The Energy-Efficient Resource Allocation of Multi-Modal Perception for Affective Brain-Computer Interactions Based on Non-Linear Iterative Prediction Scheme

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Abstract

For the whole environmental settings in this research, the conventional affective brain-computer interactions can not build a good performance on energy-efficient resource of network's forwarding ports and routing paths due to its poor allocation function of cognitive radio networks, based on the novel interactive networking architecture, the model of non-linear iterative prediction scheme in interaction was successively proposed. This research proposes a modified LSTM algorithm with a structure of non-linear iterative in complexity prediction, joins the multiple *k* modes selection and multi-agent systems, maximizes EERA of forwarding and routing while maintaining the communication quality. Firstly, considering whether this affective brain-computer interactions need the networking communication in system. Secondly, adjusting the forwarding and routing factors of energy-efficient resource allocation by selecting the best optimal energy-efficient resource for the links through the non-linear iterative prediction in a multi-modal perception. The simulation results show that compared with the other models and algorithms, the proposed scheme for affective brain-computer interactions, which has a nice performance on a higher EERA and channel utilization of a networking architecture of brain-computer interactions.

Keywords: Affective brain-computer interactions, Energy-efficient resource allocation, Forwarding ports and routing paths, Multi-modal, Non-linear iterative prediction scheme

1 Introduction

Affective brain-computer interactions [1] in construct an new bridge between the affective computing and brain-computer interaction, holding promise for the construction of networking and intelligence of brain-computer interface [2-5]. The typical electrical signals of emotion recognition from brain activities, using EMOTIV EPOC Flex [6] with up to 32 channels for high density coverage, and translate EEG signals to the different forwarding ports for routing in intelligent node. The EEG signal sampling module in most existing brain-computer interactions are based on emotion recognition technology and adopt the traditional non-linear model where the energy-efficient processing units and data computing units are physically separated. In the EMOTIV device, they convert analog neuron' signal to digital signal and then compress and process them in the digital domain using the field programmable gate array (FPGA) for MMP. Based on this system, a vast digital communication units have been made in a reality [7] of information networking data transmission. However, the design of such a platform is still facing some challenges, such as the energy-efficient resource allocations, especially in order to catch up with the increasing number of routing and switching nodes in its state-of-the-art interactions. In addition, this conventional method is fundamentally different from how the emotional data processing in forwarding and routing process that is in continuous task of eye tracking image and audio sampling. The conversion and compression of data could cause a low energy-efficient in the resource allocations of networking task, which makes ABCI cannot get a emotion recognition. These conditions inspire us to leverage novel scheme that in favour of the MMP construction for future ABCI model.

As affective computing become the entry points to the brain-computer interactions for a huge number of emotion recognition, a much larger proportion of networking size rapidly increasing the EEG, eye tracking (image), or audio sampling data will be transmitted through the informative nodes from a energy-efficient harvesting. For this propose, emotion could provide an appealing platform because they rely on the movements of ports and paths to modulate their routing states, which emulate the forwarding and routing behaviors of data transmission in path network. First, as an non-linear iterative system, affective computing have been demonstrated to be highly energy-efficient resources for the allocation. Second, the system forwarding ports and routing paths could directly process digital signals [8], and parallel computing function is also feasible in the form of FPGA logic units [9-10]. Last, but equally important in this paper, the affective computing have been shown to be fast and highly stable in the brain-computer interactions, which could be a bridge between our brain and external electronic circuits for future brain-computer interactions.

In this research, we propose an architecture: non-linear iterative prediction scheme (NLIPS) for next-generations

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DOI: 10.53106/160792642023052403009

affective computing [11] with a brain-computer interaction [12] for network monitoring. As a new proof-of-concept study in the EERA of forwarding ports and routing paths. Firstly, we use the iterative prediction method to make an optimal energy-efficient in network system to demonstrate a brain and computer interactive process. Secondly, owing to the excellent non-linearity of 2D LSTM (LPPO) model in ABCI for routing and forwarding task, the NLIPS model can achieve a high EERA (≥25.5%) in building a network emotion monitor system and get an excellent classification effect on the judgment of group emotional states.

2 Related Works

As far as we know, this is the first work to make EERA in network forwarding and routing processes for affective computing. In recent years, many network researches have been conducted to apply EERA tasks in [13]. The iterative QoS prediction is a self-adaptive [14] model, which makes the predicted QoS parameter in iterations towards the best one. Compared to the proposed EERA of MMP advances the networking of emotion data interaction to a high level. In 2015, Zou et al [15] investigate a great energy-efficient uplink radio resource allocation with QoS guarantees in heterogeneous wireless network in the same way. Hu et al. use [16] the EERA in time-sharing multi -user system with hybrid EH transmitter, the traditional object is transformed into optimization problems in network. Jiang et al. [17] present a EERA for underlay multi-cast D2D transmission, they also build the optimization for network in EERA. In 2021, Chen and Liu [18] propose a energy-efficient task offloading and resource allocation in MEN, while the DRL verifies a good performance in a HPC environment for the network of affective computing in routers and switches.

The EERA of network for ABCI is a significant state in routing nodes. The information transmission of emotions make data across multiple routers, and each router contains EEG, image and audio sampling signals, which protect the data away from control data in proposed MMP condition. Many affective computing researchers are trying to realize the network transmission implanted in ABCI [19-21]. For example, Mun and Park [22] studied and designed 3D objects and emotion pictures as a visual stimuli to lift the signal-to-noise ratios of steady-state SSVEP. Yasemin [23] using the sensor fusion of EEG and EDA for emotion state estimation. The monitors of people affective parameter in network data transmission. In addition, the brain-computer interfaces is the direct communication and interaction with scenario in processing brain signals, and thus Torres and others [24] discuss the survey of EEG-based BCI emotion recognition as a basic theory in EERA approach. However, ABCI, as the most important task for emotion recognition and affective computing, have not been used in artificial intelligence area for optimization of EERA in networks. The study is by far the first work to use a network to make the IP routing for Internet applications of brain-computer interactions in the computation of affective condition.

The linear [25] and non-linear iterative predictions [26] are the networking state that are easily considered with the routing and forwarding process. It adds some chaos data in the original statements, in 2016, Vosmeer [27] proposes an iterative linear interaction for energy method. They use an novel automated recognition of configuration transitions and construct the iterative LIE framework relies on some assumptions to predict binding affinities in data interaction. In 2020, Wu [28] proposes a non-linear predictive control (NMPC) to deal with the system point stabilization for an image-based visual servoing (IBVS), which acquired the effectiveness of iLQG model in non-linear processing. In 2020, Li [29] gets a adaptive iterative learning consensus control for a multiple orders embed on brain and computer with non-linear state. Table 1 is the notations in this work.

Table 1. The symbols and notations in this research

Symbols	Meanings
EERA	Energy-Efficient Resource Allocations
FP	Forwarding Ports
RP	Routing Paths
ABCI	Affective Brain-Computer Interactions
DRL	Deep Reinforcement Learning
CRN	Cognitive Radio Network
EH	Energy Harvesting
MMP	Multi-Modal Perceptions
NLIPS	Non-Linear Iterative Prediction Scheme

Most existing ABCI perform networking EERA only and get a good performance on linear iterative prediction in EERA [13, 17-18]. However, they may fail on non-linear NLIPS in EERA of MMP, where informative nodes in the network tend to be out of the emotion state monitoring and affective computing is needed. Thus, in this research, we focuses on the ABCI and EERA of routing and forwarding in network architecture, particularly in modified 2D LSTM method for a good performance in ABCI with NLIPS.

3 The EERA of MMP in ABCI

In the section, we propose an novel non-linear iterative prediction scheme (NLIPS) for the affective multi-modal perceptions in an energy-efficient resource allocation with the high efficiency of forwarding ports and routing paths.

3.1 Overview

In this sub-section, the conventional idea is to combine the brain request and computer response. This will enable us to maintain multi-modal perception in an affective brain -computer interactions. In the model of proposed NLIPS, we set up 3 signals perceptive planes: EEG signals, image signals, audio signals. Figure 1 is the overview of NLIPS.

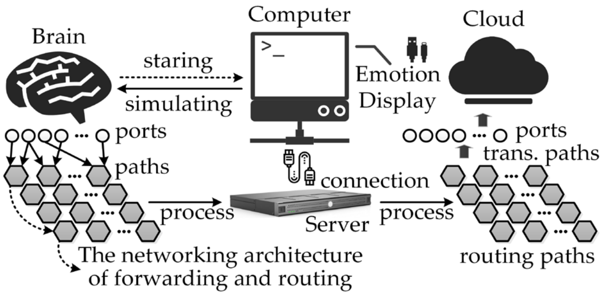


Figure 1. The overview of NLIPS architecture

Our own instructions is shown in this pictures, we have to resubmit the whole work. This will enable us to make a uniform mode in the emotion display and router as well as the mechanism in routing and forwarding by NLIPS server. We make an approximation of unknown dynamic of agent. NLIPS model has been produced the emotion recognition by discerning the EEG features.

In the networking architecture of forwarding ports and routing paths, we use the computer connected to the server. People can exchange their thoughts and ideas by using this affective brain-computer interactions. In our brain, we can sample the multiple analog signals. We use the forwarding ports to realize these signals transmission. The constitutes of these routing nodes form a local area network (LAN) in the routing paths and forwarding ports as well as in the post-memory environmental scenarios by NLIPS structure. The MMP-based device need an interactive simulating, in this action, we collect the associated signals and convert it to the digital signals. In forward port $\{FP_i\}$ and route path $\{RP_j\}$, We optimize EERA by adjusting MMP forwarding port and routing path, we set EE_{op} as this optimal EERA.

3.2 The EERA of MMP for ABCI based on NLIPS

The NLIPS aims to classify the data of different classes, the relative execution time of an affective computing in the ith processing from iterative prediction has been reduced. Our non-linear approaches may be able to include the EEG, image and audio features in the sampled data. To cope with the challenge in multi-modal affective computing, type the the framework of NLIPS architecture in Figure 2 as shown at the following of this sub-section. The NLIPS model use the three kinds of signals: EEG, image and audio signals, accordingly, the EERA in multi-modal features processing has three learners to select the appropriate modes. It enable us to maintain a optimal paths planning in affective brain-computer interactions to get the information of emotions.

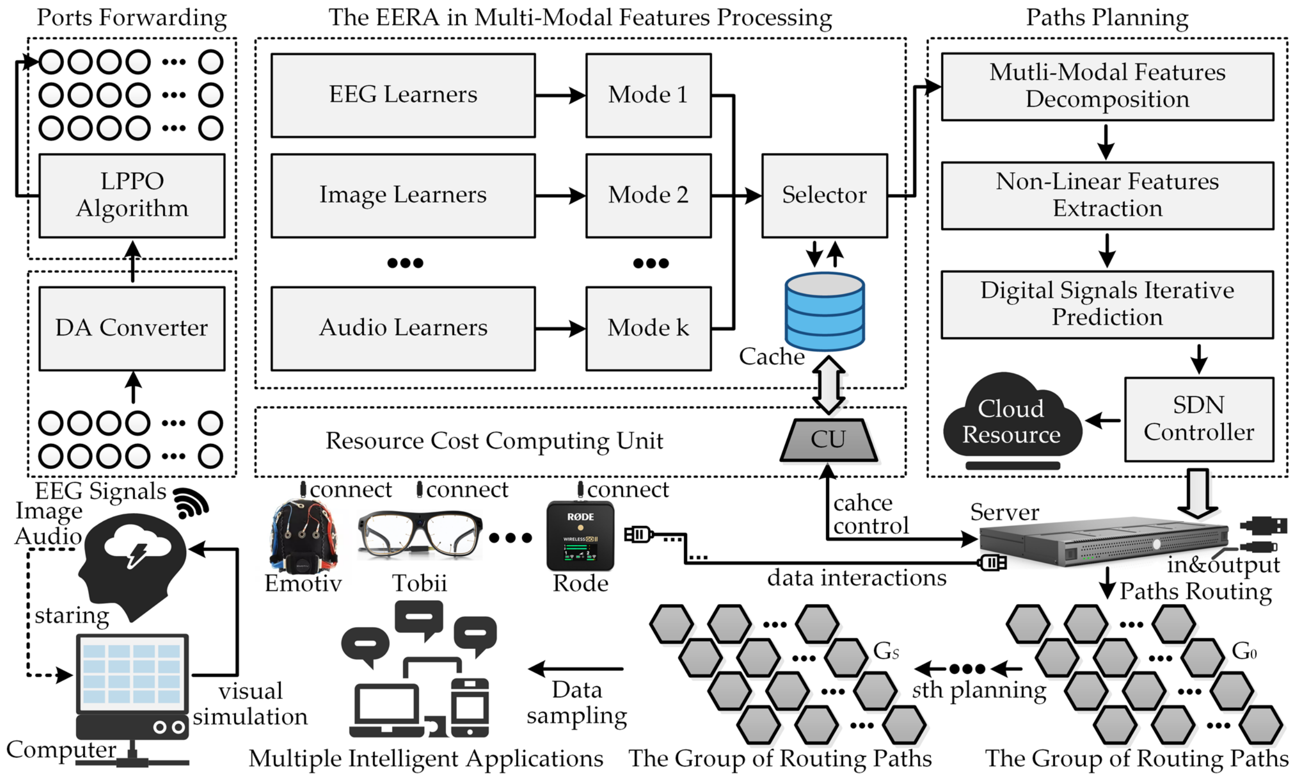


Figure 2. The frameworks of NLIPS architecture for affective brain-computer interactions in EERA

To address this NLIPS structure, we also embed visual and class semantic features to constructed. This will enable us to acquire an optimal EERA for EE_{op} in the EEG, image and audio learner as well as a variable threshold by NLIPS frameworks. We define Pe as this variable threshold, and it simultaneously set E_r, E_f as the energy of once forwarding and routing. The computation equation is shown in Eq. (1).

$$Pe = \sum E_r(t) + \sum E_f(t). \quad \textbf{(1)}$$

In the frameworks of NLIPS architecture for a ABCI in EERA. We make the MMP techniques: EEG, image of eye tracking and audio as multiple modals to monitor the static features. In digital-analog (DA) converter, we set up the forward ports to transmit the data. When LPPO listen a tap in forwarding channel, we construct k modes to select the different learners. The resource cost computing unit make the control unit as the computing unit to control the cache, it can adjust the selector when multiple k number of modes need to reduce the learner for EERA action. Then, the step of decomposition, extraction and iterative prediction one by one access to the SDN controller for the cloud resource to make a group of routing paths with E_r and E_f in k modes.

4 The MMP Optimization of NLIPS

In this section, we have proposed a MMP optimization of NLIPS for the EERA. This headline have access to the concrete methods and steps and for EERA to maintain an optimal architecture in NLIPS. The composition of this part has 3 sub-sections: The MMP model optimization, the algorithm optimization with improved LSTM frameworks and the implementation of NLIPS. The optimization of the model architecture and algorithm steps is conducive to the realization of NLIPS model in this research, which is also a prerequisite for the construction of the next evaluations.

4.1 MMP Model Optimization

In making a good performance in EERA, the first is the NLIPS models optimization. In Figure 3, the optimization for the visual stimulation with the Emotiv, Tobii and Rode devices. We make a tester for staring the emotion pictures and this action will enforce the response of our brain. The server samples multi-modal data and process it in NLIPS.

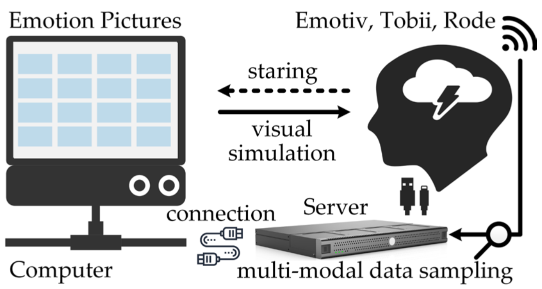


Figure 3. The optimization for the visual stimulation

When including a sub-response the server can listened, for their EEG signals sampling, the image of eyes tracking, and audio features sampling. This optimal NLIPS enhance an intuitive understanding of multi-modal emotions data and get the multiple characteristics of 3 sampling devices.

4.2 The Algorithm Optimization with Improved LSTM

In the sub-section of algorithm optimizations approach for EERA, meanwhile, we propose an improved long-short term memory (LSTM) model to optimize the EERA. This model has two parts: the port forwards and the path routes. We use the functions of long-short memory to achieve an optimal forwarding ports and routing paths and realize the good performance on EERA for ABCI networking. Figure 4 is an improved LSTM model for EERA in networking.

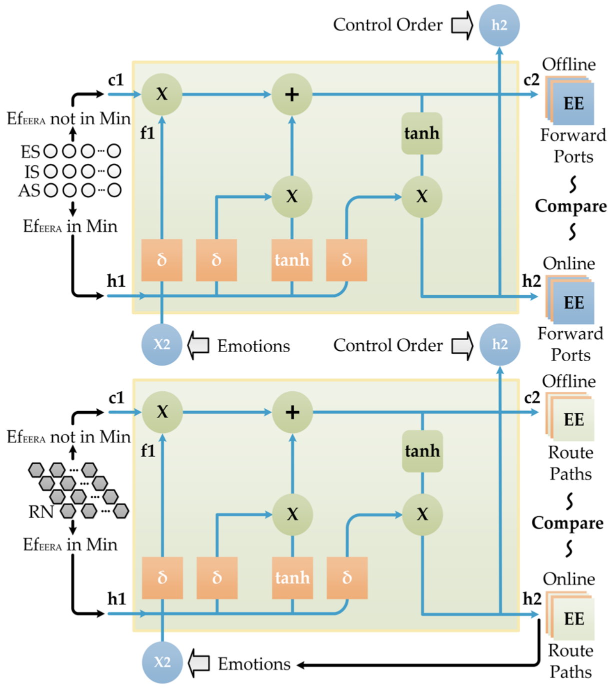


Figure 4. The improved LSTM model

As shown in this model, we put the EEG signals (ES), image signals (IS) and audio signals (AS) in a parameter of Ef_{EERA} threshold. Here, we propose a LSTM-based ports and paths optimization (LPPO) algorithm for MMP, which is formalized in the following part. To achieve the goal of optimal EERA scheme, we define a parallel unit Md for the computation of energy efficiency in networking process of the matching degrees. The steps of LPPO is as follows.

Algorithm 1. LSTM-based Ports and Paths Optimizations (LPPO)

Input: the vector of data $\boldsymbol{D}_{ports}$, $\boldsymbol{D}_{patts}$, and Ef_{EERA}

Output: the optimal vector of link trees $\boldsymbol{L}$, and QoS

1. **Initially** each nodes and parallel planes
2. set public forward and route weights E_r, E_f;
3. **while** training data Ef_{EERA} are not in minimum **do**
4. **for** each offline nodes unit parallel process **do**

5. copy public forward weight from Eq. (1) with *Pe*;
6. LSTM training and compute iterative weights;
7. use Eq. (2) to compute level similarity *Md*;
8. compare the offline and online EE_{on} value;
9. jump to step 4;
10. copy public route weight from Eq. (1) with *Pe*;
11. send the value of min*Pe* to link trees ***L***;
12. **end for**
13. **end while**
14. **while** training data Ef_{EERA} are is in minimum **do**
15. **for** each online nodes unit parallel process **do**
16. copy public route weight from Eq. (1) with *Pe*;
17. LSTM training and compute iterative weights;
18. use Eq. (2) to compute level similarity *Md*;
19. compare the online EE_{off} value;
20. send min*Pe* to slave, and use Eq. (3) to get EE_{total};
21. jump to step 15;
22. listening the long-short term data for link trees ***L***;
23. **end for**
24. **end while**
25. **return** optimal vector of link trees ***L*** and *QoS*

The LPPO algorithm use the improved LSTM model to calculate the array of forward ports and route paths. This mode enable the optimal energy-efficient to keep a channel in the MMP of ABCI. In the input and output gates, multi-modal signals transfer between online and offline states. We set up the EE_{on} and EE_{off} to represent this mode and compare the cell and hidden state to calculate the EE_{cost}.

The matching rates of two features in r_{ports} and r_{paths} of forwarding and routing under the quality of service (QoS). The forget gate corresponding to the Ef_{EERA} which is not a minimum energy in the cell states. Then, this research uses link tree to describe the table of the optimization, as shown in Eqs. (2), (3), *Md* is the level of the similarity in 2 nodes. EE_{total} is a cost of link trees for optimal route and forward.

$$Md_{\omega}^{N} = r_{ports} \cdot \frac{1}{QoS} + r_{paths} \cdot EE_{cost}. \tag{2}$$

$$EE_{total} = \sum_{i=0}^{N} links\left[L_0^S, L_1^S, L_2^S, \ldots, L_N^S\right]. \tag{3}$$

With the help of upper equations, we can calculate the level of their matching degrees from the root to each link in candidate adjacent intelligent nodes (AIN). In the Figure 5, we use LPPO algorithm to calculate the optimal routes and achieve the tables of forwarding ports and routing paths in link trees. The flow diagram is shown in the Figure 5.

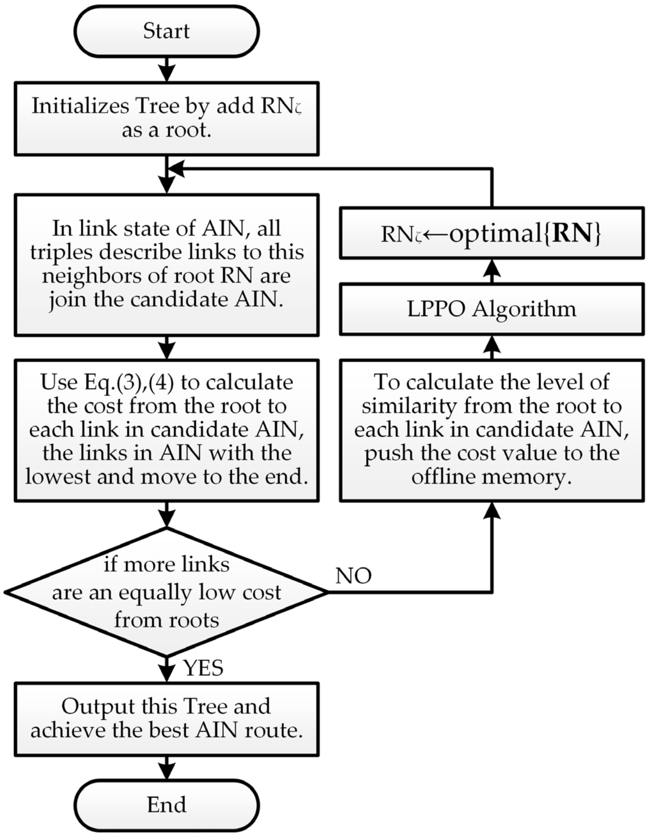


Figure 5. The optimal routing paths in link trees

In LPPO and link trees model, the constraint imposed on input and forget gates enforces the output gates of data from same condition to be similar. This time constraint can be formulated as a non-linear iterative unit in the predicted function of a basic module of link trees, which also enables indirect calculation of linking table matrix and the optimal routing channel matrix "RN_{ζ}" from optimal $\{\boldsymbol{RN}\}$.

4.3 The Implementation of NLIPS

In this section, we will introduce the implementation of NLIPS model. We perform our implementation based on a Matlab R2021a integrated development environment (IDE) and running a energy-efficient resource allocation states in the application of an affective brain-computer interactions. When setting the experiment in this study, the target of this action is making a EERA in ABCI application at the test of these multi-modal and multi-channel scenario cognition.

In the energy efficiency of 3 modals, the study need an evaluation model to describe the response time of different networks. We define the EE_{NET} as the efficient efficiency of the node networks, the cell states and hidden states are *c*, and *h*. When the S_0.

$$EE_{NET} = c + \frac{c-h}{1+S_0^p}. \tag{4}$$

To accelerate the converge speed of EERA and ensure the networking constraint being satisfied, the initialize idea are employed to generate initial root of link trees. We set up the multiple random schedules are generated for routing table initialization. In this implementing strategy, for each step in the state sensitive applications, a modal instance is randomly chosen for the NLIPS execution. Likewise, their function of MMP should be guaranteed for EE_{NET} and S_0 to achieve an optimal initialization parameter in EERA step.

5 Evaluations

In this section, we first present some evaluations of this detailed experiment setting, including the initial setting of this experiment, implementations detail and result of these evaluations. Then, we compare with the simulation results and discuss the evaluations of this NLIPS model.

5.1 Experiment Setting

We perform this evaluation on 4 scenarios, including the throughput varies with the network scale; the energy efficiency varies with the response time of networks; the multiple modals in static and dynamic environment with 4 emotions and the prediction of scheme in difference varies with the identifying number of ABCI in networking.

Table 2. The experiment setting of this evaluation in Matlab R2021a with emotion and EERA models

Modality	Parameters	Values
EEG	D_{ES}	F010
Image, eye tracking	D_{IS}	F020
Audio, audio features	D_{AS}	F030
Normal	D_{ES}, D_{IS}, D_{AS}	F010, F020, F030
LIPS+LSTM	L_{AF}, $\boldsymbol{F}_{\mathrm{LSTM}}$	0.50, 0F0F
LIPS+LPPO	L_{AF}, $\boldsymbol{F}_{\mathrm{LSTM}}$	0.50, 0F0F
NLIPS+LSTM	NL_{AF}, $\boldsymbol{F}_{\mathrm{LSTM}}$	0.50^{G}, 0F0F
NLIPS+LPPO	NL_{AF}, $\boldsymbol{F}_{\mathrm{LSTM}}$	0.50^{G}, 0F0F

Table 2 is the experiment setting of this evaluation in Matlab R2021a IDE with emotions and EERA models. In this research, the experimental modalities were randomly distributed to two categories: the 3 modals sensing method and the combination experiment of different schemes. This comprehensive approach enable LIPS, NLIPS, LSTM and LPPO to achieve a good effect of data sample in the scene of networking architecture. The integrated parameters D_{ES}, D_{IS} and D_{AS} can get the quantitative realization of multiple channel adjustment capability in linear/non-linear emotion recognition. The L, NL represent these contrary features by the different values of matching degree in multi-modals.

5.2 Simulation Result and Discussion

In this section, we talk about the simulation result and a discussion for NLIPS in throughput of network scale and it energy-efficient varies with the bandwidth of routing link. In Matlab R2021a IDE, we set up an adaptive experiments scenario and construct the transmission routes of 3 types of signals. It were the EEG, image, and audio. The first works is to simulate the throughput varies with the network scale.

Figure 6 shows the throughput varies with the different kinds of network scale, it is a number of networking nodes in experiment simulations. This results enable us to know the uniform network in the different digital signals process is similar to an analog-to-digital route process with NLIPS mode. With the increased number of sensing routing nodes, the channel throughput of three-modals sensing systems is constant basically. It proves that the multi-modal affective brain-computer interactions was used the same protocol to solve a problem of emotion recognition in MMP scenarios.

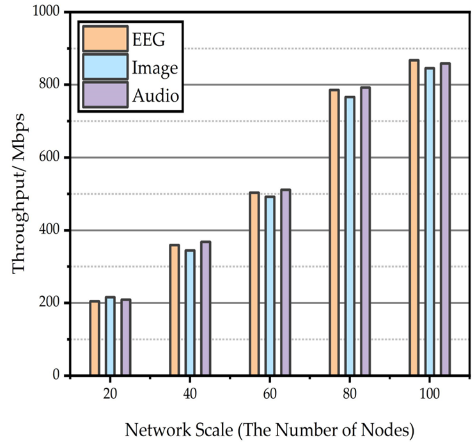


Figure 6. The throughput varies with the network scale

In essence, the network operates as follows: (1) A node send data to another node anywhere in the system; (2) The source routing node break a data to be sent into IP packets and (3) Each routing node, as it receives a packet, makes a routing decisions and forwards the packet along its way to the destination. In NLIPS-based EERA of MMP for ABCI, as the network complexity increases, the number of nodes has growth, the more selectivity of routing and forwarding we have in choosing the different emotions dimension.

Emotions are a complex psycho-physiological process, and it is manifested with internal physiology responses and external expressions. The various transferring signals from different modes describe different aspects of emotions and complementary factors from different modes can be added to a better emotion recognition structure. This multi-modal fusion technologies integrate the multiple sensor data with various planes of feature in manifold ways and make final decisions which based on these multi-dimensional factors. There are many modality signals that are associated with emotions processing, in this research, we choose the EEG, image, and audio information for affective computing.

In NLIPS architecture, the three signals were sampled by the EEG cap, eye tracking device and audio recognition system. We suppose that multi-modal $\boldsymbol{D}$ is an $M \times N$ matrix that represents multiple factors to the same affections from D_{ES}, D_{IS}, D_{AS} subjects and all kinds of EE energy efficiency. Then, the $EE = D_{ES} + D_{IS} + D_{AS}$ was proposed to get a variable quantity with EE_{NET} value. We set up this parameter: L_{REST}, it represents the return value of energy-efficient allocation. In Eq. (4), we can acquire the 3-channel energy efficiency from computational analysis of 3-modal express matrix $\boldsymbol{D}$.

Figure 7 shows the energy-efficient of different modals varies with the response time of networks. In this picture, we test the energy efficiency of 3 modals: EEG, the image of eye tracking technologies and audio features. When the response time of networks changes from 0-2500ms, MMP in 3-modal channels perceptual process. The value of *EE* is similar to the EEG, image or audio, which from 0.65-0.70. This is further proves that 3-modal perceptual process has the same ability of resource allocation in energy-efficient.

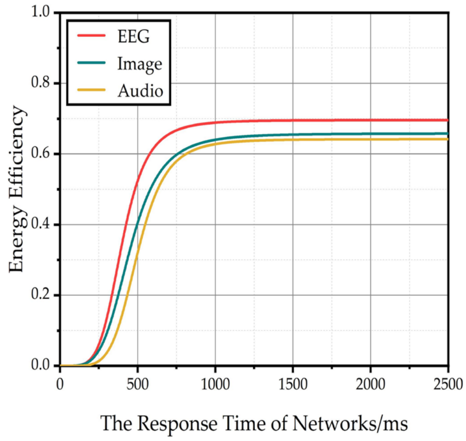
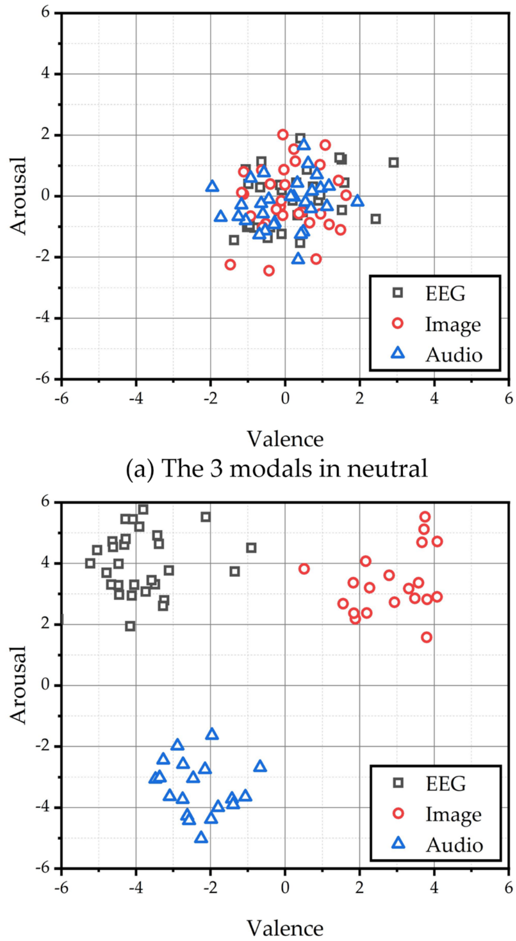


Figure 7. The energy efficiency of different modals varies with the response time of networks

In comparison with the multi-modal features fusion in experiment, the multi-modal deep learning framework can acquire a high-level shared representations in 3 modalities. Through the processing of multiple modals in NLIPS, the channel of multi-modal signals are automatically extracted. In the sensory feature fusion, it is very difficult to relate the one modal features to another modal features. In addition, the relations across various modalities are deep instead of plain. The EERA of MMP in ABCI can seize the relations across various modalities with non-linear architectures and improve the performance of resource allocation. To further research their complementary characteristics of EEG, eye movements and audio features, we analyzed the valence to arousal of each modality, which reveals their strength and weakness of each modality. Figure 8(a) presents the neutral emotions dimension of different modals digital signals. As indicated by these results, EEG, image and audio features have the complementary characteristics. We observe that 3-modal has the advantage of classifying neutral emotion compared to single modal, whereas the multiple channels outperform single channel in recognizing neutral emotions (82.20% versus 77.77%). It was hard to discern fear, happy and sad emotion using only one modal. Single recognition channel has the lowest classification accuracy for emotion. In Figure 8(b), we obverse the multiple modals in static and dynamic environment with fear, happy and sad emotions and we render each channel one single emotional features. When 3-channel is given the different emotions data, these corresponding distributions of experiments is in difference. The valence-arousal affective dimensional distributions of EEG, image and audio are in fear, happy and sad emotions. We compare the *Md* and EE_{total}, its value is also represent the region of emotion feature. As is shown in evaluations, the mean value of EEG-fear, image-happy and audio-sad is (-0.38, 4.02), (2.62, 2.89), (-2.25, -3.05). The results show that the proposed schemes and models can realize MMP in multi-channel and achieve the optimization of EERA.



(a) The 3 modals in neutral

(b) The 3 modals in fear, happy and sad

Figure 8. The multiple modals in static and dynamic environment with neutral, fear, happy and sad emotions

Considering the feasibility of the proposed NLIPS, we adopt the emotion recognition with multiple modals (i.e., neutral, fear, happy and sad affections) for evaluating two dimensions performance in this experiment. The data were collected from the ABCI experimental paradigm including 4-class (neutral, fear, happy, sad) affective classify tasks as shown in the Figure 8 using 3-channel digital signals from 60 emotional data points. 2 sessions of affective dimension tasks were recorded, each session consisted of 3 runs; each step was comprised of 20 points, yielding totally 60 points per-session. The emotional points from 2 dimensions were evenly distributed, which meant the readability of different channels to the data plannings and resource allocations of affective computing in MMP. Driven by this purpose, we need a experimental scene to test the prediction of different schemes. This paper proposes a NLIPS scheme with LPPO algorithm to get a higher prediction accuracy. In linear and non-linear problem, we build 2 scenarios: LIPS and NLIPS. In classifiers of LSTM and proposed LPPO algorithms, we construct 2 scenarios: LSTM and LPPO. In the selection of variables, we defined the identifying numbers of ABCI for prediction in different schemes. In Simulink, we open the library browser to use the multi-stage non-linear MPC and non-linear MPC controller block. The inputs of blocks are *x*, *ref* and *last_mv*, we set up the EEG, image and audio as the input *x*, the algorithm links to the *ref*, and the prediction model links to the *last_mv*. We obvious the output signals to describe *mv* (the same as predicted value in Figure 9).

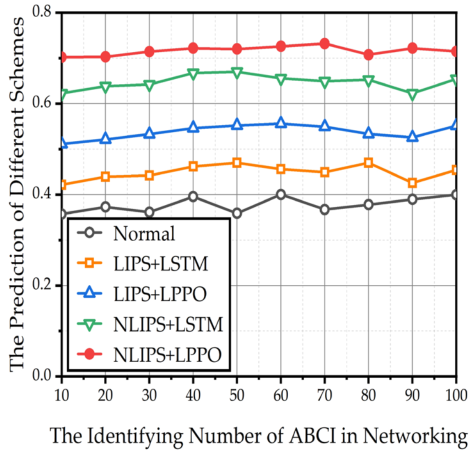


Figure 9. The prediction of different schemes varies with the identifying number of ABCI in networking

As the same comparison process in 5 multiple iterative structures, the prediction performances of using 5 schemes are shown in Figure 9. Without applying single perception, affective classification performances of all classifiers were below 0.75. The LSTM algorithm in the reference [30] in which 3-channel LIPS and NLIPS were collected achieved 0.45 and 0.62. Our proposed NLIPS+LPPO of using about multi-channel EEG, eye tracking and audio signals is more practical and feasible to obtain the ABCI application in the real-world environment. Moreover, the proposed NLIPS in LPPO enhanced a multi-channel performance with EERA of MMP from our multi-class analysis experiment and the rationality of EERA revealed that it is potential to perform multi-modal and multi-channel ABCI applications.

6 Conclusion and Future Work

This paper proposes an non-linear iterative prediction scheme (NLIPS), to simulate the energy-efficient resource allocation (EERA) of multi-modal perception (MMP) in affective brain-computer interactions (ABCI). By enabling EERA tasks in an adaptive FPGA model of acceleration, along with the construction of 3 channels (EEG, eyes track, audio) and improved port and path optimization algorithm (LPPO), the common MMP tasks achieve an average of 10.025Mbps throughput over the state-of-the-art approach [30]. First, we use a ZYNQ-7000 core between multi-party computation, and extract the multi-modal feature of EEG, image and audio signals in affective coordinates. Then, we develop a EERA model to fully utilization route-forward process of networking management for multiple emotion recognition. Experimental results show that achieves high performance of EERA across different ABCI factors.

Future research work includes: (i) applications of our proposed model to combine other affective brain-computer interactions e.g., as listed in [1], and (ii) generalization of our method for more complicated network scenarios, such as monitoring of driver's emotion in the whole Internet.

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