Investigating the Effectiveness of Transfer Learning in a

~~Develop~~ Motor Imagery Game ~~Using Transfer Learning~~

by

Pongkorn Settasompop

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Examination Committee: Chaklam Silpasuwanchai
Matthew N. Dailey
Mongkol Ekpanyapong

Nationality: Thai
Previous Degree: Bachelor of Engineering in Software Engineering
Thammasat University
Thailand

Scholarship Donor: Royal Thai Government*

Asian Institute of Technology
School of Engineering and Technology
Thailand
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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

A brain-computer interface (BCI) is system that can establish a communication between human's brain and an external device (Altaheri et al., 2021). The application of BCI can help in various field such as mapping, assisting, augmenting, or treating human (Altaheri et al., 2021; Al-Saegh, Dawwd, & Abdul-Jabbar, 2021). BCI system can be created by recording device such as invasive and non-invasive techniques (e.g. electroencephalography-EEG (Mattioli, Porcaro, & Baldassarre, 2022) and functional magnetic resonance imaging-fMRI (Lin, Zhang, & Liu, 2020)), decoding the signals to command, and a controlling tools to control a devices (Altaheri et al., 2021)(e.g. computer, intelligent wheelchairs, game).

Motor imagery electroencephalography (MI-EEG) is a ~~self regulated~~ active EEG, i.e., without an external stimulus~~, which it detected by electrodes~~ (Lun, Yu, Chen, Wang, & Hou, 2020). It is a neural response that is produced when a person performs a movement or imagine it (Riyad, Khalil, & Adib, 2020). space Recently, deep learning space (DL) model have been used in the development of MI-EEG. Deep learning techniques have been used for both feature extraction (Wu et al., 2019) and classification (Lun et al., 2020). With deep learning paradigms, CNNs model ~~have~~ found much success in MI-EEG. CNN is a renowned DNN architecture that relies on a specialized sort of linear operation known as convolution. This type of networks can be suitable models for processing different types of signals such as image, or EEG signal (Padfield, Zabalza, Zhao, Masero, & Ren, 2019). For example, 1D-CNNs was applied in MI-EEG and achieved high accuracy (Lun et al., 2020; Mattioli et al., 2022). Roots, Muhammad, & Muhammad (2020) implemented a multi-branch 2D CNN based on EEGnet that utilizes different hyperparameter values for each branch elaborate and achieved high accuracy. In addition, feature extraction technique can also be included in CNN to extract spatial and temporal information of EEG signal (Padfield et al., 2019). As a result, ~~their achieved high accuracy from~~ CNN can benefit from using feature extraction methods such as common spatial pattern space (CSP) (Zhu et al., 2019) , or filter bank technique (Wu et al., 2019).

In our paper, we aim to develop a practical Motor Imagery game. We first explore the Motor Imagery ~~classifier.~~ classification methods Second, we evaluate them ~~to find a practical model for real time system with offline dataset.~~ on a practical real-time setting ~~Then we conduct the recording session to collect EEG signal data from 10 healthy participant. Next, we use recorded EEG data to perform~~ Three different transfer learning techniques were investigated. ~~Finally, output commands from model are use as command for Unity game. Moreover, the model are measured with confusion matrix, accuracy, point system in Unity game, and interview from participant.~~

Literature review- past tense

Everywhere else - present simple

cite

1.2 Statement of the Problem

Nowaday, ~~There are~~ many researches have explored the field of Motor Imagery classification which different dataset, pre-processing, feature extraction feature selection, and neural network ~~DNN~~ architecture. Those studies have mostly focused on how to achieve better ~~performance and~~ accuracy. However, little is known regarding ~~they do not consider~~ how practical these are ~~of~~ model in real-time setting. ~~system~~. ~~This problem can cause model not being generalized~~. To address ~~solve~~ this gap ~~problem~~, we investigate the effectiveness of classification model ~~explore a practical model~~ that is ~~which~~ suitable for real-time operation ~~classification~~. ~~In addition, this model can work well in online classification, hyperparameter not too much, and work well in transfer learning.~~

A particular aspect we are interested is transfer learning, questioning whether is possible to transfer what the model learns in some big offline dataset and transfer to real-time settings, thus lowering the training time.

~~In summary, we compare~~ three different transfer learning techniques were compared. ~~First, we will find practical practice model for Motor Imagery classification. Second, we are conduct MI experiment to collect EEG data. Third, we evaluate model with three different transfer learning techniques. Finally, we will create Unity game to evaluate three transfer learning techniques.~~

no need to say because it's very standard.

1.3 Objectives of the Study

To identify the practical model and ~~training method~~ space (transfer learning methods) which are suitable for Motor Imagery game, we ~~We~~ propose three different transfer learning techniques by following:

- Use trained model from offline dataset for train with recorded dataset and evaluate it.
- Use trained model from offline dataset for evaluate with new dataset without train it.
- Use practical model without training from offline dataset for train with new dataset and evaluate it.

To measure it, we compare three model from transfer learning with accuracy, confusion matrix, point system in Unity game, and interview from user.

this is not objective, this is methodology.

Objective 1: compare models
2: compare transfer learning methods
3: evaluate the in-game performance, e.g., points and interviews.

CHAPTER 2

LITERATURE REVIEW

NEEDS a TABLE OF COMPARISON BETWEEN RELATED WORKS.

2.1 Motor Imagery EEG-Based BCI system

MI is widespread in BCI systems because it has naturally occurring discriminative properties and also because signal acquisition is not expensive. Furthermore, MI data in particular can be used to complement rehabilitation therapy following a stroke. Padfield et al., (2019) reported structure of EEG-based BCI system for MI application which it contain EEG data acquisition, pre-processing technique, feature extraction, feature selection,and classification.

there are many available datasets.

In data acquisition, ~~many researches use data recorded from many type~~. For example, in (D. Li, Wang, Xu, & Fang, 2019), they ~~their was~~ used 2008 BCI competition IV-2a EEG dataset which recorded from 22 electrodes with 250 Hz sampling rate from 9 subjects ~~for fed into network.~~ However, the data of labeled subject are very small which it can lead to overfitting. Mattioli et al., (2022) and Lun et al. (2020) ~~were~~ used Physio net dataset which was recorded from BCI2000 system using the international 10-10 system. In addition, this dataset was recorded form 64-channel EEG signal with 160 Hz sampling rate from 109 subjects. Both dataset achieved around 90% accuracy using ??? model. ~~when their fed into model. However, The practical of using their model with these dataset for real-time system need to be explored. Moreover, we conduct EEG recording session to collect EEG signal for using in real-time system same as offline dataset.~~

is

huh? this is NOT the right place to talk about limitation, you should talk about what they found!

not the right place ...

Preprocessing EEG signals can improve the signal-to-noise ratio of EEG and the classification accuracy, but it is not necessary. too strong! For example, Lun et al. (2020) used CNN to directly classify raw pair-electrode EEG signals without using preprocessing. This model achieved around 95%. However, Mattioli et al. (2022) proposed a 1D-CNN and preprocessing technique called "SMOTE" which stands for "synthetic minority over-sampling technique". This preprocessing solves the imbalance problem for classify four brain states of EEG signal. Moreover, Roots et al. (2020) proposed an CNN using raw EEG signals with preprocessing such as sliding window, notch filter,and band-pass filter to predict two state of brain signals. Y. Li et al. (2019) improved CNN with raw EEG signals and a proposed preprocessing technique called "Amplitude-pertubation" to solve the problem of data shortage, which can help the deep learning network to combat overfitting and enhance the robustness of the network, which achieved good result. ~~Mattioli et al., (2022) implemented 1D-CNN with raw EEG signals and preprocessing called "SMOTE" to solve imbalance problem of dataset. It can be seen that using the original and the preprocessed data can obtain a good result on classification. The preprocessing need to be explored to find how practical of model.~~

– elaborate

SMOTE is only for four?

elaborate

repeat XD

After we got input from prepocessing, the processed EEG data go through feature

You should use SMOTE and Amplitude pertubation!

extraction, feature selection, and feature classification phases ~~in order to achieve a decision after that~~. Zhu et al. (2019) used CSP as feature extraction to extract spatial and temporal feature. D. Li et al. (2019) used CSP with two different types which it is Hilbert transform and Logarithmic transformation. Those feature extraction achieved good accuracy. In addition, Zhang et al. (2019) used EMD as feature extraction to ~~extract EEG signal to~~ generate new frames of EEG. Some ~~system~~ researcher ~~group together~~ combined ~~the~~ feature extraction, ~~feature~~ selection and classification into one ~~block~~ module. In (Y. Li et al., 2019; Lun et al., 2020; Mattioli et al., 2022; Roots et al., 2020) used CNN model to extract spatial and temporal feature and classify EEG signal. ~~In our work, we also focus on feature extraction and selection techniques, as well as classification approaches for real-time system.~~

elaborate

full name first use

not clear

why so many works?

2.2 Online classification in Motor Imagery

Recently, many researched applied the MI classification into real situations. ~~In~~ Tayeb et al. (2019), ~~this research~~ proposed online decoding system of MI movement from streamed EEG signal for a robot arm control by using three electrodes EEG signal. ~~Their~~ They used pCNN for transfer learning ~~to get command for control robot and found that their success in real-time system~~ and achieved with less than 1.4-seconds delay. Benzy, Vinod, Subasree, Alladi, & Raghavendra (2020) implemented ~~online decoding~~ MI-based motorized arm for stroke patient. ~~This research use own dataset which they collect from 12 subjects fed into Naive Bayes classifier. As a result, their evaluate the model with same participant by motorized arm as a motivational feedback for stroke patients.~~ The result showed that ~~these technique~~ a Naive Bayes classifier achieved an average of 68.63% in online session. In (Karácsony, Hansen, Iversen, & Puthusserypady, 2019), EEG based MI-BCI and VR are combined into real-time system ~~as a motivational feedback~~ for stroke rehabilitation. DNN model is trained with two different datasets. First, PhysioNet dataset was used to train the network. ~~After, ten participant were asked to record EEG signal. Finally, recorded EEG signal is used for transfer learning in DNN model. Moreover, VR game was developed to provide a feedback to participants. In our work, we also focus on transfer learning method for Motor Imagery game~~.

full name first use

how?

which two?

that

there is no such thing as "motivational" feedback, do you mean engaging the participants?

Then the trained model is directly used on real-time setting. They found that ???

directly used or fine tune or what?

CHAPTER 3

METHODOLOGY

you propose? or from related work

In the following section, we describe the data preparation methods used in this study, the experimental study ~~for~~ to collect EEG signal, the proposed neural network ~~DNN~~ architecture, the transfer learning technique that we use, and the ~~communication of Unity Game and Python for real time system~~. The system diagram is provided in ~~Fig~~ Figure 3.1, overall architecture of our motor imagery game

3.1 Data preparation

The implemented system were trained and evaluated on two different ~~type of~~ datasets. The first dataset is the PhysioNet EEG motor movement/imagery data set. This dataset consisti~~ng~~ of over 1500 one- and two-minute labeled EEG recording which was obtained from 109 volunteers (Goldberger et al., 2000)(Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2004). EEGs were recorded with 160[Hz] sampling frequency from 64 electrode~~s~~ setting and 16 electrode setting as per the international 10-20 system ~~(excluding electrodes Nz, F9, F10, FT9, FT10, A1, A2, TP9, TP10, P9, and P10) and for the 16 electrode setting, channels FC3, FCz, FC5, C1-C6, Cz, CP3, CPZ, CP4, P3, Pz and P4 were used~~ (Karácsony et al., 2019). These recordings include both actual motor execution and imagined movements ~~MI data with class~~ of opening and closing of left fist, right fist, both feet, both fists simultaneously and the rest stage with open or closed eyes. ~~However,~~ Our study uses only data of left fist, right fist and rest stage. ~~Hence, some part of dataset which consist of ten participants were used in this study.~~ Each experimental run involves 2 tasks encoded as follows: T0 corresponds to the left fist; T1 corresponds to the right fist.

The second dataset is our actual recording data from EEG. ~~This dataset were recorded from EEG electrode cap.~~ The three recording session were organized into both MI and executed session of right and left fist each. The experiment paradigm are defined as: the subject sits relaxed in front of a screen and perform the baseline which subject open or close their eyes. Next, subject were performed MI and executed tasks in front of a screen, where visual cues are displayed to instruct the subject what to perform. The visual cues consists of instructions between fixation cross as rest task and imagin~~or~~ing executing one of the above described tasks. This visual cue is presented for 5[s] for each task with fixation cross ~~is~~ of 8[s] for each task. The experiment is provided in Fig.3.2 — combined with Fig 3.1...

you don't need to say! It's "of course"!!

Both ~~of two~~ datasets are ~~apply signal pre-processing which aim to reduce computational load of dataset. The EEG signals for each subject will us~~e preprocessed with 6th order Butterworth BP(0.5-75[Hz]) filter.In addition, ~~we are use~~ notch filter with 50[Hz] for power-line interference cancellation are applied.

You should also band pass??

you don't use any CSP??

3.2 Experimental setup

For practical model, we conduct the experiment to collect a fresh EEG data from EEG electrode cap. The experiment consists of three sessions which participant will do the experiment 3 times, 4 block which represent as MI and executed tasks. For MI task, participants are imagine that they try to close or open fist but not perform physically. In contrast, executed task will perform by close or open physical fist. For each block, participants are repeat 12 times(in our study we call ”Trials”).

The instruction is following: First, participant sit relaxed on front of screen. The visual cues show on screen to instruction participant what to perform. The visual cues are represent between instruction to take a rest and instruction to perform execution and imagine tasks.The visual cues spawn with 5 seconds for execution and imagine task and 8 second for rest stage. Second, participant perform baseline which participants are perform open eye task and close eye task. This baseline takes approximately two minutes. Third, participants are introduced to perform execution and MI task. Execution task is a task which participants are close or open physical fist. In contrast, MI tasks are take a participant to imagine that participant close or open fist but not do in physical. In experiment, The rest stage is represent as fixation cross as rest stage see in Fig. 3.3.

3.3 Implemented DNN architectures

you don't talk about related work in methodology

~~In our study, we follow dataset, preprocessing technique, feature extraction, feature selection, and DNN architecture from related work. For example, in (D. Li et al., 2019), their proposed feature fusion network to reduce losing of information.~~ ~~In addition, their~~ using BCI competition IV-2A dataset and extract them into CSP feature as a input for fed into the network. We follow thier model and preprocessing technique. In(Y. Li et al., 2019), their implemented channle-projection mixed-scale CNN to learn spatial and temporal feature for EEG. Moreover, their use raw EEG data as a input to fed into the network so we use their model and input for our study. In (Mattioli et al., 2022), 1D-CNN was implemented for classification five brain state of EEG. Their proposed new preprocessing called ” SMOTE” to solve imbalance problem of dataset.In addition, set of raw EEG signal of pair-electrode were used for fed into model. To conclude, we follow their model, preprocessing, and input formation to our study. In (Lun et al., 2020), simple 5-layer CNN were implemented by using raw EEG data of pair-electrode. Their use Physionet dataset without preprocessing for fed into network. In conclusion, we follow dataset and model to implement in out study. Last, (Roots et al., 2020) implemented multi-branch 2D CNN based on EEGnet by using raw EEG with 64 channels. Moreover, their use sliding window, Notch filter, and band-pass filter as preprocessing technique. In conclusion, we follow dataset, model, and preprocessing for

rewrite; we don't talk about related work here.

develop our model.

how practical are the models

3.4 Transfer learning for online classification

To compare ~~how practical of model~~, we conduct three different transfer learning methods for real time ~~online~~ classification. ~~First,~~ (1) first we train a model with the Physionet dataset. We use the trained model to further train recorded EEG dataset ~~from experiment section and evaluate it~~. ~~Second,~~ (2) we train a model with the Physionet dataset. Then, we use the trained model ~~to evaluate recorded EEG dataset~~ without the training. ~~Third, we choose model to train~~ (3) We train from scratch on the recorded EEG dataset and evaluate it. We measure these three further transfer learning by accuracy, confusion matrix, Unity game, and interview from playing the game.

you CANNOT measure "game"! do you mean in-game performance?

you did NOT create!

3.5 Communication system between Unity and Python

you cannot "create" classification, what do you mean?

In our study, we integrate classification from python to unity. First we create an online classification which we use EEG electrode cap to record and feed into network to get a classification command such as left and right. Next, we send the a command to unity via http server. ~~Finally, command from python use as a command control in unity. we create a simply game for motor imagery. For example,~~ We create a running game in which participant ~~use brain from EEG electrode cap to~~ control a character to move either left or right side. To compare experimental methods we use ~~point system as diamond to compare~~ the efficiency of experimental method.

we use collected diamonds as the main point system to

Figure 3.1

System Diagram of our work

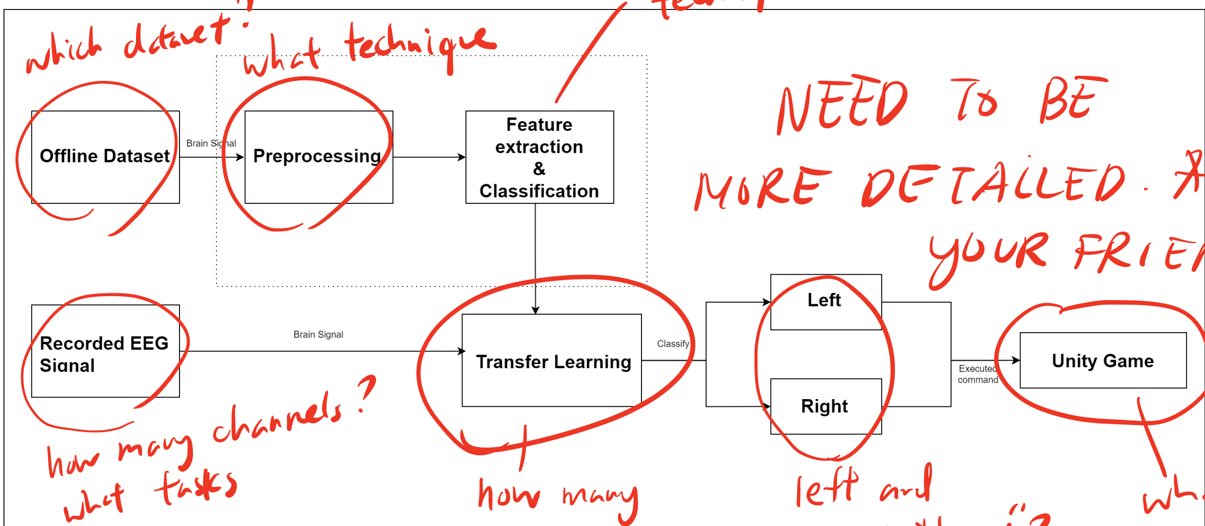
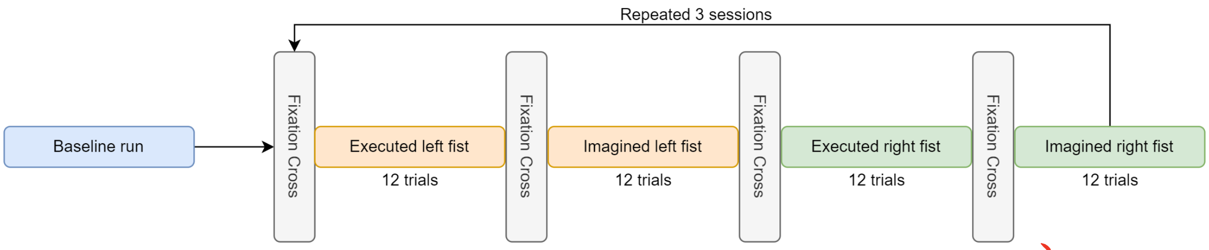


Figure 3.2

Experimental design

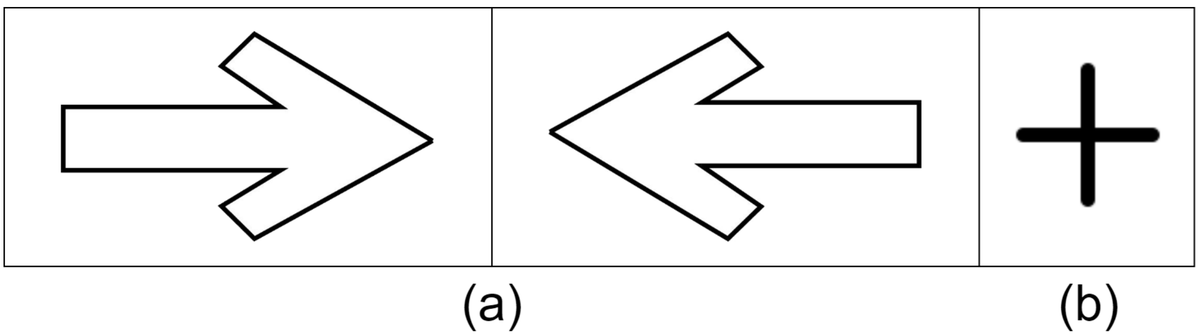


no temporal correlation? why not left > right > left rand only or this is the standard ?

too big - combined with Fig 3.1

Figure 3.3

Image(a): Left and right for executed and imagined tasks ,Image(b): Fixation cross for rest stage



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