Transfer Learning of Fuzzy Spatio-Temporal Rules in a Brain-Inspired Spiking Neural Network Architecture: A Case Study on Spatio-Temporal Brain Data

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***Abstract*—The paper demonstrates for the first time that a brain-inspired spiking neural network (SNN) architecture can be used not only to learn spatio-temporal data, but also to extract fuzzy spatio-temporal rules from such data and to update these rules incrementally in a transfer learning mode. We propose a method, where a SNN model learns incrementally new time-space data related to new classes/tasks/categories, always utilising some previously learned knowledge, and presents the evolved knowledge as fuzzy spatio-temporal rules. Similarly, to how the brain manifests transfer learning, these SNN models do not need to be restricted in number of layers, neurons in each layer, etc. as they adopt self-organising learning principles. The continuously evolved fuzzy rules from spatio-temporal data are interpretable for a better understanding of the processes that generate the data. The proposed method is based on a brain-inspired SNN architecture NeuCube, that is structured according to a brain 3D structural template. It is illustrated on tasks of incremental and transfer learning and knowledge transfer using spatio-temporal EEG data measuring brain activity, when subjects are performing tasks in space and time. The method is a general one and opens the field to create new types of adaptable and explainable spatio-temporal learning systems across domain areas.**

***Index terms* — fuzzy spatio-temporal rules; spatio-temporal learning; transfer learning; EEG data; spiking neural networks; explainable AI ; NeuCube.**

I. Introduction

Despite the advances in fuzzy systems and in the methods of transfer learning (TL), the problem of extracting fuzzy spatio-temporal rules (fSTR) from spatio-temporal data and tracing their evolution through *spatio-temporal learning* in a computational model or in the human brain is still an open problem. A main question is how to extract fSTR from incrementally trained models on spatio-temporal data of new outcomes, how to trace the changes/evolution of knowledge and how to discover the spatio-temporal features that trigger these changes.

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Early research in the field of TL included methods for leaning to learn [21] and multitask learning [22]. TL methods were introduced in [23, 24], all concerned with learning vector-based or frame-based data and not spatio-temporal data. Vector-based TL has been introduced and applied already on several tasks utilizing traditional machine learning techniques [2] [3] [23] [24]. In [52-54] methods of TL are developed for TSK fuzzy systems and applied on EEG data of epilepsy. Various methods for knowledge extraction from trained systems on vector-based data have also been explored, such as fuzzy rules, decision trees, graphs, etc. In [4] [5] a single fSTR is extracted from a SNN on EEG data, but not in a TL mode.

The human brain represents learned knowledge as patterns of neuronal clusters, connected together and activated in time and space. The knowledge is learned incrementally from spatio-temporal stimuli in a TL mode, so that when new knowledge is learned, some of the previously learned knowledge can be partially recalled and utilized, for example learning multiple languages [29]. Another example is the dynamic spatio-temporal knowledge learned through TL when humans acquire certain skills, such as recognising an object and moving a hand to grasp it, by utilising trajectories of activated neuronal clusters learned previously for different tasks [32, 49].

Human knowledge can be represented as fSTR. A fSTR rule represents an outcome as a result of a sequence of events, each happening to *certain degree*, at locations defined as fuzzy clusters (*about spatial area*), and at a time, defined as *about time*. The fuzzy terms are defined by membership functions, such as Gaussian, defining for example that neurons in the center of the cluster fire more in the middle of a time interval.

As an example, the knowledge learned in the brain shown in Fig.1 can be represented as fSTR, such as:

IF (a person is seeing an object and lifting it)
THEN (the following spatio-temporal activities take place)
(at time about t1 information is transferred from the retina, through the Thalamus to the area around V1)
(at time about t2 the area around V1 is highly activated)
(at time about t3 the area around V2 is moderately activated)
(at time about t4 the area around V4 is moderately activated)
(at time about t5 the area around IT is highly activated)
(at time about t6 the area around PFC is highly activated)
(at time about t7 the area around PMC is low activated)
(at time about t8 the area around MC is highly activated)
(at time about t9 muscles are highly activated for grasp and lift).

The challenge is, inspired by the TL ability of the brain and the already developed brain-inspired computational architectures, to achieve TL of spatio-temporal data in a computational model and to extract and trace the evolution of fSTR and their main features for a better understanding of the data and for the prediction of future events.

The main contribution of this paper is that it introduces for the first time a method for transfer learning (TL) of fuzzy spatio-temporal rules (fSTR) and for the discovery of main features from spatio-temporal data using a brain-inspired spiking neural network (BI-SNN) architecture. This research extends main principles of neural networks, fuzzy systems and brain data analysis, that have deep roots in the theory of computational intelligence [41,42,43].

The organisation of the paper is the following: Section II presents a brief description of brain-inspired SNN exemplified by NeuCube. Section III proposes new algorithms for TL of fSTR in NeuCube. Section IV presents case studies of TL of fSTR from spatio-temporal EEG data, when a single subject is performing complex tasks one after another, and section V is extracting fSTR when multiple subjects perform same complex tasks in space and time. Section VI presents a discussion on the applicability of the proposed methods and Section VII is a conclusion and an outline of future directions.

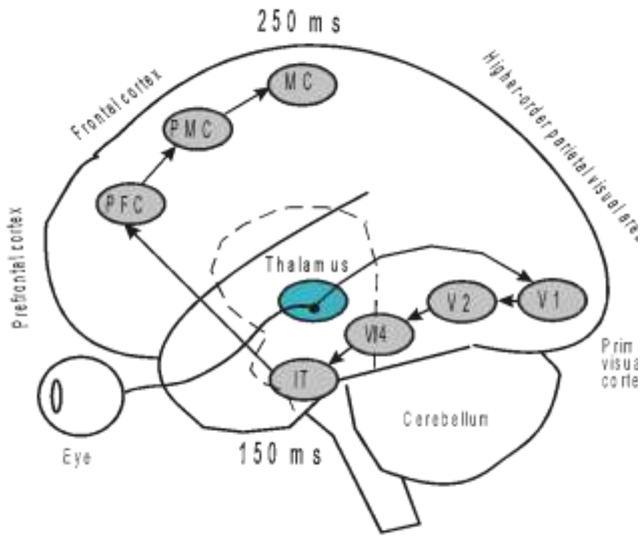

Fig.1. A learned trajectory of activated neuronal clusters when a person is seeing an object and grasping it, that can be represented as a fSTR as shown in the text. When the person is learning to grasp another object, part of the already learned trajectory is used in a TL way for another fSTR (from Benuskova and Kasabov, 2007).

II. Spiking Neural Networks (SNN) and Brain-Inspired Spiking Neural Networks (BI-SNN). NeuCube

A. SNN

Spiking neural networks (SNN) utilise important learning principles manifested in the human brain, including:

1. Spike-time information representation.
2. Evolution of knowledge as evolving connectivity of neuronal clusters in space and time.

Several types of SNN architectures and their learning algorithms have been introduced so far by many authors (see a review in [6]). In the dynamic evolving SNN (deSNN) [13] spatio-temporal data is learned incrementally in a supervised mode. deSNN is a two-layer feedforward SNN where the output neuronal layer evolves incrementally neurons that are generated to capture the temporal pattern of every spatio-temporal example /sample presented. It uses two parameters – modulation factor Mod, to set the initial connection weights for each generated output neuron i using the first incoming spike from input neurons j [13], and a drift parameter D to modify these connection weights based on the following spikes coming to this neuron (Eq.1). Spatio-temporal data samples from different tasks (classes) are presented one-by-one and learned incrementally in the deSNN model without any knowledge reinforcement from previously learned samples. Output neurons with similar connection weights, representing same class outputs, can be aggregated to represent prototypes. The deSNN incremental learning algorithm, denoted further as ImSNN, is presented in the Supplementary file and used in the experiments in this paper.

(Eq.1) $w_{j,i} = \alpha.\ Mod^{\ order\ (j,i)}$

$\Delta w_{j,i}\ (t) = e_j(t).\ D$

where: ej(t) =1 if there is a consecutive spike at synapse j at time t during the presentation of the learned pattern by the output neuron i; and (-1) otherwise. In general, the drift parameter D can be different for 'up' and 'down' drifts; α *is* a parameter.

Incremental learning in a deSNN feedforward classifier can be very efficient, fast, and accurate for learning in changing environments [37,39,40] and it is not a TL.

B. BI-SNN and NeuCube

Some SNN architectures, such as NeuCube [1] are structured according to structural 3D brain templates and designed to capture brain data [7]. They are used also for other spatio-temporal data [6]. NeuCube is schematically illustrated in Fig. 2. In NeuCube, a 3D SNN cube is spatially organised to map a 3D brain template, such as Talairach template [8], Montreal Neurological Institute (MNI) template [9], or other brain templates. Each spiking neuron corresponds to a small 3D area of the brain, having the same 3D coordinates, and neuronal clusters represent functional areas. Input data can be brain EEG, fMRI, etc. and also sensory spatio temporal information related to pollution, earthquakes etc. [6]. Spike sequence data is entered in the 3D SNNcube via input neurons which 3D coordinates corresponding to the coordinates of the input variables when measuring the data. Learning in NeuCube is a two-phase process, including unsupervised learning in the brain-structured SNNcube and a consecutive supervised learning for classification or regression purposes in a deSNN module. While spike trains are entered into the SNN model incrementally, a spike time algorithm, such as Spike-time Dependent Plasticity (STDP) learning [10] [11] [12] (Eq.2) is applied locally to each two neurons. The SNNcube learns to represent spatio-temporal patterns from the input data and is a 4D spatio-temporal learning machine (3D space and 1D time).

These patterns are learned and classified in a deSNN module [13].

(Eq.2) $W(t_{pre} - t_{post}) = \begin{cases} A_{+} exp\,(\frac{t_{pre} - t_{post}}{\tau_{+}}) & if\ t_{pre} < t_{post} \\ -A_{-}\ exp\,(-\frac{t_{pre} - t_{post}}{\tau_{-}}) & if\ t_{pre} > t_{post} \end{cases}$

where $W(t_{pre} - t_{post})$ defines the magnitude of a synaptic change based on the time interval between spikes at pre- and pos-synaptic neurons $(t_{pre} - t_{post})$, A+, A-, τ+ and τ- are parameters defining how much the weight W is increasing or decreasing.

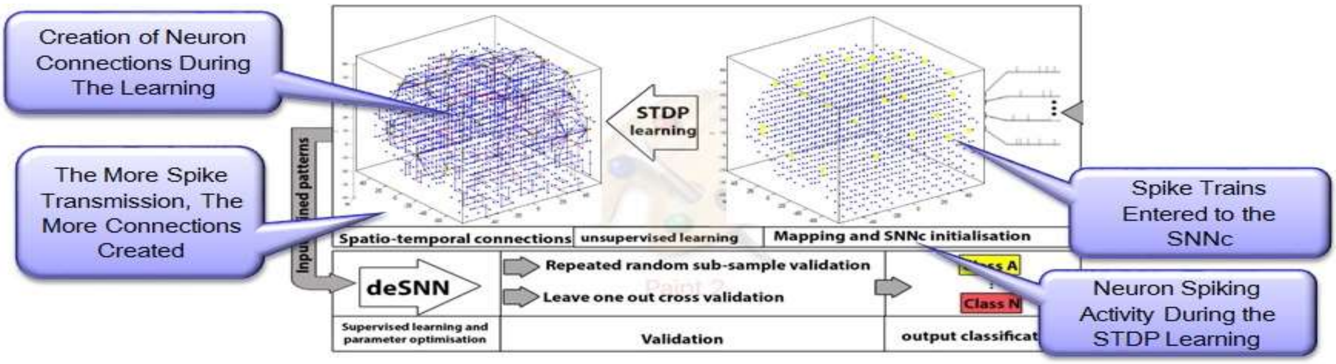

Fig 2. A general diagram of the BI-SNN NeuCube [1], showing that input data, encoded as spike sequences, learned into a 3D reservoir module shaped by a brain template (e.g., Talairach [8]). The patterns of activity of the *now 4D SNN* are learned and classified in a deSNN [13] classifier/regressor.

Catastrophic forgetting is avoided here through the flexibility of the 4D SNN cube, that does not require predefined layers for its local learning using STDP, and through the evolving output neurons and connections in the deSNN classifier.

III. *TL OF SPATIO-TEMPORAL DATA AND FSTR IN THE NEUCUBE BI-SNN*

While incremental and on-line learning in BI-SNN have been studied [1,6,13], TL of spatio-temporal data and of fSTR in BI-SNN have not been studied and this is the topic of this section.

In the SNNcube of the NeuCube architecture (Fig.2) connections, that are created during learning of previous tasks can be used to support the learning process of a new task when also new connections are created, thus TL in BI-SNN (denoted as TrSNN) facilitates sharing and reuse of knowledge.

Here, TL relates to incrementally training a SNN NeuCube model on new data related to new tasks/classes (Algorithm presented in Table 1) and at the same time extracting and analysing the connectivity of the SNN as knowledge represented as fSTR, accumulated and evolved after every new task (Algorithm presented in Table 2). As a partial case, data can be EEG brain data and the tasks can be human movements, as is in this paper.

First, connections in a SNNcube model are initialised using the small-world connectivity method, resulting in a 3D SNNcube(0) [1,6]. For every new task Ti (i=1, 2, …, N), presented to the SNNcube to learn incrementally, new connections are created along with the use of some old connections, resulting in new SNNcube(i) and new output neurons generated in the deSNN for the recognition of task Ti. Learning in the SNNcube is a local, spike time learning, e.g., STDP (Eq.2), which changes the connection weights between every two connected neurons based on their time of spiking. Two connected neurons Ni and Nj have their connection weight Wij increased during learning if there are sufficient number of examples (temporal or spatio-temporal data) of task Ti to create SNNcube(i). Learning of next task T(i+k) will be enhanced even with the use of a small number of learning examples/samples for this task, if the two tasks share same patterns in the data. So, learning task T(i+k) will be easier and faster if it shares connections with task Ti learned before. At the same time, data of task Ti have created connections between neurons (e.g., Nc and Nd) that are not relevant for the next task T(i+k) and data for task T(i+k) can create other connections between other neurons relevant to this task (e.g. Ne and Nf) (see Fig.3). The simple diagram illustrates the concept of *stability vs plasticity* when a connectionist system is learning new class/task data T(i+k) after it has learned the task Ti data.

If, for task T(i+k) there are many negative activations of the neurons Nc and Nd, that are positively involved in task Ti, the classification accuracy for future samples belonging to class Ti may decrease and the SNNcube model, while using TL method and retaining knowledge in the SNNcube connectivity, may achieve lower classification accuracy than using ImSNN algorithm for deSNN, thus manifesting forgetting of previous examples. The paper addresses this problem by introducing special operations, such as *pruning/zeroing* of small connections (Eg.3) and *aggregation* of output neurons that have similar connection weights and represent the same class (Eq.4), but other methods related to life-long learning can be investigated too [51].

(Eq.3) $for\ w_{j,i} > 0, if\ w_{j,i} < \theta_{pos}\ then\ w_{j,i} = 0$
$for\ w_{j,i} < 0, if\ w_{j,i} > \theta_{neg}\ then\ w_{j,i} = 0$

(Eq.4) $w_{j,i} = \frac{w_{new} + w_{j,i}}{M+1}$

where: θ_{pos} and θ_{neg} are the thresholds used to prune positive or negative connection weights; M is the number of output neurons being already aggregated previously into a neuron *i*, for every input *j* to this neuron.

Table 1: *The proposed TL algorithm (TrSNN)*

Input: Spatio-temporal data as sequences of samples exemplifying different tasks T1,T2,…,Ti,Tj,..,Tn for incremental and transfer learning.
Parameters: encoding parameters; SNNcube parameters; deSNN parameters.
Algorithm:

1. Initialise a NeuCube model as SNNcube$^{(0)}$ and deSNN$^{(0)}$
2. FOR every task Ti (i=1 to N)
3. FOR every spatio-temporal input sample Sij of task Ti **do**
4. Encode Sij into spike sequences
5. Perform unsupervised learning in the SNNcube$^{(i)}$ using STDP learning rules
6. Perform supervised learning for classification in the deSNN$^{(i)}$ classifier.
7. END FOR
8. Perform pruning of week connections in SNNcube$^{(i)}$ using defined pruning thresholds θ_{pos} for positive connections and θ_{neg} for negative connections, (Eq.3).
9. Perform output layer deSNN$^{(i)}$ neural pruning [13] (Eq.3)
10. Perform output layer deSNN$^{(i)}$ neuronal aggregation [13] (Eq.4).
11. Using the proposed algorithm in Table 2, extract fSTR$^{(i)}$ and feature interaction network FIN$^{(i)}$ from SNNcube$^{(i)}$ (see [6]) and compare this knowledge with the fSTR$^{(i-1)}$ and FIN$^{(i-1)}$, extracted from SNNcube$^{(i-1)}$ for task T(i-1).
12. Recall and test the SNNcube$^{(i)}$ model on all incrementally learned tasks T1, T2, … ,Ti and compare results.

END FOR

Table 2 *Algorithm for extracting and tracing fSTR in a trained NeuCube model in TL mode.*

Goal: Extract rules from a SNNcube$^{(i)}$ and deSNN$^{(i)}$ and compare them with the previously learned knowledge in SNNcube$^{(i-1)}$ and deSNN$^{(i-1)}$ to define the common knowledge and the new knowledge acquired when the task Ti is incrementally learned from task T$^{(i-1)}$

1. FOR every output neuron Nk (k=1; Nmax) from the output layer deSNN$^{(i)}$ **do**
2. Get connection weights between neurons of the SNNcube$^{(i)}$ and the output neuron Nk.
3. Cluster the connection weights according to the average time of their spiking activity in each time bi t1<t2<…<tk (first activity is registered at time t1).
4. Generate a set of fSTR of the form of:
   IF (cluster of neurons with a center ($\boldsymbol{X1}, \boldsymbol{Y1}, \boldsymbol{Z1}$) and a cluster radius $\boldsymbol{R1}$ is activated at a time "bin" t**1**) AND
   (cluster of neurons with a center ($\boldsymbol{X2}, \boldsymbol{Y2}, \boldsymbol{Z2}$) and a cluster radius $\boldsymbol{R2}$ is activated at a time "bin" t2) AND
   …………………………….
   (cluster of neurons with a center ($\boldsymbol{Xk}, \boldsymbol{Yk}, \boldsymbol{Zk}$) and a clust radius $\boldsymbol{Rk}$ is activated at a time "bin" tk)
   THEN (The output is a prototype Nk from its corresponding class)
5. Subtract SNNcube$^{(i-1)}$ from SNNcube$^{(i)}$ and extract a fSTR from the new SNNcube to trace knowledge evolution.

END FOR.

The following *experimental design* is proposed here to demonstrate transfer learning (TL) of fSTR from spatio-temporal brain data, exemplified by EEG:
(a) Multiple class spatio-temporal data is split into 50/50 for training and testing.
(b) A baseline model is trained/tested in a batch mode and used as a benchmark for comparison of the accuracy of the models incrementally obtained through TL.
(c) In section IV a model is trained on the first task EEG data from one subject and incrementally trained on the other 3 tasks performed by the same subject, one by one.
(d) The 3D SNN connectivity is visualized to evaluate what are the new connections for the currently learned task (Fig.4).
(e) Each trained model is finally tested on all class data.
(f) fSTR are extracted and compared to evaluate the level of knowledge transfer (stability vs plasticity) (Fig.6).
(g) In section V all the above procedures are applied and presented as a TL across multiple tasks and multiple subjects.

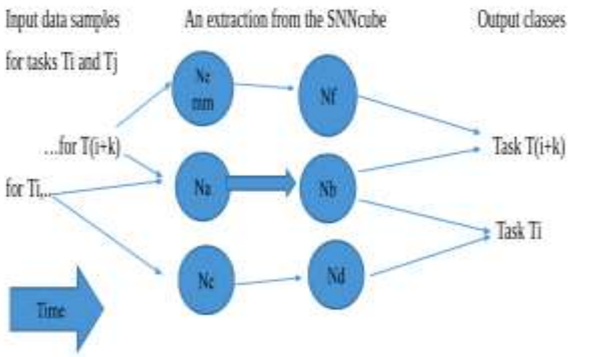

Fig.3. Task T(i+k) learned in the SNN cube shares some neuronal clusters and connections with task Ti, along with creating new ones as explained in the text.

IV. TL of fSTR from EEG data Measuring Complex Tasks Performed by a Single Subject

A. Problem and Data Specification

A TL scenario of the evolution of the SNN cube when a single subject is learning incrementally 3 simple movements of his wrist is illustrated as Fig.2S in the Supplementary file.

Here, in this section, the proposed TL and fSTR algorithms are applied on a case study of EEG data based on the scenario of task-to-task TL of complex tasks performed by a single subject. We used the functional upper limb movements dataset [15], which was recorded at the New Zealand College of Chiropractic and Aalborg University, Denmark under the ethical approval of the local ethics committee (N-20130081). The data consists of EEG data from 12 healthy subjects, recorded from 64 EEG channels at 512 Hz. Each subject was instructed to perform four complex tasks of motor imagery. They are different classification tasks learned incrementally to trace the transfer of knowledge through observing the changes in the connection weights after learning a new task and to represent them as fSTR.

Each of the following complex four tasks is represented as a class for classification purposes:
Task 1: Reach for a glass of water, drink, and place the glass on the table.
Task 2: Throw a ball from the right hand to the left hand.
Task 3: Lift a tray from the table and place the tray on the table again.
Task 4: Push a glass from position A to position B.

The baseline experiment creates one SNN model and trains/tests it with all task data in a batch mode, using 50/50 training/testing cross validation. The same data split was used through all TL experiments. For the TrSNN-CP (TrSNN with Cube Pruning of small connections) experiments (see Table 2), the following parameter values are used: Drift: 0.005; Mod: 0.8; SNNcube pruning percentage: 0.995. For the TrSNN-CP-NG (TrSNN-CP plus neuronal aggregation of the neurons in the deSNN) the following parameters are used: Drift: 0.005; Mod: 0.8; SNNcube pruning percentage: 0.995; SIM parameter: 2.

The connectivity of the TrSNN models at each stage of incremental training is visualized in Fig. 4 (a)-(d). It can be seen that stronger connectivity is observed with further training the SNNcube. To perform a better analysis of the TL, the connection weights of each SNNcube(i) learned for Task Ti were subtracted from the ones of SNN(i+1) for task T(i+1), which allows visualising the changes in neural connectivity as a result of TL over time. Figs. 4 (e), (f), and (g) show that further trained SNNcubes resulted in a similar pattern of changes in some regional activation across all new classes. However, the size of the activated connectivity was higher in SNNcube trained with class 3, compared to class 2 as Tasks 2 and 3 are very different. The connection weights varied to different degrees as new tasks were added.

Fig.5 gives a comparative analysis of the accuracy of the tested models on the same data. The results confirm that the new algorithms for TL present competitive results to the benchmark off-line learning algorithm in addition to having the significant advantages of TL, including fSTR extracted. Connection pruning and neuronal aggregation are used.

Statistical results of neurons pruned and aggregated in the TrSNN-CP (with cube pruning) and TrSNN-CP-NG (with cube pruning and neuronal aggregation in the deSNN classifier) are given in the Supplementary material, Fig.3Sa.

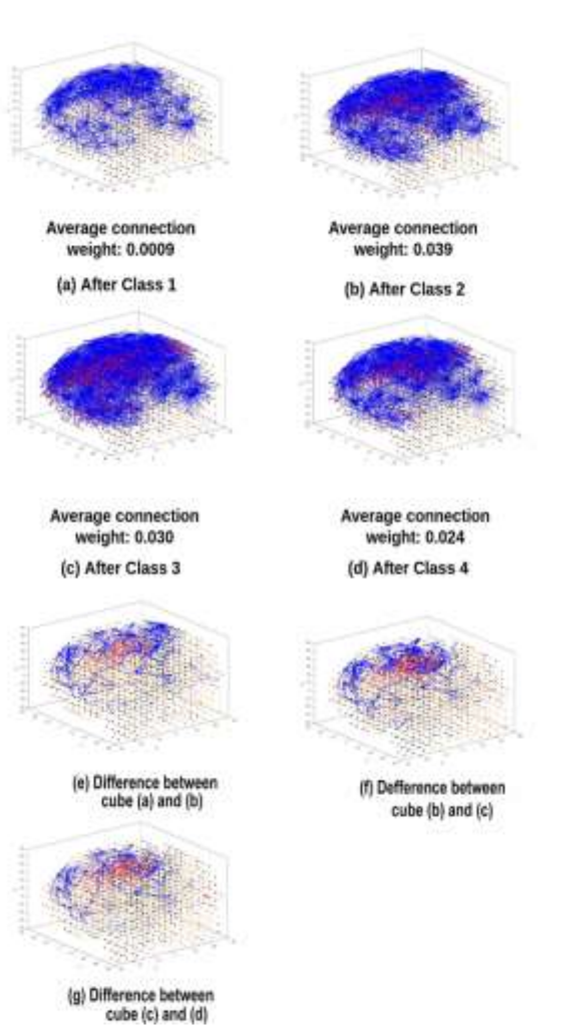

Fig. 4. The connection weights of the TrSNN models incrementally trained on the EEG data of a single subject: (a) after task 1; (b) after task 2; (c) after task 3; (d) after task 4. Differences between the connectivity in the incrementally trained SNN models are shown in figs (e),(f),(g). The more number of new classes are added, the less new connections are added, as for learning new classes, some of the previously created connections are utilized.

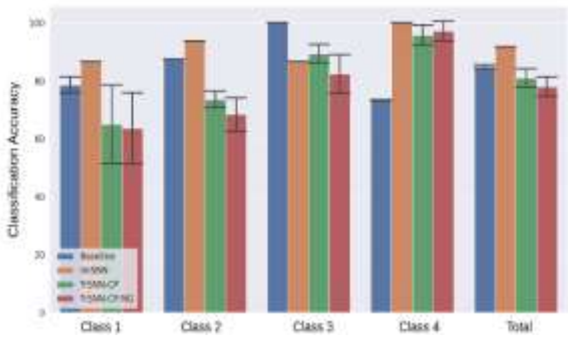

Fig. 5 Final per-task accuracy for each of the compared methods when learning four tasks/classes' data in a NeuCube model of a single subject. The models are finally tested on an independent test data. While the base line batch learning is expected to produce a better accuracy, one-iteration incremental and TL produce similar results overall, despite the complexity and the diversity of the tasks (see also Fig.3Sa in the Supplement)

B. *TL of fSTR*

Quantitative analysis of the connectivity patterns of SNNcube is here used for the extraction and for tracing the evolution of fSTR. Using the algorithm from Table 2, a neuronal cluster in the SNNcube is considered active if the normalized firing rate in the cluster surpasses a set threshold.

The activation of different clusters of neurons associated with each output class neuron Ni (prototype) at different time windows are here analysed and fSTR are extracted. For each output class neuron Ni, a chain of fSTR, associated with this output neuron Ni is extracted and presented in the following form, e.g.:

IF (firing rate of $area_{1,1}$ is A1 and $area_{2,1}$ is B1 and $area_{3,1}$ is F1, at time about t1)
AND (firing rate of $area_{1,2}$ is A2 and $area_{2,2}$ is B2 and $area_{3,2}$ is F2, at time about t2)
AND (firing rate of $area_{1,3}$ is A3 and $area_{2,3}$ is B3 and $area_{3,3}$ is F3, at time about t3)
AND (firing rate of $area_{1,4}$ is A4 and $area_{2,4}$ is B4 and $area_{3,4}$ is F4, at time about t4)
THEN (The output is prototype Ni of class Ci),

where Ak, Bk and Fk (k=1,..m) are fuzzy values represented by their membership functions, such as Gaussian (Fig.5S in the Supplement), Ci is the corresponding class label for the output neuron Ni.

As each area of a SNNcube represents a brain area according to a brain template (e.g., Talairach template) the extracted fuzzy rules can be interpreted as spatio-temporal activities in the human brain as the source of the EEG data. An example is shown in Fig.6, where extracted fSTR through the TL process on the data above are interpreted as spatio-temporal activities in brain areas indicating the difference between the latest learned task versus the previously learned tasks.

In this analysis, we first calculated the average firing rates of different spatial clusters in the trained SNNcube models, each cluster corresponding to a lobe brain area, in four different time windows/bins (t = {0.5s, 1s, 1.5s, 2s}), and the difference of firing rates for each stage of the TL process was computed through subtracting with the firing rate for the previous trained model, as shown in Fig. 6. Different activation levels of different clusters of neurons at different times are indicated. Strong firing rates were identified around the Frontal and Limbic lobes in Fig. 6 (b) after class 2 data was incrementally learned, while Frontal-Temporal lobe was more active in Fig. 6 (a), indicating that different knowledge is transferred at different stages of the TL process. The SNNcube activities from Fig.6 can be represented as a fSTR, that is formed by using the activation of different clusters of neurons at different times.

A fSTR is shown below representing the activity from Fig. 6 (a) based on the following denotation of spatio-temporal clusters representing activity of SNN neurons, corresponding to brain areas at times t1 (0.5s), t2 (1s), t3(1.5s) and t4(2s).

Denotations:

$area_{1,1}(t1)$= {Temporal Lobe}
$area_{2,1}(t1)$= {Frontal-Temporal Space, Frontal Lobe, Posterior Lobe}
$area_{1,2}(t2)$= {Temporal Lobe}
$area_{2,2}(t2)$= {Frontal Lobe, Temporal Lobe}
$area_{3,2}(t2)$= {Frontal-Temporal Space}
$area_{1,3}(t3)$= {Parietal Lobe, Temporal Lobe}
$area_{2}(t3)$= {Frontal- Temporal Space, Frontal Lobe}
$area_{1,4}(t4)$= {Temporal Lobe}
$area_{2,4}(t4)$= {Frontal-Temporal Space, Frontal Lobe, Posterior Lobe}

fSTR for Fig.6a

IF (firing rate of $area_{1,1}(t1)$ is SMALL and $area_{2,1}$ $(t1)$ is MEDIUM (at time *t1* about 0.5s)
AND (firing rate of $area_{1,2}(t2)$ is SMALL and $area_{2,2}(t2)$ is MEDIUM and $area_{3,2}(t2)$ is HIGH (at time t2 about 1s)
AND (firing rate of $area_{1,3}(t3)$ is SMALL and $area_{2,3}(t3)$ is MEDIUM (at time t3 about 1.5s)
AND (firing rate of $area_{1,4}(t4)$ is SMALL and $area_{2,4}(t4)$ is MEDIUM (at time t4 about 2s)
THEN (This is the difference in spatio-temporal knowledge in the SNNcube after the model, first trained on task 1 data, was then trained with task 2 data, i.e. the novelty in task 2 data versus task 1 data)

The above fSTR captures changes in time and space, while the extracted feature interaction graphs from a NeuCube model [6] represent aggregated information as illustrated in Fig.3S in the Supplementary material.

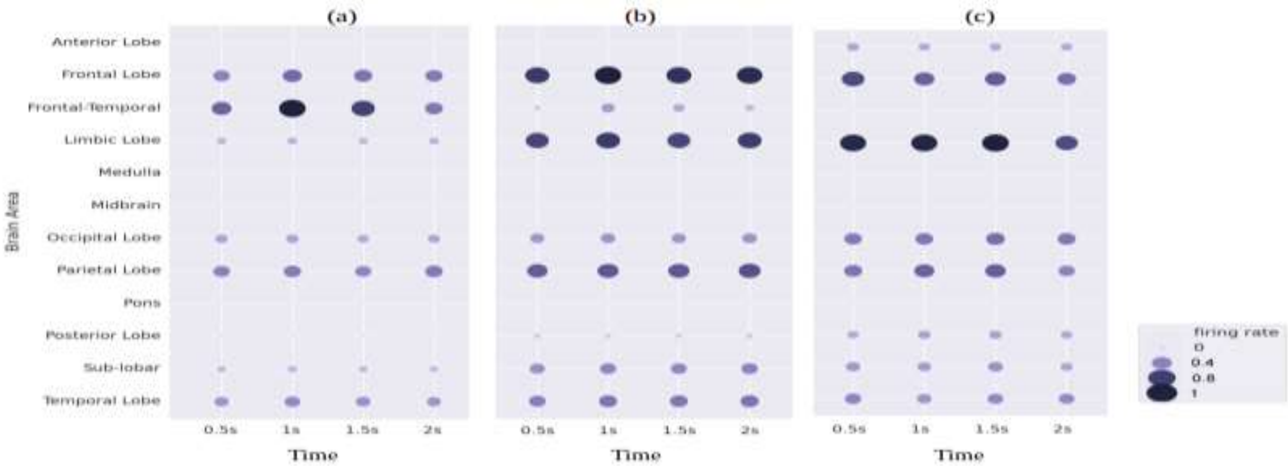

Fig. 6. Difference in firing rates of clusters of a SNNcube, corresponding to brain areas of a single subject during TL of 4 tasks: (a) task 2 is learned after task 1; (b) task 3 is learned after task 2; (c) task 4 is learned after task 3. This is represented as FSTR in the text.

V. TL of fSTR from EEG Data Measuring Multiple Complex Tasks Learned by Multiple Subjects

A. General description

Here we use the same data as in section IV, but the TL and fSTR in a NeuCube model are evolved from EEG data of several subjects, one by one when learning the tasks. The same TL and fSTR procedures, that have been described in section IV are applied in this section.

The following parameter values are used for the TrSNN-CP algorithm: Drift=0.005; Mod=0.8; SNNcube pruning percentage=0.7 and for the TrSNN-CP-NG: Drift= 0.005; Mod= 0.8; SNNcube pruning percentage=0.7; SIM parameter= 2.5 (defining the similarity of output neurons for their aggregation).

In the TrSNN experiments, we created one SNN model and trained it incrementally in a TL mode with data from two tasks belonging to four subjects. Small connections of the SNNcube models are pruned after each stage of learning data from a new subject. The learning process, when data from different subjects are learned incrementally for class 2, is visualized in Fig. 7.

It can be seen from Fig. 7 (a-d) that stronger spatio-temporal connectivity is observed with a further trained SNN cubes. Connection weights of the TrSNN model for class 3 (task 3) trained incrementally with EEG data of subjects 9, 10, 11 and 12 are shown in Fig.4S in the Supplementary material, along with the differences between the connectivity in the trained SNN models. For class 3 (Fig. 4S), the connections were particularly enhanced between neurons located in the areas of Occipital and Posterior Lobes, which were less observed in the case of class 2 (Fig.7).

Fig. 8 shows the test classification accuracy of each experimental model for each of the subjects when their EEG data is learned incrementally in a SNNcube model and also the overall accuracy across all models and across all subjects when they have learned tasks 2 and 3. The results show that the proposed TrSNN-CP (with Cube pruning) and TrSNN-CP-NG (with Cube pruning and Neuronal Aggregation) not only performed on par with the baseline model achieving accuracy above 80%, but they also outperformed the incremental learning method (ImSNN).

To perform a better analysis of changes in SNNcube models between subjects, the differences between the SNNcube, for each stage of the learning process, and the previously trained SNNcube, were computed through subtracting their connection weights as explained in Table 1. That allows for a better visualization of changes in neural activity as shown in Fig. 9.

Statistical results of neurons pruned and aggregated in the TrSNN-CP and TrSNN-CP-NG) are given in the Supplementary material, Fig.4Sa.

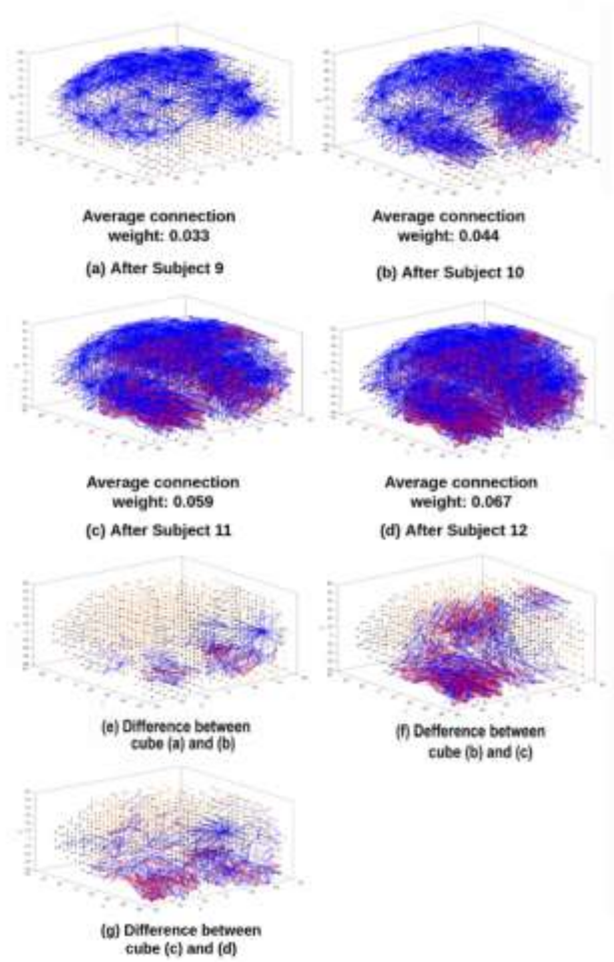

Fig.7. The 3D SNN model after incremental training on EEG data for task 2 by subjects 9 to 12 and the difference in the connectivity obtained after substruction of the connection weights of consecutively trained SNN. Learning task 3 is presented in the Supplementary material.

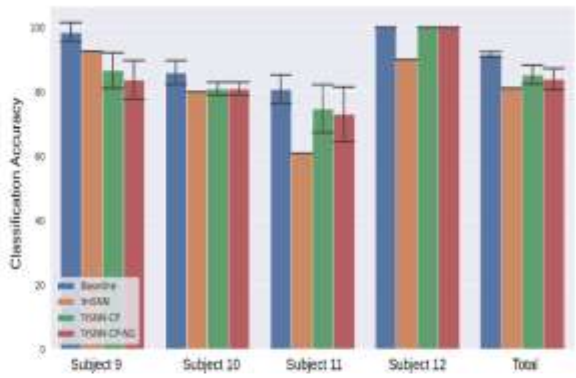

Fig.8. Classification accuracy of each of the incrementally trained model on EEG data from different subjects learning tasks 2 and 3, tested on all data (see also Fig4Sa in the Supplement).

B. TL of fSTR

Here, the average firing rates of different spatial clusters in the SNNcube models (representing brain areas according to the Talairach atlas) are estimated at different times when data from 4 subjects are used for

TL of tasks 2 and 3. In the graph shown in Fig. 9(a), the different knowledge of the model trained with subject 9 data and then continued to be trained with subject 10 data, was positioned around the areas associated with Anterior Lobe, Medulla, Midbrain, Pons, Posterior Lobe at each time bin. In Fig. 9(b), strong firing rates were mostly created around the Medulla, and less in the Posterior, Pons and Occipital lobes. Fig. 9(c) depicts the following spatio-temporal firing rates in the SNNcube: medium-to-low firing around the Sub-lobar, Pons and Temporal Lobe after 1s; low firing in Anterior and Limbic Lobes; very high firing in Medula at time around 2 sec.

The knowledge obtained above is converted into meaningful fSTR. The denotation of spatio-temporal clusters in the SNNcube, representing brain areas, and the evolved fSTR from Fig. 9(c) are shown in the text below. The fuzzy terms *small* or *medium* etc. represent the activity of the neuronal clusters measured during the learning process. They can be defined by Gaussian membership functions (Fig.5S in the Suppl.).

$area_{1,1}(t1)$= {Frontal Lobe, Anterior Lobe, Temporal Lobe, Parietal Lobe, Pons, Sub-lobar}
$area_{2,1}(t1)$= {Posterior Lobe, Occipital Lobe, Medulla}
$area_{1,2}(t2)$= {Limbic Lobe, Frontal Lobe, Frontal-Temporal Space, Parietal Lobe}
$area_{2,2}(t2)$= {Temporal Lobe, Occipital Lobe, Medulla, Sub-lobar, Midbrain, Posterior Lobe, Pons, Anterior Lobe}
$area_{1,3}(t3)$= {Parietal Lobe, Limbic Lobe}
$area_{2,3}(t3)$= {Temporal Lobe, Pons, Occipital Lobe, Sub-lobar, Posterior Lobe}
$area_{1,4}(t4)$= {Midbrain, Frontal Lobe}
$area_{2,4}(t4)$= {Anterior Lobe, Posterior Lobe, Limbic Lobe, Occipital Lobe, Pons, Parietal Lobe, Temporal Lobe, Sub-lobar}
$area_{3,4}(t4)$= {Medulla}

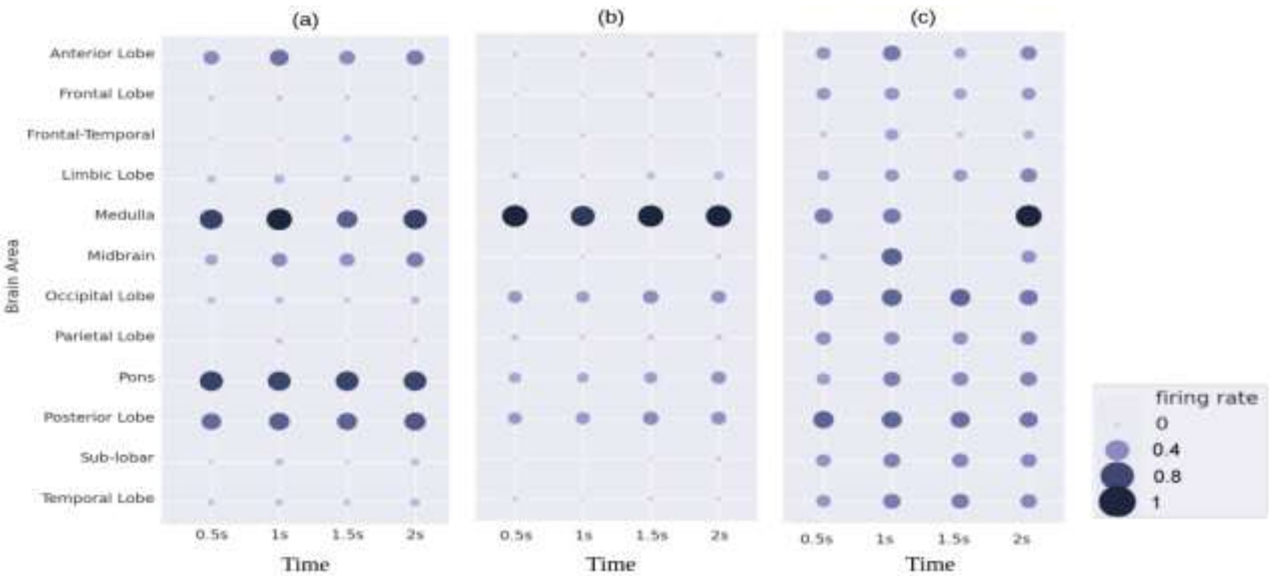

Fig. 9. Difference in firing rates of clusters of a single SNNcube, corresponding to brain areas according to Talairach atlas, during TL on EEG data of several subjects who learn Task 2 one after another: (a) subject 10 after subject 9; (b) subject 11 after subject 10, (c) subject 12 after subject 11.These are represented as FSTR and validated using neuroscience information [4,5,30,32].

fSTR for Fig.9c

IF (the firing rate of $area_{1,1}(t1)$ is SMALL, $area_{2,1}(t1)$ is MEDIUM, at time about 0.5s)

AND (the firing rate of $area_{1,2}(t2)$ is SMALL, $area_{2,2}(t2)$ is MEDIUM, at time about 1s)

AND (the firing rate of $area_{1,3}(t3)$ is SMALL, $area_{2,3}(t3)$is MEDIUM, at time about 1.5s)

AND (the firing rate of $area_{1,4}(t4)$ is SMALL, $area_{2,4}(t4)$ is MEDIUM, $area_{3,4}(t4)$ is HIGH, at time about 2s)

THEN (This is a spatio-temporal knowledge of how subject 12 performs class 2 movement differently from subjects 9,10 and 11 whose data were used to train a SNNcube model in a TL mode).

Both the visual representation and the extracted fSTR can be used to discover important features/biomarkers (e.g., EEG channels and brain areas in this case) that are important to explain the learning process of each new subject when compared to previous ones. In the case of subject 12 learning Task 2 after subjects 9,10 and 11, the dominated brain areas involved are: Temporal Lobe; Posterial Lobe; Ocipital Lobe; Midbrain (at time t2); Medulla (at time t4).

VI. Discussions on the Applicability of the Proposed Algorithms for Model Explainability and Bio-Marker Discovery from Spatio-Temporal and Longitudinal Data

Overall, TL is about learning new tasks in one model (or by a subject) by utilizing previously learned knowledge and creating new ones. It is important to be able to evaluate the novelty in the evolution of the models. And that is what Figs.4 and 7 are about, showing not only the connectivity of the SNN model at each time of learning, but the differences between consecutively trained models. These differences are shown as connection weights in Fig.4 and 7 and as corresponding fSTR in Figs. 6 and 9.

For a first time, the paper illustrates the evolution of the activities of different neuronal clusters in space (location) and time of the now 4D brain-inspired SNN model that correspond to the activity of brain areas, after incremental learning of different tasks by a single subject (Fig.6) and incremental learning of a task by different subjects (Fig.9). This evolution is represented as fSTR that are biologically plausible. They point to the most prominent features involved for future marker discovery.

In order to evaluate the contribution of different elements of the NeuCube model, experiments are conducted with removal of connection weights (pruning) (model TrSNN-CP) and also pruning plus aggregating (TrSNN-CP-NG) connections of the model. Results are shown in the accuracy comparative graphs in Figs.5 and 8.

The above features of the proposed methods make them applicable in several areas:

- *Discovering predictive dynamic features from brain and longitudinal biomedical data*

TL of fSTR from brain spatio-temporal data and from longitudinal biomedical data can be used to create multiple disease outcome predictive systems, such as co-morbidity, psychosis, schizophrenia, depression, anxiety, ADHD, AD, dementia and other, that have some common manifestations and neurological backgrounds [44, 45]. fSTR can be discovered from: longitudinal MRI data to predict dementia [46]; cognitive and clinical longitudinal data to discover features related to psychosis [47]; clinical, cognitive and genetic longitudinal data to predict schizophrenia [48]. For non-brain imaging longitudinal data, as it is the case in [48], input variables are mapped into the 3D SNN structure to preserve the temporal similarity between the variables [49]. In the proposed in this paper TL methods, only one model is trained incrementally on different class data and analyzed for features (biomarkers) that discriminate the classes, rather than new models created every time new data is collected.

All these and many other studies would benefit from the TL methods for an early prediction and a better explanation and understanding of the dynamics of a disease or co-morbidity cases, in addition to extracting statistically aggregated information as it is in the current state-of-the art methods.

- *BCI for neurorehabilitation robotics*

It has been established over the last decade that brain-computer interfaces (BCIs) based rehabilitation systems can be used to induce neural plasticity, which is believed to be the underlying mechanism of motor recovery after neural injury such as stroke [17] [18]. The improvement in use of non-invasive BCI have been made possible with the synergistic efforts in the field of neurorehabilitation and neural engineering [19] [20]. One of the existing bottlenecks for BCI technology is the generalization ability of the results. In the current manuscript, generalizability issue has been investigated by using brain-inspired neural network architecture, utilizing TL methods and fSTR. In [25] an invasive bi-directional BCI framework is proposed, where brain signals are sent to the prosthetic device and feedback from muscles is used to send to inserted electrodes in the brain. The proposed in our paper framework, that includes visualization of the incrementally trained NeuCube model reflecting brain activity, can be used to provide a visual feedback to the user, especially efficient when several brain modalities are integrated into a personalized predictive model [26] [35] [36] [50].

- *Speech, image and video data processing*

Multimedia data (speech, sound, image, videos) are important information sources and have wide applications across many fields. In this regard, TL in SNN has particular advantages as it makes it possible to learn time, space and frequency together and to use neuromorphic hardware, which is highly energy efficient and easy to be embedded into small portable devices [43].

- *Cognitive and communication studies*

Recently, an already existing method called “hyper-scanning”, that measures the process of brain synchronization between people and also the process of learning new skills, was systematically studied in [27]. The proposed TL of fSTR can be used for such studies to model and understand brain synchronization across multiple subjects over time [28].

- *Towards brain-inspired life-long learning machines*

Recent studies have been looking for biological principles of life-long learning in the human brain [33, 34, 6]. The proposed TL learning of fSTR is a further step in this direction by introducing explainability during life-long learning processes as knowledge accumulation [51].

VII. Conclusion and further directions

The paper presents a methodology for TL of fSTR in a brain-inspired SNN (BI-SNN), exemplified by the NeuCube architecture. The methodology is applied on a case study of EEG brain data, but the proposed methods have a wider applicability due to the following features:

1. Flexible structure (no fixed number of layers and neurons in activated clusters).
2. Incremental, potentially “life-long” and TL.
3. Learning fSTR, explainability.
4. Event based (asynchronous) learning.
5. Fast learning (e.g., one pass).
6. Low computational and power demand.

New theoretical and application developments are anticipated for a full exploration of the BI-SNN and their capacity for improved TL of fSTR, such as:.

1. TL of integrated multimodal data, such as audio-visual, EEG, fMRI, DTI etc.
2. TL of integrated heterogeneous data, such as: quantum-, molecular-, brain signals-, environmental.
3. Self-optimisation of parameters during TL.
4. Knowledge transfer between humans and machines.

Overall, the concept of TL of fSTR, introduced here, extends the fundamental principles of fuzzy systems and neural networks, deeply rooted now in all sciences [41,42,43], and opens a new direction for the development of adaptable and explainable spatio-temporal learning systems for AI applications.

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