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Enhanced ankle physiotherapy robot with electromyography - triggered ankle velocity control

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ABSTRACT

Previous ankle physiotherapy robots, called picobot rely on predefined trajectories continuous passive movement without considering patient intent, limiting the encouragement of user-intent motion. This study then integrates electromyography (EMG) signals as triggers into picobot with an ankle velocity-based control system. The upgraded robot activates movement in specific gait phases based on muscle activity, synchronizing therapy with the patient's intent. Functionality test on 7 young male healthy subjects investigates leg muscles, such as Tibialis Anterior, Soleus, and Gastrocnemius muscles for the most significantly contribute to ankle movements. Then, the muscle is tested to trigger picobot movements. Functionality tests revealed the Tibialis muscle significantly contributes to gait phases 2, the Soleus is prominent in phases 3 and 4, and gastrocnemius is active on phase 1. The robot successfully performs plantarflexion when EMG signals exceed a 1.58 V threshold, reaching a target position of -0.11 rad at a constant velocity of -0.62 rad/s. These findings establish a foundation for future trials since patient testing has not yet been conducted. By promoting active participation, this innovation has the potential to enhance rehabilitation outcomes. Incorporating user-intent triggers may accelerate recovery and improve healthcare accessibility in Indonesia, offering a significant advancement in physiotherapy technologies.

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1. INTRODUCTION

In line with the United Nations' sustainable development goal (SDG) 3, which focuses on ensuring healthy lives and promoting well-being for all ages, healthcare advancements are crucial, especially in developing countries like Indonesia. A significant part of SDG 3's implementation in Indonesia lies in improving healthcare technologies, particularly for non-communicable diseases such as stroke, which remains a leading cause of disability. With a growing population of stroke survivors in need of long-term rehabilitation [1], the development of homegrown physiotherapy and rehabilitation technologies becomes imperative. This is especially relevant as physiotherapy plays a vital role in restoring mobility for stroke patients [2]. Having locally developed healthcare solutions, such as lower-limb rehabilitation robots, can provide more affordable and accessible care to the Indonesian population.

One of the most promising areas in rehabilitation technology is the development of lower-limb exoskeletons, which have advanced significantly over the years. These devices are designed to assist individuals with impaired mobility, especially those recovering from conditions like stroke, spinal cord injuries, or degenerative diseases. Initially, exoskeletons provided passive assistance by guiding limbs through predefined motions [3], but more recent innovations have enabled active, patient-responsive systems [4]. The focus has shifted towards integrating more sophisticated control systems that allow the exoskeleton to respond dynamically to the user's needs. This has the potential to make rehabilitation more effective by synchronizing the robot's actions with the patient's actual muscle activity and recovery progress [5].

The development of lower-limb exoskeletons utilizing electromyography (EMG) for motion control has gained substantial attention in recent years. EMG-controlled exoskeletons use electrical signals from muscles to trigger movement, making them more intuitive and responsive [6]. These systems typically involve several components: surface EMG sensors detect electrical muscle activity, control algorithms process the EMG signals to interpret user intent, and actuation systems execute the desired movements [7]. This setup allows the exoskeleton to adapt its motion based on the user's muscle engagement, improving both assistance and rehabilitation outcomes. The intuitive nature of this interaction is particularly beneficial for patients with mobility impairments, as it allows them to actively participate in their therapy by triggering movements themselves.

Key advancements in EMG-triggered exoskeletons have demonstrated their potential in stroke rehabilitation and mobility assistance. One notable project is the ALEXO exoskeleton, which focuses on active lower limb support for walking assistance. By integrating sophisticated control architectures, ALEXO employs trajectory control methods that enable smoother, more efficient physical activity [8]. Another significant innovation is the flexible joint exoskeleton, designed to improve patient comfort during passive rehabilitation. This exoskeleton integrates both EMG and baropodometric sensors to allow controlled movements without requiring active exertion from the patient [9]. These advancements represent a significant shift from passive exoskeletons towards systems that allow more precise, adaptive interactions based on real-time muscular input.

Several studies have also explored the use of surface EMG (sEMG)-based strength enhancers. These prototypes use sEMG signals to enhance leg strength during walking or other activities, combining EMG with flex sensors to improve control responsiveness [7]. One promising development involves adapting gait patterns using EMG signals from the thigh muscles, allowing users to adjust their walking patterns dynamically. This adaptation improves both mobility and comfort for individuals, particularly in dynamic or unpredictable environments [10]. Despite these advancements, key challenges remain. Signal noise and variability are primary obstacles in the development of universally applicable control algorithms [11]. EMG signals can be affected by muscle fatigue, skin impedance, and other external factors, making it difficult to consistently detect accurate signals. Additionally, user intention detection remains a complex problem, as interpreting precise movements from EMG signals in real-time can be difficult, particularly in dynamic environments where rapid adjustments are necessary [12]. Ensuring that exoskeletons remain comfortable for extended periods and integrating them effectively with human biomechanics is also an ongoing challenge, requiring further refinement in control strategies and mechanical design.

Building on these advancements, the research aims to address the existing challenges by developing a novel EMG-triggered ankle physiotherapy robot. Unlike previous EMG-based systems where the motion trajectory [13] or torque [14] is proportional to the EMG signal's amplitude, our approach utilizes EMG solely as a trigger for specific motions which are based on ankle velocity control [15]–[17]. This novel approach simplifies the control algorithm by using muscle activation to initiate motion, rather than attempting to directly scale the intensity of movement with the EMG signal. Three EMG signals, which come from Soleus, Tibialis Anterior, and Gastrocnemius, are investigated in four specific phases of the gait cycle: i) initial contact to foot flat, ii) foot flat to heel off, iii) heel off to toe off, and iv) the swing phase. The most significant muscle will correspond to trigger ankle movement at that phase. By focusing on the activation of muscles in specific gait phases, this system enhances the robot's responsiveness and reduces the complexity involved in interpreting EMG data.

2. METHOD

The study is mainly divided into two main works, which are contributing muscle study and implementation on previously developed physiotherapy ankle robot [15], [18]. The study targets to observe the muscle activity of Soleus, Tibialis Anterior, and Gastrocnemius muscle in four gait phases, as shown in Figure 1. Each phase has different flexion or movement, where each ankle velocity reference has been investigated in the previous research [17], [19]. For instance, in phase one from initial contact to foot flat, the ankle mainly moved in the plantarflexion direction while the ankle mainly moved in dorsal direction during phase two. Different movements require different muscle activation and there will be one muscle that significantly contributes to that certain movement. Therefore, this research investigates which of the three muscles significantly contributes to ankle movement in each gait phase.

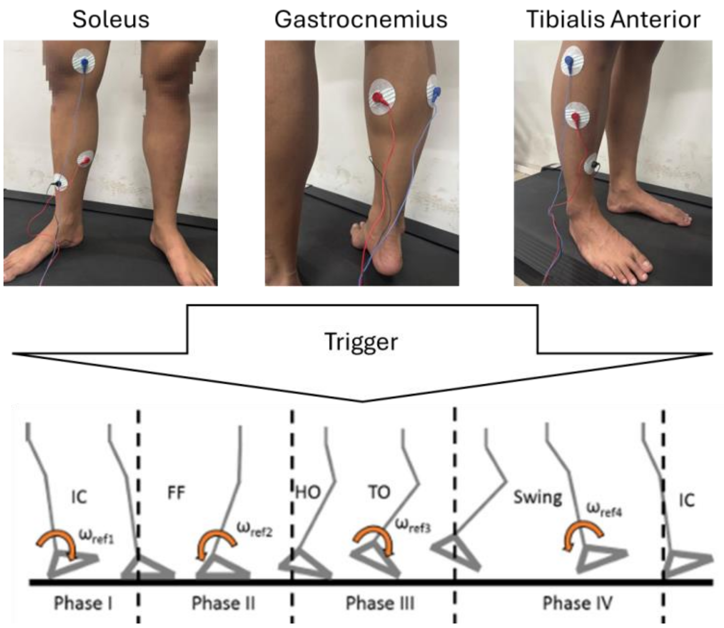


Figure 1. The goal of the research is to investigate contributing muscle to ankle movement in four gait phases

The setup is shown in Figure 2, which mainly consists of electromyography (EMG) sensors and foot insole sensors. The Grove EMG sensor is a one channel sensor that amplifies the difference between surface EMG of the muscle center and edge activation. Three electrodes are placed on muscle center, muscle edge, and bones (as reference). The location is based on recommendation from SENIAM guideline [20]. Before placing the electrodes, the skin is shaved to reduce the signal noise [21]. Here, the output is not only being amplified, but also being rectified. As a result, the sensor output is a signal that is always positive and readable unlike the raw EMG signal. This sensor features ease the muscle activity measurement for this research. Upon placing the sensor, the reading was checked by asking the subject to perform dorsiflexion and plantarflexion deliberately. If the signal is unreadable, then the placement is fixed until it is readable.

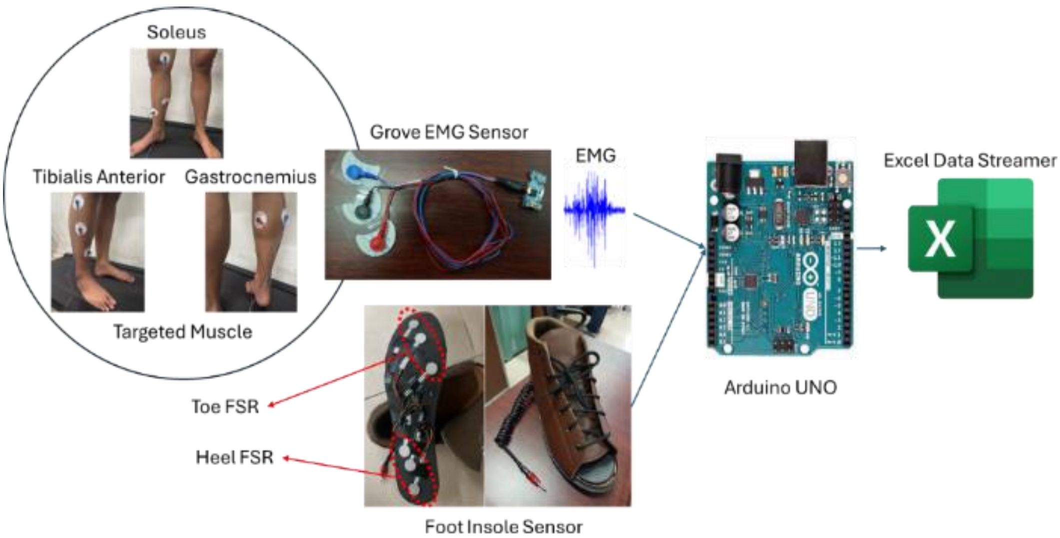


Figure 2. Contributing muscle measurements set up

The foot insole sensors build from force sensing resistors (FSR), which has its resistance lowered under pressure due to foot contact [22], [23]. Simple voltage divider circuit is used to enable voltage measurement using analog input of Arduino UNO. If the FSR resistance decreases, then the voltage on the 10k Ohm resistor will increase. This value is converted into digital value where voltage higher than 0.1 V is considered as true and false otherwise. The foot insole sensors are grouped into heel sensors and toe sensors. Three FSRs are arranged in parallel on the toe and another three FSRs on the heel in parallel configuration also. Using this configuration of foot insole sensors, the gait can be classified into four phases.

Four gait phases classification is not the only gait classification. Common classification models range from simple two-phase systems—stance (foot on the ground) and swing (foot off the ground) [24]—to more detailed six-phase models, which include sub-phases like initial swing, mid-swing, and terminal swing [25]. Three-phase models further refine stance phases into initial contact, mid-stance, and terminal stance [26], while five-phase models add loading response and pre-swing phases for greater granularity [27]. These classifications provide valuable insights into gait mechanics but often require complex methodologies, such as inertial sensors or machine learning, for precise detection [28].

A four-phase classification based on heel and toe contact offers a simplified yet effective alternative, particularly when using FSRs [22]. The phases include initial contact (heel strike), initiating plantarflexion; loading response (flat foot), marked by dorsiflexion as weight shifts forward; terminal stance (heel off), with plantarflexion for propulsion; and pre-swing (toe off), transitioning to dorsiflexion for ground clearance [29]. This model aligns with natural ankle motion patterns and is cost-effective and practical for real-time applications. It is especially suited for robotic rehabilitation devices, such as picobot, enabling synchronization with user intent and facilitating mobility assessments in clinical and research settings. Table 1. shows the four gait phases classification according to the heel and toe contact.

Table 1. Four gait phases classification according to foot contact

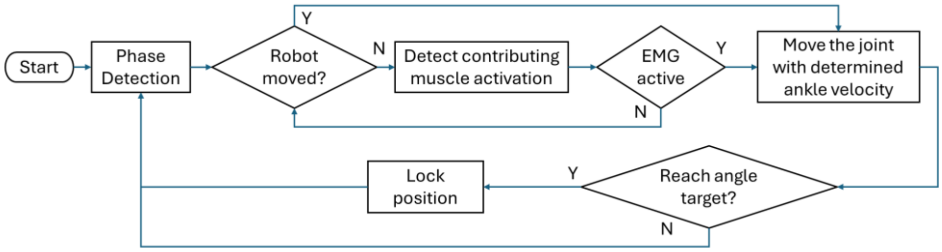
Phase	Heel contact	Toe contact
1	1	0
2	1	1
3	0	1
4	0	0

1, foot is in contact with ground;
0, foot is not in contact with ground

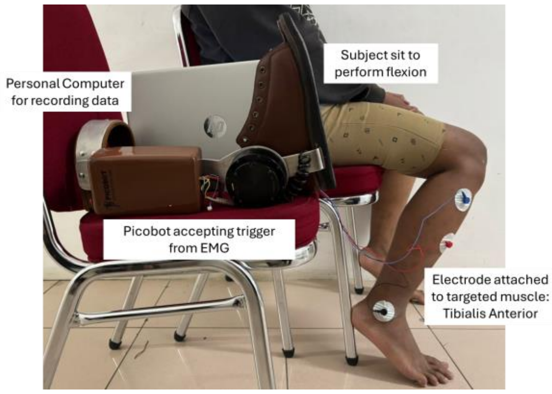
The research then recruits seven healthy young males, which is 21 years old without any gait impairment and muscle paralysis to participate in the study of contributing muscle investigation. There are three sessions of data collection. In each session the subject used the same data collection instrument, but different muscles are measured in each session. One muscle activity is measured at a time to reduce the possibility of noise due to jumbling cables from three channels of EMG. The subject had to walk on a treadmill to perform normal walking at their preferred speed. Initially, the starting speed was 2 km/H. If the subject feels discomfort and it causes them to walk differently than usual, then the treadmill speed can be increased or decreased accordingly. Walking differently might alter the EMG measurement. Therefore, the data collection is only started after the preferred speed is obtained and the patient can walk in their normal rhythm. Thirty steps data is collected in each session with sampling frequency of 1000 Hz, which are gait phase data and muscle activity data.

The collected data might have a difference in data length. This is mainly due to the walking characteristics that are not the same for all people. Even in one person, the step length and duration might differ from step to step. Because of this, the data is normalized from time-based data into cycle percentage-based data, as has been done by numerous research [30], [31] After that, the consistency of the data is checked by calculating the mean and standard deviation (σ) of data in each cycle percentage point. If the data standard deviation is high, then the data collection is repeated. Otherwise, the collected data is ready to be analyzed.

After obtaining the contributing muscle, the integration of the EMG to trigger flexion using picobot is the next step to prove the concept. The control algorithm is shown Figure 3(a). The robot detects the gait phase like usual but will not generate any flexion until the contributing muscle activity appears. When appears, the picobot follows the pre-determined flexion which is based on ankle velocity reference in each gait phase. If the ankle position reaches the maximum flexion target, then the ankle position is locked. But, if the ankle position has not reached the flexion target, then it is still moving according to the ankle velocity reference. For detecting the ankle position, picobot is equipped with a digital encoder embedded in the actuator, which is located at the ankle joint. For this proof of concept, the subject will perform plantarflexion under fixed gait phase 1, and the robot movement timing is observed, as shown in Figure 3(b). In this case, the targeted ankle position is -0.11 rad and ankle velocity is set to be -0.7 rad/s.



(a)



(b)

Figure 3. Picobot with motion trigger based on EMG proof of concept (a) control algorithm and (b) experiment set up

3. RESULTS AND DISCUSSION

The research discusses result of contributing muscle investigation and EMG trigger proof of concept on picobot. Firstly, the EMG data across 7 subjects are shown in Figure 4 – Figure 10. The data consistency is good with maximum variance $\sigma = 0.53$ for Soleus data on subject 3, $\sigma = 0.37$ for Tibialis data on subject 3 and $\sigma = 0.22$ for Gastrocnemius data on subject 1, as shown in Table 2. The participated subjects walk with preferred speed of 2.89 ± 0.19 km/h with step duration of 1.29 ± 0.15 s in average. Phase 1 spans 7.57% of the gait cycle and phase 2 took the second 41.29% of the gait cycle. After that, phase 3 took the 18.71% of the gait cycle while the rest of 32.43% is phase 4. This result is in line with typical gait cycle distribution of normal or healthy people, as also shown in previous study [30]

The baseline of EMG activation varies a bit between muscles within individual gait data, and even more varied across different individuals gait data, influencing muscle activation thresholds. For instance, in subject 2, the baseline voltage is 1.1 V for the soleus, 1.41 V for the tibialis, and 1.29 V for the gastrocnemius, highlighting the distinct starting points of electrical activity for each muscle. These baseline differences become even more pronounced when comparing individuals, as each person exhibits unique values due to various factors. One primary factor is slight inconsistencies in electrode placement, which can occur despite researchers adhering strictly to standardized positioning guidelines. Such variability underscores the need for individualized calibration when analyzing EMG data to ensure accurate interpretation of muscle activation levels.

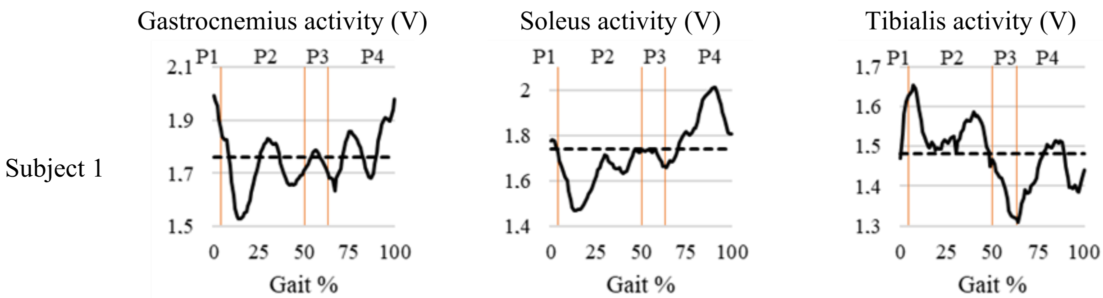


Figure 4. EMG measurement on subject 1 in one gait cycle

Subject 2

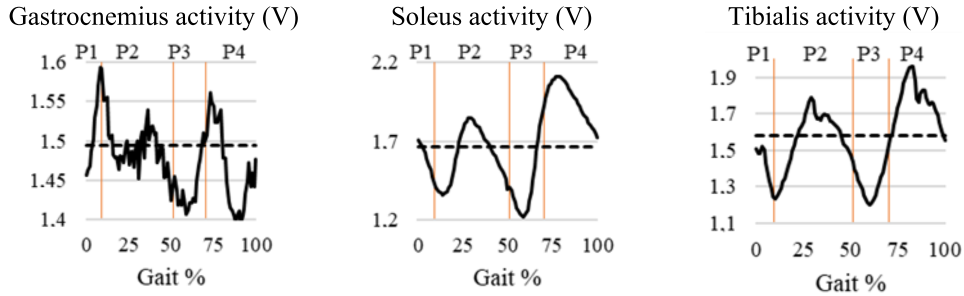


Figure 5. EMG measurement on subject 2 in one gait cycle

Subject 3

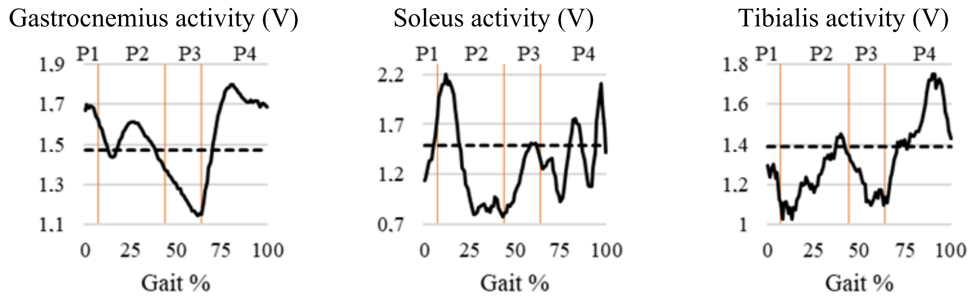


Figure 6. EMG measurement on subject 3 in one gait cycle

Subject 4

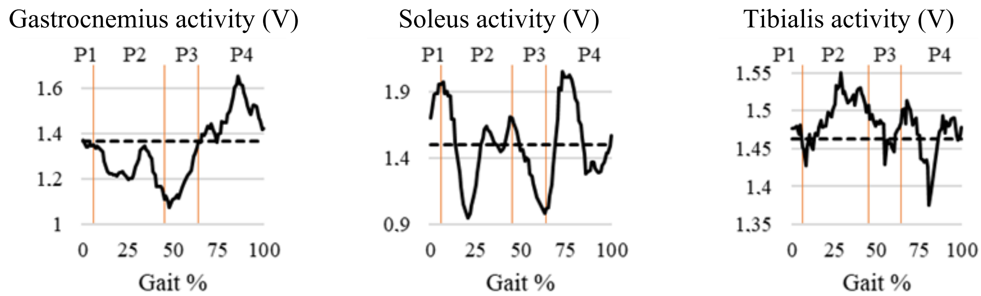


Figure 7. EMG measurement on subject 4 in one gait cycle

Subject 5

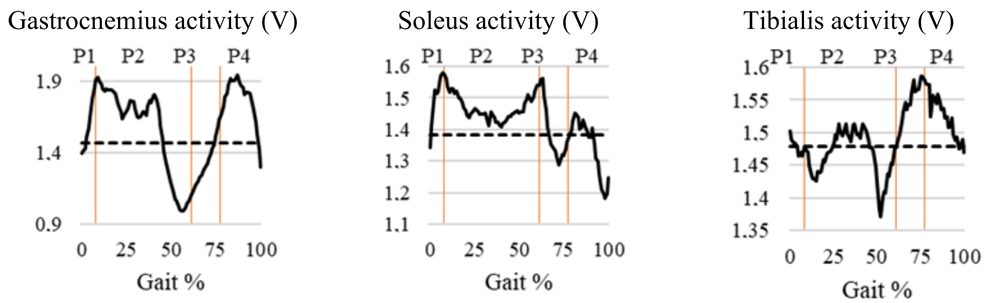


Figure 8. EMG measurement on subject 5 in one gait cycle

Adaptability in muscle activation thresholds is a significant challenge when designing and implementing assistive robotics for physiotherapy using EMG signal. However, this issue can be addressed through a quick calibration process conducted prior to using the robot. During the calibration, the patient is asked to remain in a relaxed state initially, allowing the system to record baseline muscle activation levels. Once the baseline is established, the patient is encouraged to attempt limb movement, which provides additional muscle activation data. This research uses 50% of the difference between peak muscle activation and the baseline as the activation threshold, as shown in Table 2. Establishing the threshold for muscle activity, ensuring the robot can distinguish between active and passive states effectively.

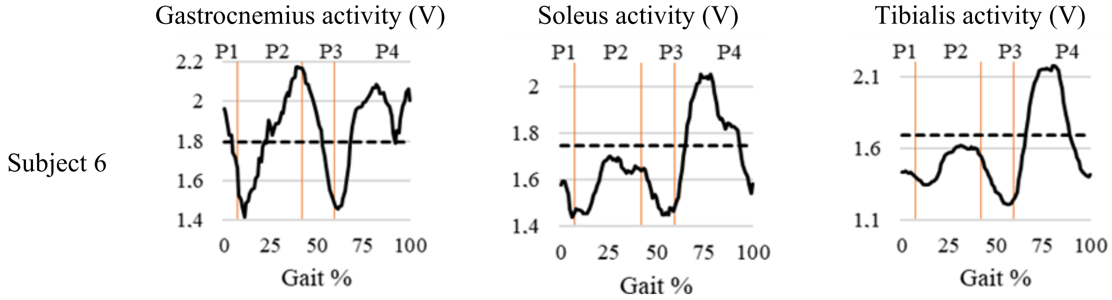


Figure 9. EMG measurement on subject 6 in one gait cycle

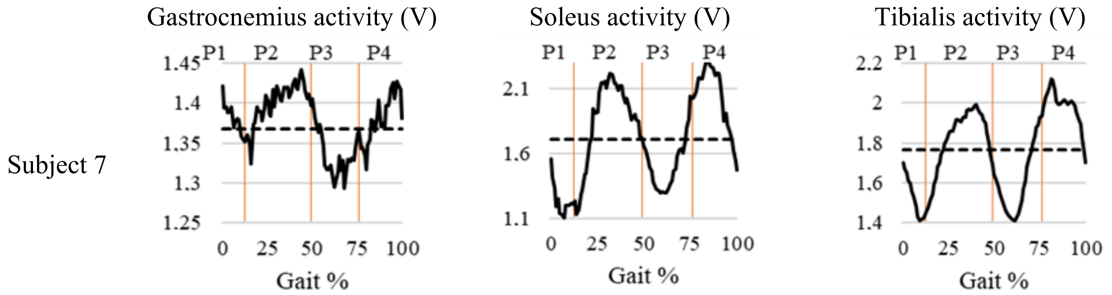


Figure 10. EMG measurement on subject 7 in one gait cycle

Table 2. EMG data across different healthy subjects

Parameter		Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Average
Gait phase %	Phase 1	4.00	9.00	7.00	6.00	8.00	7.00	12.00	7.57
	Phase 2	46.00	42.00	37.00	39.00	53.00	35.00	37.00	41.29
	Phase 3	13.00	19.00	20.00	19.00	16.00	17.00	27.00	18.71
	Phase 4	37.00	30.00	36.00	36.00	23.00	41.00	24.00	32.43
Step duration (s)		1.18	1.51	1.22	1.16	1.29	1.20	1.50	1.29
Walking speed (km/h)		2.80	2.70	3.20	3.00	2.80	3.00	2.70	2.89
Gastrocnemius	Max	1.99	1.59	1.80	1.65	1.94	2.18	1.44	1.80
Activation (V)	Min	1.53	1.39	1.15	1.08	0.99	1.41	1.29	1.26
	Range	0.46	0.20	0.65	0.58	0.95	0.76	0.15	0.54
	σ	0.22	0.15	0.12	0.19	0.22	0.18	0.12	0.20
	Threshold	1.76	1.49	1.47	1.36	1.46	1.79	1.37	1.53
Soleus	Max	2.01	2.11	2.20	2.05	1.58	2.05	2.31	2.04
Activation (V)	Min	1.47	1.22	0.77	0.95	1.18	1.44	1.10	1.16
	Range	0.54	0.89	1.43	1.10	0.40	0.61	1.21	0.88
	σ	0.28	0.16	0.53	0.39	0.21	0.13	0.17	0.29
	Threshold	1.74	1.66	1.48	1.50	1.38	1.75	1.71	1.60
Tibialis	Max	1.65	1.96	1.75	1.55	1.59	2.18	2.12	1.83
Anterior	Min	1.31	1.20	1.03	1.38	1.37	1.21	1.41	1.27
Activation (V)	Range	0.35	0.77	0.73	0.17	0.22	0.97	0.71	0.56
	σ	0.18	0.21	0.37	0.10	0.11	0.17	0.10	0.18
	Threshold	1.48	1.58	1.39	1.46	1.48	1.69	1.76	1.55

Highlighting the threshold value on each subject and each muscle, muscle activation on each phase can be observed. Across seven subjects, the gastrocnemius muscle is active during phase 1, 2, and 4, except on subjects 1 (always active), 6 (always active) and subject 4 (only active on phase 4). Meanwhile, the soleus is also similar, where it is mainly active on phase 1, 2, and 4. The activation on phase 1 especially is not significant, where only 4 out of 7 subjects that have soleus active on phase 1. However, the soleus significantly active on phase 2 and 4 out of the 7 subjects. Meanwhile, the tibialis activation is clearer, where it is dominantly active on phase 2 and 4. From this observation, it can be concluded that the muscles that are easier to observe are the tibialis anterior muscle to trigger picobot movement during phase 2 and 4.

Figure 11 illustrates the average EMG data across all subjects. The standard deviations for muscle activity among the seven subjects are σ = 0.20 for the Gastrocnemius, σ = 0.29 for the Soleus, and σ = 0.18 for the Tibialis. Muscle activation patterns show that the Gastrocnemius is active during phases 1, 2, and 3, the Soleus is active exclusively in phase 4, and the Tibialis is active in phases 2 and 4. Flexion activation in phases 2 and 4 can be effectively triggered by Tibialis muscle activity, while in phase 1, the Gastrocnemius serves as a reliable trigger signal. The Soleus is only active in phase 4 and its function overlaps with the Tibialis, so it can be considered as a trigger signal in phase 4. These findings align with conclusions drawn from both individual EMG observations and the average data. However, the results also emphasize the importance of individualized observation and calibration to accurately determine the appropriate trigger muscle.

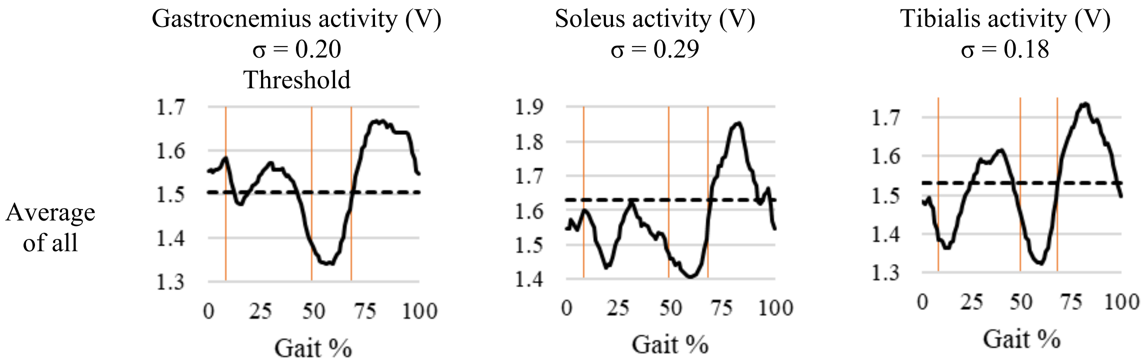


Figure 11. EMG measurement on average of all subjects in one gait cycle

The threshold of different groups of subjects presents an avenue for future research, particularly in understanding how variations in muscle activation thresholds can inform tailored rehabilitation strategies. During the setup process, these thresholds can be adjusted efficiently through a quick calibration between baseline and peak muscle activity, allowing for individualized parameter settings. Moreover, thresholds established for healthy subjects hold potential as benchmarks for recovery. They can serve as a reference point, enabling clinicians to evaluate a patient's progress by measuring their ability to approach or achieve these predefined levels. This approach not only provides a quantifiable recovery metric but also helps in setting realistic, personalized goals for rehabilitation. Future studies could explore these thresholds across diverse subject groups to refine their application in both healthy and patient populations, ultimately enhancing the precision and efficacy of therapeutic interventions.

Previous study on EMG reports that the muscles correspond to plantarflexion and dorsiflexion are Tibialis Anterior muscle, Soleus and Gastrocnemius [32]. Each muscle can perform both flexion and can work differently to each other. At some phase, the muscle works as the protagonist while the other works as the antagonist muscle. For instance, the Soleus and Gastrocnemius works dominantly as plantar flexor [33], while Tibialis muscle works dominantly as dorsiflexor [34]. The Tibialis Anterior is in the front of the lower leg and is responsible for lifting the foot (dorsiflexion), while the Soleus and Gastrocnemius, located in the calf, are responsible for pushing the foot downward (plantarflexion). These muscles exhibit antagonistic functions during gait, with the Tibialis Anterior active during dorsiflexion and the Soleus and Gastrocnemius taking over during plantarflexion.

Additionally, the precise timing of muscle activation is critical, as improper coordination between these muscles can result in inefficient or abnormal gait patterns. This interplay between agonist and antagonist muscles is essential for maintaining balance, avoid over extension and ensure smooth body weight transitions between gait phases. Finding regarding this on average muscle activation data is also shown in Figure 11. During phase 1, the tibialis muscle activation of 1.5 V, which is lower than Soleus activation of 1.6 V and Gastrocnemius activation of almost 1.6 V. Despite the dominant flexion is plantarflexion, the tibialis works almost the same magnitude due to holding the foot weight. The subject uses picobot shoes with FSR insoles during data collection which increases the foot weight, thus increasing the needs of antagonistic muscle to avoid over extension and slap foot in this phase [35]. However, the result does not portray muscle contribution in phase 3. In general, all muscles stay on its baseline. They are going up in magnitude and soleus is the highest among the others with a magnitude of 1.6 V at the end of phase 3. The main flexion is plantarflexion; therefore, it works harder compared to Tibialis muscle. If the threshold value is lowered, then the current muscle activation can be observed.

Meanwhile, in phase 2, the dominant muscle is Tibialis with a longer duration of peak above 1.6 V compared to Soleus and Gastrocnemius. This is in line with the Tibialis task to do dorsiflexion; thus, it really suits to be trigger muscle during phase 2. On phase 4 differently, the foot is lifted in the air. The main flexion is dorsiflexion so the ankle position can stay at a positive angle to prevent foot drop on the next phase 1. Therefore, Tibialis should be active higher, but the result shows that Soleus are active higher at the beginning, which is 1.85 V compared to Tibialis at 1.74 V. This is because at the beginning of phase 4, the foot is still in the process of pushing the ground, which is plantarflexion. However, soon after the ankle should dorsiflex rather than plantarflex, which explains the sharp decrease of Soleus muscle activity but not the Tibialis at the end of phase 4. However, since this research wants to find dominant muscle activity at the beginning to trigger the motion as soon as possible, Soleus is concluded as the dominant muscle at phase 4.

The results indicate that muscle activation does not occur immediately at the start of each gait phase. For example, Figure 10 shows that the Tibialis and Soleus muscles activate shortly after phase 2 begins, as the muscles engage only when needed. At the start of this phase, the body's forward momentum enables passive limb movement without immediate muscle contribution, allowing a brief rest period. This natural delay aligns with the robot's "assist-as-needed" design, which permits joint motion without initiating movement and provides support only when required. By adapting to the patient’s needs, the robot encourages natural movement patterns, reduces unnecessary exertion, and promotes active participation, enhancing recovery by compensating for deficits in muscle strength or activation.

The results have indicated that the contributing muscles are the Gastrocnemius in phase 1, the Soleus in phase 4, and the Tibialis in phase 2. In phase 3, lowering the threshold may allow Soleus to act as the trigger. Quick individual calibration is essential to determine accurate thresholds. The EMG-triggered picobot proof of concept, shown in Figure 12, targets the Tibialis Anterior of subject 2 for testing with 1.58V threshold in Table 2. When the muscle is inactive, the robot remains stationary despite gait phase detection. Once triggered, picobot maintains a constant ankle velocity, completing movements even if the EMG signal drops. For instance, the robot achieves plantarflexion at -0.11 rad during phase 1 at -0.62 rad/s, dorsiflexion at 0.3 rad during phase 2 at 0.49 rad/s, and maintains -1.5 rad/s and 4 rad/s in phases 3 and 4, respectively. This consistent velocity ensures full motion cycles, promoting stable gait patterns, enhanced muscle memory, and smoother rehabilitation while compensating for muscle weakness or signal loss.

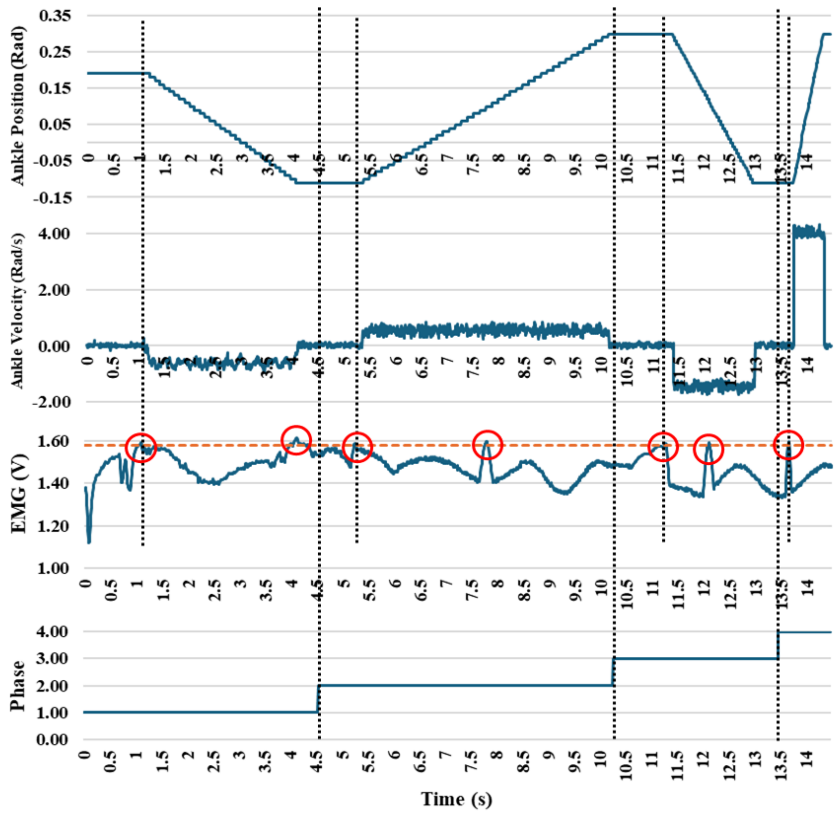


Figure 12. Picobot flexion on each gait phase is triggered by muscle activation of tibialis anterior muscle

To validate the effectiveness of this approach, testing patients in both lab and clinical settings is crucial. Lab trials will help refine the system's response to various muscle activation patterns, ensuring it accurately supports diverse patient needs. Clinical research will provide insights into how the robot impacts patient outcomes over longer rehabilitation periods, such as improved gait stability and muscle strength. Additionally, it will clarify how well the system adapts to varying levels of muscle control and signal inconsistencies commonly found in patients. This comprehensive testing will ensure the robot meets the practical demands of real-world rehabilitation and maximizes patient recovery potential.

4. CONCLUSION

This research concludes that Tibialis, Gastrocnemius and Soleus are contributing to the whole gait cycle. In phase 1, the contributing muscle is Gastrocnemius muscle. In phase 2, the contributing muscle is Tibialis muscle. In phase 3, if the threshold is lowered than the one used in this study, then Soleus is the contributing muscle. In phase 4, the dominant muscle is Soleus. Despite the antagonistic nature of these muscles in their respective gait phases, where the Soleus and Gastrocnemius typically act as a plantar flexor and the Tibialis as a dorsiflexor, their coordinated activity may still suit patients using assistive devices. Since the data was collected using picobot shoes with an FSR insole, it reflects the real-world dynamics of walking with robotic assistance to facilitate more stable and controlled movements in patients with compromised gait function. The EMG trigger proof of concept also shows that the picobot can maintain constant motion once triggered and can complete the movement even if the EMG signal is lost during the process. This consistency is expected to help patients develop stable gait patterns, especially in the early stages of rehabilitation. The groundwork has been laid, but future research should validate this approach's effectiveness and test it with patients in both lab and clinical settings is crucial.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
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Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and has been approved by ethics committee from Husada Utama Hospital under ethics declaration number: 16/KEP-RSHU/IV/2025.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, Dimas Adiputra. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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