Chapter 30
Temporal Comparison Between NIRS and EEG Signals During a Mental Arithmetic Task Evaluated with Self-Organizing Maps

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Abstract Simultaneous monitoring of brain activity with near-infrared spectroscopy and electroencephalography allows spatiotemporal reconstruction of the hemodynamic response regarding the concentration changes in oxyhemoglobin and deoxyhemoglobin that are associated with recorded brain activity such as cognitive functions. However, the accuracy of state estimation during mental arithmetic tasks is often different depending on the length of the segment for sampling of NIRS and EEG signals. This study compared the results of a self-organizing map and ANOVA, which were both used to assess the accuracy of state estimation. We conducted an experiment with a mental arithmetic task performed by 10 participants. The lengths of the segment in each time frame for observation of NIRS and EEG signals were compared with the 30-s, 1-min, and 2-min segment lengths. The optimal segment lengths were different for NIRS and EEG signals in the case of classification of feature vectors into the states of performing a mental arithmetic task and being at rest.

Keywords NIRS • EEG • Self-organizing map • Laterality index

1 Introduction

Simultaneous monitoring of brain activity with near-infrared spectroscopy (NIRS) and electroencephalography (EEG) has been studied to investigate cognitive and emotional processing [1]. Recent findings show that EEG activity is intrinsically

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associated with cortical hemodynamic responsiveness to the negative valence on the right side [2], which may provide an important context for early detection of various types of illnesses during telehealth or remote patient monitoring.

Recent studies have identified the prefrontal cortex (PFC) as a key region for the experience and regulation of emotional responses, and NIRS is a well-suited technique for investigation of PFC activity [2]. Tanida, Katsuyama, and Sakatani [4] reported that the degree of right-lateralized asymmetry in the PFC activation patterns is positively correlated with heart rate changes during a mental arithmetic task. On the other hand, EEG records brain activity that is produced by the firing of neurons directly within the brain. Brain activity is recorded noninvasively by placing electrodes on the scalp. Both event-related desynchronization (ERD) and event-related potential (ERP) have been used to measure mental work or memory load with statistical significance [5]. In particular, the ERD-based approach decomposes EEG signals into power spectra, such as theta (4–6 Hz), low alpha (6–8 Hz), middle alpha (8–10 Hz), high alpha (10–12 Hz), and beta (12–30 Hz), to find desynchronization, i.e., a reduction in band power of particular frequencies in response to an event such as initiation of a mental arithmetic task. ERD-based approaches have recently shown that theta band power responds to prolonged visual emotional stimulation [6, 7]. In addition, desynchronization in low alpha band power correlates to a presented warning stimulus [8]. Researchers have found affective state changes related to negative valence typically trigger anterior asymmetry in alpha reduction [5, 9, 10].

However, affective states or states related to mental tasks can vary in length during observation [3]. One emerging issue with data-mining techniques is that the accuracy of state estimation during mental arithmetic tasks is often different depending on the length of the segment for sampling of NIRS and EEG signals. In the present study, the results of a self-organizing map (SOM) and analysis of variance (ANOVA) were compared to determine the optimal length of the segment.

2 Methods

2.1 NIRS Recordings

Feature values of the concentration changes in oxyhemoglobin in the left and right PFCs at time t are assigned $h_l(t)$ and $h_r(t)$, respectively. These feature values are discretized into $h_l(t_n)$ and $h_r(t_n)$ with the length of the segment $t_n - t_{n-1}$.

$$h_l(t_n) = \frac{\int_{t_{n-1}}^{t_n} h_l(t)\,dt}{t_n - t_{n-1}}$$
$$h_r(t_n) = \frac{\int_{t_{n-1}}^{t_n} h_r(t)\,dt}{t_n - t_{n-1}} \tag{30.1}$$

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Then, the laterality index (LI) is introduced to measure the valence on the PFC that is related to the stress level [4, 11]. Laterality $l(t_n)$ for input of the SOM is defined as the difference between hemodynamic responses on both sides of the PFC during time frame t_n as below:

$$l\left(t_n\right)=\frac{h_r\left(t_n\right)-h_l\left(t_n\right)}{h_r\left(t_n\right)+h_l\left(t_n\right)} \tag{30.2}$$

2.2 EEG Recordings

The feature value of the EEG index $w(t)$ is defined as the ratio of $s_i(t)$ to $d_i(t)$ for chosen electrodes at position i, where the spectral power between 8 and 12 Hz is assigned $s_i(t)$, and the spectral power between 13 and 30 Hz is assigned $d_i(t)$, which is sensitive to changes in the mental tasks that are related to working memory.

$$w\left(t\right)=\frac{\sum_{i=1}^{I} s_i\left(t\right)}{\sum_{i=1}^{I} d_i\left(t\right)} \tag{30.3}$$

In particular, let $w_l(t_n)$ be the average of $w(t)$ for four channels in the left PFC (AF3, F3, F7, T3) during time frame t_n. Likewise, $w_r(t_n)$ is the average of $w(t)$ for four channels in the right PFC (AF4, F4, F8, T4). Thus, these feature values for both the left and right PFCs can be compared within time frame t_n as below:

$$\begin{aligned} w_l\left(t_n\right)&=\frac{\int_{t_{n-1}}^{t_n} w_l\left(t\right)dt}{t_n-t_{n-1}} \\ w_r\left(t_n\right)&=\frac{\int_{t_{n-1}}^{t_n} w_r\left(t\right)dt}{t_n-t_{n-1}} \end{aligned} \tag{30.4}$$

2.3 Cluster Analysis by SOM

The feature values discussed in the previous sections form feature vectors for generation of an SOM, which allows visualization and exploration of a high-dimensional data space by nonlinearly projecting it onto a 2-D plane. NIRS and EEG signals may involve outliers and unknown patterns of waveforms, whereas SOM provides more robust learning compared to other types of cluster analyses such as k-means [12]. Each feature vector for SOM includes $l(t_n)$, $w_l(t_n)$, and $w_r(t_n)$ in a segment length of 30 s, 1 min, or 2 min. For assessment of the experimental result, the quantization error (QE) explains reliability of measurement of SOM by calculating the average distance of the feature vectors to the cluster centroids; in other words, the higher QE is taken from the SOM, the more errors in classification of feature vectors can be found.

An experiment of a mental arithmetic task performed by 10 participants (young males) was conducted to observe the state transition between the mental arithmetic task (2 min) and being at rest (2 min). Each participant performed the mental arithmetic task in three cycles (12 min total). NIRS sensors (PocketNIRS; DynaSense Inc., Japan) and EEG sensors (Emotiv EPOC system; Emotiv Inc., U.S.A.) were equipped to monitor brain activity in the PFC. Body movements were prohibited during the experiment except those required for reading the arithmetic problems. NIRS and EEG signals were first verified with video data each second to look for the appearance of artifacts caused by body movement, and the corresponding feature vectors were sampled for cluster analysis using the SOM. Because the artifacts in this experiment had a smaller impact on SOM than 5 % of QE, no major artifact removal was performed from the NIRS and EEG signals.

3 Results

Figure 30.1 shows an example of $l(t)$ and $w_l\,(t)$ from the first participant, which are continuous values before discretization into $l(t_n)$ and $w_l(t_n)$. The states of performing a mental arithmetic task (**a**) and being at rest (**r**) were periodically changed every 2 min. For most participants, the value of $l(t)$ increased as the mental arithmetic task was performed, and the value of $w_l\,(t)$ changed periodically.

Each feature vector after sampling from the example in Fig. 30.1 is composed of feature values of $l(t_n)$, $w_l\,(t_n)$, and $w_r\,(t_n)$ as shown in Table 30.1. Then, these were normalized so that all the feature values were assigned a value of 0 to 1 for input to the SOM.

SOMs (training length: 300 iterations, map size: 40 × 40) were created with the feature vectors obtained from all ten participants. From the results shown in Fig. 30.2, compared to the 30-s segment, the feature vectors of the 1-min segment were well separated into the **a** and **r** states. QE was the smallest if the 1-min segment was chosen, whereas QE was the largest with the 30-s segment. The difference between the results according to the length of the segment was considerably larger because each value in the feature vectors does not exceed 1. Other SOMs (training length: 500 iterations, map size: 100 × 100) were also created, and the results were the same, with a 1 % difference in QE.

One-way ANOVA was performed to compare the effect of the feature values on the two states as shown in Table 30.2. We found a significant effect of $l(t_n)$ on the two states except $l(t_n)$ with the 30-s segment ($F(1, 118) > 1.38$, $p < 0.3$). In contrast,

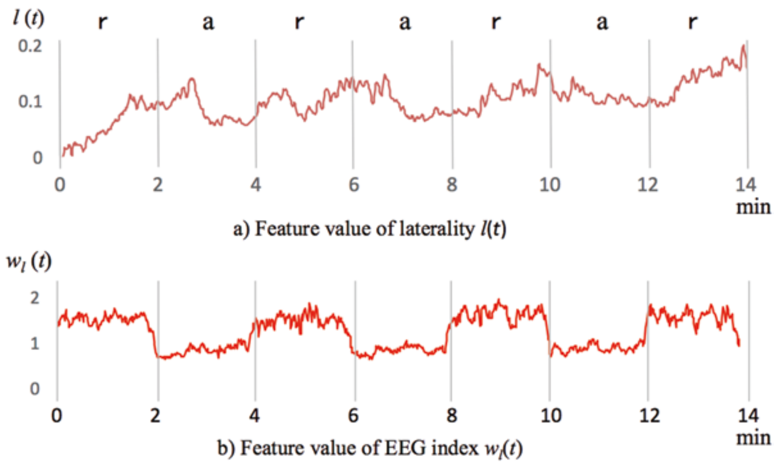

Fig. 30.1 Plotted values obtained from NIRS and EEG signals. The states of performing mental arithmetic task and being at rest are labeled with **a** and **r**, respectively

Table 30.1 Feature vectors (length of the 1-min segment) sampled from the example in Fig. 30.1

t_n	$l(t_n)$	$w_l(t_n)$	$w_r(t_n)$
1	0.375	0.617	0.577
2	0.253	0.387	0.399
3	0.418	0.239	0.276
4	0.568	0.446	0.454
5	0.507	0.576	0.559
6	0.546	0.478	0.520
7	0.678	0.249	0.332
8	0.702	0.521	0.544
9	0.538	0.692	0.681
10	0.397	0.445	0.496
11	0.581	0.273	0.381
12	0.759	0.485	0.565

F-values of both $w_l(t_n)$ and $w_r(t_n)$ were higher than the others if the 30-s segment was applied; i.e., for both $w_l(t_n)$ and $w_r(t_n)$, mean values in the **a** state and mean values in the **r** state were clearly separated from each other.

4 Discussion

From the experimental results, the optimal lengths of segments for mental arithmetic tasks were different between NIRS and EEG signals. The NIRS signal may have required a segment of more than 1 min for sampling, whereas the EEG signal took

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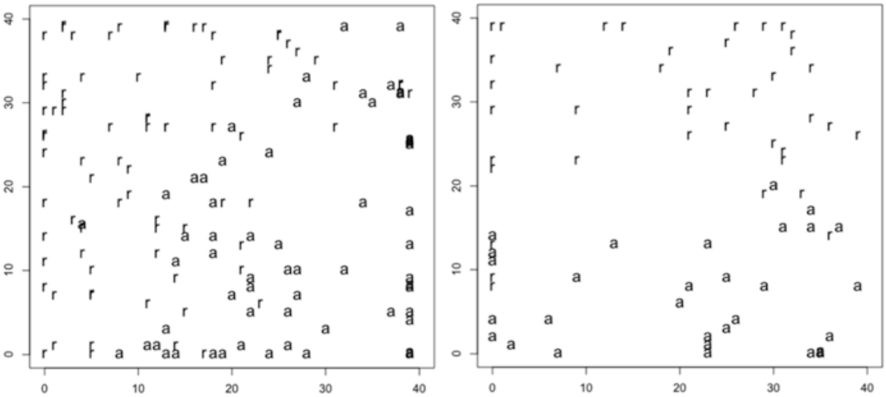

a) Feature vectors in the 30-sec segment
(QE = 0.25)

b) Feature vectors in the 1-min segment
(QE = 0.17)

Fig. 30.2 SOMs with feature vectors in the 30-s and 1-min segments. Each feature vector is labeled with the state. Similar feature vectors are clustered by competitive learning

Table 30.2 Results of ANOVA

Feature value	Segment length	*F*-value	*p*-value
$l(t_n)$	30 s	1.38	$p<0.3$
	1 min	3.75	$p<0.1$
	2 min	7.19	$p<0.01$
$w_l(t_n)$	30 s	83.34	$p<0.001$
	1 min	45.49	$p<0.001$
	2 min	36.73	$p<0.001$
$w_r(t_n)$	30 s	45.29	$p<0.001$
	1 min	22.88	$p<0.001$
	2 min	9.446	$p<0.01$

a segment of less than 30 s; in other words, the reaction time for the concentration change in oxyhemoglobin during the transition between the states was longer than the EEG power spectra.

The results of SOM and ANOVA suggested a relationship between QE and the *F*-value. The combination of SOM and ANOVA may contribute to instant monitoring of parameters such as the optimal length of a segment for state estimation. However, more experimental parameters (e.g., different types of feature values and tasks) must be further validated to determine the comprehensive relationship between QE and the *F*-value.

In this paper, the lengths of the segments in each time frame for observation of NIRS and EEG signals were compared using SOMs and ANOVA. Our experimental results suggested that the optimal segment lengths were different for NIRS and EEG signals. Further works will involve application of SOM and ANOVA to real-world case studies. Development of an algorithm for real-time monitoring of the mental state may eventually provide a potential for early detection of illness and healthcare support to service users.

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