Al-Khwarizmi Engineering Journal
ISSN (printed): 1818 – 1171, ISSN (online): 2312 – 0789
Vol. 20, No. 2, June, (2024), P P. 86- 93

Al-Khwarizmi Engineering Journal

Enhanced Gait Phases Recognition by EMG and Kinematics Information Fusion and a Minimal Recording Setup

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(Received 6 May 2024; Accepted 27 May 2024; Published 1 June 2024)
https://doi.org/10.22153/kej.2024.05.002

Abstract

The limited mobility of lower limb amputees highlights the need for advancements in prosthetic control strategies to restore natural locomotion. This paper proposes an information fusion approach for gait phase recognition using surface electromyography (sEMG) and kinematics data. Time-domain (TD) features were extracted from the myoelectric data and three data-driven models, specifically Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Artificial Neural Network (ANN), were compared in three different input conditions i.e. sEMG features, hip angle, and their fusion. Gait phase estimation results averaged from 40 healthy participants during normal walking with 10 strides per each demonstrated that the proposed fusion approach has consistently outperformed *($p<0.0001$)* the other two conditions achieving a maximum accuracy of 85.48% with SVM. The findings suggest promising applications in prosthetic motion control and rehabilitative exoskeletons, highlighting the potential for improved user-driven strategies in lower limb prostheses.

***Keywords**: sEMG, Kinematics; SVM, prosthetic control; gait; Information fusion*

1. Introduction

Lower limb amputation is a widespread concern globally, affecting millions of individuals, especially those with transfemoral (TF) amputations [1]–[3]. Diabetes, vascular diseases, and injuries are the principle causes of such amputations [2]. Passive prostheses were initially used to compensate for the limb function loss but they imposed limitations on walking symmetry and metabolic cost [4], [5]. Therefore, literature underlined the necessity for improving user-driven control strategies in lower limb prostheses, to allow amputees to regain their natural locomotion abilities [1], [3], [6], [7]. Surface electromyography (sEMG) and mechanical signals serve as the main sources of information for the high-level control of prostheses and exoskeletons [4], [8]. Mechanical signals are deterministic signals that appear as a result of the motion, while the myoelectric activity has a stochastic nature and precedes the occurrence of the motion, thus reflecting the user intention [3], [9]–[12]. Although previous studies have employed either one of these signals [3], [6], [13]–[15] recent literature indicates that enhanced motion prediction performance can be achieved through the fusion of myoelectric and mechanical information [9], [16]. Such an approach leverages the predictive nature of sEMG signals and the stability offered by the mechanical information for an improved decision output [9], [11], [16]. The decoding of motion from the relevant biosignals can be broadly categorized into physical-based models and data-driven approaches [3], [8]. In the former, complex physical relationships must be explicitly expressed, and subject-specific parameters optimization is required, thus imposing limitations on running latency and tolerable complexity for real-time applications [8], [12], [17].

The data-driven approaches are further sub-categorized into two main classes: pattern recognition and regression [3], [8]. In pattern recognition, also known as classification, the decoded motor tasks are divided into a finite number of clusters of pre-planned trajectories [6], [8]. Although it's burdened by the incapability to generalize to unseen motor tasks, this approach was largely employed by previous studies, due to its promising performances [9], [18]. On the other hand, regression approaches involve direct decoding of the signal information into continuous output variables, thus being more adaptive to different contexts, providing higher autonomy to the user [8], [18]. This approach remains challenging in a practical context, due to the high non-linearity between the myoelectric information and the targeted joint angle or torque that limits the prediction accuracy [8]. Walking is a cyclic motor task constituted of sequential gait events, each of them characterized by a specific motor program, involving coordinated muscular activity aimed to flex or extend specific joints during a gait cycle [19], [20]. This suggests that dividing the gait cycle into several phases and leveraging sEMG information to infer them could achieve high prediction performance that allows for natural motion patterns and seamless transition between subphases of walking [4], [19].

In this context, Luo et al. [19] have fed a long short-term memory (LSTM) deep learning model with 4 thigh muscles sEMG signals to estimate 4 subphases of the gait cycle, providing an average accuracy of around 90% during treadmill-constrained speed walking. Although high accuracy is attained, the estimation performance could be reduced in an uncontrolled context such as normal walking due to the constraints imposed on muscle activations in the treadmill case [21]. In [22], support vector (SVM) the model was employed to predict 5 gait subphases using 3 IMU data acquired from the thigh, shank, and foot with a classification accuracy of about 90%. Although the promising classification performance, it lacks the applicability on TF amputees, since it utilizes sensors attached below the knee. Furthermore, Mobarak et al. [16] have recently shown that fusing hip joint flexion-extension angle with thigh myoelectric information provides consistent improvement in ankle position control through a regression approach. These studies lack the investigation of neuromechanical information fusion acquired exclusively from the proximal part of the lower limbs in gait phase recognition during normal walking and using shallow models. Therefore, the two main hypotheses investigated in this study are as follows:

- Thigh muscle's myoelectric activity carries sufficient information to infer gait phases using data-driven algorithms during unconstrained walking.
- The fusion of the hip joint angle in the sagittal plane with the sEMG signals could significantly boost the estimation accuracy.

In this study, conventional time domain (TD) features were extracted from the thigh sEMG due to their robustness and real-time applicability [25]. Three data-driven models widely adopted in literature were employed to predict the gait phases including K-Nearest Neighbours (KNN) [3], SVM [22], and Artificial Neural Network (ANN) [9].

2. Materials and Methods

A. Data description

The data used in this study is a publicly available dataset acquired at Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences [23], in which 9 sEMG signals of the lower limbs muscles of 40 healthy participants (30 males and 10 females) with an average age of 24.5 years were acquired at 1920 Hz. Raw markers data and ground reaction force were also recorded using motion capture system sampling at 60 Hz and force platforms at 1920 Hz respectively. The markers data was upsampled to match the force data and were used to compute joint kinematics and kinetics [23]. In the experimental protocol of their dataset, several lower limb motor tasks were performed by the subjects. What is of concern in this study is the normal walking task, which includes 10 walking trials from each subject acquired separately [23]. The kinematics and kinetics information was then used to segment the gait cycle into 5 subphases that lie between the following 6 consecutive gait events: heel-strike (HS), maximum knee stance flexion (MSF), maximum knee stance extension (MSE), toe-off (TO), maximum knee swing flexion (MWF), and the next cycle HS as in Fig. 1 [23]. In this study, only the hip joint flexion-extension angle and 4 sEMG signal of the thigh muscles were considered since they mainly focused on gait phase pattern recognition using the minimal amount of information acquired from the proximal part of the lower limb. These thigh muscles are tensor fascia lata (TFL), rectus femoris (RF), vastus medialis (VM), and semimembranosus (SM), which have different roles during the stance and swing phases [19].

A. Preprocessing and feature extraction

Butterworth fourth-order bandpass filter between 10 Hz and 400 Hz cutoff frequencies was employed to remove the noise from the myoelectric signals. TD features including root mean square (RMS), mean absolute value (MAV), and waveform length (WL) were extracted from the sEMG signal windows that were segmented with a length of 150 samples and sliding increment of 40 samples. The hip joint angle and gait phase label were both downsampled by a factor of 40 to match the final update rate of 48 Hz which is very suitable for real-time purposes [24]. The TD features were considered due to their light computational cost and suitability for real-time applications [25]. Both the hip joint angle and the extracted features were normalized using Z-score normalization, as in Eq. (1):

$$\Omega_n = \frac{\Omega - \mu}{\sigma} \quad \dots (1)$$

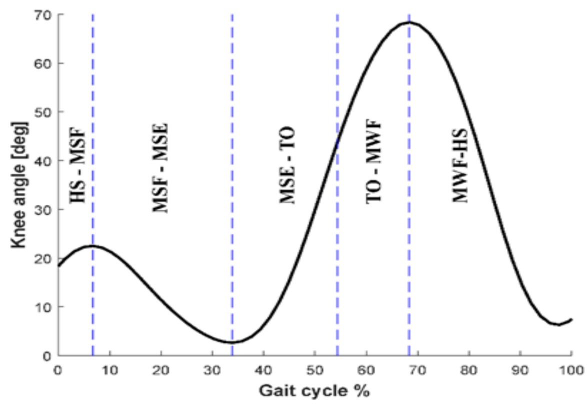

Fig. 1. The black curve represents a plot of the knee flexion-extension angle during a single gait cycle with the vertical blue dashed bars indicating the main gait events separating the subphases written on the plot.

where Ω_n and Ω are respectively the normalized and non-normalized feature, μ is the mean of the corresponding feature data from the training sets, and σ is its standard deviation. Training and testing hip joint angle and myoelectric features data were normalized using the mean and standard deviation calculated from the training set. A flowchart of the experimental procedure is reported in Fig. 2

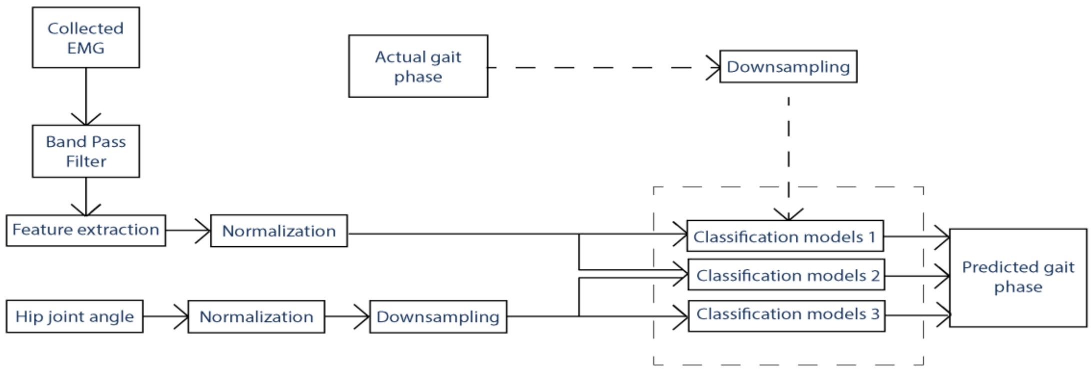

Fig. 2. This diagram illustrates the methodology path implemented in this paper. TD features were extracted from the filtered sEMG signals and fed to the selected learning models for estimating the gait phases. The hip angle was also fed to the pattern recognition models as well, as a fused feature space of the hip angle and the extracted myoelectric activity in the last experiment. Actual gait phases as indicated by the dashed line were fed to the models only in training.

B. Pattern recognition models and experiments

Three learning models were employed to evaluate their capability to predict the gait phase during walking. KNN with K=5 and SVM model with radial basis function (RBF) kernel were applied to leverage its capabilities to capture the nonlinearities between the myoelectric information and the lower limb mechanical status [8]. In addition, a shallow artificial neural network (ANN), composed of a single layer of 50 neurons, was also bench-marked against SVM.

Given the experimental data structure, a 5-fold cross-validation scheme was employed for each subject, in which 80% is allocated for training and the remaining 20% is for testing to eliminate any potential overfitting of the implemented models [16]. Firstly, two separate pattern recognition experiments were performed to evaluate the capability of the selected models to utilize the information carried solely either by the sEMG features of the thigh muscles or by the hip joint angle. Furthermore, a last classification experiment was done to assess if fusing both the myoelectric and kinematic information can improve the estimation performance as done in [16] for the ankle angle regression task.

C. Evaluation metrics and statistics

The confusion matrix was also computed to locally visualize the models' performance in each phase of the gait cycle. It's expressed as follows:

$$Confusion\ matrix = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{15} \\ x_{21} & x_{22} & \cdots & x_{25} \\ \vdots & \vdots & \ddots & \vdots \\ x_{51} & x_{52} & \cdots & x_{55} \end{bmatrix} \quad \text{... (2)}$$

$$x_{ij} = \frac{N_{ij}}{N_i} \times 100\% \quad \text{... (3)}$$

where $\boldsymbol{N_i}$ is the number of instances with actual class $\boldsymbol{i}$ while $\boldsymbol{N_{ij}}$ is the number of instances predicted as class $\boldsymbol{j}$ and belong to the actual class $\boldsymbol{i}$. Furthermore, for the overall evaluation of the pattern recognition experiments, three metrics were computed from each testing trial, i.e. accuracy, precision, and recall. The accuracy represents the number of correctly predicted samples from the entire classification decisions and is expressed in the following formula:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad \text{... (4)}$$

where $\mathbf{TP}$, $\mathbf{TN}$, $\mathbf{FP}$, $\mathbf{and\ FN}$ are the number of true positives, true negatives, false positives, and false negatives respectively. The precision and recall were computed to eliminate any misinterpretation that could be made by the accuracy due to class distribution imbalance especially since phases of gait have different durations. These are computed as follows:

$$Precision = \frac{TP}{TP + FP} \quad \text{... (5)}$$

$$Recall = \frac{TP}{FN + TP} \quad \text{... (6)}$$

Mann-Whitney U-test was performed to assess the statistical significance of the achieved results to since it’s insensitive to data distribution. The significance level was set to 0.05, and Bonferroni correction for multiple comparisons was applied to handle error rates of type I. A $\boldsymbol{post-hoc}$ statistical power analysis has confirmed the validity of results given the number of participating subjects with 100% statistical power.

3. Results

The three learning models (KNN, ANN, and SVM respectively) provided the lowest accuracy in the case of considering only the sEMG features as input, with a classification accuracy of around 63% (Fig. 3). The performance was improved when considering the hip angle time series as input to reach around 70% (Fig. 3). However, a significant boost of the classification accuracy *(p < 0.0001)* was observed in the case of fusing the two input modalities for all the three models, reaching a maximum value of 85.48% when SVM was employed (Fig. 3). In terms of different models performances, ANN and KNN have shown comparable accuracy, while SVM has demonstrated slightly higher performances in all the three input conditions.

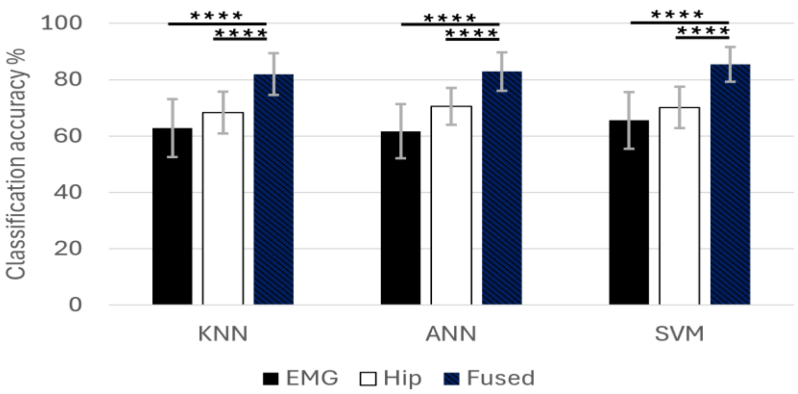

Fig. 3. Classification accuracy of the three classification models in the three different input conditions. The error bars indicate the standard deviations around the average accuracy. The asterisks ** refer to the significance threshold *(p < 0.0001)***

The enhanced performances of fusing the hip angle and myoelectric data were further confirmed by the precision and recall values, as shown in Table 1, where both metrics have reached up to 80%. However, the precision shows that the SVM performance is not superior concerning the KNN and ANN in case of considering only the hip angle as input, and it drops to 48.27%, in contrast to what has been shown by the accuracy. In addition, both the precision and recall also contradict the accuracy. Indeed, considering only the latter shows that the performances of the 3 models in case of considering only the myoelectric data as input are not lower than those purely driven by hip kinematics. This was further confirmed by the confusion matrix (Fig. 4(b)), where the SVM fed with hip angle mislabeled 91.51% of the actual TO-MWF phase as MSF-MSE and 75.75% of the actual HS-MSF phase as MWF-TO. These phases' extreme underestimations were not observed in the case of using only sEMG, as shown by Fig. 4(a), where the off-diagonal terms have very low values. Furthermore, the confusion matrix of the SVM with fused input (Fig. 4(c)) confirmed its boosted performances, as shown by the high classification accuracy that lies on the diagonal.

Table 1,
Precision and Recall values of the three models in three different input conditions.

	Precision (%)			**Recall (%)**		
	EMG	**Hip**	**Fused**	**EMG**	**Hip**	**Fused**
KNN	59.66	60.66	78.09	59.06	59.88	78.03
ANN	57.72	56.94	78.25	57.23	59.28	78.89
SVM	61.75	48.27	81.02	60.66	56.58	81.31

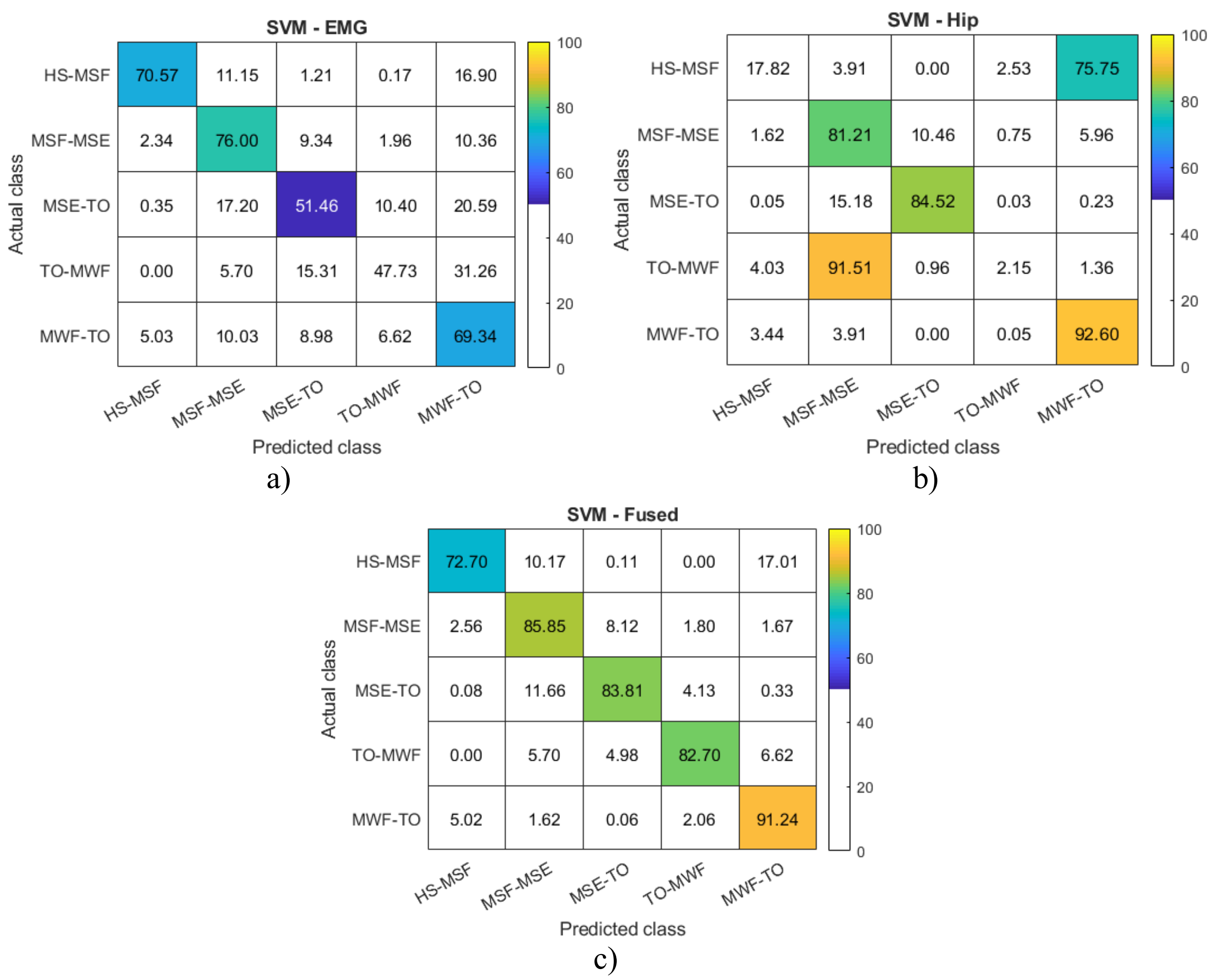

Fig. 4. Panels (a), (b), and (c) are the confusion matrices for the SVM model when fed by sEMG, hip angle, and fused condition respectively. The SVM is considered here due to its superior performance. A heat map was used for accuracies between 50% and 100% for better visualization.

4. Discussion

This paper aims to exploit the possibility of predicting the gait phases during unconstrained walking using a minimal amount of myoelectric and kinematics information acquired exclusively from above the knee. This assessment extends the ankle angle regression approach proposed in [16] for pattern recognition, being potentially applicable for TF amputees. Further, it could be suitable for different actuation needs and approaches, due to the inclusion of five subphases of the gait cycle, as in [22].

In particular, Fig. 3 and Table 1 show that fusing the hip angle with thigh myoelectric information provides consistent improvements *(p < 0.0001)* concerning using either one of these modalities separately in all the models, aligning with [16]. This improvement confirms that both signals carry complementary information for the estimation of the gait phases [11]. This finding is further validated by observing the confusion matrix (Fig. 4(c)), where fused data information fed to the SVM has demonstrated consistent high classification accuracy for the majority of gait phases. However, the lowest performance occurred for the HS-MSF phase, which could be attributed to the similar activation profile adopted by SM, RF, and VM muscles at the beginning and the end of the gait cycle, as well as the similar hip joint angle values, since it’s in flexed position in the corresponding periods [26]. This is supported by the fact that 16.9%, 75.75%, and 17.01% of the actual first phase, i.e., HS-MSF, were misclassified as the last phase (MWF-TO) in the case of SVM fed with myoelectric data, hip data, and fused data respectively (Fig. 4). This suggests to look towards information sources that could behave distinctly solely at the beginning of the gait cycle.

Furthermore, regarding the comparison between the models' performance in the case of using either sEMG features or hip angle alone, the higher classification accuracy of the hip-based models indicated in Fig. 3 could be misleading due to the class samples imbalance in the task of gait phase recognition because of the different durations of each subphase (Fig. 1). This can be observed in their comparable performances shown by the precision and recall values (Table 1), with superiority for the myoelectric information in case of SVM, at values around 60%. These findings are further supported by confusion matrices in Fig. 4(b), where a huge portion of the first and fourth gait phases were respectively mislabeled, as the fifth and second phases of the gait cycle. This could be imputed due to the quasi-symmetric shape of the hip angle profile in the sagittal plane around the middle of the gait cycle, which corresponds to the third phase in this case [26].

Eventually, it is worth noticing that the proposed approach has shown high performances in estimating the gait phases during walking at a comfortable speed, in contrast to other studies where their approaches were tested on a treadmill or by using a constrained walking speed [27], [28]. In addition, these results appeared to be consistent in 40 subjects, which is higher than in other studies [11], [19], [29]. Eventually, possible further improvements could involve the investigation of different postprocessing techniques or of adding other sources of information to boost the model's performance, especially in the HS-MSF phase. It should be highlighted that although the proposed approach was evaluated using only TD features, results motivate future studies to investigate if higher performances could be achieved in this motor task using other feature sets.

This study has two main limitations that deserve to be declared. At first, the proposed approach was applied only in offline mode, thus motivating the development of a real-time interface to validate such a high-level control approach in prosthetic motion. In addition, the proposed method was validated only on walking subphases, thus suggesting the validation of this approach on phases of other locomotion modes as well as the transitions between these locomotions as suggested by the literature [6], [14].

5. Conclusion

This study proposes a promising approach for gait sub-phase recognition during normal gait for TF amputees, by fusing a minimal amount of myoelectric and kinematics data captured exclusively from the proximal part of the lower limbs. The proposed method proved to be consistently robust in 40 subjects with recognition accuracy up to 85.48%, thus further supporting its potential applicability. The high estimation performance of several subphases of the gait cycle could offer flexibility for different actuation scenarios, depending on the prosthetic device's specifications as well as a smooth transition between the gait phases. Therefore, the results of this study represent a step in the advancement of lower limb prosthetic control and rehabilitative exoskeletons, thus motivating future work to validate the proposed setup for different locomotion recognition tasks to have a broader control scheme that can adapt to the user demand.

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