Command Recognition Based on Single-Channel Electroencephalography

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This study proposes to recognize a user’s intentions in selecting from a set of machine-controlling commands by measuring his/her brainwaves. Our strategy is to convert a multiple-choice decision into yes-no decisions. For example, in a task of dialing assistance, our system prompts the user to select from each of the digits, and then analyzes his/her brainwave to determine if each digit is what he/she wants. Assume that the user’s intention is 7. Then, when the system prompts the user whether to choose digit 7, the resulting electroencephalogram (EEG) measured from the user should present a certain pattern of “Yes”; otherwise, the result should present a certain pattern of “No”. Hence, our system’s goal is to determine whether the user’s intention is “Yes” or “No” based on the measured EEG. This study uses a simple, portable, and cheap instrument that extracts a single-channel EEG from the user’s frontal lobe. The underlying beta waves of EEG are then distilled and examined by a recurrent neural network to determine the user’s intention. Our experiments conducted using 2400 test EEG samples from 10 subjects show that the recognition accuracy obtained with our system is 79.2%.

Keywords: binary decision, brainwave, command recognition, electroencephalogram, recurrent neural network

1. INTRODUCTION

Nowadays computers have so much involved with our daily lives. This development is not only mainly caused by the rapid improvements in computing efficiency, but also by the successful designs of human-computer interfaces. At first, computers using a keyboard as the interface to key-in instructions were mostly used in laboratories or factories. Later on, computers using a mouse as the operating interface spread to offices and houses. Now, tablet computers and smart phones that use a touch screen as the operating interface make computers omnipresent. As people tend to rely on computers more and more, it obviously becomes increasingly important to develop more user-friendly human-computer interfaces. However, the mainstream human-computer interfaces are mostly operated with hands. In cases when hands are occupied or not available, it becomes not very convenient for people to use these interfaces. Therefore, interfaces operated by voices, eye motions, lip motions, etc. have been the focus of R & D. Yet, respective constraints in using these human-computer interfaces remain. For instance, in situations when people are unable or inconvenient for them to utter a voice, voice-operated

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interfaces will not be able to be used.

For computer-operating instructions originate from the brain, this research tries to measure and analyze brain intentions, further decipher the user’s instructions to the computer, and finally create a brain-control interface. Nevertheless, there is no denying the severe challenges in developing a brain-control interface [1-3]. Besides, equipment used to measure the brain’s intentions may not be user-friendly or convenient to use. The purpose of this research is only to offer a tentative research and a feasibility evaluation on developing such an interface, and continual improvements based on the results in this research are expected.

Specifically, this study investigates how we can recognize a user’s intentions in selecting from a set of machine-controlling commands by measuring his/her brainwaves. Our strategy is to convert a multiple-choice decision into yes-no decisions. For example, in a task of identifying digits from 0 to 9, our system prompts the user to select from each of the digits, and then analyzes his/her brainwave in order to determine if each digit is the user’s intention. Let us assume that the user’s intention is 7. Then, when the system prompts the user whether to choose digit 7, the resulting electroencephalogram (EEG) measured from the user should present a certain pattern of “Yes”, and when the system prompts the user whether to choose each of the other digits, the result should present a certain pattern of “No”. Hence, the purpose of our system is to determine whether the user’s intention is “Yes” or “No” based on the measured EEG.

Although the EEG recognition based on yes-no decision strategy is inconvenient as comparing to other existing human-machine interfaces, such as keystroking, hand writing, and speech, it can serve as a useful alternate for handicap people or in hand-busy and mouth-busy situations. For example, when a people is injured and on the sickbed, the EEG-recognition may be the best means for him/her to express what he/she wants to.

In fact, several studies discussing such kind of binary EEG classification problems preexist. The work in [4-7] investigate the differences of the EEG signals for human in discriminating between target and non-target images. The work in [8,9] proposes to control the direction of an electric wheelchair using EEG signals. [10,11] investigates the methods of extracting EEG features for mental fatigue EEG classification. [12] presents a computer interface that combines gaze tracking with brainwave measurements in an integrated head-mounted device. There are also several studies [13,14] dedicated to investigate the differences of the brainwaves between thinking about “yes” and “no”. However, all of the above-mentioned studies use 32 or more EEG channels to develop their systems, which involve inconvenient and uncomfortable head-recording nets as well as expensive equipment, therefore unsuitable for real human-machine-interfaced applications. In contrast, this study proposes using a simple, portable, and cheap instrument that extracts a single-channel EEG from the user’s frontal lobe. The underlying beta waves of EEG are then distilled and used as the feature to determine the user’s intention.

The remainder of this paper is organized as follows. In Section 2, we describe the concept of Brainwave and Electroencephalography. Section 3 presents the methodology of the proposed Command Recognition of Brainwave system. Section 4 discusses our experiment results. Then, in Section 5, we present our conclusions and indicate the direction of our future work.
2. BRAINWAVE AND ELECTROENCEPHALOGRAPHY

2.1 Brainwave

Brain is composed of numerous neurons, which communicate via electricity with each other. The electrical activity in the brain is quasi cyclic, resulting in a wave-like pattern, which is hence called brainwave. In general, brainwave comes in five different types.

1. **Delta wave**, with frequency ranging from 0.5 to 4 Hz, appears mainly during deep and dreamless sleep. It represents a completely unconscious state.
2. **Theta wave**, with frequency ranging from 4 to 8 Hz, appears mainly during light sleep or extreme relaxation. It represents a subconscious state.
3. **Alpha wave**, with frequency ranging from 8 to 13 Hz, appears mainly during just awakening naturally from sleep or relaxed. It represents a state of between consciousness and subconsciousness.
4. **Beta wave**, with frequency ranging from 13 to 28 Hz, appears during wide awakening, especially in thinking and studying. It represents a completely conscious state.
5. **Gamma wave**, with frequency ranging from 28 to 50 Hz, may appear during the formation of ideas, language and memory processing, and various types of learning. However, Gamma wave is infrequent, and whether or not it is related to consciousness is still an uncertainty and being debated.

2.2 Electroencephalography

In 1929, Hans Berger [15] published a pioneer paper on recording the electrical activity of the human brain from the surface of the head, which is called electroencephalogram (EEG). After that, research on EEG further found the relationship between the areas of cerebral cortex and the functions for controlling every part of a human body. For example, frontal lobe is associated with reasoning, planning, and parts of speech, movement, emotions. Parietal lobe is associated with orientation, recognition, and perception of stimuli. Occipital lobe is associated with visual processing. Temporal lobe is associated with perception and recognition of auditory stimuli.

To ensure EEG studies could be compared to each other, the International Federation of Societies for Electroencephalography and Clinical Neurophysiology developed an internationally recognized method, called the 10–20 system of electrode placement [16], which standardizes the location of scalp electrodes at specific intervals along the head in the context of an EEG experiment. As shown in Fig. 1, each electrode site is given a letter to identify the lobe, along with a number to identify the hemispheric location. Specifically, "F" represents Frontal lobe, "T" represents Temporal lobe, "C" represents Central lobe, "P" represents Parietal lobe, and "O" represents Occipital lobe.

There are a number of EEG equipments following the 10-20 system of electrode placement. However, most of them involves inconvenient and uncomfortable head-recording nets as well as heavy cost, which is unsuitable for real human-machine-interfaced applications. We therefore seek to develop our brain-control interface by using a simple, portable, and cheap instrument.
3. METHODOLOGY

Fig. 2 shows the proposed framework for brainwave-based command control. Our strategy is to convert a multiple-choice decision into yes-no decisions. For example, in a task of identifying digits from 0 to 9, the system prompts the user to select from each of the digits, and then analyzes his/her brainwave in order to determine if each digit is the user’s intention. Let us assume that the user’s intention is 7. Then, when the system prompts the user whether to choose digit 7, the resulting electroencephalogram (EEG) measured from the user should present a certain pattern of “Yes”, and when the system prompts the user whether to choose each of the other digits, the result should present a certain pattern of “No”. Hence, the purpose of our system is to determine whether the user’s intention is “Yes” or “No” based on the measured EEG.

![Diagram of the proposed command recognition system]

**Fig. 2.** The proposed command recognition system.

### 3.1 EEG Measurement

We use Mindband® produced by NeuroSky Inc. to extract single-channel EEGs from a user’s frontal lobe (Fp1 or Fp2). As mentioned earlier, frontal lobe is associated with reasoning, planning, and parts of speech, movement, emotions; hence, EEGs from frontal
lobe should be able to reflect a user's intention. In addition, considering beta wave is related to thinking and active concentration, we propose using beta wave extracted from the frontal lobe to determine a user's intention.

MindBand® is a headband device that senses electrical activity through use of a dry-electrode. The electrode is placed on the forehead to capture the brainwave appearing in the area of frontal lobe. The captured signals are transmitted to a computer via Bluetooth. Because brainwaves captured from the surface of the head is tiny, MindBand® performs amplification and filtering as shown in Fig. 3. After that, signals are quantized with 12-bit resolution. In addition, the power spectral density of the signal is then computed for every 0.125 sec with frequency resolution of 0.25Hz. Specifically, the signal is windowed with length of 32 samples into non-overlapping frames. Each frame undergoes the short-term Fast Fourier Transform (FFT), and the periodogram is then computed for every FFT frequency bin. Fig. 4 shows an example of the captured beta wave represented by the power spectral density of the EEG. We can see from Fig. 4 that beta wave in lower frequencies is somewhat different from that in higher frequencies. Hence, in general, beta wave can be further divided into two bands, 13-20Hz and 21-28Hz, respectively, denoted by $\beta_1$ and $\beta_2$ hereafter.

Fig. 3. EEG measurement with MindBand®.
Although in a number of signal classification studies, power spectral densities are usually further converted into cepstral coefficients, this may not be suitable for EEG classification. Recall that the reasons of using cepstral coefficients mainly lie in 1) separating a signal into source and filter components; 2) reducing the feature dimensionality; 3) orthogonalizing the feature. However, for EEG signals, there is no literature showing that EEG signals are generated from a source-filter model. By intuition, an EEG signal contains multiple sources, each associated with different areas of cerebral cortex, and hence its generative process would be more complicated than the conventional source-filter model. Accordingly, the most relevant features for EEG classification so far are power-spectrum-based. Depending on the classifier used, either static or dynamic, the features can be divided into two categories. One is the power spectral density itself, and the other is some index derived from the power spectral density, such as dominant frequency, average power of dominant peak, center of gravity frequency, and frequency variability [17]. Since the latter is computed by exploiting the information embedding in the power spectral density over a period of time, it is disadvantageous to support real-time processing. Recognizing this, our system simply uses power spectral densities as features.

Fig. 4. An example of the captured beta wave represented by the power spectral density of the EEG.
3.2 Intention Recognition Based on Simple Recurrent Neural Network (SRNN)

The intention recognition modular operates in two phases, training and testing. The training phase begins with EEG data collection, which acquires a large amount of EEG data labeled with "Yes" or "No". As our preliminary investigation found that the EEG pattern is diverse across different people significantly, we focus only on developing a user-dependent recognition system, i.e., the system is trained using the pre-recorded EEG data of an individual user, and works exclusively for the user. Although a user-dependent EEG recognition system is not as convenient as a user-independent one for some applications, it has an advantage when the applications involving personalization or privacy, which is often the shortage that a user-independent system is awkward to offer.

During the EEG training data acquisition, subjects are asked to stare the screen from which commands are prompted at random. Before that, each subject needs to choose a command in mind. If the prompted command is what the subject chose, then he/she should be concentrated as possible as he/she can, in order to show his/her intention. On the contrary, if the prompted command is not what the subject chose, then he/she should keep relaxed. Thus, the "Yes/No" patterns of the EEG are connected to concentration/relaxing, which could be inferred from the beta wave. The EEG recordings are then labeled with "Yes" or "No" for every 0.5 second.

As mentioned earlier, beta wave is related to thinking and active concentration. Hence, an intuitive approach for determining a user’s intention is based on the average power of the beta wave, similar to some work [18,19] using the NeuroSky's EEG device. Specifically, the average power is the arithmetic mean for all the FFT frequency bins in a frame. Fig. 5 (a) shows an example of the beta waves represented by the average power of all the frequencies. We can see from Fig. 5 (a) that the largest value of the average power appears during the period when the user's intention is "Yes". However, this is not always the case. Fig. 5 (b)-(d) shows other examples of the beta wave. It can be seen from Fig. 5 (b)-(d) that very often, the largest value of the average power does not appear the period when the user's intention is "Yes". As a result, it is not reliable to determine a user's intention by simply considering the average power of the beta wave. So instead, recognizing that brainwave patterns change with time, we propose using a Simple Recurrent Neural Network (SRNN) [20] to capture the dynamic information of the EEG signals.

The structure of an SRNN is shown in Fig. 6. It consists of three layers of neurons, namely, input layer, hidden layer, and output layer. The SRNN is featured by a recurrent mechanism, in which previous outputs of hidden nodes are delayed and then feedback to the input layer, and hence it can capture the sequential information of the processed data. In this task, the input layer receives the beta wave feature stream, the hidden layer models the dynamic structure, and the output layer provides the hypothesis of the user's intention recognized.
Fig. 5. Examples of the beta waves represented by the average power of all the frequencies, where the marked arrow region corresponds to the period when the user’s intention is "Yes".

Given a stream of $K$-dimension beta wave feature vectors $\mathbf{x}[n] = [x_1[n], x_2[n], \ldots, x_K[n]]'$, which is the power spectral density of the EEG, the activation function of hidden neuron $j$ at frame time $n$ is defined as

$$h_j[n] = f \left( \sum_{k=1}^{K} w_{jk} x_j[n] + \sum_{i=1}^{J} r_{ij} h_i[n-1] \right),$$

where $J$ is the number of neurons in the hidden layer, $w_{jk}$ is the feed-forward connection strength from input neuron $k$ to hidden neuron $j$, $r_{ij}$ is the recurrent connection strength from the delayed hidden neuron $i$ to hidden neuron $j$, and $f(\cdot)$ is a sigmoid function associated with a tunable parameter $\alpha$:

$$f(\alpha) = \frac{1}{1 + e^{-\alpha \cdot \cdot \cdot}}. \quad (2)$$

The activation function of the output neuron $\ell$ at time $n$ is defined as
$y_j[n] = f\left(\sum_{j=1}^{J} W_{j\ell} h_j[n]\right),$ \hspace{1cm} (3)

where $W_{j\ell}$ is the feed-forward connection strength from hidden neuron $j$ to output neuron $\ell$, and $\ell = 1$ or $2$. It is our aim to estimate the strengths $w_{ij}$, $r_{ij}$, and $W_{j\ell}$, such that in an average sense over time $n$, $y_1[n] > y_2[n]$ when $x[n]$ belongs to “Yes”, and $y_1[n] < y_2[n]$ when $x[n]$ belongs to “No”.

![Fig. 6. Structure of an SRNN.](image)

The estimation can be done using a back-propagation learning algorithm based on gradient descent minimization for the mean square error defined by

$$E = \frac{1}{2} \sum_{\ell=1}^{2} \sum_{n=1}^{N} (T_{\ell} - y_{\ell}[n])^2,$$ \hspace{1cm} (4)

where $T_\ell$ is the output target function, defined by

$$(T_1, T_2) = \begin{cases} (1,0), & \text{if } x[n] \text{ belongs to "Yes"} \\ (0,1), & \text{if } x[n] \text{ belongs to "No"}. \end{cases}$$ \hspace{1cm} (5)
Then the strengths are adjusted iteratively by using the delta rule, i.e., the strengths at the 
$t$-th iteration are updated from their previous ones at the $(t-1)$-th iteration using
\[
w_{kj}^{(t)} = w_{kj}^{(t-1)} + \Delta w_{kj}^{(t)},
\]
\[
r_{ij}^{(t)} = r_{ij}^{(t-1)} + \Delta r_{ij}^{(t)},
\]
\[
W_{ji}^{(t)} = W_{ji}^{(t-1)} + \Delta W_{ji}^{(t)},
\]
where
\[
\Delta w_{kj}^{(t)} = -\eta \frac{\partial E}{\partial w_{kj}^{(t-1)}},
\]
\[
\Delta r_{ij}^{(t)} = -\eta \frac{\partial E}{\partial r_{ij}^{(t-1)}},
\]
\[
\Delta W_{ji}^{(t)} = -\eta \frac{\partial E}{\partial W_{ji}^{(t-1)}}.
\]

and $\eta$ is the learning rate. The partial derivative terms in Eqs. (9)-(11) can be calculated using the chain rule.

In the testing phase, the SRN takes as input the beta wave feature vectors, and produces as output the decision on "Yes" or "No" using
\[
\begin{cases}
"Yes", & \text{if } \sum_{n=1}^{L} y_1[n] \geq \sum_{n=1}^{L} y_2[n] \\
"No", & \text{otherwise}
\end{cases}
\]
(12)

In our implementation, two system design approaches are considered. The first approach creates two SRNNs, one taking care of the high beta wave EEG and the other taking care of the low beta EEG. The two SRNNs are then combined using a weighting strategy. Specifically, a test EEG signal is hypothesized as either "Yes" or "No" using
\[
\begin{cases}
"Yes", & \text{if } a \sum_{n=1}^{L} y_1'[n] + (1-a) \sum_{n=1}^{L} y_2'[n] \geq a \sum_{n=1}^{L} y_1[n] + (1-a) \sum_{n=1}^{L} y_2[n] \\
"No", & \text{otherwise}
\end{cases}
\]
(13)

where $y_1'[n]$ and $y_2'[n]$, $\ell = 1$ and 2, are the outputs of the $\beta_1$-trained SRNN and $\beta_2$-trained SRNN, respectively. On the other hand, the second approach creates a single SRNN without dividing the beta feature into $\beta_1$ and $\beta_2$, i.e., the input to SRNN is a concatenation of the $\beta_1$ and $\beta_2$ features. Both of the design approaches are evaluated in the experiments detailed in Section 4.
4. EXPERIMENTS

4.1 Databases

We invited 10 male subjects to participate our EEG data collection for a dialing experiment. The user's intentions simulated in our experiment contain digits 0 to 9 plus "#" and "*". The data collection was done on 6 discontinuous days for each subject, in which the data collected on the former three days were used for training, and the data collected on the latter three days were used for testing. In the testing set, we segmented the EEG recordings into 2400 test samples. Each sample is associated with a ground-truth of "Yes" or "No" when a subject saw the text prompted on the screen. There are 240 "Yes" test samples and 2160 "No" test samples.

4.2 Experiment Results

The performance of the intention recognition is characterized by the accuracy defined as

$$\frac{\text{Correctly Recognized Samples}}{\text{Testing Samples}} \times 100\%.$$

For the purpose of performance comparison, we also implemented two baseline systems. The first one is based on the average power of the beta wave. Specifically, if the average power of the beta wave extracted from a user's EEG is larger than a threshold, then the decision is "Yes"; otherwise, the decision is "No". The threshold is setting as the mean of the average power of all the "Yes" segments in the training beta wave data. The second baseline system is based on Multi-Layer Perceptron (MLP), which does not consider the sequential information in EEGs.

Table 1 shows the intention recognition results obtained with the first baseline system. We can see from Table 1 that the accuracy is around the chance probability (50%). Apparently, the capability of the intention recognition method based on the average power is far from acceptable.

Table 1. Results of the intention recognition based on the average power of the EEG.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>51.3</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>45.8</td>
</tr>
</tbody>
</table>

Then, we examined the second baseline system and the proposed SRNN-based method. Table 2 shows the results of the intention recognition obtained with the $\beta_1$-trained MLP and $\beta_2$-trained MLP. Table 3 shows the results of the intention recognition obtained with the $\beta_1$-trained SRNN and $\beta_2$-trained SRNN. Compared to the results in Tables 1 and 2, we can see that the proposed SRNN-based method is much superior to both the one based on the average power and the one based on MLP. This indicates the importance of the sequential information in the EEGs. In addition, it can also be seen from Table 3 that
the performance of the $\beta_2$-trained SRNN is slightly better than that of the $\beta_1$-trained SRNN.

Table 2. Accuracy (%) of the intention recognition obtained with the $\beta_1$-trained MLP and $\beta_2$-trained MLP.

<table>
<thead>
<tr>
<th>No. of Neurons in the Hidden Layer</th>
<th>$\beta_1$-trained MLP</th>
<th>$\beta_2$-trained MLP</th>
</tr>
</thead>
<tbody>
<tr>
<td>16</td>
<td>60.3</td>
<td>63.2</td>
</tr>
<tr>
<td>17</td>
<td>60.8</td>
<td>64.8</td>
</tr>
<tr>
<td>18</td>
<td>60.6</td>
<td>64.3</td>
</tr>
<tr>
<td>19</td>
<td>63.1</td>
<td>65.1</td>
</tr>
<tr>
<td>20</td>
<td>62.7</td>
<td>65.9</td>
</tr>
<tr>
<td>21</td>
<td>63.5</td>
<td>64.6</td>
</tr>
<tr>
<td>22</td>
<td>64.4</td>
<td>64.3</td>
</tr>
<tr>
<td>23</td>
<td>63.7</td>
<td>62.9</td>
</tr>
<tr>
<td>24</td>
<td>63.2</td>
<td>63.1</td>
</tr>
<tr>
<td>25</td>
<td>61.9</td>
<td>62.7</td>
</tr>
<tr>
<td>26</td>
<td>61.6</td>
<td>62.0</td>
</tr>
</tbody>
</table>

Table 3. Accuracy (%) of the intention recognition obtained with the $\beta_1$-trained SRNN and $\beta_2$-trained SRNN.

<table>
<thead>
<tr>
<th>No. of Neurons in the Hidden Layer</th>
<th>$\beta_1$-trained SRNN</th>
<th>$\beta_2$-trained SRNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>72.9</td>
<td>72.5</td>
</tr>
<tr>
<td>11</td>
<td>72.1</td>
<td>72.9</td>
</tr>
<tr>
<td>12</td>
<td>72.5</td>
<td>73.3</td>
</tr>
<tr>
<td>13</td>
<td>74.2</td>
<td>74.6</td>
</tr>
<tr>
<td>14</td>
<td>73.8</td>
<td>74.2</td>
</tr>
<tr>
<td>15</td>
<td>73.8</td>
<td>75.4</td>
</tr>
<tr>
<td>16</td>
<td>73.3</td>
<td>75.0</td>
</tr>
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<td>72.9</td>
<td>73.8</td>
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<td>18</td>
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<tr>
<td>19</td>
<td>72.5</td>
<td>72.9</td>
</tr>
<tr>
<td>20</td>
<td>71.3</td>
<td>71.7</td>
</tr>
</tbody>
</table>

Next, we investigated if the performance of the intention recognition can be benefited from the combined use of the $\beta_1$ and $\beta_2$ features. Table 4 shows the recognition results obtained with Eq. (13). In addition, Table 5 shows the recognition results obtained with a single SRNN trained using the concatenation of the $\beta_1$ and $\beta_2$ features. We can see from Tables 4 and 5 that both of the combination approaches improve the performance of
the intention recognition, compared to the results in Table 3. It can also be seen that the combination approach based on Eq. (13) outperforms the one based on a single SRNN trained using the concatenation of the $\beta_1$ and $\beta_2$ features.

Table 4. Results of the intention recognition obtained with Eq. (13).

<table>
<thead>
<tr>
<th>Value of $a$</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>75.0</td>
</tr>
<tr>
<td>0.3</td>
<td>76.7</td>
</tr>
<tr>
<td>0.4</td>
<td>78.8</td>
</tr>
<tr>
<td>0.5</td>
<td><strong>79.2</strong></td>
</tr>
<tr>
<td>0.6</td>
<td><strong>79.2</strong></td>
</tr>
<tr>
<td>0.7</td>
<td>76.3</td>
</tr>
<tr>
<td>0.8</td>
<td>75.8</td>
</tr>
</tbody>
</table>

Table 5. Results of the intention recognition obtained with a single SRNN trained using the concatenation of the $\beta_1$ and $\beta_2$ features.

<table>
<thead>
<tr>
<th>No. of Neurons in the Hidden Layer</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>75.0</td>
</tr>
<tr>
<td>16</td>
<td>75.8</td>
</tr>
<tr>
<td>17</td>
<td>76.3</td>
</tr>
<tr>
<td>18</td>
<td>76.3</td>
</tr>
<tr>
<td>19</td>
<td><strong>77.1</strong></td>
</tr>
<tr>
<td>20</td>
<td>76.7</td>
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<td>75.8</td>
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<td>22</td>
<td>76.3</td>
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<tr>
<td>23</td>
<td>76.3</td>
</tr>
<tr>
<td>24</td>
<td>75.4</td>
</tr>
<tr>
<td>25</td>
<td>75.8</td>
</tr>
</tbody>
</table>

Table 6 shows the confusion matrix obtained with the intention recognition system based on Eq. (13), where $a = 0.5$ was used. We can see from Table 6 that the system slightly tends to misrecognized "Yes" as "No". This might be because the amount of the data used for training "Yes" pattern is smaller than that for training "No" pattern. Despite this, the results indicate that more than 75% users' intention can be correctly recognized, which confirm the possibility of command recognition via single-channel EEG.
Table 6. Confusion matrix obtained with the intention recognition system based on Eq. (13), where $a = 0.5$ was used

<table>
<thead>
<tr>
<th>Recognized</th>
<th>Actual</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>Yes</td>
<td>75.0%</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>25.0%</td>
</tr>
<tr>
<td>No</td>
<td>Yes</td>
<td>20.4%</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>79.6%</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS

We have investigated the problem of recognizing a user's intentions in selecting from a set of machine-controlling commands by measuring his/her brainwaves. Compared to the existing studies, this work is featured by the following novelties.

1. The proposed system converts a multiple-choice decision into yes-no decisions by prompting the user to select from each of the commands, and then analyzing his/her brainwave to determine if each command prompted is what he/she wants.

2. The proposed system is particularly suitable for mobile devices, as it uses a simple, portable, and cheap instrument that extracts a single-channel EEG from the user's frontal lobe.

3. The proposed system uses a recurrent neural network fed with the beta wave features to determine the user's intention.

Although the recognition accuracy obtained with our system is only 79.2%, the result in such a pilot investigation is encouraging and lays a good foundation for the future development of a command recognition system using single-channel EEGs. To maximize its practicability and applicability, the first necessity is to improve the recognition accuracy. Recognizing that the beta wave features acquired from Mindband® may not be sufficient to determine a user's intention, we will investigate other features extracted from EEG in the future.

REFERENCES


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