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Probability-Based Rejection of Decoding Output Improves the Accuracy of Locomotion Detection During Gait*

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***Abstract*— Prosthetic users need reliable control over their assistive devices to regain autonomy and independence, particularly for locomotion tasks. Despite the potential for myoelectric signals to reflect the users' intentions more accurately than external sensors, current motorized prosthetic legs fail to utilize these signals, thus hindering natural control. A reason for this challenge could be the insufficient accuracy of locomotion detection when using muscle signals in activities outside the laboratory, which may be due to factors such as suboptimal signal recording conditions or inaccurate control algorithms.**

This study aims to improve the accuracy of detecting locomotion during gait by utilizing classification post-processing techniques such as Linear Discriminant Analysis with rejection thresholds. We utilized a pre-recorded dataset of electromyography, inertial measurement unit sensor, and pressure sensor recordings from 21 able-bodied participants to evaluate our approach. The data was recorded while participants were ambulating between various surfaces, including level ground walking, stairs, and ramps. The results of this study show an average improvement of 3% in accuracy in comparison with using no post-processing (p-value < 0.05). Participants with lower classification accuracy profited more from the algorithm and showed greater improvement, up to 8% in certain cases. This research highlights the potential of classification post-processing methods to enhance the accuracy of locomotion detection for improved prosthetic control algorithms when using electromyogram signals.

***Clinical Relevance*— Decoding of locomotion intent can be improved using post-processing techniques thus resulting in a more reliable control of lower limb prostheses.**

I. INTRODUCTION

Lower limb amputation is the most common type of limb loss [1]. By 2050, it is estimated that around 2.2 million people in the USA will be living with a lower limb amputation [1]. The major need of this patient population will be a prosthetic limb that they can rely on to be independent, and that enables natural movement with reliable control [2]. Currently, there is no commercial leg prosthesis that can be controlled naturally using signals from the remaining muscles [3]. One reason for this may be the insufficient accuracy and reliability of locomotion decoding algorithms outside the laboratory [3,4]. Tools to develop more accurate and reliable algorithms for detecting different locomotion modes during gait would therefore contribute to more functional leg prostheses.

There are several research groups around the world that are working toward better control strategies for lower limb prostheses using electromyography signals (EMG) [3,4]. These algorithms can perform adequately in laboratory setups or in controlled settings outside the laboratory, but they may have flaws that result in insufficient accuracy in daily life.

Not having locomotion detection is preferred over having an inaccurate detection.

In common classification methods such as Linear Discriminant Analysis (LDA) [5], there are no further steps after classification to evaluate the reliability of the output. Post-processing methods can greatly enhance the accuracy of classification algorithms through various means. One widely used approach is the majority vote technique, which involves taking the most common output out of multiple windows. This method can effectively reduce the impact of spurious misclassifications and enhance the overall performance of the algorithm [6,7].

Another post-processing method involves rejecting data that may negatively impact the classification accuracy. For example, in the case of EMG data, a distorted channel may be rejected to improve the overall accuracy. Similarly, rejecting weak predictions (low confidence) can add an extra layer of precaution against misclassifications, although this approach may also result in the rejection of valid data [8–10].

In upper limb studies, there is more research on different methods of rejection-based post-processing [11,12]. Scheme *et.al.* used a rejection method with LDA and Fits law test [13,14] that calculates the posterior probability of the classification (confidence) of each window and only make a decision if it is higher than a certain threshold, rejecting the classification otherwise. This method showed promising and improved results in the Fits law test. There is yet no demonstration of this method of post-processing in locomotion detection during gait.

In this study, we implemented LDA with rejection-based post-processing on an open-access database of EMG, IMU, and pressure sensor of 21 able-bodied participants to further improve the reliability and accuracy of locomotion detection algorithms.

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II. METHOD

In this research, we employed the LocoD dataset, an open-source dataset that consists of EMG, IMU, and pressure sensor data recorded from 21 able-bodied subjects while they were ambulating between different terrains (level ground, ramps, and stairs). The data were recorded while participants were walking in a circuit of ramp ascent, level ground walking, stair descent, stair ascent, and ramp descent (5 locomotion modes) for around 30 repetitions. The data were recorded from 8 EMG channels, 3 IMU channels (each channel has 3 accelerometers and 3 gyroscopes), and one pressure sensor. EMG signals were collected from the biceps femoris long head and short head, tensor fasciae latae, semitendinosus, vastus lateralis, rectus femoris, vastus medialis, and gracilis muscles. IMUs were placed on the foot, below the knee, and above the knee. A pressure sensor was built into a shoe insole for each research participant [15].

We utilized LocoD, an open-source software platform, to effectively process and decode our data [16]. Our method involved four-steps, including signal pre-processing, feature extraction, classification and validation, and classification post-processing. To ensure optimal results, we employed LocoD's default processing methods for the initial three steps of the process. Additionally, the open-source nature of the software allowed us to incorporate a final post-processing step.

In the signal pre-processing phase, raw data were filtered. At each heel contact and toe-off 300 milliseconds of data extracted ad then divided into 200 milliseconds windows with 30 milliseconds increment. From each signal window of EMG, four features are extracted: mean absolute value, waveform length, number of zero crossings, and slope sign change, whereas, from each IMU and pressure sensor channel window, we extract mean, maximum, minimum, and standard deviation features, resulting in a total of 108 features.

The extracted features were passed to an LDA classifier with mode-specific and phase-dependent characteristics. Phase-dependent means that classification takes place on two occasions: during heel contact and toe-off. Mode-specific means that we have more than one classifier, an array of LDA classifiers that are used based on the previous locomotion mode. For example, if the previous mode is stair ascent, we choose the stair ascent classifier, and the possible prediction of this classifier can be remaining in stair ascent or transitioning to level ground walking. This trend is the same for all the locomotion modes except for walking where the possible outcome can be to remain in walking mode or transitioning to any other locomotion modes [17].

We used an LDA classifier with 10-fold cross-validation. LDA classification is based on the Bayes theorem. If we have K classes and an input feature vector x, we classify to predict which class X belongs to, with the highest probability $P(Y = i|X)$.

The Bayes theorem is as follows:

$$(Y|X) = \frac{P(X|Y)P(Y)}{P(X)} \tag{1}$$

This indicates the probability of X belonging to one of the K classes is related to the probability of input taking on the value of X in each class. Also, we should note that $P(X|Y)$ is a probability density that shows the probability of input X in each class. We assume this has a normal distribution.

P(Y) is the prior probability of class k, and P(X) is a normalization constant, namely, the sum over k of P(X|Y) P(Y).

Conventional LDA chooses the class that maximizes the posterior probability of belonging X to a class. In our method, we calculate the posterior probability and in addition to choosing the class that has the maximum posterior probability, we check if the probability is higher than a certain threshold. If so, the signal window belongs to the class with the highest probability. However, if the probability fails to be higher than the threshold, no prediction will be made for that window.

$$Prediction = \begin{cases} Y, & P(Y|X) > Threshold \\ Reject, & Otherwise. \end{cases} \tag{2}$$

We experimented with different threshold values between 0.65 and 0.989, with 0.989 being the highest threshold we could use before reaching 100% rejection. The outcome measure of the algorithm is defined as the classification accuracy of different locomotion modes under two conditions: steady-state and transition. Steady-state accuracy is defined as the percentage of windows correctly classified when there was no transition, while transitional accuracy is defined as the percentage of windows accurately classified from one locomotion mode to another (e.g., transition from walking to stair ascent).

To measure the effectiveness of our post-processing technique, we calculated the difference between the classification accuracy achieved with and without post-processing for each threshold value and the number of rejected windows at each threshold. To compare the accuracy of classification between the two conditions, we performed a nonparametric paired t-test on 21 participants. This approach enables us to fine-tune the trade-off between the number of rejected windows and classification accuracy, to achieve a more robust and reliable control for lower limb prosthetics.

III. RESULT

To find the effect of post-processing on the locomotion detection accuracy, we calculated the locomotion detection accuracy for 21 participants with and without post-processing, under two conditions: 1) steady-state (no change in locomotion mode), 2) transition (change in locomotion mode). To demonstrate the results, we averaged the accuracy of locomotion detection in steady-state and transition mode for each participant.

We illustrate the percentage of rejected windows in relation to the rejection threshold (ranging from 0.65 to 0.989) in Figure 1. We also illustrate the difference in locomotion detection accuracy with and without post-processing in relation to the rejection threshold in Figure 2, as well as presenting the locomotion detection error for each participant with and without post-processing in Figure 3.

Statistical analysis of the data revealed that post-processing significantly increases the accuracy of locomotion detection (p-value < 0.05) for all the thresholds.

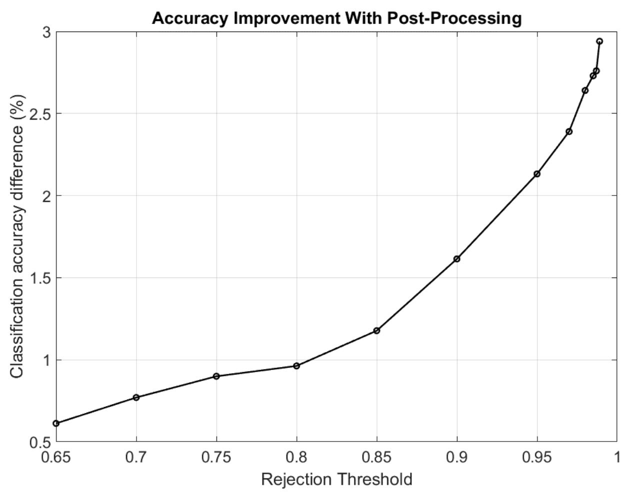

Figure 1 The grand average of classification accuracy difference with and without rejection-based classification post-processing is plotted across different rejection threshold values, ranging from 0.65 to 0.989. The grand average is calculated for each threshold value within this range

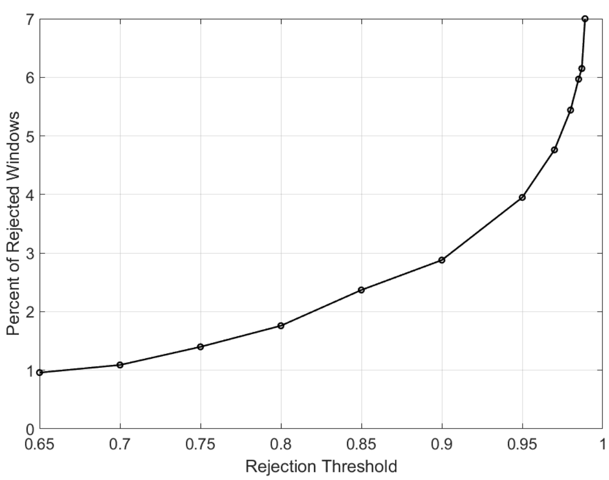

Figure 2 . The x-axis represents the rejection threshold, which is a predefined value used to determine whether a window should be rejected or accepted. The rejection threshold can take any value within the range of 0.65 to 0.989. The grand average of the proportion of rejected windows is calculated for each threshold value within this range.

IV. Discussion

The results of our study demonstrate that rejection based post-processing can significantly enhance the accuracy of locomotion detection in lower limb prosthetics control algorithms (see Figure 1). This finding is consistent with previous research on upper limb control in which it was suggested that using rejection-based post-processing will enhance classification and thus control [13,14]. Also, it is in-line with the studies that showed that performing classification post-processing in locomotion detection tasks will lead to higher accuracy of detection [6,7].

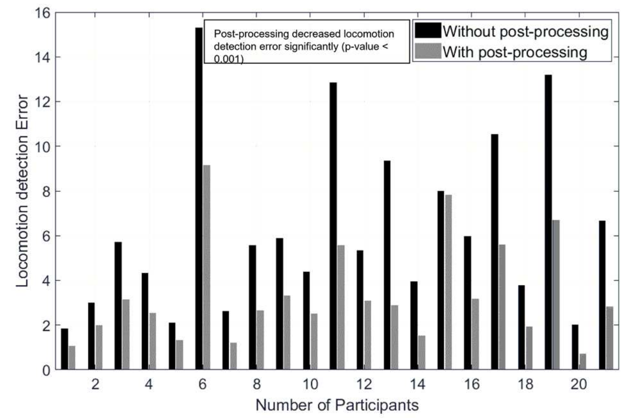

Figure 3 The locomotion detection error for 21 participants is illustrated on this graph, with the data for both transition and steady-state phases being averaged together. The graph compares the locomotion detection error in two conditions: 1) when there was no rejection-based classification post-processing applied, and 2) when there was rejection-based classification post-processing applied with a threshold of 0.989. This comparison allows us to evaluate the impact of the post-processing technique on the accuracy of locomotion detection

One of the key advantages of this post-processing technique is its simplicity, making it easy to implement and understand. Unlike other methods, like majority vote that add delays, this method is faster in response.

Our study also found that participants with lower accuracy scores may benefit more from this method than others (see Figure 3). This finding is important because it suggests that this technique could be particularly beneficial for individuals who encounter challenges with traditional methods. However, it's important to bear in mind that this method can only provide benefits if the low accuracy is due to poor EMG signals. Furthermore, as per Figure 2, the highest rejection rate is only 7%, which is minimal and will not significantly impact the amount of available data. This means we can expect a steady flow of real-time information.

Although our study has shown promising results regarding the potential of post-processing methods to enhance the accuracy of lower limb prosthetics control algorithms, it is important to consider some limitations. For instance, the study was conducted offline, which limits our ability to assess the algorithm's real-time performance [18]. Additionally, it would be valuable to test the algorithm on people with amputation, who have a different muscle structure than able-bodied individuals.

Further research is needed to evaluate the full benefit of this method in real-time situations and to test its implementation with other classifiers such as Support Vector Machine. These considerations should be kept in mind when interpreting the results and when designing future studies.

V. CONCLUSION

In this study, we propose a novel post-processing technique for enhancing the accuracy of locomotion detection during gait. Our method has the potential to be integrated into control algorithms for lower limb prosthetics and is yet to be fully explored for this purpose.

By incorporating a rejection-based approach in our post-processing technique, we achieve significantly improved classification results, resulting in less misclassification in locomotion detection. This makes the control algorithms more reliable for users, near 100% accuracy for locomotion detection is important to avoid falls and injury. Our study showed that the algorithm was particularly effective for participants with lower scores of locomotion detection accuracy, resulting in substantial improvements in their results compared to other participants.

Our findings demonstrate that this simple post-processing technique brings us closer to using EMG signals as input for prosthetic legs, holding potential for laboratory settings and as a take-home device to improve the quality of life for lower limb amputees. As a next step, this method can be implemented in real-time to enhance the control of prosthetic legs, allowing users to walk more naturally and efficiently.

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