their data to the spinal cord through these *posterior* horns, which is an example for *uplink* transmission. On the other hand, the data generated in the brain comes to the *anterior* parts of the spinal cord and is delivered to the body, which may be considered as a *downlink* transmission. This structure is a simple justification for the communication analogy of the spinal cord.
- Computation capability: The spinal cord can directly process the data coming from the peripheral nerves without the brain. To illustrate, it can control muscular system such as an involuntary movement that your arm might make if your finger was to come into contact with a flame, or another example can be the walking capability of a cat when its brain is separated from the spinal cord [7]. Furthermore, the spinal reflexes managed by the spinal cord demonstrate the computation capability of a spinal cord, which is an unlearned reaction to the stimuli given by a spinal cord without any processing in the brain [7].

- Storage capability: There are motor skills in the spinal cord that are first learned in the brain and then stored at the spinal cord such as driving, swimming, dancing, etc. This can be treated as the relevant information in the brain is stored at the spinal cord, and delivered to the peripheral nerves by spinal cord. Doing so provides a response to the stimuli in a rather short time interval and reduces the overload in the brain. This feature is quite similar to the caching in fog aided wireless networks, which decreases the latency and network load.

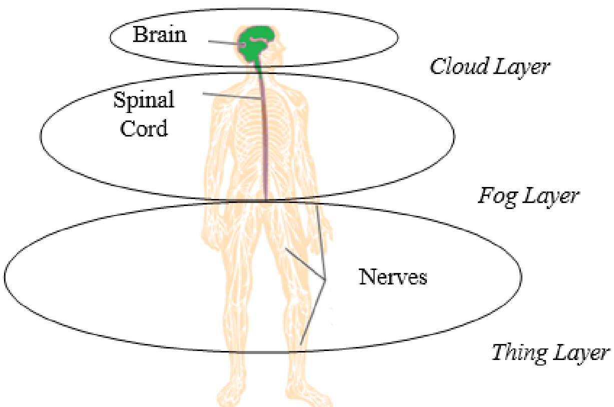

FIGURE 1. The *brain-spinal cord-nerve* network and the *cloud-fog-think* network models.

The network model of the central nervous system is depicted in Fig. 1. Accordingly, the brain has several characteristics in common with the cloud such as global centralization and large processing capability. Interestingly, the spinal cord functions as a fog network in many respects. First, it has a distributed nature, i.e., it spreads from the brain down to the body or from the medulla oblongata to the vertebral column. This corresponds to the principle of widely geographical distribution of fog nodes. Second, the spinal cord provides location and content aware services, that is, the spinal cord has 31 pairs of spinal nerves and each of which is responsible from one part of the body. These nerves serve millions of peripheral neurons that comprises a large-scale network, which can be associated with a very large number of distributed service in fog networking. Third, the spinal cord is located closer to the peripheral neurons than the brain and provides low latency services. Typical examples of low latency services are reflexes. Notice that one of the main aims in fog networking is to locally provide low latency services to the end devices [1]. The other similar features are that spinal cord has heterogeneous neurons and seamless coverage such as the fog aided wireless networks. The last layer in this network topology, i.e., nerves have an analogous behavior with the end devices in a *cloud* $-$ *fog* $-$ *thing* architecture.

III. A STOCHASTIC GEOMETRY ANALYSIS FOR SPINAL CORD PLASTICITY

Spinal cord plasticity, which is the ability of intrinsically strengthening or weakening the signal over time while transmitting information, may occur at numerous neurons in the spinal cord [13]. The main aim of this analysis is to specify the optimum number of neurons at the spinal cord where plasticity takes place, which are named as fog neurons. Indeed, the motivation is to determine the optimum number of fog neurons to achieve the maximum average data rate and the minimum average transmission delay in terms of the number of peripheral neurons, though it is not possible to find how many so-called fog neurons are exactly placed in the spinal cord. Specifically, the approach is to pick the number of fog neurons for a given total neurons to optimize the throughput. This analysis can be useful in terms of understanding the spinal cord plasticity more clearly, which is responsible for fundamental functions in the spinal cord such as locomotion, rapid withdrawal from pain as well as acquiring and maintaining new motor skills [13]. Our method is based on stochastic geometry, and thus one can also consider this analysis as an application area of stochastic geometry.

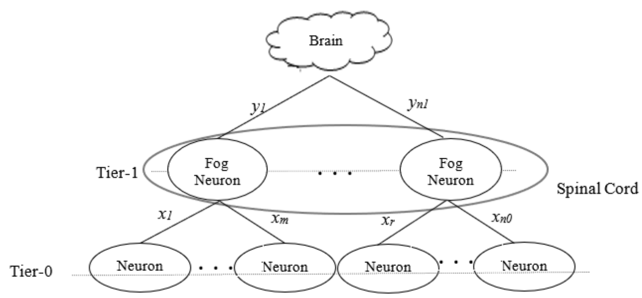

FIGURE 2. A simplified tree based network model including brain, fog neurons and peripheral neurons.

In this analysis, the interest is on the *uplink* transmission such that a portion of the data coming from peripheral nerves is partially processed in the spinal cord while the rest is relayed to the brain. In this regard, the network model given in Fig. 1 can be equivalently converted to a hierarchical tree model as depicted in Fig. 2. Accordingly, there is a brain on top of the network, and under the brain many fog neurons exist located at the spinal cord, each of which serves many peripheral neurons at the bottom that transmit data to the brain through the spinal cord. In this paper, the fog neurons are modeled as a homogeneous PPP with density λ_1 for a total number of n_1 nodes in which n_1 has a Poisson distribution. The n_0 number of peripheral neurons that is connected to these fog neurons are also modeled as a homogeneous PPP with density λ_0. Note that n_0 has a Poisson distribution as well. Based on these, it is straightforward to see that

$$n = n_0 + n_1 \tag{1}$$

where n is the superposition of two independent PPP, and thus it is also a PPP with density $\lambda = \lambda_0 + \lambda_1$ [9]. The overall aim of this section is to find a relation between n_0 and n_1 by assigning $n_0 = n(1-p)$ and $n_1 = np$, and optimizing p so as to maximize the average data rate and minimize the transmission delay where p is the proabability of being a fog node. A similar method is applied for a Binomial Point

Process (BPP) to maximize the average data rate in our earlier paper [14].

The peripheral neurons transfer information to the spinal cord by creating synapses, and similarly the spinal cord sends data to the brain via synapses.[2] Based on this fact, the average signal power of the i^{th} peripheral neuron for $i = 1, 2, \cdots, n_0$ at the j^{th} fog neuron for $j = 1, 2, \cdots, n_1$ can be represented in terms of molecules as

$$M_j = M_i \frac{D_i}{\alpha_i} x_i^{-2} \tag{2}$$

where M_i and M_j are the number of molecules at the pre-synaptic terminal where the transmission begins and at the post-synaptic terminal in which the transmission ends, respectively. Here D_i is the diffusion coefficient and quantified as a number between 0 and 1 in terms of μm^2/ms, α_i is the decay rate with unit ms^{-1} [15], [16], and x_i is the distance between the pre-synaptic terminal and the post-synaptic terminal. The data rate at the j^{th} fog neuron due to the i^{th} peripheral neuron can be expressed as

$$R_{fog} = Wlog\left(1 + \frac{M_j}{\sigma^2 + I_{fog}}\right) \tag{3}$$

where W is the bandwidth, σ^2 is the noise power and I_{fog} is the residual interference at the fog neuron. It is worth emphasizing that there are several (additive) noise sources in the synaptic channel [8], and thus they converge to Gaussian noise by virtue of the Central Limit Theorem.

The signal power in (2) is further attenuated while going from a fog neuron to the brain as

$$M_b = M_j \frac{D_j}{\alpha_j} y_j^{-2}. \tag{4}$$

Here, y_j is the distance between a fog neuron and the brain. Similarly, the data rate at the brain becomes

$$R_{brain} = Wlog\left(1 + \frac{M_b}{\sigma^2 + I_{brain}}\right) \tag{5}$$

where I_{brain} is the interference level in the brain. Assume that the messages are M bits such that K of these bits are processed in the fog neurons, and the rest, i.e., $M - K$ bits are relayed to the brain. This yields the following transmission delay associated with the data rates in (3) and (5)

$$\hat{J} = \frac{M}{R_{fog}} + \frac{M-K}{R_{brain}}. \tag{6}$$

Minimizing the average value of (6) when the i^{th} peripheral neuron transmits to the brain through the j^{th} fog neuron can be simplified to

$$\hat{J}_{avg} = \min\left(\frac{\sigma^2 + I_{fog}}{M_i} E\left[\frac{x_i^2 \alpha_i}{D_i}\right] + \frac{\sigma^2 + I_{brain}}{M_j} E\left[\frac{y_j^2 \alpha_j}{D_j}\right]\right) \tag{7}$$

for given $M_i, M_j, \sigma^2, I_{fog}$ and I_{brain}, which may be either given as *a priori* information or estimated at the receiver. Notice that the W, M, K and $log(.)$ function are eliminated from (7), because they do not have any effect in the optimization. Considering that the diffusion coefficients and decay rates are independent of the distances and they are constant values produces

$$J_{single} = \min\left(E[x_i^2] + E[y_j^2]\right) \tag{8}$$

for a single peripheral neuron and a single fog neuron. If we generalize (8) for n_0 peripheral neurons and n_1 fog neurons, the objective function becomes

$$J = \min_p \left(\sum_{i=1}^{n_0} E[x_i^2] + \sum_{j=1}^{n_1} E[y_j^2]\right). \tag{9}$$

The second moment of the distance between a peripheral neuron and a fog neuron for one realization of n or $E[x_i^2|n]$ can be found with the assumptions that peripheral neurons are uniformly and independently distributed in a region A, each peripheral neuron is served by the closest fog neuron, and each fog neuron is considered to provide services for an equal number of peripheral neurons. This leads to [17]

$$\sum_{i=1}^{n_0/n_1} E[x_i^2|n] = \frac{\lambda_0}{\pi\lambda_1^2} + 0.147\frac{\lambda_0^2}{\lambda_1^3} + \left(\frac{\lambda_0}{2\lambda_1^{1.5}}\right)^2 \tag{10}$$

where $\lambda_0 = \lambda(1-p)$ and $\lambda_1 = \lambda p$. Generalizing (10) for all fog neurons in a spinal cord yields

$$\sum_{i=1}^{n_0} E[x_i^2|n] = np\left(\frac{\lambda_0}{\pi\lambda_1^2} + 0.147\frac{\lambda_0^2}{\lambda_1^3} + \left(\frac{\lambda_0}{2\lambda_1^{1.5}}\right)^2\right). \tag{11}$$

One can find the second moment of the distance between a fog neuron and the brain for one realization of n, i.e., $E[y_j^2|n]$ as

$$E[y_j^2|n] = \frac{1}{d}\int_0^d y^2 dy = \frac{d^2}{3} \tag{12}$$

assuming that fog neurons are uniformly distributed in a 1-dimensional spinal cord between 0 and d. Then, it is straightforward to express that

$$\sum_{i=1}^{n_1} E[y_j^2|n] = \frac{npd^2}{3}. \tag{13}$$

Summing (11) and (13) yields the cost function given in (9) for a fix realization of n as

$$J|n = \frac{npd^2}{3} + np\left(\frac{\lambda_0}{\pi\lambda_1^2} + 0.147\frac{\lambda_0^2}{\lambda_1^3} + \left(\frac{\lambda_0}{2\lambda_1^{1.5}}\right)^2\right) \tag{14}$$

that results in

$$\begin{aligned} J &= E[J|n] \\ &= \frac{A\lambda pd^2}{3} + A\lambda p\left(\frac{\lambda_0}{\pi\lambda_1^2} + 0.147\frac{\lambda_0^2}{\lambda_1^3} + \left(\frac{\lambda_0}{2\lambda_1^{1.5}}\right)^2\right) \end{aligned} \tag{15}$$

[2]In the nervous system, a synapse is a structure that permits a neuron to pass an electrical or chemical signal to another neuron.

where $E[n] = A\lambda$. Note that the objective function in (15) is non-linear with respect to p.

Lemma 1: There is a unique optimum global value of p that minimizes (15).

Proof: The first and second derivative of (15) with respect to p can be simply written after some straightforward mathematical calculations as

$$\frac{\partial J}{\partial p} = \frac{A(500\pi d^2\lambda p^3 + (1191\pi - 1500)p - 1191\pi)}{1500\pi p^3} \tag{16}$$

and

$$\frac{\partial^2 J}{\partial p^2} = \frac{A(1191\pi - (794\pi - 1000)p)}{500\pi p^4} \tag{17}$$

respectively. Note that the second derivative of J is greater than 0 for $0 < p < 1$ suggesting that the function in (15) is strictly convex. Then, the real root of (16) gives the optimum p value. Recognizing the roots of (16) reveals that there is only one single real root that can be approximately found as

$$p \approx \left(\frac{2.38}{d^2\lambda}\right)^{1/3} \tag{18}$$

where $d \gg 1$ and $\lambda \gg 1$. Since the root of the first derivative of (15) is unique stated in (18) for this convex function, it is globally optimum. $\square$

From (18) it is straightforward to express that the number of fog neurons can be specified in terms of n_1 peripheral neurons as

$$n_1 = \frac{n_0 \left(\frac{2.38}{d^2\lambda}\right)^{1/3}}{1 - \left(\frac{2.38}{d^2\lambda}\right)^{1/3}} \tag{19}$$

because

$$n_1 = n_0 \frac{p}{1-p}.$$

Now, the objective function in (15) is numerically evaluated to acquire the optimum value of p that specifies the relation between the number of peripheral neurons and the number of fog neurons in the spinal cord so as to maximize the average data rate and minimize the average transmission delay. Note that the numerically obtained results are directly compared with the derived closed-form solution in (18). Without any loss of generality, the region A is selected as a square planar whose one side is $2a$ where a = 10cm, and the distance d is assumed to be equal to a. The acquired objective function in (15) is plotted in terms of p for different values of λ such as 100 neurons/cm^2, 500 neurons/cm^2, and 1000 neurons/cm^2 as depicted in Fig. 3. As can be observed, the higher the value of λ, the smaller the value of the optimum p. However, the decreasing rate of p is smaller than the increasing rate of λ implying that the number of fog neurons rises in case of high density neurons. This may explain how millions of neurons can transmit their data to the brain without any significant interference, since the increased number of fog neurons may better coordinate transmissions.

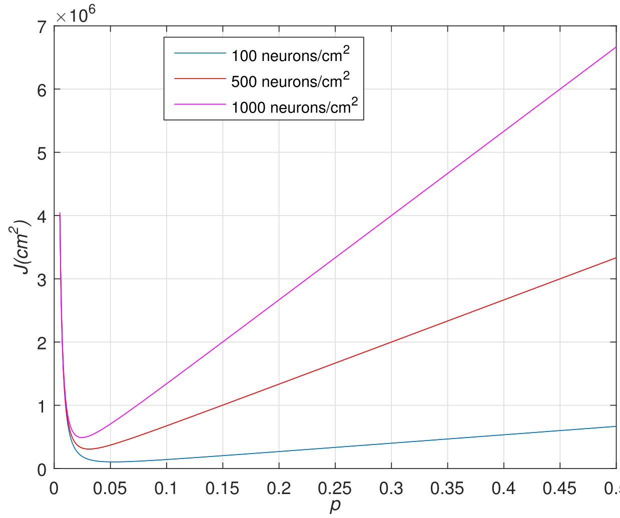

FIGURE 3. The objective function for λ = 100 neurons/cm^2, λ = 500 neurons/cm^2 and λ = 1000 neurons/cm^2 where p is the probability that a neuron is a fog neuron.

TABLE 2. The comparison of the analytical and numerical values.

	Analytically found p	Numerically found p
$\lambda = 100$	0.0620	0.0538
$\lambda = 500$	0.0363	0.0314
$\lambda = 1000$	0.0288	0.025

To show how tight the derived optimum p value in (18), it is compared with the numerical values obtained in Fig. 3 in Table 2 for different values of λ. Accordingly, it is clear that the derived closed-form expression gives more accurate results for higher densities. Note that the density of neurons is quite high in the human body, and thus the derived expression can be accurately used to estimate the number of fog neurons in which plasticity occurs in the spinal cord.

One of the most important consequences of the optimized p value is related to the average data rate. A simulation is performed to observe how significant the impact of the optimum p value on the average data rate while transmitting data from the peripheral neurons to the brain for λ = 500 neurons/cm^2. Accordingly, there are two scenarios such that in the first one, the optimized average data rate, R_{opt} is found with respect to the optimized number of fog neurons in the spinal cord, i.e., according to the optimum value of p. In the second case, p is not optimized rather it is simply taken as 0.5, and the unoptimized data rate, R_{unopt} is found. The ratio of the average data rate between the optimized and unoptimized p is presented in Fig. 4. As can be observed, there is a significant improvement when the value of p is optimized although it decreases for large signal-to-noise ratios (SNRs). That is, there is a nearly 20-fold data rate increase for low SNR. Notice that SNR is defined for our case as

$$SNR = \frac{M_i D_i D_j}{\alpha_i \alpha_j \sigma^2}. \tag{20}$$

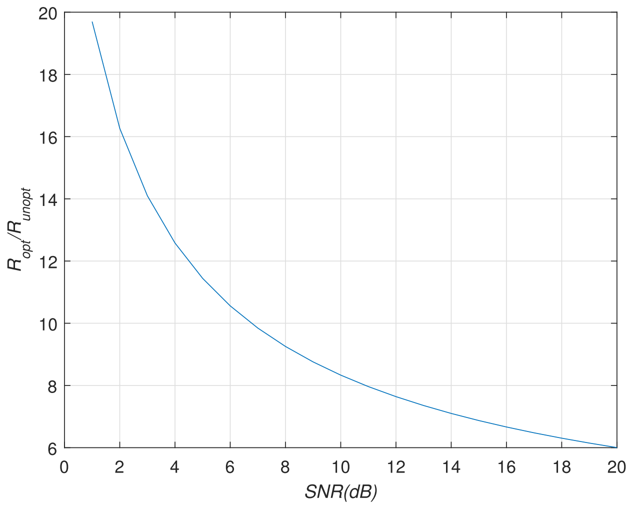

FIGURE 4. The ratio of the average data rate between the optimized and the unoptimized number of fog neurons in the spinal cord.

IV. THE RELATION BETWEEN ACQUIRING MOTOR SKILLS AND CACHING

Acquiring and storing a new motor skill with the help of the brain such as driving a car, swimming, dancing are one of the most important functions of spinal cord. Although it is known that a motor skill is obtained through practice or experience associated with plasticity, which refers to a change in neuron property [7], the complete mechanism has not been clearly understood, i.e., there are many open issues [18]. To address this challenging task, we will model the acquisition and storage of a new motor skill as caching inspired from the fog aided networks. In fog networking, popular files are acquired and stored at the fog nodes by assistance from the cloud through practice [1]. By doing so, fog nodes can serve these files to the end devices in a rather short time as well as reducing the network load. Similarly, motor skills are acquired and stored at some neurons in the spinal cord by practice with the help of brain so that faster responses can be given to the incoming stimuli, and the overload in brain is reduced.

The aim of this section is two-fold. In the first part, the acquaintance and storage of a new motor skill is modeled as caching. More precisely, this structure is treated as a coded caching that has been recently proposed for content distribution networks in [10]–[12]. This may help neuroscientists in their future studies. In the second part, the aim is to design a novel coded caching for fog networks inspired by how the brain coordinates spinal cord plasticity (i.e., memory).

A. MODELING MOTOR SKILLS USING CODED CACHING

Here, motor skills obtained by the spinal cord are modeled as caching inspired from *cloud-fog-thing* networks where there is an interplay between cloud and fog nodes. A similar relation exists between the brain and spinal cord for motor skills. To illustrate, consider the simplest motor skill that is the spinal stretch reflex (SSR) or H-reflex conditioning in which the conditioning refers to strengthening or weakening in the signal amplitude. The experimental results of H-reflex conditioning revealed the strong cooperation of the brain with the spinal cord [13], [18]. Specifically, the H-reflex conditioning is not solely governed by the spinal cord although its pathway is wholly spinal, i.e., the pathway of a H-reflex is between the muscle and the spinal cord. Clear evidence for this is patients suffering from a stroke resulting from a damage in the brain. These patients cannot activate the H-reflex even if the spinal cord itself is undamaged. This shows the strong interplay between brain and spinal cord in maintaining motor skills.

Despite the above fundamental notions, there is limited knowledge about the exact functions of the brain and spinal cord regarding motor skills. In this sense, treating the process as caching may lead to a helpful model. Within this scope, acquiring and storing new motor skills are modeled considering the structure of caching popular files in *cloud-fog-thing* networks. In this model, motor skills are treated as files, the cloud represents the brain, fog nodes correspond to neurons at the spinal cord responsible for motor skills, and the fronthaul network between fog and cloud nodes are denoted as the corticospinal tract, which is the pathway between the brain and spinal cord.

Having in mind perfect information flow between brain and spinal cord, it makes sense to model the motor skills by an information theoretically optimum caching method. It has been recently proven that coded caching is the information theoretically optimum method [10]–[12], and thus it can be employed to better understand how motor skills are obtained. Although it is not possible to exactly know the intrinsic structure of even the simplest motor skill, this approach can provide some insights.

In coded caching, there is one server and all the nodes that have memory for caching are connected to this server with a shared single fronthaul link corresponding to the corticospinal tract between brain and spinal cord. Accordingly, some parts of the popular files are stored at some nodes in a distributive manner, and one node can contain contents that belong to more than one file. When file requests come to nodes, they notify the server about the requests and the server sends a coded multicasting message in response to their requests. Once a node takes this message, it can provide a service using the incoming message from the server and its own content.

In this mechanism, motor skills are considered as partitioned into many pieces, each of which is stored at different sites, i.e., at the neurons in the spinal cord where plasticity occurs. Accordingly, a motor skill capability is divided into many neurons, and a neuron can have more than one motor skill content, which is the case. Interestingly, the experimental results for H-reflex conditioning support this modeling [13], e.g., see Fig. 2(c). In this regard, the H-reflex conditioning spreads into many neurons, and the combination of incoming information from the corticospinal tract, which can also explain the reason of disappearance of H-reflex when the brain is damaged in case of stroke, and the neurons constitute the motor skill of H-reflex conditioning.

Depending on this motivation, we further elaborate on this structure. Suppose that there are many stimuli that require N motor skills, and each motor skill is stored in K number of fog neurons at the spinal cord. Specifically, the library of N motor skills is denoted as $M = \{M_1, M_2, \cdots, M_N\}$, and each motor skill is composed of subsets such as $M_i = \{M_{i1}, M_{i2}, \cdots, M_{is}\}$ for $i = 1, 2, \cdots, N$. Each fog neuron F_j for $j = 1, 2, \cdots, K$ stores some part of the motor skill M_i by the XOR operation as

$$F_j = M_{1l} \oplus M_{2l} \oplus \cdots \oplus M_{nl} \tag{21}$$

where $l = 1, 2, \cdots, s$, and $n \leq N$. When a stimulus comes from one part of the body, this signal is relayed to the corresponding neurons through the receptors, and the current content of the neurons along with the cooperation of other neurons that contain contents for the relevant motor skill and the incoming information from the brain constitute the overall motor skill.

B. A CODED CACHING SCHEME INSPIRED FROM THE BRAIN

The key challenge in caching is the selection of contents to be cached in a limited memory space for distributed networks. To illustrate, caching a file that is never going to be used consumes memory resources to no end, i.e., without bringing any benefit. Then, which files have to be cached among a large number of different alternatives, how can we measure the relevance of these time-varying files, and determine the cached contents accordingly are some natural questions that come to mind at first glance. One can obtain fundamental insights for these questions once a relation is established between how a large number of different motor skills are stored in the *brain − spinalcord − nerve* network, and how popular files should be stored in a *cloud − fog − thing* architecture. Here, the analogy is between keeping the motor skills at the spinal cord and storing the popular files at fog nodes.

Interestingly, there are certain similarities for the impulse response of a motor skill and the popularity of a file as highlighted in Fig. 5, in which the upper figure is taken from an experiment [18] and the lower figure is obtained from a paper that has accessed the Netflix database and has plotted the popularity of a movie [12]. The vertical axis of the former demonstrates the strength of the motor skill in terms of volts in response to incoming stimuli over time, which is the horizontal axis. Similarly, the vertical axis of the latter indicates the popularity or duration, i.e., so-called strength of a file over time. As can be seen, the curves have nearly the same pattern, and thus it makes sense to mimic the behavior of how the central nervous system handles such system impulse responses to determine which files are cached at the nodes.

In the previous sub-section, the motor skills distributed to many neurons at the spinal cord, each of which has also other motor skills, along with the incoming signal from the corticospinal tract due to brain is modeled as coded caching.

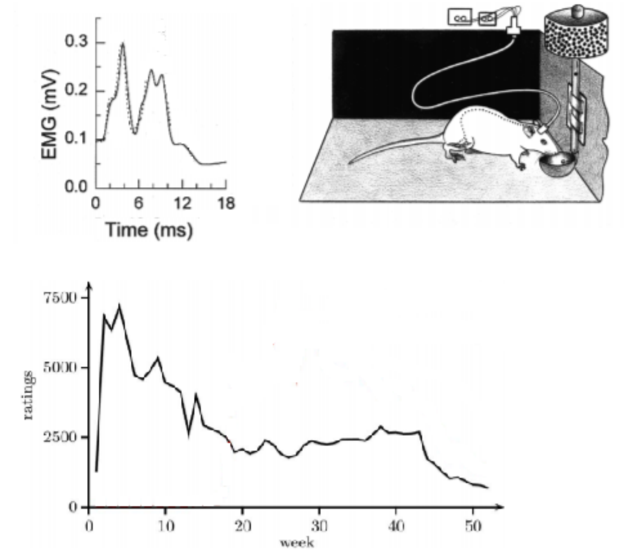

FIGURE 5. The comparison of the impulse response of a motor skill [18] with the popularity of a file [12] where the vertical axis of the upper figure demonstrates the strength of the motor skill in terms of volts and the vertical axis of the lower figure indicates the popularity of a file.

More precisely, a recent finding for content distribution networks such as a *cloud − fog − thing* network, which is that coded caching significantly reduces the network load [10]–[12], and is better adapted to model the motor skills in the *brain − spinalcord − nerve* network. In this section the experimental results and the structure that clarifies the maintenance of motor skills in the *brain − spinalcord − nerve* network is incorporated into the *cloud − fog − thing* network to determine the files to be cached.

Motor skills are complex behaviors, and thus their characterizations are rather difficult. An experiment was set up in 1970s for the simplest motor skill, which is the SSR or H-reflex conditioning to elucidate its fundamental properties [13]. This experiment revealed an important finding such that there is a periodic data flow between brain and spinal cord through the corticospinal tract to keep a motor skill alive [13], [19]. Supporting this idea another study shows that if the cerebellar part of the brain is ablated, the H-reflex conditioning decreases for 40 days and it rapidly disappears after about 10 days [20]. This implies that there is a continuous and periodic information flow, or refresh, between the brain and spinal cord to keep motor skills at the spinal cord. This structure is exploited in the proposed novel coded caching algorithm so that each file is assigned to a latent variable that is periodically updated by the center station. Then, some portions of the files that correspond to the highest L latent variables from the overall N files at a time are cached at the nodes according to the memory space where $L < N$.

Suppose that motor skills $M = \{M_1, M_2, \cdots, M_N\}$ are partitioned into s pieces as $M_i = \{M_{i1}, M_{i2}, \cdots, M_{is}\}$ for $i = 1, 2, \cdots, N$, and their combination is stored at the nodes in the set of $F = \{F_1, F_2, \cdots, F_K\}$. Here, the idea is to assign a latent variable for each content at time n as

$$\Gamma_n = \begin{bmatrix} \gamma_{1,1} & \gamma_{1,2} & \cdots & \gamma_{1,s} \\ \gamma_{2,1} & \gamma_{2,2} & \cdots & \gamma_{2,s} \\ \vdots & \vdots & \cdots & \vdots \\ \gamma_{N,1} & \gamma_{N,2} & \cdots & \gamma_{N,s} \end{bmatrix} \tag{22}$$

where each entry in (22) or $\gamma_{k,l}$ denotes the coefficient of the l^{th} content of the k^{th} motor skill. Notice that this matrix is continuously updated, and the motor skills that have the L highest values out of N contents are stored at the nodes. Without any loss of generality, one can assume that the variables that belong to a single motor skill are the same, i.e., $\gamma_{k,1} = \gamma_{k,2} = \cdots = \gamma_{k,s}$.

Another experimental finding in the maintenance of motor skills is the criticality of a skill instead of when it was last used. To illustrate, the motor skill that is responsible to withdrawal from a pain is not deleted from the spinal cord even if it has not been used for a long time. Another example can be inborn motor skills that may not be used all the times, but they are always in the spinal cord. This suggests the importance and criticality of content in caching policies instead of time. It is apparent that this is quite different that the traditional caching policies that delete the least recently used file from the memory [21]. A counterpart of this behavior in content distributed networks may be to prioritize preserving the files related to the state of emergency, e.g., this can be a control file for real-time critical systems. Accordingly, the popularity matrix in (22) is first initialized by giving high values for the emergency content, and then updated according to the previous value at time $n-1$ and the incoming demands at time n as

$$\Gamma_n = \Gamma_{n-1}\beta + \mathbf{d}_n \tag{23}$$

where β is the plasticity variable between 0 and 1, and $\mathbf{d}_n$ is the matrix whose rows are all 1 if there is an incoming request or stimuli for the corresponding motor skill or become all 0 if there is not any incoming request.

Based on these rules, a brain inspired coded caching policy is designed. The proposed method is a compromise between offline coded caching [10], [11] and online coded caching [12]. Unlike offline caching [10], [11], the popularity of files is continuously trained, and the cache is periodically updated as long as it does not coincide with the heaviest network traffic. Unlike online coded caching [12], the cache is updated after a training period before the delivery and not after the delivery. This can be seen as a kind of proactive approach as opposed to classical reactive methods [22]. Additionally, the method in [12] updates the content of a file at its first occurrence. However, a user may request a non-popular file which may never be used again. So, it may not be meaningful to cache all user requests, and hence we propose an update rule in (23).

The proposed algorithm inspired from the continuous support of the central controller over the nodes in central nervous system and the criticality of the cached content is presented in Algorithm-1 below. The inputs of the algorithm are $M = \{M_1, M_2, \cdots, M_N\}$ and the outputs are $F = \{F_1, F_2, \cdots, F_K\}$. That is, the proposed algorithm takes the motor skills or files as inputs, which may be extremely large, partitions each of them into s pieces as $M_i = \{M_{i1}, M_{i2}, \cdots, M_{is}\}$ and stores them at the nodes as outputs. According to the popularity matrix given in (22), each portion has a priority of $\gamma_{i,j}$ that indicates the survivability.

Algorithm 1 Brain Inspired Coded Caching

1: **Periodic Process** (Inputs: $\{M_1, M_2, \cdots, M_N\}$, Outputs: $\{F_1, F_2, \cdots, F_K\}$)
2: **procedure** TRAINING
3: Estimate the popularity matrix in (22) at time n based on (23)
4: **end procedure**
5: **If** (Off-Peak Hours)
6: **procedure** CACHE UPDATE
7: Perform the placement procedure in coded caching [11] according to the matrix specified at step 3
8: **end procedure**
9: **procedure** DELIVERY
10: Perform the delivery procedure in coded caching [11] according to the updated cached
11: **end procedure**
12: **end if**
13: **If** (Peak Hours)
14: **procedure** DELIVERY
15: Perform the delivery procedure in coded caching [11] according to the latest cache contents
16: **end procedure**
17: **end if**
18: **end Periodic Process**

This algorithm allows the cache update periodically except for the peak hours during the day as opposed to the offline approaches that store the files to the caches in the morning and do not make any updates until the next morning. Also, this algorithm can address the practicality problems of online caching methods in which the files are updated on the fly, e.g., this cannot be practical when the cache content update corresponds to peak hours. Also, updating the file at its first occurrence may not be the best strategy in case of a user request a non-popular file. It is apparent this algorithm converges to the offline coded caching algorithm [11] at the worst case, i.e., when the popularity matrix changes once in a day.

V. CONCLUSIONS

This paper draws an analogy between the large-scale network in the central nervous system and cloud and fog networking that has been proposed for 5G wireless systems. It has been shown that the efficiency of the central nervous system in processing big data depends on the architecture of the *brain − spinalcord − nerve* network. An analog of this network architecture has been proposed for future IoT/5G networks, i.e., a *cloud − fog − thing* hierarchical network architecture that seems promising for processing big data. Based on this analogy, one can better model the central nervous system using the basic notions and tools for *cloud − fog − thing* network to understand the physiology of central nervous system more clearly. Within this scope, the optimum number of neurons at the spinal cord in which synaptic plasticity occurs is determined using stochastic geometry, which is also employed to model cloud and fog networking. Additionally, the acquisition and maintenance of motor skills are modeled as coded caching. Motor skills are the most important part of the spinal cord and are responsible for many critical functions. Hence, this model can be inspiring for those working in this exciting area including neuroscientists. Another contribution of this paper is to develop novel efficient algorithms/protocols for 5G networks that are inspired by the brain and spinal cord network and a new coded caching algorithm is presented.

Another contribution of this paper is pointing out the important problems that significantly degrade the quality of human life due to serious diseases such as stroke, trauma, depression from a network science point of view, which makes this inter-disciplinary paper appealing and promising. It is anticipated that our findings can inspire many other papers in this important and exciting area that can lead to further contributions in the treatment of severe central nervous system diseases.

REFERENCES

[1] F. Bonomi, R. Milito, J. Zhu, and S. Addepalli, "Fog computing and its role in the Internet of Things," in *Proc. Workshop Mobile Cloud Comput.*, Helsinki, Finland, Aug. 2012, pp. 13–16.

[2] M. Chiang and T. Zhang, "Fog and IoT: An overview of research opportunities," *IEEE Internet Things J.*, vol. 3, no. 6, pp. 854–864, Dec. 2016.

[3] B. Tang, Z. Chen, G. Hefferman, T. Wei, H. He, and Q. Yang, "A hierarchical distributed fog computing architecture for big data analysis in smart cities," in *Proc. ASE BigData Soc. Informat.*, 2015, pp. 28:1–28:6.

[4] I. Stojmenovic, "Fog computing: A cloud to the ground support for smart things and machine-to-machine networks," in *Proc. Telecommun. Netw. Appl. Conf. (ATNAC)*, Nov. 2014, pp. 117–122.

[5] T. H. Luan, L. Gao, Z. Li, Y. Xiang, and L. Sun. (Feb. 2015). "Fog computing: Focusing on mobile users at the edge." [Online]. Available: https://arxiv.org/abs/1502.01815

[6] S. Yi, C. Li, and Q. Li, "A survey of fog computing: Concepts, applications and issues," in *Proc. ACM Workshop Mobile Big Data*, 2015, pp. 37–42.

[7] D. Purves *et al.*, "Spinal cord circuitry and locomotion," in *Neuroscience*, 2nd ed., 2001.

[8] E. Balevi and O. B. Akan, "A physical channel model for nanoscale neuro-spike communications," *IEEE Trans. Commun.*, vol. 61, no. 3, pp. 1178–1187, Mar. 2013.

[9] M. Haenggi and R. K. Ganti, "Interference in large wireless networks," *Found. Trends Netw.*, vol. 3, no. 2, pp. 127–248, 2009.

[10] M. A. Maddah-Ali and U. Niesen, "Fundamental limits of caching," *IEEE Trans. Inf. Theory*, vol. 60, no. 5, pp. 2856–2867, May 2014.

[11] M. A. Maddah-Ali and U. Niesen, "Decentralized coded caching attains order-optimal memory-rate tradeoff," *IEEE/ACM Trans. Netw.*, vol. 23, no. 4, pp. 1029–1040, Aug. 2015, doi: 10.1109/TNET.2014.2317316.

[12] R. Pedarsani, M. A. Maddah-Ali, and U. Niesen, "Online coded caching," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2014, pp. 1878–1883.

[13] J. R. Wolpaw, "Spinal cord plasticity in acquisition and maintenance of motor skills," *Acta Physiol.*, vol. 189, no. 2, pp. 155–169, 2007.

[14] E. Balevi and R. D. Gitlin. (Jan. 2018). "Optimizing the number of fog nodes for cloud-fog-thing networks." [Online]. Available: https://arxiv.org/abs/1801.00831

[15] M. Ueda, Y. Sako, T. Tanaka, P. Devreotes, and T. Yanagida, "Single-molecule analysis of chemotactic signaling in *Dictyostelium* Cells," *Science*, vol. 294, pp. 864–867, Oct. 2001.

[16] P. Thomas, D. Spencer, S. Hampton, P. Park, and J. Zurkus, "The diffusion mediated biochemical signal relay channel," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 16. 2004, pp. 1263–1270.

[17] S. Foss and S. Zuyev, "On a Voronoi aggregative process related to a bivariate Poisson process," *Adv. Appl. Probab.*, vol. 28, no. 4, pp. 965–981, 1996.

[18] J. R. Wolpaw, "The complex structure of a simple memory," *Trends Neurosci.*, vol. 20, pp. 588–594, Dec. 1997.

[19] X. Y. Chen, J. S. Carp, L. Chen, and J. R. Wolpaw, "Corticospinal tract transection prevents operantly conditioned H-reflex increase in rats," *Experim. Brain Res.*, vol. 144, no. 1, pp. 88–94, 2002.

[20] L. Chen, Y. Chen, R. L. Liu, Y. X. Chen, and J. R. Wolpaw, "Bilateral globus pallidus ablation in rats prevents down-conditioning of H-reflex," *Program*, vol. 417, no. 3, 2004.

[21] D. D. Sleator and R. E. Tarjan, "Amortized efficiency of list update and paging rules," *Commun. ACM*, vol. 28, pp. 202–208, Feb. 1985.

[22] E. Bastug, M. Bennis, and M. Debbah, "Living on the edge: The role of proactive caching in 5G wireless networks," *IEEE Commun. Mag.*, vol. 52, no. 8, pp. 82–89, Aug. 2014.

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