# Exploration of A Brain Activity-Metabolic Cost Relationship for Human-in-the-loop Optimization during Incline Walking

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Abstract— Exoskeletons have the potential to enhance human performance, with the design of effective humanmachine interaction (HMI) playing a crucial role in improving operability. However, the quest for optimal human-machine control remains an open field for further investigation. The key to success lies in establishing a flexible mode of communication between humans and machines, employing diverse methods and adjustments of parameters. Tailoring optimization to each individual user is pivotal for achieving significant advancements. This study presents a novel approach to human-in-the-loop optimization that leverages the correlation between brain activity and metabolic cost. This approach not only aims to reduce the energy expenditure of users during walking but also seeks to optimize gait patterns for healthy individuals across various walking environments. Our findings reveal that the  $\mu$  and  $\gamma$  frequency bands display notable eventsynchronization (ERS) and event-related related desynchronization (ERD) phenomena during walking. Notably, the  $\gamma$  band power is positively correlated with changes in inclined terrain. Pearson correlation indicates a stronger correlation between y band power and metabolic cost than in other bands. This study thus built a regression model that links brainwave patterns to metabolic rates, enabling the prediction of current metabolic costs based on brain activity. This relationship could facilitate the realization of human-in-the-loop optimization, enhancing the walking economy.

## I. INTRODUCTION

Exoskeletons hold the potential to assist in overcoming human limitations and even enhancing human capabilities [1][2][3]. Despite significant advancements in exoskeleton technology for assistance or enhancement, a deeper understanding of the physiological signals generated by users under control is crucial [4]. Many developments are often based on knowledge from the fields of biomechanics or mathematical control [3][5], resulting in open-loop control states that simplify the importance of HMI. However, these assistive devices not only need to adapt to individual user intentions for effective assistance or enhancement but also must self-adapt to differences in various individuals and usage environments to provide optimal assistance across diverse scenarios. Most importantly, the assistive hardware itself should minimize interference with normal human activities, allowing users to retain their autonomy [1][2]. Constructing

control strategies based on the concept of a human-machine loop can significantly enhance the efficiency of exoskeleton assistance. This allows existing exoskeletons to overcome individual and environmental differences in users and provides real-time coordination and controller optimization based on the user's state before and after assistance, thus improving human activity performance [1][2][6]. This loop enables the controller to utilize physiological signals from users during activity as feedback. It continuously adjusts the assistance mode, altering stride length and frequency, and enables users to perceive the effects of different assistance modes [1]. This continuous adaptive adjustment of the controller during user activity through the human-machine loop not only enables customized assistance for different individuals but also enhances flexibility in adapting to environmental conditions [1][2], unlocking the full potential of exoskeletons and assistive devices.

The metabolic cost serves as an extensively employed and intuitive criterion in gait-assisted exoskeleton development studies for assessing effectiveness [1][2][7]. Nevertheless, given the human body's ability to utilize brain electrical activity signals to achieve walking and other activities, establishing a correlation between metabolic costs and brain electrical activity becomes crucial [8][9]. Therefore, if a correlation between metabolic cost and brain activity can be identified, the realization of the human-machine loop can become more feasible. If such a correlation is identified, it could enable the prediction of metabolic conditions through EEG (Electroencephalogram), optimizing the implementation of human-machine circuit. This advancement holds the potential to make the control of exoskeletons and assistive devices more natural in the future. In the field of rehabilitation medicine, many studies have demonstrated the significant contributions of brain-machine interfaces to motor rehabilitation [8][9][10]. Through practical movement or motor imagery experiments, researchers measure EEG in the motor cortex of participants, which captures the intention behind movements [8][9][10]. This information can be utilized to control periodic movements such as gait cycles. Previous studies have conducted experiments measuring EEG during walking cycles, using event-related spectral perturbation (ERSP) in the  $\mu$ ,  $\beta$ , and  $\gamma$  frequency bands to identify different phases of walking, including the stance and swing phases [11].

Combining other physiological signals in the control loop should enhance the effectiveness of control assistance and contribute to the overall robustness of the human-machine framework [1][2][8]. However, contamination of EEG by

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Figure 1. Proposed Human-in-the-Loop Optimization Architecture.

various sources, such as electromyography (EMG), eye movements, and artifacts, often makes it challenging to directly control different phases of the gait cycle using EEG alone [6][9][10]. More importantly, while research in the fields of human-in-the-loop optimization and EEG has advanced [12], the correlation between metabolic cost and EEG remains unclear.

This study focuses on the relationship between EEG and metabolic cost, aiming to develop an adaptive control framework for human-in-the-loop optimization. We validate differences in signal patterns within exercise-related frequency bands during walks on varying slopes. Additionally, we explore correlations between EEG and metabolic cost to construct a regression model, which enables the prediction of current metabolic costs based on brain activity.

#### II. METHOD

As depicted in Fig. 1, the study introduced a human-inthe-loop optimization architecture where environmental slopes and human physiological signals, such as respiratory data and EEG, were utilized as inputs during movement. This study integrated brain activity, metabolic cost, and ground slope within an optimization loop through correlation and statistical analyses of EEG signals with metabolic cost. This analysis identified EEG indicators, including channel and frequency band characteristics, that were closely associated with metabolic costs. Further applications could extend this approach to enhance assistive devices and exoskeleton systems, thereby improving their effectiveness in supporting physical activity and optimizing human performance and adaptability.

### A. Experimental Design and Data Collection

This study recruited three healthy participants with no history of neurological conditions, walking impairments, or lower limb skeletal abnormalities. The experiment involved having participants engage in a walking task on a treadmill (7.4AT-03, HORIZON, JOHNSON) at a fixed speed of 1.5 m/s for 28 minutes to extract physiological signals under various conditions. Each condition walking experiment lasted

for 7 minutes. The overall experimental procedure is illustrated in Figure 2 The experiment has received approval from the Research Ethics Committee of Jen-Ai Hospital, Taichung City, Taiwan, with IRB number 111-55.

First, participants were instructed to stand with closed eyes for the first standing phase. This initial phase aimed to minimize the impact of resting and inactive tasks on EEG data, which was subsequently used as the baseline EEG signal for analysis. After 7 minutes, the standing phase concluded, and participants began the walking task. To simulate real ground environments and observe significant changes in physiological data during prolonged and high-demand tasks, the experiment introduced variable walking conditions by adjusting the treadmill incline (0%, 5%, 10%). No rest intervals were scheduled between each variation, and keeping with the incline increased progressively throughout the experiment.

The collection of physiological data included EEG: a measurement system with 32 channels wet EEG electrodes (24-bit, St. EEG TM 32 channels, Artise Biomedical Co., Ltd.); surface EMG (sEMG) system (24-bit, St. EEGTM Gemini 8 channels, Artise Biomedical Co., Ltd.); heart rate measurement system (Polar H10, JOHNSON); and an oxygen consumption assessment system (O2 Paramagnetic, Quark CPET, COSMED). Reflective markers were attached to the participants to enable real-time tracking of joint movements during exercise. Experimental recordings were conducted using a high-speed camera (120 fps, NiNOX), paired with standard color temperature 5600K LED lights (Forza 60B, NANLITE). 2D motion capture software (MR310 myoVIDEO, Noraxon) was employed to chronicle the participants' kinematic data in real-time, assessing changes in various kinematic parameters such as limb posture, joint angles, and gait metrics before and after the experiment.





## B. Data processing

This study analyzed the EEG at different stages of the experiment to understand the neural activities in various brain regions and the neuro-correlations during different gait phases. This analysis was conducted following the EEG processing procedure proposed by Ko et al [8]. Initially, a preprocessing pipeline was applied to the measured EEG to eliminate most of the noise. The preprocessing steps in this experiment included bandpass filter (1~50Hz) and artifact removal, followed by a re-referencing to the average of the entire brain [6][8][12]. Subsequently, independent component analysis (ICA) [7][9][12] using the MATLAB<sup>®</sup> EEGLAB toolbox [8][10][11] was employed to eliminate non-brain signal sources and isolate the component variations primarily observed in the targeted brain regions. ICA retained only the components originating primarily from the brain for further examination. Additionally, the EEG may be interfered with by muscle artifacts and movement-related signals during walking, artifact subspace reconstruction (ASR) [8][10][12] was thus applied for signal reconstruction and denoising.

This study conducted time-frequency analysis on EEG signals to understand the dynamic changes in brain activity during different phases of the gait cycle, including stance and swing phases. This analysis aimed to observe the induced potentials and disturbances in brain regions under varying slope conditions. The ERSP was utilized as a feature to observe changes, focusing on frequency bands like  $\delta$  wave (0.5~4 Hz),  $\theta$  wave (4~8 Hz),  $\alpha$  wave (8~14 Hz),  $\mu$  wave (8~12 Hz),  $\beta$  wave (14~30 Hz), and  $\gamma$  wave (30~50 Hz). Waves such as  $\alpha$ ,  $\mu$ , and  $\gamma$  waves are highly correlated with lower limb movements, allowing for the identification of ERD and ERS coupling with the gait cycle [7][8][11].

This experiment focuses on observing changes in brain regions during lower limb movements. Based on Brodmann areas [9] and the brain structure, the lower limb motor area is primarily distributed in the posterior part of the precentral gyrus and around the central sulcus in the frontal and parietal lobes. Following the international 10-20 system, the main observation targeted the changes in ERSP at five electrodes adjacent to this region: FCz, CPz, Cz, C3, and C4. Considering the cortical control of the brain in an opposing and inverted manner between left and right, as well as front and back, the averages of left and right (C3, C4) and front and back (FCz, CPz) were separately calculated. Subsequently, the averages for each direction were combined with the mid-central electrode Cz to observe the ERSP values under different experimental slopes, by changes in the gait cycle. In addition, a comparison was made using the power spectral density in different frequency bands and their differences. The sEMG data in this experiment undergoes a series of standard signal preprocessing steps, including a fourth-order Butterworth bandpass filter with a range of 20-460 Hz, and full-wave rectification of the data [7]. Simultaneously, to extract the timing of the walking cycle for physiological signal assessment, sEMG was used to segment each gait cycle.

## C. Metabolic Cost Estimation

An oxygen gas analyzer captures participants' respiratory volumes of carbon dioxide and oxygen for precise measurements during the experiment, enabling the calculation of the biological metabolic cost. The oxygen consumption rate  $(\dot{V}_{O2}, L/s)$ , carbon dioxide production rate  $(\dot{V}_{CO2}, L/s)$ , and nitrogen intake (N, g) are collected during walking trials using the oxygen uptake assessment system. Furthermore, the biological metabolic rate  $(-\Delta H, kJ/s)$  was estimated through Brockway's standard formula (refer to Eq. (1)) [13]. The net metabolic rate for walking energy demand was calculated by taking the difference between the total metabolic rate and the metabolic rate during eyes-closed standing.

$$-\Delta H = 1.658 \dot{V}_{02} + 4.51 \dot{V}_{C02} - 5.90N.$$
(1)

## D. Statistical Analysis

This study employed IBM<sup>®</sup> SPSS Statistics 21 for conducting statistical analyses on the metabolic costs measured during the experiment, the power intensity of each frequency band, and the experimental slope. Initially, the 7-minute experimental data for each slope were averaged every 30 seconds. To examine if there were differences between the two continuous datasets for each frequency band power and metabolic cost, facilitating statistical analysis, paired t-test were conducted on the data.

Also, to assess whether there were significant differences in the significance of each frequency band and power intensity and to identify the frequency band more relevant to power changes, this study performed a univariate two-way ANOVA. The Shapiro-Wilk (S-W) test was employed to verify whether the power and metabolic cost data for each frequency band adhered to normal distribution assumptions. The initial assumption of the S-W test is that the data conforms to a normal distribution. In such a scenario, Pearson correlation analysis was conducted (refer to Eq. (2)), where r is the correlation coefficient;  $\bar{x}$  and  $\bar{y}$  are the mean of variables; n is the total number of samples.

$$r_{pearson} = \frac{\sum_{i=1}^{n} (x_i - \bar{x}) (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}}$$
(2)

Multiple regression analysis was carried out on the data, with slope and frequency band power intensity serving as independent variables, to calculate the correlation coefficient and residual error.

#### III. RESULTS

## A. Metabolic Cost Estimation

During the experimental sessions, the respiratory data of participants were recorded using an oxygen gas analyzer. As the estimated values of human metabolic cost gradually approach a steady state during exercise, this experiment employed a first-order dynamic model for fitting metabolic costs and predicting their steady-state values. Physiological metabolic cost estimates for every 7 minutes under three different terrain conditions as illustrated in the lower image of Figure 3A, Figure 3B, and Figure 3C. Before the commencement of the experiment, the energy expenditure of participants in a resting state was measured. This study assessed the task load imposed on participants in different environments by actively comparing the metabolic costs during walking with the metabolic costs during rest while taking into account the differences. In the experiment, different slopes are distinguished by various colors. The

horizontal axis represents the experimental duration, and the vertical axis represents the estimated metabolic cost calculated through the aforementioned equations (0% inclined: gray; 5% inclined: orange; 10% inclined: red). Each blue dashed line represents the trendline of the data. Through fitting with a first-order oscillator, distinct green convergence lines are obtained for each slope experiment. Utilizing these convergence lines, steady-state estimates of metabolic cost consumption can be obtained within approximately three minutes of the experiment. It can be observed that in Figure 3, as the experiment progresses and the incline increases, the oscillation of metabolic cost values in Figure 3A is less pronounced compared to the other two participants. Additionally, the ERS signs in the  $\gamma$  and  $\beta$  bands are also less noticeable compared to the other two individuals.

#### B. Neural Activity

By examining the average ERSP in the primary motor area, as depicted in the upper images of Figure 3A, Figure 3B, and Figure 3C, we can emphasize the red box first, which represents the  $\mu$  and  $\alpha$  frequency bands. In the analysis results for all three participants, there was a clear presence of ERD phenomena in these bands. Additionally, in the  $\gamma$  frequency band, it can be observed in the purple box with significant ERS patterns during uphill terrain, especially in the range of 42 to 48Hz, and between 36 to 40Hz, the ERS is more pronounced. By cumulatively comparing ERSP, variations in power intensity across individual frequency bands can be observed as participants navigate different inclinations during walking. The black dashed lines represent the separation of different slopes experiments. By analyzing the upper portion of Figure 3A, Figure 3B, and Figure 3C, it can be inferred that under more challenging terrain conditions, meaning greater physical exertion, the motor cortex exhibits more intense activity. This is evident from the significant changes in ERS corresponding to the slope variations. Furthermore, in Figure 4, the average ERSP for  $\gamma$  and  $\mu$  frequency bands under different incline conditions from Figure 3 is presented. The results reveal a significant increase in cortical potential changes in the  $\gamma$  band, with 1.87 times and 2.19 times elevation during 5% and 10% incline walking compared to level walking. This effect is more pronounced when compared to the  $\mu$  frequency band. The band power during the active state was subtracted by that during the rest state, and the result was normalized by dividing it by the band power during the rest state, considering the rest state as the baseline. From Figure 5, it was evident that there was an overall increase in the average power across different frequency bands.

However, during analysis, all experimental values were normalized to the baseline values under the rest period. The emphasis was on the trend of power, and the positive or negative values also indicate whether the power during activity is greater or smaller compared to the rest period. Therefore, focusing on Figure 5, it was noticeable that both the  $\delta$  and  $\gamma$  frequency bands exhibit larger values compared to the rest period, and their variations show a significant trend. During the 10% inclined experiment, especially in C3 and C4, the power was approximately 2 times that of the rest period. also shifted from negative to positive, showing a relative increase in power in these bands with the inclined slope compared to the rest period. The remaining four frequency bands also show increased power with the change in slope, though the trend of variation is relatively minor, and their values are still lower than those in the rest period. The  $\alpha$  and  $\mu$  bands, being in proximity, yield relatively similar results.

To observe the gait cycle, we intuitively examine the motor area of C3 and C4 to observe the correspondence between the left and right hemispheres. Figure 6 depicts the averaged results of ERSP, the left graph showing C3 corresponds to the right leg and the right graph C4 corresponds to the left leg, indicating the average ERSP for the two channels during a walking cycle for three subjects. The horizontal axis represents the gait cycle, which uses the ground contact of the contralateral foot as the starting and ending points of the gait.



Figure 3. ERSP (Upper) and Metabolic Cost (Lower) of three participants (A), (B), and (C).



Figure 4. The average ERSP in the  $\gamma$  and  $\mu$  frequency bands during different incline conditions.



Figure 5. The power variations for each frequency band across channels in the motor cortex.



Figure 6. Averaged ERSP of C3 and C4 in walking cycle.

The ERSP values are normalized by comparison with the baseline of the rest period, calculated as the difference divided by the baseline. The result shows strong ERS and ERD can be observed in the  $\mu$  frequency band within the yellow box and  $\gamma$  frequency band within the red box. Focus on observing the stance phase from 0% to 30% of the gait cycle, as indicated by the green box in Figure 6. With an incline increase, a more

significant ERD is observed in the  $\gamma$  band, especially notable in the C4 channel of the right brain. Compared with walking on level walking (0%), the task of walking uphill causes ERD in the contralateral motor area. This means that the change in slope causes the brain to react to process it. As the incline increases, ERD during the early to mid-stance phase becomes more pronounced.

Finally, averaging the metabolic cost data in the time domain and the power of each frequency band over 30-second intervals. The experimental data for each slope were then plotted on a two-dimensional map in Figure 7. The origin represents the start of each slope experiment, while triangles indicate the end of the respective slope experiments. In Figure 7, all frequency bands exhibit a positive correlation between metabolic cost and power intensity. Notably, the  $\delta$  band shows an almost fourfold increase in power during the 10% inclined experiment compared to the rest period, resembling an exponential growth pattern. The  $\gamma$  band also demonstrates a twice increase during the 5% and 10% inclined experiments. Furthermore, in the  $\theta$  and  $\beta$  bands, both metabolic cost and band power increase towards the end, surpassing rest values. Particularly in the  $\theta$  band during the 10% inclined experiment. The result was subjected to statistical analysis, which revealed the power in the  $\delta$  and  $\theta$  frequency bands (p < 0.01), as well as the metabolic cost data (p = 0.023). The power in the other four frequency bands adhered to a normal distribution, and Pearson correlation tests were used for the correlation analysis. However, at 0% and 5% incline, there is no significant change in the  $\delta$  band, with noticeable variation observed only at a 10% incline. On the other hand, the relationship between  $\gamma$  band and metabolic cost shows a positive correlation with treadmill incline changes, exhibiting significant variations. With a Pearson correlation coefficient of 0.639, the  $\gamma$  band demonstrates a moderate and more significant correlation than other frequency bands. Most data falls within the 95% interval, highlighting the potential of the  $\gamma$  band as a predictor for metabolic cost. Using a 3-order polynomial regression, we derived Eq. (3) to predict metabolism based on brainwave states, where  $M_{Est.}$  represents the estimated metabolic cost, and y represents y band power. Figure 8 illustrates the relationship between  $\gamma$  band power and metabolic cost.

$$M_{Est.} = -0.1\gamma^3 + 1.36\gamma^2 - 5.72\gamma + 7.75$$
(3)

## IV. DISCUSSION

In the results of Figure 3, this study had discovered similar findings with others [6][7][8]. During the experiment, significant ERD phenomena were observed in the  $\mu$  or  $\alpha$  frequency bands. However, our study additionally discovered that variations in slope lead to a more pronounced ERS phenomenon in the  $\gamma$  band. From Figure 3, it is also observed that during changes in walking slope conditions, the cortex of the brain's motor area can extract more significant information. In the future, this finding could be applied to HMI control, enabling the manipulation of machine adjustments to user gait and assistance intensity, ultimately enhancing human performance. Combining results from

Figure 3 and Figure 4 indicate the significance of  $\gamma$  band cortical potential changes in the primary motor area during incline, which points out the potential of  $\gamma$  band alterations as a key feature for future human-machine control applications.

Integrating the findings presented in Figure 5, significant cortical variations, particularly at C3 and C4 in the primary motor area, are observed as terrain changes. Thus, C3, C4, and even Cz become key channels for effective control measures within the entire motor region in the human-machine loop. Moreover, the results for each gait cycle and each participant (Figure 6) to observe changes in C3 and C4, like others have been discovered [11]. representing the right and left foot, respectively. The results show similarities with Severens et al [11], indicating ERD and ERS during the stance and swing phases corresponding to heel contact (0% cycle) and toe-off (about 60% gait cycle). In conclusion, Figure 7 and Figure 8 present Eq. (3), suggesting that estimating metabolic cost is possible by monitoring significant changes in  $\gamma$  band power, particularly associated with incline. This implies potential applications in human-machine control based on ground condition-related features. Furthermore, consistent with Figure 3, notable variations in y band ERSP indicate increased ERD with higher treadmill incline during different gait cycles.







Figure 8. Regression model between  $\gamma$  band power and metabolic cost

## V.CONCLUSION AND FUTURE WORK

The study reveals significant variations in channels C3, C4, and Cz within the primary motor area, especially in response to changes in terrain. Furthermore, the  $\gamma$  band shows more pronounced changes in metabolic cost and incline compared to other frequency bands. Notably, during the early stance phase of each gait cycle, a distinct ERD phenomenon is observed, influenced by the slope. Building upon these findings, this study establishes a regression model and relationship between the  $\gamma$  band and metabolic cost, enabling the prediction of metabolic cost and the detection of terrain conditions through EEG extraction. This suggests a promising assistive control method suitable for human-in-the-loop optimization. Combining this technology will enhance the efficiency of human-machine interaction.

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