A Comprehensive Approach for Physical Rehabilitation Assessment in Multiple Sclerosis Patients Based on Gait Analysis

Vitoantonio Bevilacqua[1(✉)], Gianpaolo Francesco Trotta[2], Antonio Brunetti[1], Nicholas Caporusso[1], Claudio Loconsole[1], Giacomo Donato Cascarano[1], Francesco Catino[1], Pantaleo Cozzoli[1], Giancarlo Delfine[1], Adriano Mastronardi[1], Andrea Di Candia[3], Giuseppina Lelli[3], and Pietro Fiore[3]

[1] Department of Electrical and Information Engineering, Polytechnic University of Bari, Bari, Italy
{vitoantonio.bevilacqua,antonio.brunetti, nicholas.caporusso,claudio.loconsole}@poliba.it, gd.cascarano@gmail.com, cozzoli.l@gmail.com, giancarlodelfine@gmail.com

[2] Department of Mechanics, Mathematics and Management, Polytechnic University of Bari, Bari, Italy
gianpaolofrancesco.trotta@poliba.it

[3] Department of Physical Medicine and Rehabilitation, University of Bari "Aldo Moro", Bari, Italy
andrea_dicandia@yahoo.it, pinalelli@virgilio.it, pietro.fiore@uniba.it

Abstract. The assessment of gait features of subjects affected by Multiple Sclerosis supports physicians in defining customized rehabilitation treatment which, in turn, can lead to better clinical outcome. In the standard assessment protocol, an optoelectronic motion system, surface electromyography sensors, and a set of piezoelectric sensors on a force platform acquire large amount of data which is evaluated by physicians for defining treatment. In this paper, we introduce an automatic procedure based on Fuzzy-Granular Computing for evaluating gait metrics: three features extracted from each muscle involved in gait enable to summarize, quantify, and simplify the assessment protocol. Finally, we employ a Support Vector Machine to measure the relevance of the extracted features in classifying healthy subjects and patients using the simplified set of features.

Keywords: Gait analysis · Multiple sclerosis · Support vector machine · Fuzzy granular computing · Dynamic time warping · Gait profile score · Classification

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1 Introduction

Multiple sclerosis (MS) is a chronic autoimmune, inflammatory neurological disease of the central nervous system (CNS) which leads to damage of myelin and axons. MS shows a highly varied and unpredictable course; in most patients, the early stage of the disease is characterized by episodes of reversible neurological deficits which are often followed by progressive neurological deterioration over time [1]. There is no cure for MS and its management aims to both prevent relapses and reduce the progression of the disease. There are several symptoms of MS, including weakness, paresthesia, spasticity, cognitive dysfunction, fatigue, and walking impairments [2].

Focusing on gait disorders, reduced mobility heavily impairs the quality of life, and the associated accidents increase morbidity and mortality [3]. As gait varies over time, it is necessary to design systems which are able to measure and quantify temporal intra-patient variations by evaluating several parameters and by comparing them with a control group.

In this work, we design an innovative system for the physical rehabilitation assessment of MS patients using a set of gait features able to analyze and monitor the follow-up phase of the disease. This goal is achieved by means of Gait Analysis, which allows to synchronously record 3-Dimensional spatial position of anatomical landmarks, ground reaction force exerted on platforms, and sEMG signal from sensors placed on the muscles of the lower limbs.

After the data acquisition phase, temporal, spatial, kinetic, and kinematic gait parameters are computed to evaluate patients' conditions and walking capability. Then, physicians examine large amount of data and evaluate the condition of the patient. In this work, we aim at optimizing standard gait analysis measurement protocols by introducing a novel type of index which summarizes, quantifies, and simplifies the assessment of the impairment.

Furthermore, a more detailed and accurate analysis of human gait can be achieved by decomposing the walking-cycle in seven phases that are, loading response (LR), mid-stance (MST), terminal stance (TST), pre-swing (PSW), initial swing (ISW), mid-swing (MSW), and terminal swing (TSW). This categorization provides physicians with the opportunity of prescribing specific rehabilitation treatment for a defined group of muscles. As a result, each individual patient receives a personalized therapy.

2 Related Work

In the literature, several studies focus on the evaluation of walking patterns and on the estimation of the differences between healthy subjects and patients. For instance, novel metrics include distance measurement based on Dynamic Time Warping (DTW) [4], Gait Profile Score (GPS) [5], and similarity measures based on Fuzzy-Granular Computing [6]. The latter specifically enables focused rehabilitation treatment on the most impaired phases of the gait cycle.

As a result, they enable monitoring the intra-patient follow-up of the condition to validate the efficacy of the proposed rehabilitation therapy.

2.1 Dynamic Time Warping

The problem of finding time correspondence between two different data sets is known in the majority of scientific research areas. One of the well-known techniques which can be used to cope with this issue is Dynamic Time Warping (DTW) [7].

DTW is an algorithm which aligns two sequences and provides an estimation of their distance. This algorithm is particularly useful to compare signals when the simple linear compression or expansion does not yield satisfactory results. It has been used in various applications, from movement recognition in humans [8] to bioinformatics [9].

DTW defines a cost function and uses nonlinear transformation to warp the two sequences to minimize the cost function. The optimal value of the cost function is the distance measure between the two sequences [4]. For this reasons, DTW is suitable for comparing human gait cycle sequences, because each of them includes the same gait phases having different duration.

2.2 Gait Profile Score

Gait Profile Score (GPS) is a measure of gait quality based on the Gait Deviation Index [10]; it quantifies the deviation in the gait pattern of the patient with respect to the normality range. A correlation between Gait Variable Score (GVS) and Expanded Disability Status Scale (EDSS) has been discovered and presented in several studies [11], showing the potential effectiveness of this metric.

In a gate cycle, we consider nine variables v_i: pelvis (i.e., tilt v_1, rotation v_2, and obliquity v_3), hip (i.e., flex-extension v_4, adduction-abduction v_5, and rotation v_6), knee flex-extension v_7, ankle dorsal-plantar flexion v_8, and foot progression v_9. For each variable v_i, a GVS is defined as the v_i Root Mean Square (RMS) difference between the subjects and the control group. An example of GVS computation for knee flexion-extension is shown in Fig. 1.

After the computation of the nine GVS, the GPS value can be evaluated using the following Eq. (1):

$$GPS = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N} GVS_i^2} \quad (1)$$

2.3 Fuzzy-Granular Computing

Fuzzy-Granular Computing differs from previously-defined techniques because it enables accurate analysis of each phase of the gait cycle. The application of a Fuzzy-Granular model produces an accurate representation and quantification of the information in the sEMG signal of each gait phase [6]. Usually, for slowly time-varying signals, the mean value is used for granule representation. Conversely, sEMG are irregular time-varying signals having typical peaks and valleys. Thus, we adopted a fuzzy-triangular membership function to characterize, quantify and represent each phase in a more accurate way. Further details on Fuzzy-Granular Computing and the proper application on the sEMG signal and on the gait phase is presented in Sect. 3.4.

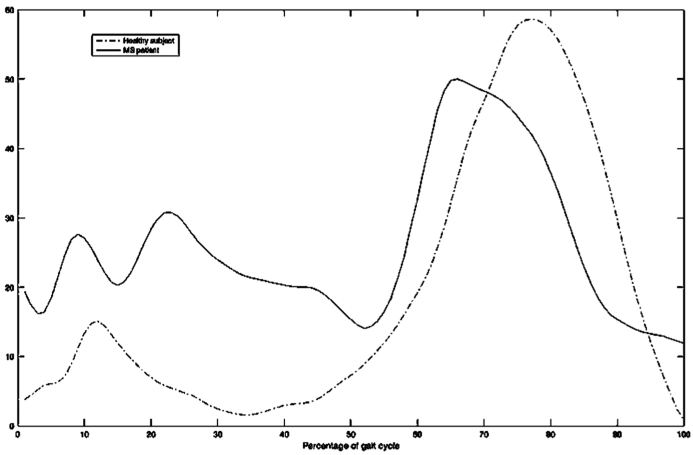

Fig. 1. Examples of GVS calculation for the flexion-extension of the knee. The higher the GVS value is, the larger will result the deviation from the physiological gait of the individual with higher EDSS.

3 Materials and Methods

3.1 Participants

In the study, 7 MS patients (2 male and 5 female, aged 19–45 years) were enrolled in the test group. The matched control group consists of 7 healthy volunteers (6 male and 1 female, aged 25–49 years) with no previous history of neurological disorders or any disease that could affect gait parameters. Table 1 summarizes information about subjects.

Table 1. Age, weight, and height in MS and Control subjects (average and standard deviation).

	MS subjects	Control subjects
Age	32.43 (± 9.22)	29.57 (± 8.68)
Weight (kg)	60.71 (± 10.86)	71.00 (± 16.36)
Height (cm)	168.29 (± 7.89)	174.14 (± 4.74)
BMI (kg/m^2)	21.30 (± 2.11)	23.25 (± 4.29)

3.2 Acquisition System

In this section, we discuss the acquisition and analysis of data from gait. Our system enables synchronous recording of: (1) the 3-dimensional spatial position of anatomical landmarks according to the Davis protocol [12], (2) surface EMG signals of the main muscles of the lower limbs involved in gait, and (3) ground reaction data acquired by force platforms.

The system was provided by BTS Bioengineering® (BTS, Milano, Italy) and located in the Gait Analysis Lab of the Department of Physical Medicine and Rehabilitation of the University of Bari “Aldo Moro”. The optoelectronic motion system is based on 8 infrared cameras recording at 100 FPS for the detection of movements of 20 reflective spherical markers. Surface electromyography (sEMG) signals are recorded with a set of 8 wireless sEMG sensors at a sampling rate of 1 kHz. Ground reaction forces are recorded with 2 piezoelectric force platforms at a sampling rate of 400 Hz. RGB videos of examinations are recorded from 3 different points of view using 3 IP cameras at a rate of 25 FPS.

3.3 Clinical Examination

In the first step of the exam, personal data are collected from each subject. Data include personal details (name, age, height, and weight) and anthropometric measurements of the lower limbs (hip width, hip height, total limb length, knee diameter, and ankle diameter). The second step consists in placing the 20 markers on the anatomical landmarks described in the Davis protocol [12]. Two additional markers are placed on each calcaneus for the first phase of the recording process. After skin preparation, 8 sEMG sensors are placed above the main muscles involved in gait, that is, Tibialis Anterior, Gastrocnemius Medialis, Rectus Femoris, and Semimembranosus.

After the initial setup, a standing session of about 10 s is recorded to evaluate the resting state of the joints; this will be used during data pre-processing for the computation of angles offset. Then, the subject is required to realize a variable number of walking sessions at a self-selected walking speed. During each walking session, the subject walks along the platform without being aware of the position of force sensors. This is to avoid any external influence in the evaluation of the walking ability of the subject.

3.4 Fuzzy-Granular Computing

In this study, we used Fuzzy-Granular Computing (FGC) to find an optimal representation of the sEMG signal. To enhance reliability and specificity of the analysis, we subdivide the gait cycle into seven phases; also, we compute a granular representation for each of them.

The computation of fuzzy granulation requires a preliminary step in which we pre-process the raw sEMG signals (Fig. 2.left). First, the full-wave rectification is evaluated to filter negative values out of the original time-series. Then, we filter the signal using a 2^{nd} order low-pass Butterworth filter [13] with 10 dB cut-off frequency (Fig. 2.right).

Individual differences in walking speed are avoided through min-max normalization of the original time-series data S_0 according to Eq. (2):

$$S = \frac{S_0 - \min(S_0)}{\max(S_0) - \min(S_0)} \tag{2}$$

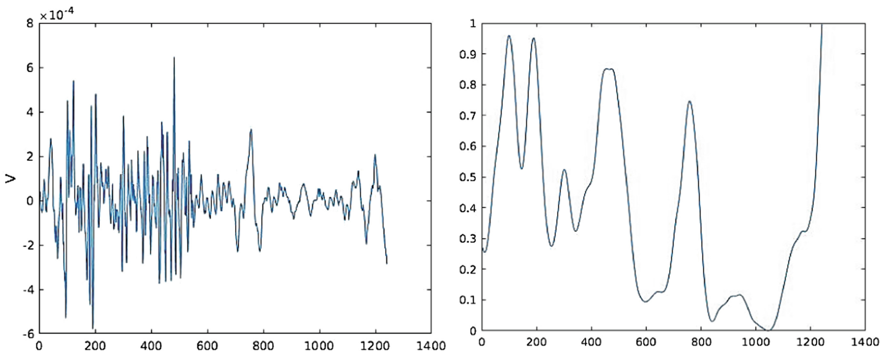

Fig. 2. Raw sEMG signal from the right gastrocnemius medialis (left). Filtered and normalized sEMG signal from the right gastrocnemius medialis (right).

After normalization, for each segment in the interval [a, b], the triangular fuzzy set membership function is established as:

$$\mu_{a,m,b}(x) = \frac{x - \mathrm{a}}{m - \mathrm{a}},\ \mathrm{x} \in [\mathrm{a}, \mathrm{m}] \tag{3}$$

$$\mu_{a,m,b}(x) = \frac{b - \mathrm{x}}{b - \mathrm{m}},\ \mathrm{x} \in [\mathrm{m}, \mathrm{b}] \tag{4}$$

where a is the left bound, b is the right bound and m is the modal or core value.

As reported in [14], we chose the median as the core value because it is a robust estimator because its value does not depend on any outliers (despite the mean value).

In Eqs. (3) and (4), the core value splits the data into two subsets that are processed separately to yield the computations of the left and right portions of the membership function (i.e., increasing and decreasing portion).

To obtain the optimal values for a, we search through all data points of the increasing portion [a, m] considering each of them as a potential value of the parameters of the membership function. A visual explanation is shown in Fig. 3.

Equation 5 finds the optimal value of a which maximizes the performance index:

$$Q(a) = \sum_{\substack{k=1 \\ x_k < m}}^{N} \frac{\mu_{a,m,b}(x_k)}{m - a} \tag{5}$$

where N is the number of data points in the increasing portion.

In the same way, the optimal value for b is evaluated maximizing the performance index:

$$Q(b) = \sum_{\substack{k=1 \\ x_k > m}}^{T} \frac{\mu_{a,m,b}(x_k)}{b - m} \tag{6}$$

where T is the number of data points in the decreasing portion.

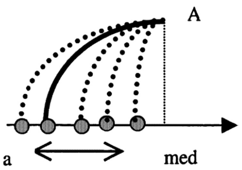

Fig. 3. Computation of a as a parameter in the increasing portion

Using the granular matrix such as the one shown in Eq. (7) reporting the matrix related to the right gastrocnemius medialis, the final representation of the original time series is defined; columns and rows represent the gait phases and the fuzzy parameters, respectively. The granular matrix for each muscle is evaluated.

$$G = \begin{pmatrix} & P_1 & P_2 & P_3 & P_4 & P_5 & P_6 & P_7 \\ a & 0,5391 & 0,2742 & 0,0935 & 0,1102 & 0,0298 & 0 & 0,2852 \\ m & 0,6241 & 0,4865 & 0,4933 & 0,1669 & 0,2450 & 0,0808 & 0,2899 \\ b & 0,9594 & 0,5429 & 0,5028 & 0,6165 & 0,7466 & 0,1173 & 0,9765 \end{pmatrix} \tag{7}$$

An example of granulated signal is shown in Fig. 4.

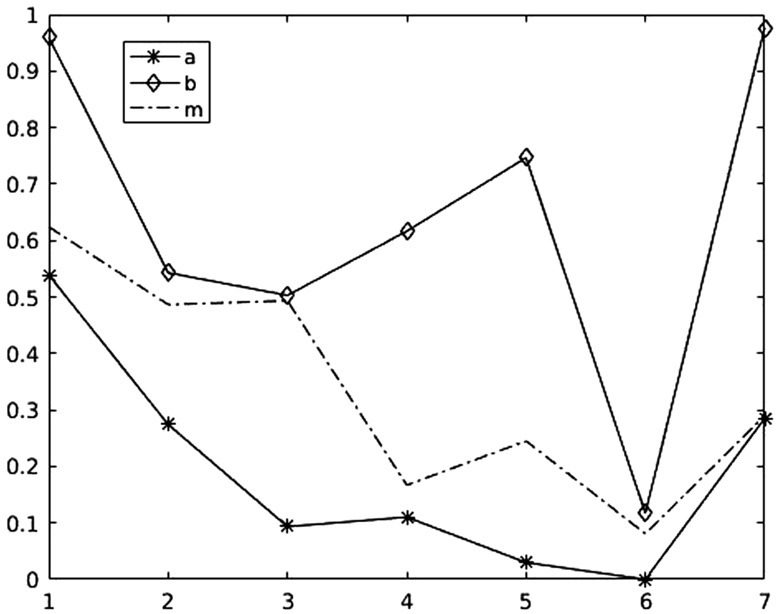

Fig. 4. Granulated representation of the sEMG signal from the right gastrocnemius medialis.

We can define the fuzzy similarity between two granulated sEMG signals as:

$$S = G^{*}H = \frac{\min(g_{ij}, h_{ij})}{max(g_{ij}, h_{ij})} \tag{8}$$

where G and H are the granular matrices of the two compared time-series, "*" is the fuzzy-correlation operator, "min" and "max" are the fuzzy-intersection and fuzzy-union, respectively. The values of the fuzzy similarity matrix S are spread in [0, 1], where 0 represents no similarity and 1 represents maximum similarity.

In this study, we collected eight similarity matrices, one for each of the considered muscles, resulting in a large amount of data that entails a difficult interpretation.

For this reason, in order to evaluate a separation between MS patients and healthy subjects, we decided to leverage the Fuzzy similarity approach and to use the granulated matrices as input for the classifier, as described in Sect. 5.

3.5 Classification Method

The Support Vector Machine (SVM) classifier [15] has been considered to realize a preliminary inspection of the processed data. SVM is a binary classifier whose goal is to find the best linear decision surface that separates the training features space. SVMs have high generalization capability because they can be extended to separate a space of non-linear input features. This classification method has been used in many different applications [16].

4 Results

As previously discussed, to evaluate a separation between MS patients and healthy subjects, we used the fuzzy granulated matrices as input for a classifier, due to the huge number of features. Two machine learning approaches have been considered: Artificial Neural Network (ANN) and Support Vector Machine (SVM). The input dataset comprises 41 instances (21 control subjects and 20 MS patients) and the pattern consists of the 168 variables resulting from 3 features acquired from 8 muscles for each of the 7 phases ($3 \times 8 \times 7$).

No other preprocessing operations were needed, because of the normalized-nature of the features values.

The best results have been achieved using the SVM classifier with third order polynomial kernel. To avoid data overfitting, we used 5-fold cross-validation considering all 168 variables. As the dimension of the dataset is relatively small, we realized multiple tests to get more reliable results.

The SVM approach yielded an average accuracy around 96%, showing the existence of a clear separation between the two input sets. The confusion matrix of the best SVM model is showed in Fig. 5, and the performance indexes are reported in Eqs. (9), (10) and (11):

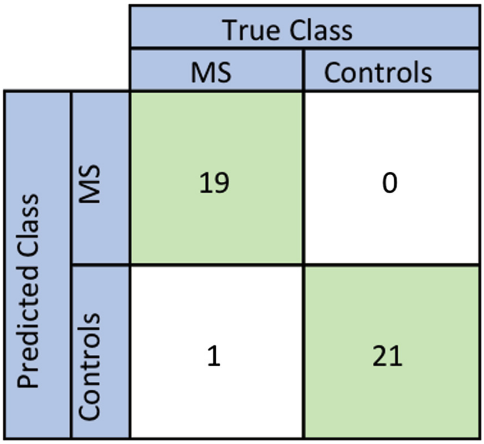

Fig. 5. Confusion Matrix of the best SVM model

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = 0.97 \tag{9}$$

$$Sensitivity = \frac{TP}{TP + FN} = 0.95 \tag{10}$$

$$Specificity = \frac{TN}{TN + FP} = 1.0 \tag{11}$$

However, the low number of instances in the input dataset suggests to further investigate these promising results.

5 Conclusion

In this paper, we present a procedure that evaluates three features for each muscle involved in gait to summarize, quantify, and simplify the assessment of gait impairment in patients affected by Multiple Sclerosis.

We aim at supporting physicians in identifying the rehabilitation treatment for a specific group of muscles, and in defining a personalized therapy for each patient. To this end, we extract a dataset consisting of the three features involved in gait, and we exploit SVM to separate healthy subjects and patients. Our method shows an average accuracy of 96%, proving the relevance of features. Nevertheless, future work will include a detailed investigation of our results in studies involving a larger group of subjects.

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