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Synergies between Cloud-Fog-Thing and Brain-Spinal Cord-Nerve Networks

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***Abstract*—This paper is directed towards describing the striking similarities and synergies between cloud and fog nodes that constitute the *cloud-fog-thing* [Fog Network] architecture proposed for 5G networks and the human *brain-spinal cord-nerve* network model. On the one hand, the central nervous system can be better modeled considering the duality with Fog Networks, and, on the other hand, novel algorithms/protocols inspired from the central nervous system can be developed for throughput and latency performance improvement in Fog Networks.**

Designing and managing large-scale Fog Networks using stochastic geometry and machine learning is applied to determine the optimum number of fog nodes and their locations that optimize throughput and latency for 5G networks. Having observed the close relation between the Fog Networks and the spinal cord, these results may be adapted to increase understanding of the role of spinal cord plasticity in learning and ultimately suggest new means of treating central nervous system disorders associated with the spinal cord plasticity. Inspired by the cooperation between the brain and the spinal cord, a modified coded caching policy is proposed for Fog Networks, that is, the files to be stored at the fog nodes are determined as a result of continuous information flow between cloud and fog nodes through the latent variables assigned to files.

***Index Terms*—Fog networking, stochastic geometry, machine learning, spinal cord, central nervous system.**

I. Introduction

Many system advances are achieved by observing analogies between systems, that while seemingly disparate, share common properties and knowledge that has been acquired for one system is applied to improve performance of the other. In this paper, the striking similarities and synergies between the *cloud-fog-thing* architecture based on Fog Networks that have been proposed for 5G networks and the human *brain-spinal cord-nerve* network model are highlighted, and then possible cross fertilization opportunities are proposed.

A. Fog Networking

Latency sensitive use cases of 5G networks, such as autonomous vehicles, smart cities, and certain Internet of Things (IoT) applications, along with exponentially growing data traffic are driving a paradigm shift in network architecture by using computing and memory resources in the network edge, which is referred to as fog or edge computing, while maintaining cloud resources for appropriate functions [1]. This architecture extends cloud-like functions closer to the end devices so that faster service can be provided to these devices while reducing the load in the network core. Fog computing capable units, i.e., fog nodes with communication, computation and storage capability, along with other resources create a fog network [1]. Fog nodes may be upgraded from the existing nodes in the network such that each node can be a fog node, e.g., a base station, an access point or even a mobile [2]. At this point, it is rather important and appealing to find the number and locations of these fog nodes for a given network while going from theory to practice.

Fog networking does not obviate the cloud; on the contrary, the goal is productive cooperation with the cloud. A novel wireless network architecture emerging from this cooperation is the *cloud-fog-thing* network that can manage the large-scale heterogenous data supporting a wide variety of 5G use cases and IoT applications as shown in Fig. 1 [2]. This architecture has been suggested as being matched to many different cases such as in smart traffic lightning systems, autonomous vehicles, smart grid [1], smart building [3], smart pipeline monitoring [4], augmented reality and real-time video analytics [5]. Despite the popularity of the *cloud-fog-thing* architecture, there have been many unexplored questions related to fog nodes, e.g., how many fog nodes should there be in a given area, and what are their locations? Interestingly, the answers of these questions not only improve the performance of fog networking but, as is discussed later, may also help in the treatment of the fundamental disorders in the central nervous system where the spinal cord network is viewed as a fog network.

B. Central Nervous System Network

Current knowledge about the central nervous system basically comes from experiments; however, these experiments are not sufficient to identify the intrinsic mechanism that leads to inefficiency in the treatment of serious spinal cord injury and other central nervous system disorders [6]. In this regard, modeling the central nervous system in terms of cloud and fog networking can bring a new dimension in which cloud and fog networking technology may be used for further understanding of the central nervous system, and thus this may facilitate future treatment of disorders.

The treatment of spinal cord injury and other disorders are related to spinal cord plasticity, which refers to the learning capability ensured by some specialized neurons at the spinal cord similar to the fog nodes, and hence they are denoted as so-called *fog neurons* in this paper. Finding the number and locations of the *fog neurons* by adapting the analyses that will be performed for *cloud-fog-thing* networks is quite appealing, because this may ease the treatment of spinal cord injury and other central nervous system disorders, by localizing the *fog neurons* that can also localize the potential causes of disorders stemming from loss of plasticity.

C. Potential Fog and Spinal Synergies

An assessment of the basic principles of the fog and spinal cord networks reveals astonishing similarities. For example, the location and content aware, distributed, low latency services of fog networking are found in the spinal cord that rapidly provides specific services to the local parts of the body. Indeed, the communication, computation and storage functions performed by a fog network are very analogous to what a spinal cord does in the central nervous system, which is composed of the brain and the spinal cord creating the *brain-spinal cord-nerve* network analogy with the *cloud-fog-thing* architecture. It is worth emphasizing that the similarity between these architectures can create synergies so that both networks can benefit. On the one hand, the central nervous system can be better modeled considering the duality with the cloud and fog nodes. On the other hand, novel algorithms/protocols can be inspired from the central nervous system for content distributed networks involving cloud and fog nodes.

In this paper, the optimum number of fog nodes to support a high average data rate and low transmission delay is analyzed using stochastic geometry [7] for the *cloud-fog-thing* network. Additionally, the locations of these equivalent fog nodes are found using clustering [8], a classic unsupervised machine learning algorithm, where the leaders of clusters will become fog nodes. Both hard and soft clustering are considered to find the locations of fog nodes. In hard clustering a node can only connect to one cluster leader, whereas in soft clustering there can be connection to more than one cluster leader. Next, the number and locations of the so-called *fog neurons*, which are responsible for plasticity that can ensure healing and that play a key role in the treatment of serious diseases in the central nervous system, are determined using the same analyses as for *cloud-fog-thing* network after modeling the central nervous system as *brain-spinal cord-nerve* network owing to the strong analogy with *cloud-fog-thing* architecture. Note that it may be quite meaningful to model the spinal cord as a fog network, not only for facilitating the treatment of various disorders, but also for developing new algorithms/protocols for wireless networks. In this latter sense, a coded caching mechanism is proposed later in the paper for fog networks inspired from the interplay between the brain and the spinal cord.

The structure of this paper is as follows. In Section II, the optimum number and locations of fog nodes are determined. The central nervous system is modeled in terms of cloud and fog, and the synergies with fog networks are highlighted in Section III. The paper ends with the concluding remarks in Section IV.

II. Finding the Number and Locations of Fog Nodes in Heterogenous Networks

Fog networking is based on the idea of extending cloud-like functions towards the end devices through some specialized nodes so that location and content aware, distributed, and lower latency services can be provided to the end devices, e.g., to the mobiles, IoT devices or sensors [2]. In this regard, some existing nodes in the network infrastructure, which may be a picocell, a femtocell, an access point, a router or a mobile, are provided with the necessary resources and upgraded to a fog node. Whatever the fog nodes are upgraded from, each fog node must have appropriate communication, computation and storage capability.

The efficient usage of resources by upgrading some nodes to fog nodes in the future wireless networks can be necessary to ensure the low latency requirements of 5G applications [9]. Also, the huge amount of data in the network cannot be solely managed by cloud servers and it is not reasonable to process the low-latency data in the cloud. These challenges have revealed the intriguing interplay and dependencies between cloud and fog networking, which has been proposed for many areas [1]-[5]. Accordingly, the global large-scale data processing capability of cloud networking is combined with the location and content aware, distributed fog nodes. An example of this network architecture is depicted in Fig. 1, where some nodes in the existing infrastructure were updated to fog nodes. Some data is processed at the fog nodes, and the rest is conveyed to the cloud for processing.

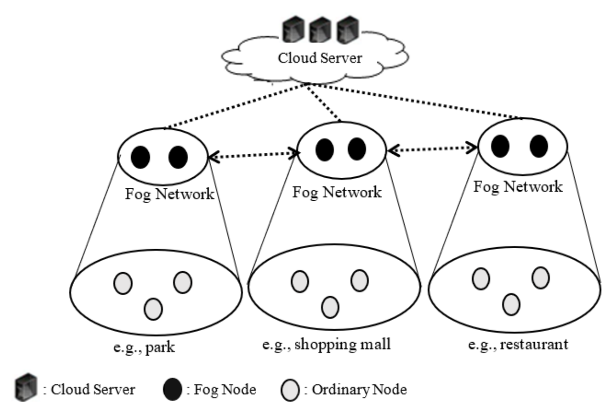


Fig. 1. The integration of cloud and fog networking

There are some fundamental questions that need to be addressed to optimize fog networking. These questions are as follows: How many nodes should be upgraded as fog nodes in a local area such as a park, a shopping center or a restaurant that is covered by a fog network, and what are the locations of those fog nodes, i.e., which nodes are the fog nodes in a given network topology within the area of interest? The former question will be addressed using stochastic geometry in which each existing node is considered as a point. The latter question is discussed within the context of machine learning. These issues shall be discussed in the subsequent sub-sections.

A. The Optimum Number of Fog Nodes in a Fog Network

Consider a heterogenous network in a local area, e.g., in a park with many different nodes such as picocells, femtocells, access points, routers and mobiles, where some of the nodes will be upgraded to fog nodes while the remaining are ordinary nodes with the (possibly unrealistic) assumption that any node can become a fog node in a cloud-to-things continuum [2]. One of the fundamental question arises is what number of fog nodes should be upgraded from the existing nodes? Indeed, this is an optimization problem that will be solved by defining a proper criterion. Before defining a criterion, let's remember the basic situations that require fog networking, which are big data processing and low latency. In this manner, it makes sense to define a criterion so as to maximize the data rate associated with big data, and minimize the transmission delay regarding the low latency.

Suppose that packets of size M are transmitted from the end devices to the cloud through the fog nodes. In this regard, the incoming data packets are aggregated at the fog nodes and assume that K bits of each packet are processed while the rest are conveyed to the cloud. Doing so yields the following transmission delay depending on the data rate

$$\tau_{trans} = \frac{M}{R_{fog}} + \frac{M-K}{R_{cloud}} \tag{1}$$

where the Shannon rates are

$$R_{fog} = Wlog(1 + SINR_{fog})$$

and

$$R_{cloud} = Wlog(1 + SINR_{cloud}).$$

Conventional expressions employed in stochastic geometry can be used to express the signal-to-interference-plus-noise-ratio (SINR) as

$$SINR_{fog}(i) = \frac{P_i h_i x_i^{-\alpha}}{\sigma^2 + I_{fog}} \tag{2}$$

where P_i is the desired transmission power and h_i is the power fading coefficient (gain) for the i^{th} end device whose distance from a fog node is x_i. Additionally, α is the path loss coefficient, σ^2 is the noise power and I_{fog} is the residual interference power at the fog node. Similarly,

$$SINR_{cloud}(j) = \frac{P_j h_j y_j^{-\alpha}}{\sigma^2 + I_{cloud}} \tag{3}$$

where P_j is the desired transmission power and h_j is the power fading coefficient (gain) of the j^{th} fog node and the cloud is at a distance of y_j from the fog node.

Based on (1)-(3), and the assumption that each node can become a fog node with a probability p, yields the following objective function, which minimizes the total packet transmission time of $N - Np$ ordinary nodes to the cloud through Np fog nodes, when each fog node aggregates the packets coming from the ordinary nodes before transmission to the cloud

$$J_\alpha = \min_p \left(\sum_{i=1}^{N-Np} E[x_i^\alpha] + \sum_{j=1}^{Np} E[y_j^\alpha] \right) \tag{4}$$

such that N is the total number of nodes in a given area and p is the probability of being a fog node in which (4) is optimized according to this value of p, which yields Np fog nodes and $N - Np$ ordinary nodes after the optimization. This follows by expressing R_{fog} and R_{cloud} in (1) in terms of (2) and (3) and then generalizing the result for Np fog nodes and $N - Np$ ordinary nodes. Hence, optimizing (4) minimizes the total transmission delay, which requires the maximization of the data rates of R_{fog} and R_{cloud}. Note that (4) can be written as a closed form expression in terms of p for a path loss exponent of 2 as [10]

$$J_2 = \frac{(N - Np)\pi^2 R^2}{2(Np)^2} + \frac{2Npa^2}{3} \tag{5}$$

that leads to [10]

$$p = \left(\frac{6\pi^2 R^2}{4a^2 N^2} \right)^{1/3} \tag{6}$$

when the fog nodes constitute a circular network, whose radius is R in which there is a cloud centered at a planar square whose one side is $2a$ as illustrated in Fig. 2. Note that one can refer to [10] for the analyses with different path loss exponents.

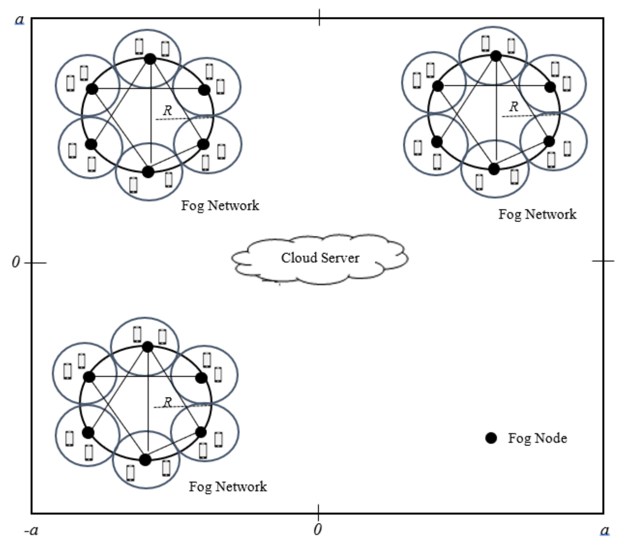


Fig. 2. The underlying network model

It is worth mentioning that in stochastic geometry there are some simplifying assumptions made to obtain closed form solutions including assuming that fog nodes constitute a circular mesh network topology with radius R and from which (6) is obtained. Further simulations were made to observe how the optimum number of fog nodes, which is equal to Np, is affected by this assumption. A simulation is performed such that the cloud is located at the center of a planar square whose one side is 20km and a given number of nodes are uniformly randomly distributed around the cloud, which can be termed as ordinary nodes and then some nodes are upgraded to fog nodes to constitute the fog network. In the simulation, there is not any assumption that fog nodes constitute a circular network topology. In this setting, the optimum number of fog nodes for $N = 200$, $N = 400$ and $N = 800$ are given in Fig. 3. It can be inferred from Fig. 3 that there is an optimum number of fog node that minimizes the objective function, which is smaller than N for all cases. This emphasizes that upgrading all nodes as fog nodes does not minimize the objective function, and thus it becomes sub-optimum. Intuitively, a node far from the cloud can significantly increase the objective function given in (4) if it can directly send the packets to the cloud (as a fog node), it is, therefore, more reasonable to send the packets to the closest fog node instead of being a fog node, which intuitively suggests that not all nodes should be upgraded to fog nodes.

The average optimum number of fog nodes, which can be found analytically with the assumption of a circular network topology, is compared with these simulation results for the same number of total nodes in Table I where R is the radius of the circular fog network and a is half of the one side of the planar square covered by a cloud such that $R \leq a$. As can be seen, the analytical expression (6) gives a very good approximate result when $R = a$ and the total number of nodes is not high. Notice that each fog network covers a local area such as a park, a shopping mall or a restaurant where the total number of network nodes is not so high that implies the accuracy of our analytical result for practical scenarios.

TABLE I
THE AVERAGE OPTIMUM NUMBER OF FOG NODES

	Simulation Result	Analytical Result for $R = a$	Analytical Result for $R = a/2$
$N = 200$	15	14.35	9.04
$N = 400$	19	18.09	11.39
$N = 800$	24	22.79	14.35

B. The Locations of Fog Nodes in a Fog Network

Next, the optimum locations of the fog nodes will be determined for an example heterogeneous network composed of one high power node (HPN) and many low power nodes (LPNs) as shown in Fig. 4, where some LPNs are upgraded to fog nodes in case of fog networking.

Clustering, a classical unsupervised machine learning technique, is employed to find the locations of fog nodes. Nodes are clustered based on their distances for hard clustering or channel quality for soft clustering, so that the leader of each cluster or cluster-head becomes a fog node. In this regard, both hard clustering and soft clustering are studied to specify the locations of fog nodes. In the former, each ordinary node has to be connected to only one fog node that will be determined according to the K-means clustering algorithm [8]. On the other hand, nodes can be connected to more than one fog node in soft clustering with a certain probability.

1) Hard Clustering: One of the basic clustering methods in machine learning is the hard or K-means clustering algorithm in which the data set is clustered in an iterative procedure, where each iteration has two successive steps such that the K center points of clusters are first determined, and then each data is connected to the closest central point [11]. This procedure is iterated, and thus the center points of clusters change until the algorithm converges, i.e., up to some number of iterations. In this paper, this algorithm is modified in an attempt to find the locations of fog nodes among many alternatives within the area of interest. The original K-means clustering algorithm is modified, because in the original algorithm the cluster-head is at the center for each cluster. Here, the cluster-head does not have this restriction, because there is not necessarily a node at the center of the cluster, and for this reason the nodes that have the closest distance to the center are deemed cluster-heads. Additionally, K is given as *a priori* information in the standard K-means clustering algorithm, whereas in the modified algorithm the value of K is analytically determined as Np where N is the total number of nodes and p is found analytically, e.g., as (6) when the path loss exponent is 2.

In the proposed algorithm, the locations of fog nodes are found by hard clustering such that the geographical locations of the nodes residing in a 2-dimensional Euclidean space constitute the data set and this data set is partitioned into K clusters, where each cluster-head will be upgraded to a fog node. The cost function to form the clusters, is given as

$$J = \sum_{n=1}^{N-K} \sum_{k=1}^{K} \gamma_{nk} ||z_n^1 - z_k^2||^2 \tag{7}$$

where z_n^1 and z_k^2 represent the locations of ordinary nodes and fog nodes or cluster-heads, respectively, and

$$\gamma_{nk} = \begin{cases} 1 & : k = argmin_j ||z_n^1 - z_j^2||^2 \\ 0 & : o.w. \end{cases} \tag{8}$$

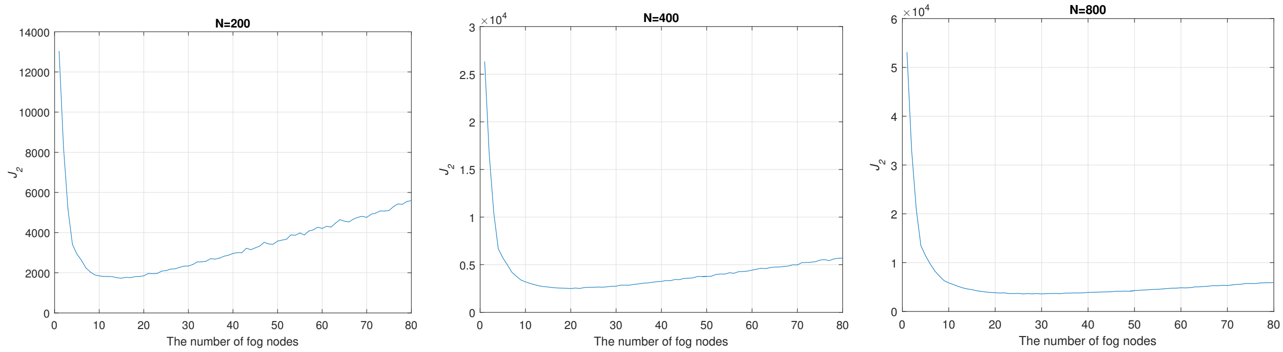
which means that each point is assigned to the closest cluster-head, or each node is connected to the closest fog node among K alternatives according to the minimum distance criterion. It is critical to note that there may be no node at the center points, and thus the cluster-heads are selected among the nodes that are the closest to these central points that lead to

$$z_k^2 = argmin_{z_j^2} \left|\left| z_j^2 - \frac{\sum_n \gamma_{nj} ||z_n^1 - z_j^2||}{\sum_n \gamma_{nk}} \right|\right|^2. \tag{9}$$

Since J in (7) is reduced at each iteration, the algorithm converges [8]. Notice that the algorithm that produces the locations of fog nodes with modified hard K-means clustering is presented as follows:

Algorithm-1: Finding the locations of fog nodes with hard clustering

1: Set the value of N to the total number of nodes in the area
2: Find the value of p for a given network geometry
3: Set the number of clusters as $K = Np$
4: Select the K fog nodes randomly among the N number of nodes
5: **Begin:** Two-step iterative procedure
6: Assign the other nodes to one of the K fog nodes so as to minimize the Euclidean distance as given in (8)
7: Calculate the center points of clusters
8: Determine the cluster-heads or fog nodes according to (9)
9: **If** (even one cluster-head or fog node changes)
10: Go to step 6
11: **end if**



(a) (b) (c)

Fig. 3. The simulation results for the optimum number of fog nodes (a) $N = 200$. (b) $N = 400$. (c) $N = 800$.

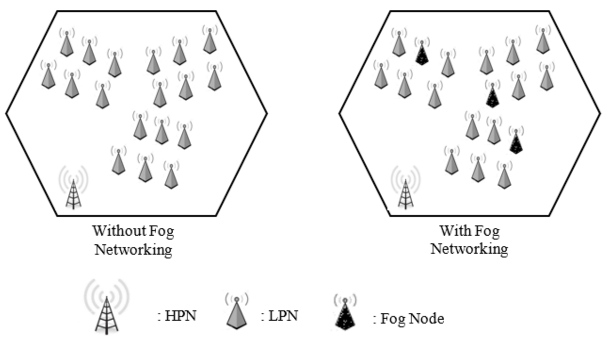


Fig. 4. The location of fog nodes for a heterogeneous network

12: **else**
13: Algorithm converges
14: **end else if**
15: **End** Two-step iterative procedure

At the end of the algorithm, the locations of Np fog nodes are found, and the other $(N - Np)$ nodes are assigned to one of the fog nodes.

2) Soft Clustering: Hard clustering algorithm ignores the quality of channels among nodes while clustering, which can be a problem when it comes to optimizing the data rate. In particular, the minimum Euclidean distance, which is employed in hard clustering, can produce the poorest channel. Based on this motivation, the locations of fog nodes are found by a soft clustering algorithm that considers the quality of channels. Accordingly, each node residing in the area of interest can be a fog node depending on channels. Indeed, the locations of fog nodes change dynamically from one channel realizations to another. That is, if the channels among nodes change, the location of fog nodes can change as well. A node that is not upgraded as a fog node, can be connected to more than one fog node, unlike the hard clustering approach. Hence, the locations of the fog nodes as well as which node should take service from which fog nodes are the fundamental questions that arise here.

To address these problems, the channel matrix among nodes are first obtained such that the nodes that have better channels than others will become fog nodes. Then, a probabilistic soft clustering method is followed so that each ordinary node can connect to any fog node with a probability between 0 and 1, e.g., $\gamma_{nk} \in [0, 1]$. The determination of γ_{nk} is critical, because this can directly affect the overall data rate or throughput of the network, which is one of the main parameters associated with the channel quality.

The channel model where a node transmits to many fog nodes at the same time can be considered as a *downlink*. Note that the optimum power allocation that maximizes the data rate for a *downlink* channel is found with a water-filling algorithm [12]. When the connection probability is treated as a power allocation where power is normalized to unity, the water-filling algorithm can be used to determine the values of γ_{nk} to maximize the data rate for clustering [13],[14]. Notice that although water-filling algorithm has primarily been used for power optimization, here it is used to find the similarity measure or connection probability among nodes.

The problems of which nodes should be updated as fog nodes, and which ordinary nodes are connected to which fog nodes are jointly addressed in Algorithm-2. Accordingly, there are N nodes at the beginning of the optimization whose number is given as *a priori* information. The $N \times N$ channel matrix is obtained so that each index in the row or column represents one node placed at one particular location. That is, there is a one-to-one correspondence between the locations of the nodes and the matrix indices. It is important to emphasize that K nodes out of N will be upgraded as fog nodes, where K can be calculated using stochastic geometry similar to hard clustering. Then, the connection or membership matrix Γ that demonstrates the similarity between nodes is obtained using a water-filling algorithm. More precisely, the coefficients of each row of the matrix is determined using a water-filling algorithm whose sum is normalized to 1. Then, taking the average of all rows, the K highest indices of the matrix Γ are determined and the corresponding nodes are updated as fog nodes whereas the rest remains ordinary nodes. A step-by-step definition of the algorithm is given below:

Algorithm-2: Finding the locations of fog nodes with soft clustering

1: Set the total number of nodes within the area of interest to N as *a priori* information
2: Create the $N \times N$ channel matrix H in which each index in the row or column corresponds to one specific node

3: Set the number of fog nodes to K out of N nodes that is found using stochastic geometry
4: Obtain the matrix Γ that demonstrates the connection probability among nodes using water-filling algorithm [14]
5: Find the K highest column indices taking the average of the rows in the matrix Γ
6: Set 0 to the entries in each row of associated with the indices of fog nodes
7: Normalize each row of Γ to 1

III. Modeling the Central Nervous System with Fog Networking Technology

The central nervous system, composed of the brain and spinal cord, has many vital functions that control actions, shapes behaviors, and feelings such as happiness, distress, etc. Despite the complicated mechanism behind those functions, they are simply the natural outcome of the data processing at the brain and spinal cord in which data comes from the millions of peripheral neurons. A close look at the big data processing performed in the central nervous system reveals the interplay between the centralized large-scale data processing capability of the brain and the distributed low-to-medium scale data processing capability of the spinal cord. To be more precise, the spinal cord does not only convey messages between the brain and peripheral neurons but also process some parts of the incoming messages coming from the peripheral neurons. Clear evidence for the processing capability of spinal cord is the spinal reflexes managed by spinal cord, e.g., immediately pulling a hand away from a hot object. Another example of spinal cord processing is the movement capability ensured by the spinal cord, e.g., a cat can walk even if its brain is separated from the spinal cord [15]. Besides communication and computation or data processing functions, the spinal cord has storage capability. For instance, motor skills developed through practicing such as driving, biking, swimming are stored in the spinal cord so that these skills are performed in a rather short time interval compared to the tasks that are performed in the brain [6].

Having communication, computation and storage capability, the spinal cord demonstrates astonishing resemblance to fog networking. In particular, the main goals of the spinal cord are rapid reactions, i.e., low-latency services in response to incoming stimuli, and to help the brain in the processing of big data. These two features are in fact the salient features of fog networking. That is, fog networks provide low latency services to the end devices and partially process the data to reduce the computational burden of the cloud [1].

The spinal cord is composed of 31 pairs of spinal nerves, and each spinal nerve provides location and content aware services to the specific part of the body. For example, the $C5$ and $C6$ pairs of the spinal cord control the shoulder and arm. This structure is similar to fog networking that can provide location and control aware services to the end users. Another point is that spinal cord is closer to the peripheral neurons than the brain so that it can ensure low latency services similar to fog networking which can meet low latency requirements due to being close to the end devices. Additionally, the distributed nature of the spinal cord that spreads from the medulla to the lumbar region of the vertebral column is similar to the distributed architecture of fog networking. The other similar features are that spinal cord has heterogeneous neurons and seamless coverage similar to fog networks. The above similarities describe the close analogy between spinal cord and fog networking.

A promising network model that can be used in 5G use cases or IoT applications is based on the integration of cloud and fog networking termed as *cloud-fog-thing* architecture [2]. Here, the global centralization and large-scale data processing capability of the cloud is combined with the distributed location and content-aware, low-latency service capability of fog networking. Bearing in mind the strong analogy between spinal cord and fog networking, a dual network of the *cloud-fog-thing* in the central nervous system is the *brain-spinal cord-nerve* network model. This architecture is depicted in Fig. 5 such that the brain corresponds to the cloud, the spinal cord corresponds to fog, and the thing is the analogous with nerves or peripheral neurons.

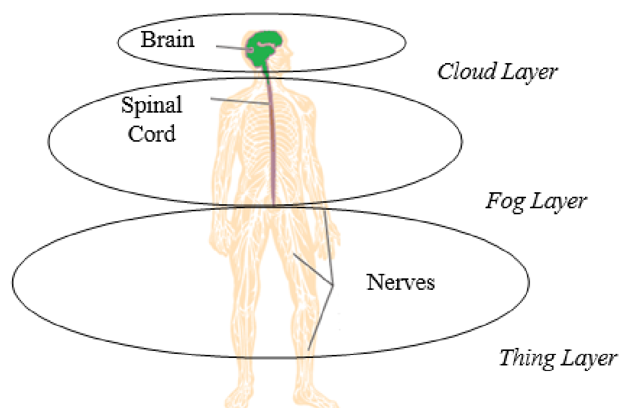


Fig. 5. Modeling the central nervous system in terms of cloud and fog layers

The analogy of *cloud-fog-thing* architecture and *brain-spinal cord-nerve* model can create synergies so that both parties can benefit. On the one hand, modeling the central nervous system as cloud and fog layers can bring a new dimension so that the analysis used in fog networking can be adapted to the central nervous system. This can be appealing and intriguing not only for engineers but also for others who wish to advance understanding of the complex mechanism behind the fundamental tasks of the central nervous system that, hopefully, may facilitate the treatment of disorders in the central nervous system. On the other hand, the current knowledge about the cooperation between brain and spinal cord can inspire methods in cloud and fog networks for the handling of big data. That is, understanding the central nervous system can inspire development of novel algorithms/protocols for fog-based wireless networks. More specifically, the acquiring and maintenance of motor skills at the spinal cord by the coordination of brain are analogous to caching in the fog networks. Here, the motor skills correspond to the files, and the action of acquiring and maintenance of motor skills are treated as searching the popular files and storing them at the fog nodes, i.e., caching.

A. Using Fog Networking Analysis for Increased Understanding of Spinal Cord Plasticity

Once the *brain-spinal cord-nerve* hierarchical network model is treated as *cloud-fog-thing* architecture, the analyses performed for the fog layer of this architecture in Section II can be directly adapted to the spinal cord layer of *brain-spinal cord-nerve* model with the ultimate aim of increasing understanding of spinal cord plasticity. Recall that spinal cord plasticity refers to some neurons at the spinal cord that have the ability of strengthening or weakening the signal over time, in response to increases or decreases in their activity to ensure learning. That is, some neurons at the spinal cord are specialized for plasticity, which is also responsible for acquisition and maintenance of motor skills. Since the acquisition and maintenance of motor skills can be treated as storing files at the fog nodes, these neurons can be considered as having storage capability along with communication and computation capability, and thus they may be viewed as *fog neurons*. Recall that a fog node must have communication, computation and storage capability, so that the neurons at the spinal cord that are not capable of plasticity cannot be identified as *fog neurons*.

The learning mechanism or spinal cord plasticity is quite important in the treatment of spinal cord injury and other disorders as well as acquisition and maintenance of motor skills [6]. Although the structure of spinal cord plasticity is explained in [6], how many neurons should have plasticity and what are their locations are some open critical problems. That is, specifying the optimum number of *fog neurons* as well as their locations can be quite important to localize the causes of diseases, e.g., spinal cord injury and other disorders, and thus may facilitate their treatment. In this regard, the analysis that specifies the optimum number of *fog neurons* given in Section II-A can be directly used when the optimality is based on the data rate and low transmission delay, both of which are required in the central nervous system due to the fact that huge amount of data has to be processed in a rather short time. Here, wireless communication is replaced with molecular communication, which deals with the communication among neurons [16], in which molecules diffuse from one node to another as

$$M_j = M_i \frac{D_i}{\alpha_i} x_i^{-2} \tag{10}$$

where M_i is the number of molecules at the input node, and related to the transmission power P_i, and the channel h_i can be associated with the diffusion coefficient D_i/α_i. Determining the locations of *fog neurons* is as important as finding the number of *fog neurons* that is desired in the clarification of synaptic cord plasticity. Within this scope, both hard and soft clustering can be utilized to find the locations of *fog neurons* using the analysis given in Section II-B.

B. Inspiring from the Central Nervous System for Caching in Fog Networking

One of the important features of fog networking is caching so that popular files are first trained, and then a local copy of these files is stored at the fog nodes. Since fog nodes are closer to the end devices than a cloud server, they can meet the requests of users in a shorter time interval. Caching at the fog nodes also reduces the network load, as well as the computational complexity of the cloud. A dual behavior with caching occurs in the central nervous system in the acquisition and maintenance of motor skills such as driving, biking, swimming. Accordingly, the spinal cord first acquires the motor skills through the strong cooperation with brain, which learns these motor skills with practice, and then it maintains them. Doing so results in faster responses, because the spinal cord is closer to the peripheral neurons than the brain, and it alleviates the burden in the brain, both of which are well suited to the aim of caching in fog networking.

The key point in maintaining many motor skills in the spinal cord depends on the continuous information flow between brain and spinal cord through the corticospinal tract [6]. This means that even if a motor skill is stored in the spinal cord, the brain continues to send some information. This corresponds to the sending of information from cloud to fog nodes through the fronthaul network after caching to keep the files up-to-date. Notice that the information acquiring the motor skills between the brain and spinal cord is sent through the corticospinal tract, which can be considered as the fronthaul network between the cloud server and a fog node. These analogies are summarized in the Table II.

TABLE II
ANALOGIES BETWEEN CACHING, AND ACQUIRING AND MAINTAINING MOTOR SKILLS

Brain-Spinal Cord-Nerve Network	*Cloud-Fog-Thing* Network	Comments/Notes
Brain	Cloud	Centralized controller
Spinal Cord	Fog networking	Distributed networking
Corticospinal tract	Fronthaul	The pathway between the centralized controller and distributed nodes
Motor skills	Files	Stored entities in the distributed nodes

Motor skill capabilities have spread into many *fog neurons*, e.g., consider one of the simplest motor skills, H-reflex conditioning, that spreads into many neurons at the spinal cord responsible for plasticity [6]. The incoming signal from the brain through the corticospinal tract is combined with the information from all relevant *fog neurons* that constitute the motor skill. Note that here the necessity of brain is crystal clear due to the fact that the patients suffering from a stroke cannot use this motor skill although the damage is in the brain, i.e., there is no damage in the spinal cord. Another important point regarding motor skills is that one *fog neuron* can store many different motor skills. Considering these factors, acquiring and maintaining of motor skills suggest a caching method similar to the one that has been recently proposed as coded caching whose main advantage comes from the reduced network load [17]-[19].

Inspiration from the continuous data flow between the brain and the spinal cord through the corticospinal tract, and the fact that motor skills are stored according to their criticality

[6] can lead to a new modified coded caching algorithm for fog networks. The former feature can also be explained by an experiment where the H-reflex conditioning disappears when the brain is ablated [20]. The latter property suggests a model where that the least critical file should be deleted instead of the least recently used, which is quite different than the traditional caching that deletes the least recently used file [21]. For instance, the motor skill of pulling hands away from a hot object is never deleted even if this is the least recently used motor skill. Based on these observations, a modified version of coded caching seems appropriate. Accordingly, each file is assigned a variable and this variable is continuously updated. The files that have the highest variable is stored in the node with a limited storage area. This approach ensures the cache is updated at any time, as opposed to offline methods where the files are updated only at the beginning of the day [18]. Additionally, the proposed coded caching policy inspired by the central nervous system can be classified as a proactive method because the popularity of the files is predicted with the assigned variables for the files before the request is made unlike online coded caching in which the files are obtained in response to incoming requests [19].

IV. Conclusions

This paper described the striking synergies between *cloud-fog-thing* [Fog Network] architecture proposed for 5G networks and the human *brain-spinal cord-nerve* network model. Fog networking will likely have an important role in the management of large-scale data networks, such as 5G networks, that enable low latency as well as high throughput. By determining the optimum number and locations of the fog nodes for a given network to optimize the average data rate and transmission delay, via stochastic geometry and machine learning, these results were proposed to enhance the understanding of the hierarchical network model in the central nervous system dubbed *brain-spinal cord-nerve* model. That is, the architecture that models the relation between the cloud and fog layer can be used in the modeling of the central nervous system depending on the strong analogy between the spinal cord and fog networking. Modeling and analyzing the inherent mechanism within the central nervous system using the models and tools from wireless networking may be a promising approach to shaping the understanding of the physiology of the central nervous system as well as potentially facilitating the future treatment of disorders in the brain and spinal cord. Using the analogy can be inspiring in the design of novel algorithms and protocols for wireless networks such as the novel caching algorithm proposed in this paper.

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