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Brain-computer interface of focus and motor imagery using wavelet and recurrent neural networks

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ABSTRACT

Brain-computer interface is a technology that allows operating a device without involving muscles and sound, but directly from the brain through the processed electrical signals. The technology works by capturing electrical or magnetic signals from the brain, which are then processed to obtain information contained therein. Usually, BCI uses information from electroencephalogram (EEG) signals based on various variables reviewed. This study proposed BCI to move external devices such as a drone simulator based on EEG signal information. From the EEG signal was extracted to get motor imagery (MI) and focus variable using wavelet. Then, they were classified by recurrent neural networks (RNN). In overcoming the problem of vanishing memory from RNN, was used long short-term memory (LSTM). The results showed that BCI used wavelet, and RNN can drive external devices of non-training data with an accuracy of 79.6%. The experiment gave AdaDelta model is better than the Adam model in terms of accuracy and value losses. Whereas in computational learning time, Adam's model is faster than AdaDelta's model.

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1. INTRODUCTION

Humans in every day always carry out activities that involve the movement of limbs. The brain instructs the resulting action through motor nerves. Every human activity requires a focus on carrying out activities for particular purposes. Nevertheless, the focus can be influenced by several factors such as stimulation of sound or vision that can affect the activities being carried out. In meanwhile, the command to move a limb occurs over a state of mind called motor imagery (MI). However, moving the object can be carried out without involve gestures, muscles, sounds, and other motor functions. These commands are obtained from the brain through intermediate devices to translate brain commands, known as the brain-computer interface (BCI). This system can help people with physical disabilities in moving external devices. Currently, BCI has been widely used to drive games [1, 2], robots [3], to help post-stroke patients [4] and neuromuscular disabilities [5].

BCI consists of three parts, particularly command input, intermediate device, and command control. BCI usually uses standard tools such as electroencephalogram (EEG) signals to translate brain commands [6]. The EEG signal is bioelectric in the brain that is captured on the surface of the scalp. EEG signal has a low amplitude, non-stationary, and complicated patterns. The signal consists of frequency components such as

Alpha waves (8-13 Hz), Beta waves (14-30 Hz), Theta waves (4-7 Hz), Delta waves (0.5-3 Hz), and Gamma waves (> 30 Hz). EEG signal identified mental task variables as appropriate actions on a computer [7]. Therefore, the representation of EEG signals into the frequency domain is very considerate for getting conditions particular thoughts. Some previous studies in extracting EEG signals using wavelet transform [8-11] in BCI. Wavelets can filter signals from precise frequency components. So that method is proper for non-stationary signals such as EEG. However, with a short time segmentation, it is possible to use other methods such as fast Fourier transform (FFT) for extracting non-stationary signals [12]. FFT has advantages in terms of computational speed, although wavelet is usually more accurate. Wavelet extraction can increase accuracy by 3.6% and accelerate detection time by 0.003 seconds. The last study obtained 93.6% accuracy of training data, and 90% of non-training data [13].

Some variables that affected EEG signals are determinants of classification in previous studies, such as emotions [14], disorder [15] and focus [16]. Meanwhile, usually, the EEG signal variable translated in BCI is focus [16], attention level [17], relax [1], emotion [18, 19], hand grasping imagination [20] and hybrid of motor imagery and speech imagery [21]. Usually, the studies used one characteristic variable in the classification process. Previous studies used BCI to move characters in arcade games based on focus feedback [22], controls for computer applications, or action on imagined conditions of the mind [6] and wheelchair robotic [23].

In pattern recognition, after extraction features, then into the classification system. In BCI application, the previous research used some methods such as learning vector quantization (LVQ) [1], recurrent neural networks (RNN) [24], and convolutional neural networks (CNN) [25]. There was using CNN to BCI game control [26]. Meanwhile, time series cases often use RNN, which facilitates the connection of sequential data with past time [19]. In previous studies using RNN to recognize emotions from EEG signals with an accuracy rate of 87% [14]. This research proposed the BCI model to drive the drone simulator from the focus state and motor imagery. Models developed using wavelet and recurrent neural networks (RNNs). The drone simulator is designed to be driven by an imagery motor into four, particularly "forward", "right", "left", and "silent". Besides, the simulator action added focus factor (two classes: focus or not focus), which is described as the rotation speed. So that eight classes are obtained.

2. RESEARCH METHOD

This research proposed BCI to drive the drone simulator through EEG signals using wavelet and RNN, as shown in Figure 1. The system used variable MI and Focus that were processed by simultaneous. So that are eight classes of both variables. The model used data set with emotiv epoch EEG recording as shown in Figure 2.

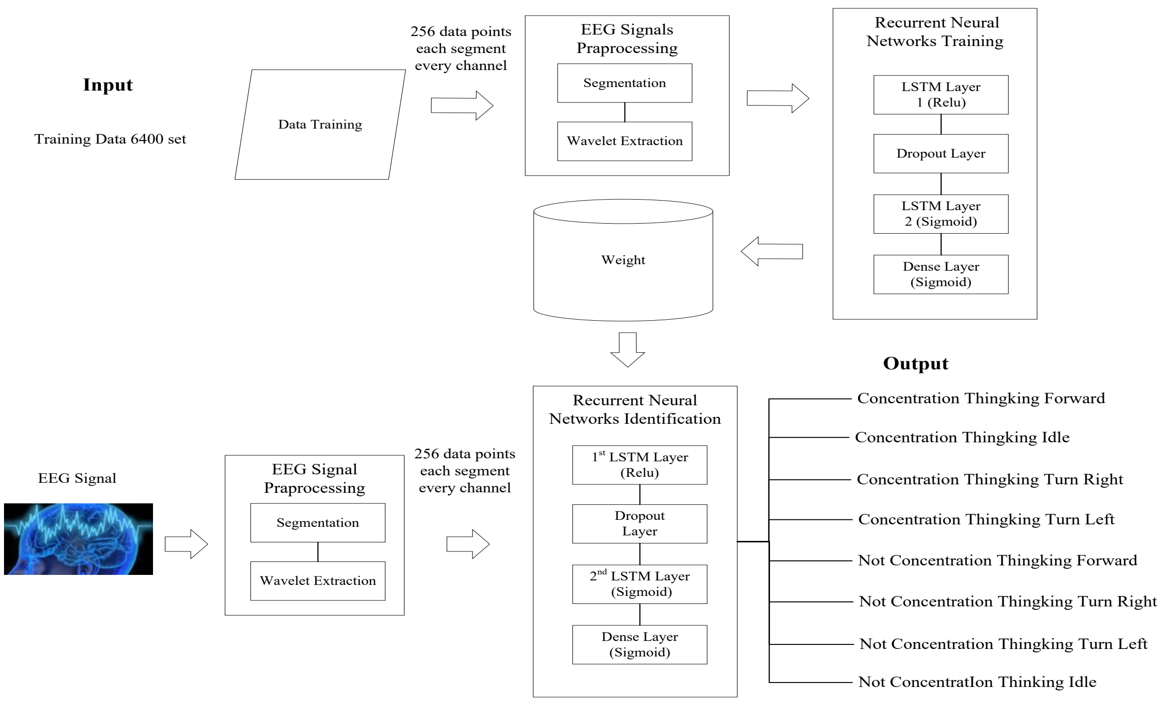


Figure 1. BCI based on focus and MI variable of EEG signal

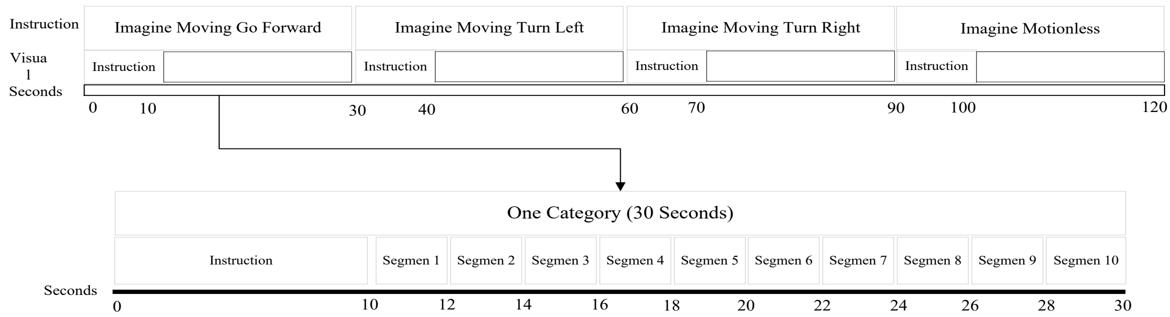


Figure 2. Recording scenario

2.2. Wavelet extraction

The wavelet transform can extract the needed signal components, hence reducing the number of data without losing important information. Besides, this method is suitable for non-stationary signals. The output of the wavelet transform into a time-domain allows its application as a pre-model [6]. Wavelet transformation has two main processes, specifically decomposition, that extract a signal into a specific frequency and reconstruction that recombine extracted signals into their original form [27]. Wavelet works in a convolution signal with mother wavelet. Various forms of wavelets used for EEG signal extraction from previous studies, such as Daubechies Haar and Symmlet. The researchers did not specifically mention the basic shape of the wavelet that gives good accuracy. But in general, the asymmetric Daubechies [7], combine of Daubechies and Symlet [28] and Symmlet [29]. Both forms are compatible with EEG signal characteristics. One type of wavelet transform is wavelet packet decomposition (WPD). Wavelet packets are linear combinations of wavelet functions [9]. A wavelet function has three indices, j: index scale (integer), k: translation coefficient, n: oscillation parameter and t is time as (1).

$$W_{j,k}^{n} = 2^{j/2} W^{n}(2^{j}t - k) \tag{1}$$

The wavelet packet functions are a scaling function $\varphi(t)$ and the mother wavelet function $\psi(t)$. Wavelet packet functions with higher filter are:

$$W_{0,0}^{2n} = \sqrt{2}\sum_{k} h(k) W_{1,k}^{2n}(2t - k) \tag{2}$$

$$W_{0,0}^{2n+1} = \sqrt{2}\sum_{k} g(k) W_{1,k}^{2n}(2t - k) \tag{3}$$

The factor h(k) and g(k) indicate quadrature mirror extraction [30]. The value (h(k) and g(k) related to the scaling function and the mother wavelet function. The inner product signal f(t) with wavelet packet functions in a range of t show (4):

$$W_{j,k}^{n} = f(t)^{*} W_{j,k}^{n} = \sum_{t} f(t) W_{j,k}^{n}(2t - k) \tag{4}$$

For original signal S, the left-side is obtained in low pass filter h(k) as an approximation coefficient and the right side as high pass filter g(k) or detail. In (6) showed the scale, translation, and oscillation values. In (4), the signal can be decomposed into a scale factor j in a particular frequency, either high or low. In this study, using the standard form Daubechies 4, which consists of four low-pass filter coefficients [29]. Wavelets decompose signals into specific frequency ranges, such as delta, alpha, beta, theta, and gamma waves, such as Figure 3.

2.3. Recurrent neural networks

RNN is one method used in Deep Learning for sequential data [31], by looping to store information from the past [32]. This configuration is shown in Figure 4. RNN is activated with a function such as sigmoid as Figure 5. RNN has the problems of short memory, so it needs control to forget some parts throughout the gate. Some of the methods are gated recurrent unit (GRU), backpropagation through time (BPTT), and long short-term memory (LSTM). This research used the LSTM gate to overcome short-term memory problems or often called vanishing gradient [14], which has a increase in capability from a single layer [33].

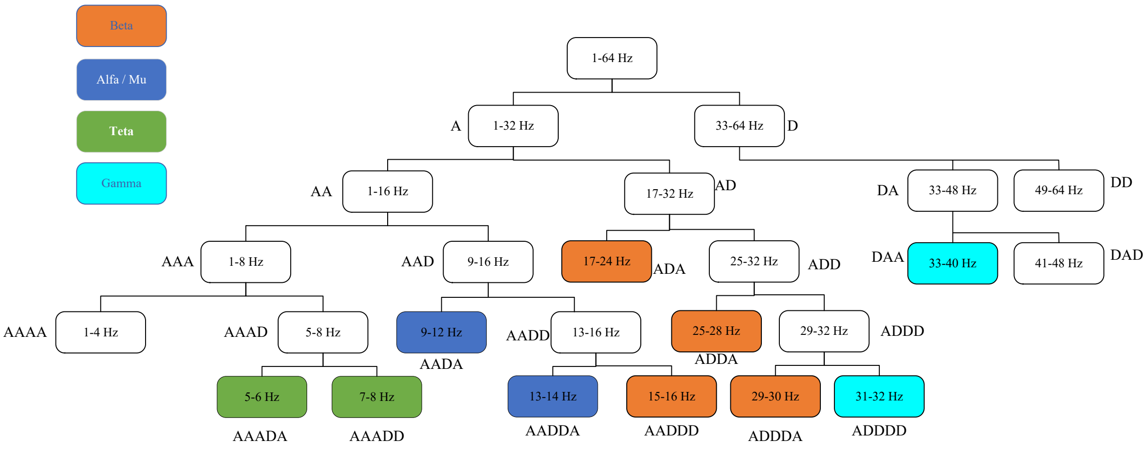


Figure 3. Wavelet multilevel

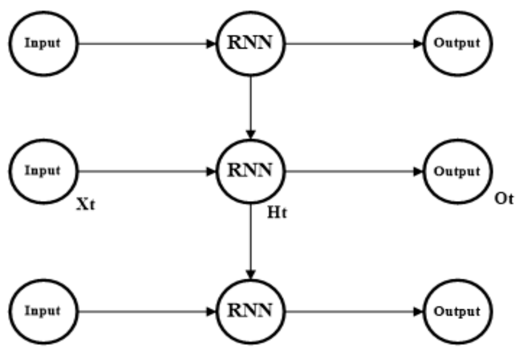


Figure 4. Recurrent neural network architecture

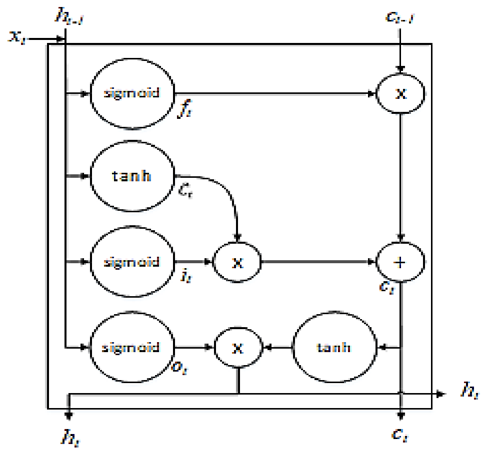


Figure 5. LSTM cell architecture

The LSTM network consists of modules with repetitive processing, as in Figure 4. Memory in LSTM is called cells that take input from the previous state (h_{t-1}) and current input (x_t). The collection of cells decides what will be stored in memory and what will be removed from memory. LSTM combines the previous state, current memory, and input. LSTM has three gates, particularly the forget gate, to determine which eliminating information from the cell using the sigmoid layer [34]. In (5) with the activation function used is the release shown in (8).

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{5}$$

$$ReLU(x) = \max(0, x) \tag{6}$$

The second gate is the input gate (i), which of the sigmoid layer (σ) will be updated, and tanh of the layer will be formulated as a vector of the updated value. It can be seen at (7) and (8) where x_t is input for each current step time. At this layer, a vector of updated values will be produced [35].

$$i_t = \sigma(W_f.[h_{t-1}, x_t] + b_i) \tag{7}$$

$$\tilde{C}_t = \tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{8}$$

Then the cells of (7), (8) will be updated using (9).

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{9}$$

Finally, the output gate will be calculated based on cell updates, and the sigmoid layer looks like (10) and (11).

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{10}$$

$$h_t = o_t * \tanh(C_t) \tag{11}$$

where σ is the sigmoid activation function, and tanh as the tanh activation function used for the results of multiplying the weight of each gate, namely W_f, W_t, W_c, W_o with input values and added bias including b_f, b_i, b_c, b_o. Gate used is gate input i_t, forget f_t, and output o_t. Each passing gate will be searched for hidden state candidates $\tilde{C}_t$ obtained from the gate calculation with the current hidden state C_t furthermore, the previously hidden state C_{t-1} to produce the latest hidden state, which is used as the output of the hidden layer.

In the identification layer, there is an effort to minimize the difference between the target output and the output of computational results. Objective functions are often referred to as cost functions or loss functions so-called "loss". One of the loss functions that can be used is cross-entropy, as in (12). Where loss is a distance, S is the result of the activation function, and L is the target of each class label. A loss function is used to measure convergence in the learning process.

$$Loss(S, L) = -\sum_i L_i \log(S_i) \tag{12}$$

In machine learning such RNN, it is essential to set input features. This research used MI and focus variable, so alpha, mu, beta, and gamma (32-40Hz) waves relate that. Based on Figure 3, we got the waves of four channels, as shown in Table 1. The BCI works every two seconds. While the RNN configuration is as shown in Table 2. In the first model, the number of neurons of the model is faced with the same amount as the input vector with a two-dimensional shape that applies the return sequence to the second LSTM model. The LSTM model has a one-dimensional vector, which results in the dense layer, which has eight neurons, according to the number of classes produced.

Table 1. RNN features of BCI

No	Component	Number of points	Description	All channel
1	Alpha, Beta, Gamma (9-40 Hz)	128	Four-channel	512
2	Mu (9-14Hz)	24	FC5 and FC6 only	48
	Total			560

Table 2. Architecture model recurrent neural networks

Model	Neuron	Output shape
LSTM	560	1,560
Dropout	0.2	1,560
Dense	8	8

3. RESULTS AND ANALYSIS

The experiment was carried out by comparing the effect of using wavelet as the extraction of alpha, mu, beta, and gamma waves. Experiments were also carried out on the model in terms of providing the highest accuracy and considering the computational time of learning. Identification involves eight classes, namely "Forward", "Right", "Left", and "Silent" each in focus and not. In using BCI, performance depends on translating variables from the EEG signal being reviewed. Identification performance is very dependent on the use of extraction methods. Therefore, testing begins with wavelet performance.

3.1. Wavelet extraction

Wavelet extraction uses Daubechies 4 at 9-40Hz, which has been normalized as in Figure 6. Wavelet extraction is shown in blue compared to the original signal using orange. The EEG signal after going through wavelet extraction is more stable because it is adjusted to the waves which are in the frequency range. Then eliminate unused waves and signal noise. The results of each channel are stored sequentially into input vectors.

3.2. Compared between optimization model

This study used three-weight correction models that are adaptive moment estimation (Adam), adaptive learning estimation (AdaDelta), and stochastic gradient descent (SGD). We experience optimizer models and optimal learning parameters that higher accuracy and shortest time computing. Adam has a fast convergence property, but it is only unstable due to very rapid error reduction. Besides the optimizer model, we compared using wavelet and without wavelet, as in Figure 7 of Accuracy and Figure 8 of losses value. There are three models. Adam and AdaDelta are convergent of 100 epoch learning, except for the SGD model. So that 100 epochs are optimal enough, except with SGD with 500 epoch addition. Each color in Figure 7 and Figure 8 indicates the testing of training data with wavelet (blue), training data without wavelet (green), non-training/validation data with wavelet (orange), and validation data without wavelet (red). From the three models shown in Figure 7 that using wavelet can increase accuracy and reduce computing time. The exact values of the three models are shown in Table 3. Likewise, the value of Losses from using wavelets for the three models generally decreases. This result told that wavelet could improve accuracy by reducing the non-stationary properties of EEG signals.

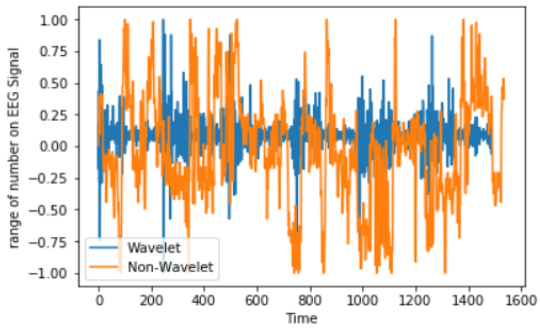


Figure 6. Wavelet extraction

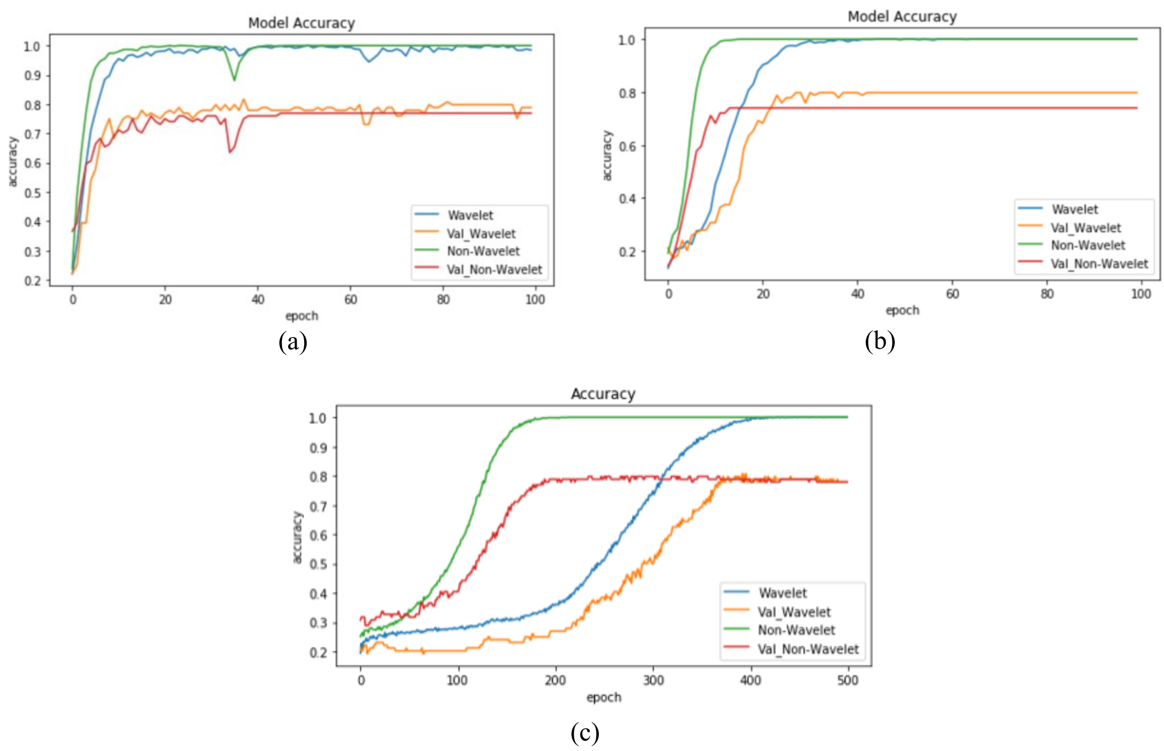
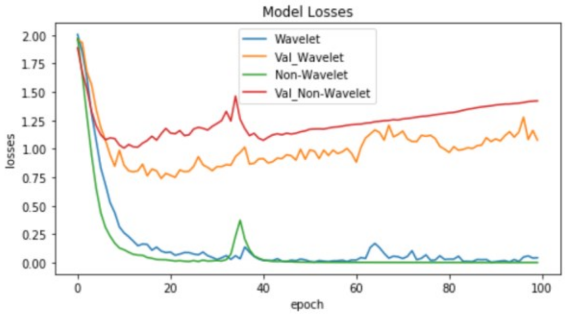
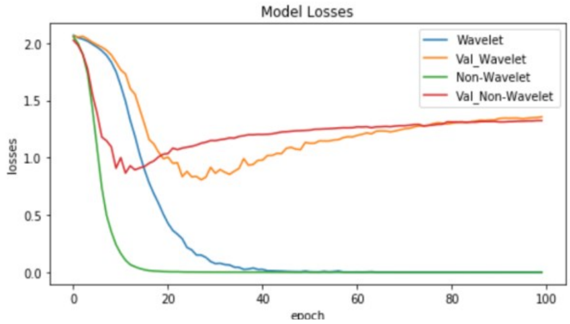


Figure 7. Accuracy of the optimizer model; (a) Adam, (b) AdaDelta (c) SGD

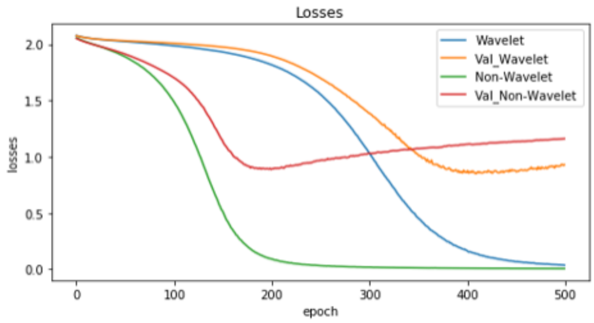
The accuracy of the three models is relatively the same, mainly between 76-80% for validation data while 100% for training data. Even so, the highest AdaDelta model is 79.81%. The exciting thing is that the Adam model quickly corrects weights, which causes accuracy to increase rapidly and losses to decrease at the beginning of the iteration. However, conditions of small fluctuations continue at the end of the epoch. While the AdaDelta model tends to be stable at the end of the epoch, it achieves longer than the Adam model. But it is understood that the weight correction method of the Adam model tends to jump like a ball that rolls easily. Besides, the SGD model had almost no ripples of instability during the training. But the disadvantages require longer iterations. Even in the 500th epoch, the accuracy is still increasing.



(a)



(b)



(c)

Figure 8. Losses of the optimizer model: (a) Adam, (b) AdaDelta (c) SGD

Table 3. Comparison of loss and accuracy using Adam, AdaDelta, and SGD model

Model	epochs	Wavelet				Without Wavelet			
		Train Data		Validation Data		Train Data		Validation Data	
		Accuracy	Loss	Accuracy	Loss	Accuracy	Loss	Accuracy	Loss
Adam	100	98,5	0,0422	78,84	1,0767	100,0	0,0003	76.92	1,4218
AdaDelta	100	100,0	0,0005	79,81	1,3561	100,0	0,0002	74,04	1,3240
SGD	100	17.7	2.0512	17.31	2.0158	32.05	1.9622	22.12	2.0304
SGD	500	100,0	0.0349	77,82	0.9281	100,0	0.0052	77.88	1.1612

From various experiments, showed that RNN and wavelet could be used to support BCI using MI and Focus variables with an accuracy of almost 80% non-training data. The future experiment needs to look out the configuration of the input features and channel usage of the EEG signal. So that can improve accuracy. This research gave the duration of computational learning using Adam, AdaDelta, and SGD optimization with several configurations. A comparison of the length of time from the three optimizations can be seen in Table 4 with several configurations in 100 epochs.

Table 4. Computing time of 100 epochs

Model	Methods	Learning time (second)
Adam	With Wavelet	516
	Without Wavelet	540
AdaDelta	With Wavelet	606
	Without Wavelet	642
SGD	With Wavelet	370
	Without Wavelet	380

4. CONCLUSION

This research showed that brain-computer interface could use motor imagery and focus variable of EEG signal to move drone simulator. Nevertheless, the emphasis is real-time action with other computing time applications that can be used. Proposed methods using RNN and wavelet could support BCI with MI and focus variables with an accuracy of almost 80% non-training data. The research gave that the use of wavelet as a pre-process can improve accuracy, lead to stability, and reduce the training data computation time. This result is consistent with the hypothesis referring to previous research that wavelet is suitable for non-stationary signals such as EEG signals. In using RNN, it is necessary to pay attention to the optimization model for the correction of weights and the number of epochs used. Adam's model reaches asymptotically faster, but still fluctuates at the end of the epoch, so it requires the right number of iterations. The SGD model is quieter in performance but requires far more epochs. While the AdaDelta model adopts both models, it provides stable and high accuracy. The next thing to look out for is the configuration of the input features and channel usage of the EEG signal.

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