استيفاء الأنشطة العصبية العضلية باستخدام تحليل المشي والتعلم العميق لأغراض إعادة التأهيل

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الملخص

يعد تحليل المشية باستخدام تقنيات تتبع الحركة الحديثة بما في ذلك قياس المتغيرات الحركية طريقة مهمة في أبحاث وتطبيقات إعادة التأهيل. يعد التحفيز الكهربائي الوظيفي (FES) للمرضى المصابين بالشلل والأمراض الدماغية أحد أهم تطبيقات علم إعادة التأهيل. يتطلب التحفيز الفعال للعضلات معرفة مسبقة بحركة الأطراف ومشاركة العضلات في تنفيذ الحركات. في هذا البحث، نعمل على تتبع تغيرات زاوية الفخذ والساق أثناء مراحل المشي بناءً على حساسات التسارع والسرعة الزاوية، وتقدير زاوية الفخذ ومشتقاتها باستخدام مجموعة بيانات HuGaDB. تُستخدم هذه الميزات الثلاثة مع الشبكة العصبية ذات التغذية الأمامية (FNN) لتحديد نشاط عضلة الفخذ المستقيمة عن طريق التدريب المسبق للشبكة العصبية مع تحليل المشي كمدخلات والخرج هو الاشارة الكهربائية للعضلة (EMG) لنفس المريض والمدربة عليها مسبقاً. توضح النتائج قدرة FNN على إعادة اشارة EMG للعضلة المستقيمة لكل دورة مشي لنفس المريض بمتوسط دقة يساوي 96٪ كتدريب و 92.5٪ اختبار. تقدم الطريقة المقترحة أداة جيدة لأنظمة FES، خاصة لمراحل رقمنة EMG.

الكلمات المفتاحية: تحليل المشي، الشبكة العصبية ذات التغذية الأمامية، الاشارة الكهربائية العضلية (EMG).

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Estimation of Neuromuscular Activities Using Gait Analysis and Deep Learning for Rehabilitation Purposes

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Abstract

Gait analysis using modern motion tracking techniques including measurement of kinematic variables is an important modality in rehabilitation research and applications. Functional electrical stimulation (FES) for patients with paralysis and cerebral diseases is one of the most important applications of rehabilitation science. Efficient muscle stimulation requires a pre-knowledge about limb motility and muscles synergy. In this paper, we are working to track the angle changes of the thigh and shin during walking phases based on accelerometer and gyroscope sensors, and estimating the thigh-shin angle and its derivative using HuGaDB dataset. Those three features are used with a feedforward neural network (FNN) to determine the activity of the rectus femoris muscle by pre-training of neural network with gait analysis as input and electromyography (EMG) signal as the output of the same patient. The results illustrate the ability of FNN to reproduce EMG for each gait cycle of the same patient with average precision equal to 96% as training and 92.5% as testing. The proposed method presents a good tool for FES systems, especially for EMG encoding stages.

Keywords: Gait Analysis, Feedforward neural network, Electromyography (EMG).

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Introduction

Brain injuries usually lead to paralysis or weakness of movement and those range from hemiplegia or incomplete paralysis of the lower extremities to complete paralysis. In the case of partial paralysis and motor weakness, electrical stimulation of the peripheral sensorimotor systems increases voluntary movement and muscle strength, and thus increases the activities of daily living (ADL) [1]. The rehabilitation modality of electrical stimulation (ES) which contains functional electrical stimulation (FES) and therapeutic electrical stimulation (TES), is much recommended in Adult Stroke Rehabilitation and Recovery and is considered as a supplementary modality with the standard care methods [2].

Gait analysis using modern motion tracking techniques including measurement of kinematic variables is an important modality in rehabilitation research and applications [3]. The estimated features and information from gait analysis and assessment are used widely in rehabilitation modalities because they offer a reference and control parameters and inputs for potential physiotherapy and exoskeleton-based muscle training methods [4]. In lower extremities case, we are able to track the joints angles, angular velocity and angular acceleration, and simultaneously, we are able to record electromyography (EMG) signals of participated muscles in gait motion which could offer a plenty information and features to conduct a comprehensive understanding about muscle synergy and mobility of lower limbs [5]. Recently, those integrate features have been used in rehabilitation modalities, especially in FES to train and stimulate muscle of patients with brain and spinal cord injuries [6]. Artificial intelligence and machine learning are involved in rehabilitation applications and research because of their powerful ability in classifying kinematic features and EMG signals during the gait cycle and phases and prediction of the relationship between those data [7]. Machine learning-based classification of surface electromyographic (sEMG) signals was used to detect gait-event prediction in control subjects during walking and in hemiplegic-child walking. Long Short Time Memory (LSTM) neural network was used as a prediction algorithm. Morbidoni et al (2021) proved the ability of neural networks in predicting the two main gait events (heel-strike (HS) and toe-off (TO)) using surface EMG signals in hemiplegic cerebral palsy [8]. In previous research of Morbidoni et al. (2019), multi-layer perceptron (MLP) neural networks were used to classify gait phases and predict foot–floor-contact signal from sEMG signals during level ground walking among 23 healthy adults. This approach showed an average classification accuracy of 94.9% for learned subjects and 93.4% for unlearned ones [9]. Lower limb angles and EMG signals in five kinds of gait (walking on flat ground, uphill, downhill, up-step and down-step) and four kinds of movement (squat, lunge, raised leg and standing up) of healthy subjects were used with back-propagation (BP) neural network to re-estimate lower limbs movements using EMG signals. The results show detection accuracy of 93.76% for five kinds of gait events [5]. An artificial neural network (ANN) was employed to classify gait data (walking over flat-ground, upstairs, downstairs, uphill, and downhill) and sEMG signals. The triceps surae muscle activation showed the highest classification accuracy of 88.9% [10].

In this paper, we are working with the available online HuGaDB dataset that contains angular acceleration and velocity data of lower extremities with EMG of rectus femoris muscle during many types of ADL with 18 participants. The proposed method consists of using some important kinematic features of gait analysis as input for a feedforward neural network to estimate the appropriate EMG signal of the muscle that participated in achieving movements. By training the neural network on kinematic features during one gait cycle with the real EMG signal, we will be able to reproduce the same EMG signal of each gait cycle. The main objective of our work is to prepare a good tool for generating reference patterns of muscle activities which later could be used with FES modalities.

Methods

1. Gait and EMG Dataset

In this paper, we are using HuGaDB dataset which is a human gait database for activity recognition based on wearable inertial sensors [11]. This dataset contains detailed gait data during daily activities such as walking, running, standing up etc. Gait data in this dataset consists of two types, the first type is angular velocity and acceleration data were measured by six inertial sensors were placed on the right and left thighs, shins and feet. The second type is EMG signals using two EMG sensors were placed on the right and left rectus femoris muscles and connected to the skin with three electrodes. Each EMG sensor has a voltage gain is about 5000 and a band-pass filter with bandwidth (10-500 Hz). The MPU9250 inertial sensors consisted of a 3-axis accelerometer and a 3-axis gyroscope integrated into a single chip. The sampling rate of all data equals 60 Hz. The places of HuGaDB dataset sensors are illustrated in (Figure 1), where blue “Ir1” refers to right foot inertial sensor, “Ir2” refers to right shin sensor, and “Ir3” refers to right thigh sensor. Red “EMGr1” sensor refers to EMG sensor of right rectus femoris muscle. In our work, we estimated the angle of the thigh (θ_1) by calculating the angle changes from the angular velocity of the thigh during a specific recording time. The same method is used to calculate shin angle (θ_2). The difference angle (θ_{12}) between thigh and shin axes is calculated too.

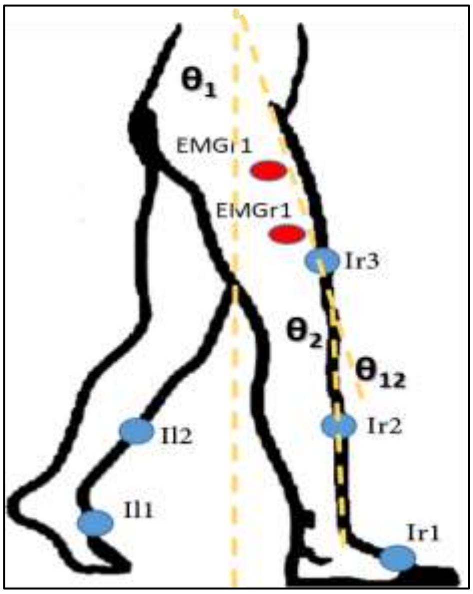

Figure 1. Sensors and EMG electrodes positions in the lower extremities that are used in the HuGaDB dataset.

2. Joints and EMG signals during gait cycle

The human walk consists of a repeated gait cycle. Each gait cycle contains a stance phase and swing phase. The stance phase represents 60% of the gait cycle and it could be categorized into the heel strike, support, and toe-off phases. The swing phase is the remaining 40% of the gait cycle and contains the leg lift and swing phases. Using the dataset, we found in each gait cycle of each patient that thigh angle (θ_1), thigh-shin angle (θ_{12}), and the derivative of thigh-shin angle ($\Delta\theta_{12}$) have a constant differential rate of change between angles and event-related features with EMG signal of rectus femoris muscle (EMGr1) as shown in (Figure 2). In our research work, we are using the enveloped signal of the original EMG signal using the Hilbert analytic envelope to smooth the curve outlining of the EMG signal.

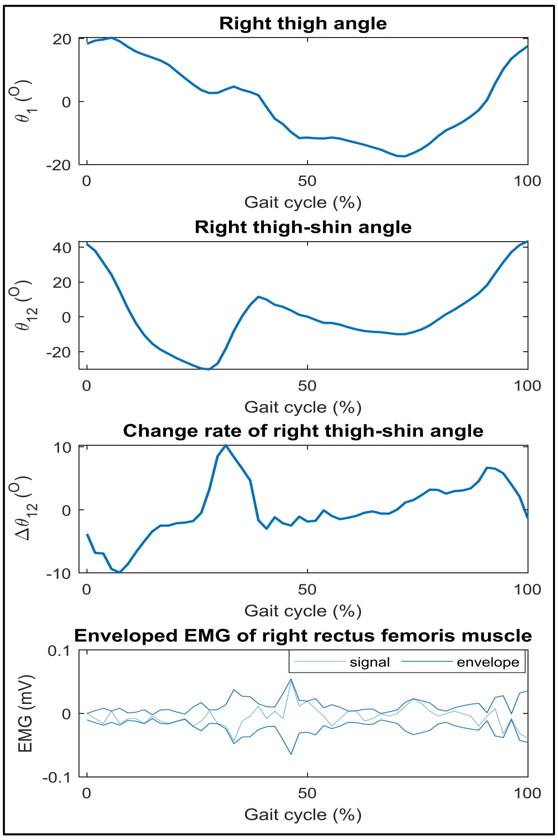

Figure 2. Changes of thigh and thigh-shin angles in one gait cycle with enveloped EMG signal of EMGr1 sensor.

3. Neural network and EMG prediction

After we prepared the necessary features of the gait cycle of a patient, we found that θ1, θ12, and Δθ12 have a powerful influence on the EMG signal of rectus femoris muscle. Now, we are going to use a multilayer feedforward neural network (FNN) in classifying the EMG signal for each patient using the value of (θ1, θ12, and Δθ12) features. The FNN is a type of artificial neural network that has no feedback or closed-loop between nodes or layers. It is often referred to as a multi-layered network of neurons. An FNN consists of an input layer of neurons, a number of hidden layers, and an output layer. The FNN is implemented using Deep Learning Toolbox in MATLAB (The MathWorks, Inc. 2021) according to the following specifications: size of input layer equals 3 (θ1, θ12, and Δθ12), the size of output layer equals 1 represents EMG signal, the size of the hidden layer is 100, and epochs number equals 100.

The first step is training the neural network with the three features (θ1, θ12, and Δθ12) regarding the EMG signal. And as a testing stage, we will use other gait cycles of the same patient to estimate the EMG signals and compare them with the reference EMG in the dataset as shown in (Figure 3).

To measure the accuracy of FNN output, we are not able to use the classical metrics like accuracy and specificity. We used the similar procedure in literature [9, 12] by calculating the average of actual EMG signal for 100 msec and consider it as true positive, and if average of estimated (predicted) EMG signal in the same time slot is not equal to actual value, it will be considered as false positive. The final precision is calculated using the formula:

$$\textbf{Precision} = \frac{\textbf{\textit{True positive}}}{\textbf{\textit{True positive}} + \textbf{\textit{Fasle positive}}} \quad (\mathbf{1})$$

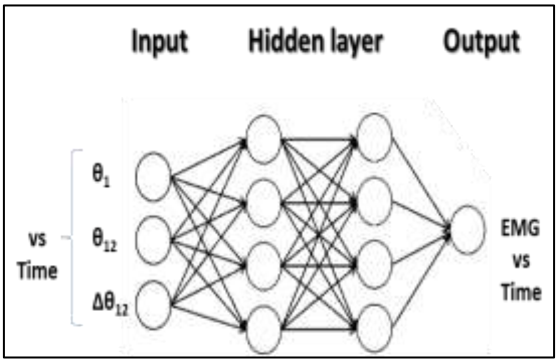

Figure 3. Feedforward neural network with inputs and output.

Results and discussion

To test our proposed method, we used gait analysis data of 5 patients with 200 gait cycles of each one during walking in addition to EMG signals. For each patient, we trained FNN with 50 gait cycles, then we tested it with 150 cycles.

As demonstrative results, we examined the trained FNN of 3 patients using their testing gait data, and the actual enveloped EMG signal is plotted with the estimated ones using FNN as shown in (Figure 4).

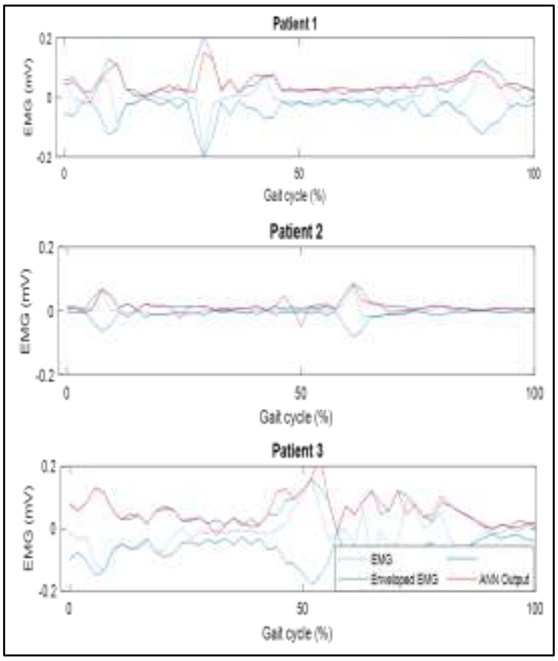

Figure 4. Comparison between actual EMG signal and estimated one of three patients in one gait cycle.

By repeating the experiment for each patient and training FNN using 150 gait cycles and testing it using 90 gait cycles to reproduce EMG signals. We were able to get average precision equal to 96% as training and 92.5% as testing of five patients as shown in (Figure 5).

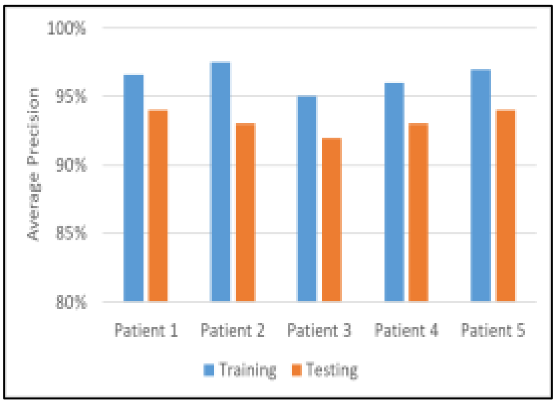

Figure 5. Average precision of five patients using 150 gait cycles to predict EMG signals.

The results demonstrate that by estimating powerful and reliable kinematic signals from gait analysis we can provide sufficient features for neural networks and deep learning approaches to re-produce EMG signal which in the same context code converted to control signal for FES modalities.

Conclusion

In this paper, we worked with the available online HuGaDB dataset that contains angular acceleration and velocity data of lower extremities with EMG of rectus femoris muscle. The proposed method consists of using some important kinematic features of gait analysis as input for a feedforward neural network to estimate the appropriate EMG signal of the muscle that participated in achieving movements. We found that thigh angle (θ_1), thigh-shin angle (θ_{12}), and the derivative of thigh-shin angle ($\Delta\theta_{12}$) have a powerful influence on the EMG signal of rectus femoris muscle. By training the neural network on kinematic features during one gait cycle with the real EMG signal, we were be able to reproduce the same EMG signal of each gait cycle. The results demonstrate that proposed kinematic features from gait analysis can provide sufficient input for neural networks and deep learning approaches to re-produce EMG signal which in the same context code converted to control signal for FES modalities.

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