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Hybrid Brain-Computer Interface: a Novel Method on the Integration of EEG and sEMG Signal for Active Prosthetic Control

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Abstract

This paper describes a novel method for controlling active prosthetics by integrating surface electromyography (sEMG) and electroencephalograph signals to improve its intuitiveness. This paper also compares the new method (RTA-2) with other existing methods (AND and OR) for controlling active prosthetics. Based on analysis, RTA-2 features higher true positive rate (TPR) and balanced accuracy (BA) than AND method. On the other hand, the new method (RTA-2) yields lower false detection rate (FPR) than OR method. Analysis also shows that RTA-2 possesses equal TPR, FPR, and BA with the detection of movement intention using sEMG-based system. Although the RTA-2 method shows equal performance with the sEMG-based system, it presents an advantage for driving active prosthetics to move faster and to reduce its total time response by generating more movement commands.

Abstrak

Hybrid Brain-Computer Interface*: Metode Baru dalam Integrasi Sinyal EEG dan sEMG untuk Pengendalian Aktif *Prosthetics. Paper ini menjelaskan metode baru untuk mengendalikan *prosthetics* aktif dengan mengintegrasikan sinyal elektromiograf (sEMG) dan elektroensefalograf (EEG) dalam rangka meningkatkan sifat intuitif yang dimilikinya. Selain itu, dalam paper ini juga membandingkan metode baru (RTA-2) dengan metode lain yang telah ada (AND dan OR) untuk mengendilikan *prosthetics* aktif. Berdasarkan analisis, metode RTA-2 memiliki nilai *True Positive Rate* (TPR) dan *Balanced Accuracy* (BA) lebih tinggi dibandingkan metode AND. Selain hal terebut, metode RTA-2 memilki kesalahan deteksi (FPR) yang lebih rendah dibandingkan metode OR. Berdasarkan analasis, nilai TPR, FPR dan BA yang dimiliki metode RTA-2 ini sama dengan akurasi deteksi intensi gerakan berbasis sinyal sEMG. Namun demikian, meskipun TPR, FPR dan BA dari metode RTA-2 sama dengan metode yang hanya berbasis sinyal sEMG, metode RTA-2 memiliki keunggulan dalam mengendalikan *prosthetic* aktif sehingga dapat bergerak dengan kecepatan lebih cepat dari sebelumnya dan mengurangi total waktu responnya dengan cara menghasilkan perintah keluaran kecepatan gerakan yang lebih banyak.

Keywords: active prosthetic, AND method, electroencephalography (EEG), intuitive, OR method, RTA-2 method, surface electromyography (sEMG)

1. Introduction

In the last decades, experiments on active prosthetics based on surface electromyography (sEMG) signals have increased significantly. Such experiments aimed to increase functionalities by using multichannel sEMG signals and to decrease the total response time [1-4]. Hence, active prosthetics will be more intuitive and possess close functionalities from the limbs. Consequently, active prosthesis could move along with body movement with short time difference or delay.

An active prosthetic is considered to be a real-time system if it features a time delay below 250 ms [1]. Some methods have been developed to shorten the time delay or total time response in active prosthetics. A proportional prosthetics can shorten the total time response by controlling its movement velocity (such as quick grasping) based on the amplitude of sEMG signals [2]. A proportional prosthesis can use multi-stage threshold to control the movement velocity of active prosthetics [2]. On the other hand, an experiment conducted by Khokhar *et al.* [1] showed that the sEMG-based system can classify movement commands after detecting sEMG signals with high accuracy (up to ±96%) and a short total time response (250 ms). Figure 1 illustrates the general block diagram of sEMG-based active prosthetics: (a) general diagram block of active prosthetics for controlling its velocity; (b) a general block diagram of active prosthetic controlling its velocity and functionality [4].

Kirchner *et al.* developed another method to shorten the total time response of active prosthetics [5]. Another experiment conducted by Kirchner *et al.* showed the possibilities of brain-computer interface (BCI) system to control actuators, such as active prosthetics. This system predicts body movement from non-invasive electro-encephalograph (EEG) signals before the onset of actual movement. Lew *et al.* [6] and Shibaki *et al.* [7] have explained that the BCI system could predict movement intention up to 2 s before the onset of movement. This advantage enables the BCI system to drive or command active prosthetics before the onset of actual body movement. However, the BCI system features a drawback in detection of movement intention in rest condition. EEG-based systems yield higher false positive rate (FPR) (false detection of movement intention) in rest condition interval than sEMG-based systems [5-8]. Figure 2 illustrates the basic diagram of the BCI system.

Kirchner *et al* [5]. Planellas *et al.* [8] and Lew *et al.* [6] showed that the BCI system could be used as a controller in detection of movement intention before actual movement onset with TPR of ±0.7 up to ±0.8. On the other hand, experiments also showed that the BCI system features a FPR in rest interval from ±0.1 up to ±0.3. Ideally, system should possess a FPR value equal to 0.0. Compared with sEMG-based system, Lew *et al.* showed the lower FPR value of sEMG-based systems than EEG-based systems.

Kirchner *et al*. [5] and Leeb *et al*. [9] have shown that the integration of sEMG-based system into BCI or EEG-based system (hybrid BCI) can improve BCI performance (TPR and FPR). Kirchner *et al.* [5] also showed that the hybrid BCI can improve the intuitiveness of active prosthetics using AND and OR method. Based on the experiments of Kirchner *et al*. [5] and Leeb *et al*. [9] and the advantages and disadvantages of sEMG-based and EEG-based systems, this paper will describe other new methods and analyses for integrating sEMG into the BCI system to improve the intuitiveness of sEMG-based active prosthetics by reducing their total time response.

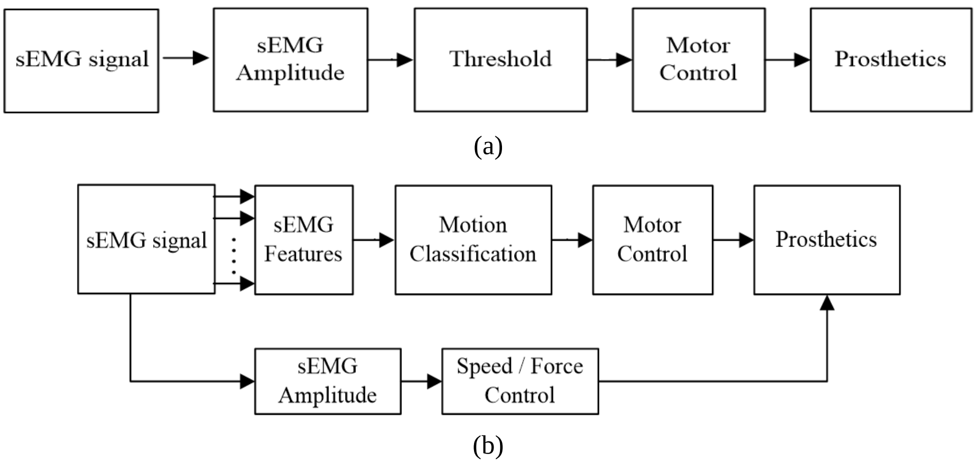

Figure 1. Block Diagram of Active Prosthetics. (a) Non-Pattern Recognition Approach; (b) Pattern Recognition Approach [4]

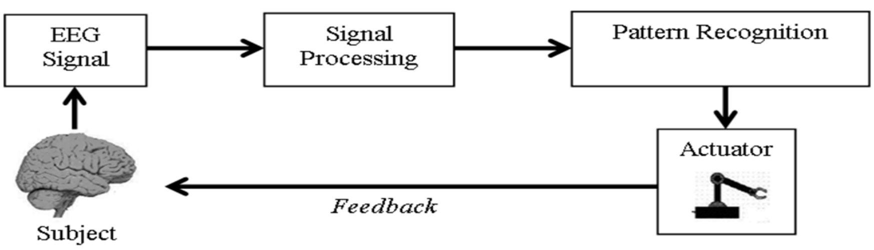

Figure 2. Basic BCI System

2. Methods

Based on the analysis of both systems (sEMG-based and EEG-based systems), one way of reducing the total time response of sEMG-based active prosthetics is increasing the movement velocity of prosthetics to reach the desired position [10, 11]. Figure 3 illustrates this analysis. Referring to the movement detection from Figure 3 with block diagram of active prosthetics in Figure 1(a) or 1(b), the active prosthetic moves after detecting movement intention from the sEMG signal. By increasing the movement velocity of the active prosthetic, the time to reach the desired position can be reduced. Although proportional prosthetics can reduce the total time response, this paper proves that the proposed method can be applied in both non-pattern recognition and pattern recognition approaches, Herle et al. [4] by smoothing the movement velocity of proportional active prosthetics.

In this analysis, an on/off sEMG-based active prosthetic [12,13], is used to prove the effectiveness of the alternative method (RTA-2). This consideration is based on the fact that the on/off active prosthetic system is the simplest function for active prosthetics [12,13]. On the other hand, this analysis also uses the BCI system that was implemented by Kirchner *et al.* [5], Lew *et al.* [6] and Planellas *et al.* [8]. They used "rest" and "pre-movement" (or movement intention) detection to decide whether active prosthetics move. This analysis integrates the sEMG-based and EEG-based systems. Figure 4 illustrates the diagram block for this analysis. To simplify the approach, this analysis focused on the "Integration Method" block with two inputs and one output.

The data of this analysis are obtained from another sEMG and EEG-based system experimental results. To analyze the TPR, FPR, and BA of sEMG-based and EEG-based systems, this analysis assumes that the TPR,

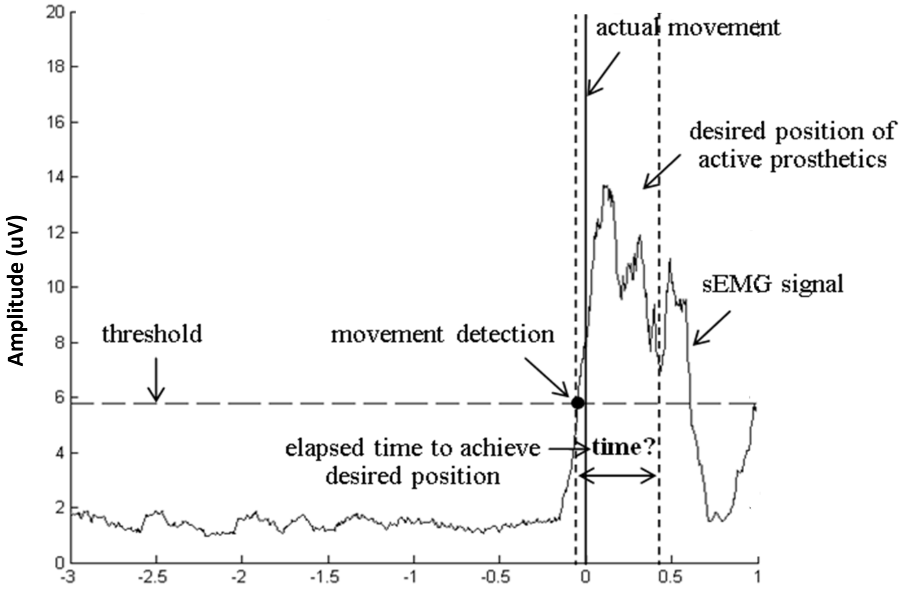

Figure 3. Time Analysis of Arm Detection of Movement Intention Using an sEMG Signal [9]

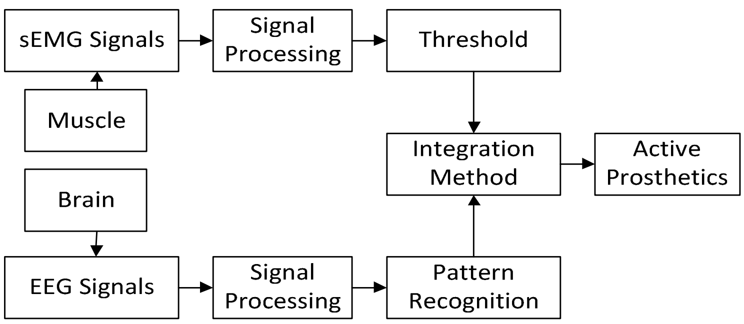

Figure 4. Block Diagram of sEMG and EEG Signal Integration for Active Prosthetic Control

FPR, and BA of the systems are stochastic events that are probabilistic nature. Therefore, this analysis uses a probabilistic approach to calculate the TPR, FPR, and BA of the systems. On the other hand, the TPR, FPR, and BA of sEMG-based and EEG-based systems are also time-dependent. To analyze these variables at a specific time interval, the data will follow the results and conclusions from other experiments that used EEG-based and sEMG-based systems.

Based on the conclusions of their experiments, Shibaki and Harlett [7], Lew *et al.* [6], Kirchner *et al*. [5] and Bai *et al*. [14] have shown that (1) the movement intention based on EEG signal could be detected up to 2 s before actual movement onset; (2) movement intention based on sEMG signal could be detected around 250–500 ms before the actual movement onset. If we define the following: 1) $P(D_{EEG})=P(A)$ is the probability of movement intention detection based on EEG signals, and D_{EEG} is a detection of EEG-based system, where D_{EEG} = {0,1}. Decision value "0" indicates that the system detects no movement intention, whereas "1" denotes detection; 2) $P(D_{EMG})=P(B)$ is the probability of movement intention detection using sEMG signals. D_{EMG} is a detection based on sEMG-based system, where D_{EMG} = {0,1}. Decision value "0" indicates that the system detects no movement intention, whereas "1" denotes detection.

Then, the *P(A)* value for $t < ta$ reaches below 0.5 (chance level), whereas the *P(A)* value for $t \geq ta$ totals $0.6 \leq P(A) \leq 0.8$ [5-8]. On the other hand, the *P(B)* value for $t < tb$ measures below 0.001, and the *P(B)* value for $t \geq tb$ features a range of values of $0.8 \leq P(B) \leq 1$ [5-6]. Hence, the data can be illustrated by Eq. (1) for the EEG-based system and Eq. (2) for the sEMG-based system with $ta < tb$. Figure 5 illustrates the time diagram of movement intention detection of sEMG-based and EEG-based systems.

$$P(A) = \begin{cases} 0.1 \leq P(A) \leq 0.5, & t < ta \\ 0.6 \leq P(A) \leq 0.8, & t \geq ta \end{cases} \tag{1}$$

$$P(B) = \begin{cases} 0.0001 \leq P(A) \leq 0.001, & t < tb \\ 0.8 \leq P(A) \leq 1, & t \geq tb \end{cases} \tag{2}$$

Estimating TPR and FPR of and and OR Methodology. Kirchner *et al*. [5] used two methods for integrating sEMG-based and EEG-based systems. They used binary logic-like methodologies: AND and OR. In binary systems, the AND and OR methodologies can be illustrated by Figure 6.

To calculate the TPR and FPR of a system with AND and OR method, the analysis uses Eq. (3) and Eq. (4) [15]. To control the active prosthetic, the mapping function $f(.) \rightarrow \omega$ in Eq. (5) and Eq. (6) is used to convert the system's decision from movement intention detection to movement velocity of active prosthetics.

$$P(A \cap B) = P(A)P(B) \tag{3}$$

$$P(A \cup B) = P(A) + P(B) - P(A \cap B) \tag{4}$$

$$f_{AND}(D_{EMG}, D_{EEG}) = \begin{cases} 0 \rightarrow 0 \\ 1 \rightarrow \omega 1, \omega 1 \in \Re \end{cases} \tag{5}$$

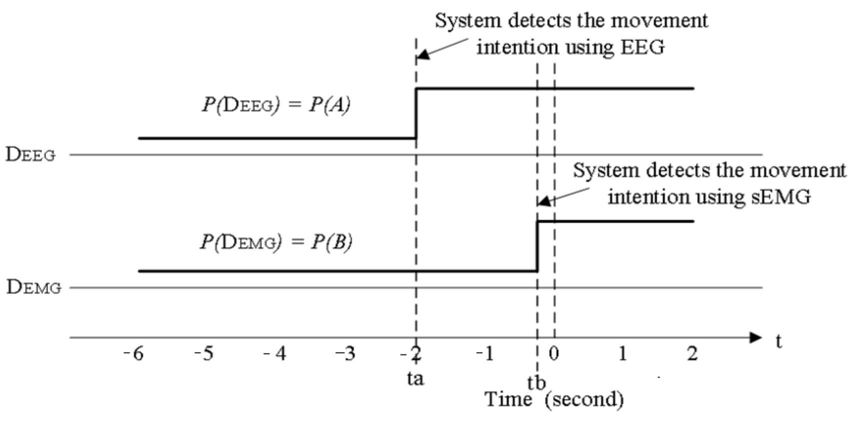

Figure 5. Time Diagram of Movement Intention Detection of sEMG-Based and EEG-Based Systems

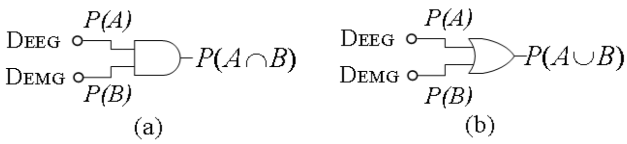

Figure 6. Logic Diagrams of (a) AND Method and (b) OR Method

Using the results from Kirchner's experiments [5]. Eq. (3) and Eq. (4) can estimate the TPR, FPR, and BA of AND and OR methods. The TPR value indicates true detection of movement intention before actual movement onset, whereas the FPR value indicates false detection of movement intention in "rest" condition. Table 1 shows the comparison of TPR, FPR, and BA from the work of Kirchner *et al*. and the estimated values obtained using Eq. (3) and Eq. (4). Based on calculations, the TPR, FPR, and BA of AND and OR methods can be estimated by using Eq. (3) and Eq. (4) with an error of ±0.0001.

Derivation of RTA-2 Methodology. The RTA-2 method is developed based on movement in the human body [16]. The brain receives all sensory information or stimuli from body sensors. After all sensory information are received by the brain, humans deliberates on procedural activities to response to stimuli. Some examples of this phenomenon can be observed from event-related desynchronization/event-related synchronization of brain signals if the response(s) shows correlation with body movements [5-18]. Thus, a movement starts when an individual thinks or intends to move his body until the end of movement.

All movement intentions do not always become body movements. Somatosensory motor cortex, pre-motor cortex, primary motor cortex, and the thalamus are important brain areas for producing body movements [16-18]. Although a command signal has been generated by primary motor cortex, the signal can reach the muscles if the thalamus continually relays this signal. Based on this information, humans possess time to think (decide) whether to move their body or stay still from the time a command signal is generated by the primary cortex area until such command signal is relayed to the muscles by the thalamus [16]. Based on this phenomenon, this paper proposes Eq. (7) to control an active prosthetic:

$$\begin{aligned} f_{RTA-2}(D_{EMG}, D_{EEG}) &= D_{EMG} + (D_{EEG} \bullet z^{-t})D_{EMG} \\ &= (1 + D_{EEG} \bullet z^{-t})D_{EMG} \end{aligned} \quad (7)$$

Table 1. Estimated Accuracy from The System Based on The Experiments of Kirchner *et al* [5]

Par	Input		Output			
	EEG	EMG	OR	AND	OR*	AND*
TPR	0.88	0.86	0.98	0.76	0.98	0.76
FPR	0.1	0.001	0.1	0.0002	0.1	0.0001
BA	0.89	0.93	0.94	0.88	0.94	0.88

*estimation uses Eq. (3) and Eq. (4)

where D_{EEG} refers to a detection of the EEG-based system, D_{EMG} is a detection of the sEMG-based system, and z^{-t} is a delay function at t. This delay function represents the decision time where a command signal originating from the primary cortex area travels to the muscles through the thalamus. Eq. (7) covers all movements: reflex by D_{EMG} and voluntary movement by $D_{EEG} \cdot z^{-t} \cdot D_{EMG}$.

To analyze and estimate the accuracy of RTA-2 method, this paper generates a model from Table 2 for the new methodology with the following model feature: (1) high accuracy for detecting movement; (2) suppresses mistake decisions or detection of rest condition; (3) yields short total time response by increasing movement velocity. Table 2 illustrates that the output of RTA-2 method possesses the same value with the detection output of the sEMG-based system. The background behind this design is attributed to the high TPR, low FPR, and high BA of the sEMG-based system. Hence, parameters (1) and (2), which are required to generate the new method (RTA-2), can be achieved by deriving the output of the sEMG-based system. On the other hand, Figure 6 is generated as a model of RTA-2 methodology based on Table 2.

Based on the phenomenon, the detection of EEG-based system (D_{EEG}) and that of sEMG-based system (D_{EMG}) are independent. Hence, the estimated probability of TPR and FPR, *P(C)* and *P(D)*, are as follows:

$$P(C) = P(A \cap B) = P(A)P(B) \quad (8)$$

$$P(D) = P(A' \cap B) = (1 - P(A))P(B) \quad (9)$$

Table 2. Possible Output of OR, AND, and RTA-2 Methods with D_{EMG} and D_{EEG} as Input

No	Input		Output		
	D_{EMG}	D_{EEG}	OR	AND	RTA-2
1	0	0	0	0	0
2	0	1	1	0	0
3	1	0	1	0	1
4	1	1	1	1	1

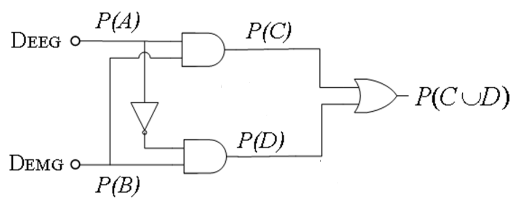

Figure 6. Logic Diagram of RTA-2 Method

Referring to Eq. (4), the estimated probability of TPR and FPR of RTA-2 method, $P(C \cup D)$, is as follows:

$$P(C \cup D) = P(C) + P(D) + P(C \cap D) \tag{10}$$

As *P(C)* and *P(D)* are mutually independent, $P(C' \cap D') = 0$ and Eq. (10) becomes Eq. (11):

$$P(C \cup D) = P(C) + P(D) \tag{11}$$

To achieve parameter (3), RTA-2 is designed to map the output value of Eq. (7) into three different movement velocities. This relation function can be observed in Eq. (12).

$$f_{RTA\text{-}2}(D_{EMG}, D_{EEG}) = \begin{cases} 0 \rightarrow 0 & , D_{EMG} = 0, D_{EEG} = \{0,1\} \\ 1 \rightarrow \omega_1 & , D_{EMG} = 1, D_{EEG} = 0, \omega_1 \in R \\ 2 \rightarrow \omega_2 & , D_{EMG} = 1, D_{EEG} = 1, \omega_2 \in R \end{cases} \tag{12}$$

Assuming that the first movement velocity is ω_1, the second movement velocity is ω_2, and $\omega_2 > \omega_1$, then time t_2, which is required for active prosthetics to reach the same desired position with movement velocity ω_2, is always smaller than the time required by movement velocity ω_1. This statement can be proven by Eq. (13). Using Eq. (7) enables the on/off active prosthetics to possess one more state. If the available state is filled with a high-speed command, the system will reduce its total time response.

$$t_2 = \left(\frac{\omega_1}{\omega_2}\right) t_1 \tag{13}$$

3. Results and Discussion

Calculating the estimated accuracy from the three methods (AND, OR, and RTA-2) by using the experimental results from the work of Kirchner *et al*., we observe that RTA-2 features the same accuracy (TPR and FPR) and BA with sEMG-based systems. The BA of sEMG-based system and RTA-2 is higher than that of the AND method but lower than that of the OR method. Although the RTA-2 method yields a lower BA than OR method, the FPR of RTA-2 is lower than that of the OR method. These values imply that the RTA-2 method yields lower false detection in rest condition than OR. Based on this observation, the RTA-2 method presents higher probability to be implemented than the OR method.

Comparing the performances of RTA-2 method with AND method, we note that the RTA-2 exhibits higher FPR than AND method (difference value of 0.0009). Although AND method features better FPR value parameter, RTA-2 yields higher TPR and BA values. These results are also proven by the results of OR, AND, and RTA-2 methods in Tables 4, 5, and 6, respectively.

In "rest" interval, as illustrated in Table 3, the estimated detection of movement intention forms the relation *P('OR') ≤ P('*RTA-2*') ≤ P('AND')*. By increasing the value of *P(A)* and/or *P(B)*, the estimated detection of movement intention is consistently *P('OR') ≤ P('*RTA-2*') ≤ P('AND')*. Including all input possibilities, the estimated detection of movement intention from all methods is constantly *P('AND') ≤ P('*RTA-2*') = P(A) ≤ P(B) ≤ P('OR')*. As this detection is on "rest" interval, then this estimated detection of movement intention is FPR.

In transition interval, Table 5 shows that the estimated detection of movement intention features the relation *P('OR') ≤ P('*RTA-2*') ≤ P('AND')*. By increasing the value of P(A) and/or P(B), the estimated detection of movement intention is consistently *P('OR') ≤ P('*RTA-2*') ≤ P('AND')*. Comparing with all possible methods that could be implemented in active prosthetics, the estimated detection of movement intention of all methods is *P('AND') ≤ P('*RTA-2*') = P(A) ≤ P(B) ≤ P('OR')*. From Eq. (7), this transition interval defines the delay function.

In pre-movement interval, Table 6 shows that the estimated detection of movement intention presents the relation *P('OR') ≥ P('*RTA-2*') ≥ P('AND')*. By increasing the value of *P(A)* and/or *P(B)* the estimated detection of movement intention for the method is invariably *P('OR') ≥ P('*RTA-2*') ≥ P('AND')*. Returning to all possible methods, the estimated detection of movement intention methods manifests the correlation *P('OR') ≥ P('*RTA-2*') = P(A) ≥ P(B) ≥ P('AND')*. From the point of view of the RTA-2 method, the following are deduced: 1) If the system detects movement intention from the EEG-based system in the transition time interval and EMG-based system in the pre-movement time interval, then the prosthetics will move with velocity ω_2. 2) If the system detects movement intention from EEG-based systems in transition time interval but not movement intention from EMG-based systems in pre-movement time interval, then the prosthetics will move with velocity ω.

Table 3. Estimated TPR, FPR, and BA by Using Kirchner's Results

Par	Input		Output		
	EEG	EMG	OR*	AND*	RTA-2*
TPR	0.88	0.86	0.98	0.76	0.86
FPR	0.1	0.001	0.1	0.0001	0.001
BA	0.89	0.93	0.94	0.88	0.93

*estimated

Table 7 illustrates the possibilities of velocity output from the RTA-2 method. We can observe that the RTA-2 method fulfills all requirements needed to shorten the total time response. The RTA-2 method shows possibility to move active prosthetics depending on the decision of sEMG and EEG signals with high accuracies, low false movement detection in "rest" condition, and it could move rapidly by increasing the movement velocity of active prosthetics.

One problem arises from the RTA-2 method. If the EEG system can detect **every** movement intention that occurs 0–2 s before the onset of movement, [5-8] the subject cannot select the velocity command for active prosthetics (ω_1 or ω_2). By using motor imagery approach before doing voluntary movement onset might overcome this velocity problem. Hence, the delay time parameter (z^{-1}) in Eq. (7) is determined by the time where motor imagery occurs statistically. Figure 7 illustrates this delay function phenomenon (gray area).

Table 4. Estimated Detection of Movement Intention of OR, AND, and RTA-2 Method in Rest Interval ($t < t_a$)

No	P(A)	P(B)								
		0.1000			0.2000			0.3000		
		OR	AND	RTA-2	OR	AND	RTA-2	OR	AND	RTA-2
1	0.0001	0.1001	0.0000	0.0001	0.2001	0.0000	0.0001	0.3001	0.0000	0.0001
2	0.0003	0.1003	0.0000	0.0003	0.2002	0.0001	0.0003	0.3002	0.0001	0.0003
3	0.0005	0.1005	0.0001	0.0005	0.2004	0.0001	0.0005	0.3004	0.0002	0.0005
4	0.0008	0.1007	0.0001	0.0008	0.2006	0.0002	0.0008	0.3006	0.0002	0.0008
5	0.0010	0.1009	0.0001	0.0010	0.2008	0.0002	0.0010	0.3007	0.0003	0.0010

Table 5. Estimated Detection of Movement Intention of OR, AND, and RTA-2 Method in Transition Interval ($t_a \le t < t_b$)

No	P(A)	P(B)								
		0.6000			0.7000			0.8000		
		OR	AND	RTA-2	OR	AND	RTA-2	OR	AND	RTA-2
1	0.0001	0.6000	0.0001	0.0001	0.7000	0.0001	0.0001	0.8000	0.0001	0.0001
2	0.0003	0.6001	0.0002	0.0003	0.7001	0.0002	0.0003	0.8001	0.0002	0.0003
3	0.0005	0.6002	0.0003	0.0005	0.7002	0.0003	0.0005	0.8001	0.0004	0.0005
4	0.0008	0.6003	0.0005	0.0008	0.7002	0.0005	0.0008	0.8002	0.0006	0.0008
5	0.0010	0.6004	0.0006	0.0010	0.7003	0.0007	0.0010	0.8002	0.0008	0.0010

Table 6. Estimated Detection of Movement Intention of OR, AND, and RTA-2 Method in Pre-Movement Interval ($t \ge t_b$)

No	P(A)	P(B)								
		0.6000			0.7000			0.8000		
		OR	AND	RTA-2	OR	AND	RTA-2	OR	AND	RTA-2
1	0.8000	0.9200	0.4800	0.8000	0.9400	0.5600	0.8000	0.9600	0.6400	0.8000
2	0.8500	0.9400	0.5100	0.8500	0.9550	0.5950	0.8500	0.9700	0.6800	0.8500
3	0.9000	0.9600	0.5400	0.9000	0.9700	0.6300	0.9000	0.9800	0.7200	0.9000
4	0.9500	0.9800	0.5700	0.9500	0.9850	0.6650	0.9500	0.9900	0.7600	0.9500
5	1.0000	1.0000	0.6000	1.0000	1.0000	0.7000	1.0000	1.0000	0.8000	1.0000

Table 7. Probability of RTA-2 Method to Generate Movement Velocity ω_1 and ω_2 in Pre-Movement Interval ($0 \geq t \geq t_b$)

No	P(A)	P(B)								
		0.6000			0.7000			0.8000		
		0	ω1	ω2	0	ω1	ω2	0	ω1	ω2
1	0.8000	0.2000	0.3200	0.4800	0.2000	0.2400	0.5600	0.2000	0.1600	0.6400
2	0.8500	0.1500	0.3400	0.5100	0.1500	0.2550	0.5950	0.1500	0.1700	0.6800
3	0.9000	0.1000	0.3600	0.5400	0.1000	0.2700	0.6300	0.1000	0.1800	0.7200
4	0.9500	0.0500	0.3800	0.5700	0.0500	0.2850	0.6650	0.0500	0.1900	0.7600
5	1.0000	0.0000	0.4000	0.6000	0.0000	0.3000	0.7000	0.0000	0.2000	0.8000

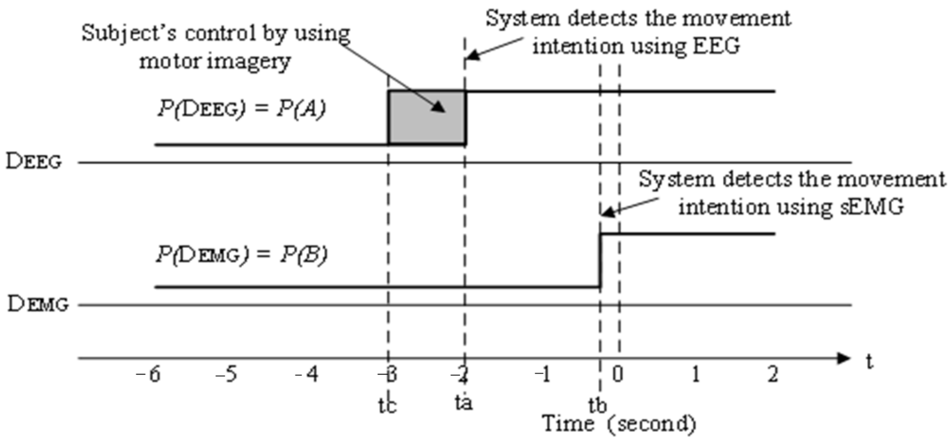

Figure 7. Time Diagram of RTA-2 Method with Motor Imagery

4. Conclusions

Based on the analysis above, this paper shows another possibility to control active prosthetics using different movement velocities based on the integration of sEMG and EEG signals. The RTA-2 method shows equal performance with sEMG-based systems. Comparing with the EEG-based system, the RTA-2 method exhibits better performance by yielding lower FPR and higher BA. On the other hand, comparing RTA-2 method with AND method, RTA-2 shows higher TPR and BA and lower FPR. Comparing with OR method, RTA-2 presents lower FPR, higher FPR, and lower BA. Considering that EMG-based system has been implemented and passed safety considerations, [19] the RTA-2 method can also be implemented as it shows an equal performance (TPR, FPR, and BA) with the EMG-based system. The RTA-2 method can reduce total time response by rapidly moving the active prosthetic. This assumption is attributed to the capability of RTA-2 method to make other alternative commands to the active prosthetics. From the analysis, RTA-2 performs one more alternative command into on/off active prosthetics. If this command is used for faster movement velocity command, the active prosthetics can reach the desired position faster or require a shorter total time response.

The RTA-2 method can also be implemented in proportional active prosthetics. As movement velocity command of active prosthetics uses the threshold method, [12-13] hence, by integrating with the BCI system, the active prosthetics will feature a $2xN$ level of movement velocity command (with N existing at the level of active prosthetics based on sEMG signals).

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