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Classification of stance and swing gait states during treadmill walking from non-invasive scalp electroencephalographic (EEG) signals

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***Abstract*— In [1] Contreras-Vidal and colleagues have shown the feasibility of inferring the linear and angular kinematics of treadmill walking from scalp EEG. Here, we apply a discrete approach to the same problem of decoding the human gait. By reducing the gait process to a mere succession of *Stance* and *Swing* phases for each foot, the average decoding accuracy reached 93.71%. This is sufficient to design a gait descriptor that relies only on this classification of two possible states for each foot over time as input, which could complement the model-based continuous decoding method that lacks in some aspects (foot placement at landing, weight acceptance, etc.)[5]. A final implementation of this method could be used in a powered exoskeleton to help impaired people regain walking capability.**

I. INTRODUCTION

Continuous decoding of human gait kinematics using scalp EEG signals and a Wiener filter has been proven in [1]. Here we show that a discrete decoding of the gait is also possible. By defining two well differentiated classes: Stance and Swing for each foot, corresponding to foot in contact with the floor or in the air, respectively. A Linear Discriminant Analysis (LDA) classifier between these two possible classes is then trained and tested using cross-validation procedures. With this discrete classification between the two classes over time we believe that the gait kinematics could be reconstructed for later use in an exo-skeleton.

II. MATERIALS AND METHODS

A. Experimental Procedure

We have used the same data as in [1] which consist of kinematic and EEG data recorded from five healthy adults walking on a treadmill for five minutes each. The average speed was approximately *0.6 m/s* and the average number of gait cycles completed was *200*. Subjects were told to avoid stepping on a white stripe (5.08 cm.- wide) glued diagonally on the treadmill belt. This increased the attentional demand during treadmill walking [2]. Joint kinematics of the hip, knee, and ankle joints were recorded with an infrared optical motion capture system at 100 Hz. Whole scalp 60 channel EEG was also recorded with electrodes placed following the 10-20 International System at a sampling rate of 500 Hz using electrode *A2* (right ear lobe) as reference. For details about the protocol, see [1].

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B. Signal preprocessing

Most frontal electrodes (*FP1*, *FP2*, *FPz*) were removed offline as they are known to contain artifacts from eyeblinks. All of the temporal electrodes (*T**) were also removed as they are usually contaminated with artifacts coming from facial and cranial muscles [3]. Thus out of the initial 60 electrodes, 48 were kept for the analysis.

Each EEG channel signal was decimated by a factor of 5 and then filtered with a zero-phase, 3rd-order, band-pass Butterworth filter (0.1-2 Hz low Delta band). Then it was normalized by subtracting its mean and dividing by its standard deviation [1],[4].

Each kinematic signal was filtered with a zero-phase 3rd-order band-pass Butterworth filter (0.1-3 Hz). This frequency range was selected as it contains about 90% of the signal energy.

C. Labeling

In order to perform discrete classification, we labeled the EEG data, using two possible classes: *Stance* or *Swing*, corresponding to right foot on the ground and right foot in the air. The labels were generated using the kinematic data, by computing the derivative over time of the position (the speed) of the right ankle. A positive derivative indicates Swing phase, while a negative derivative indicates Stance.

D. Windowing and Feature Extraction

Each EEG channel signal was windowed using a rectangular window of 50 ms with a 60% overlap. Each time window has 5 samples per EEG electrode. In all of the experiments, for a given set of electrodes, their samples are concatenated to obtain the feature vector.

E. Decoding Method

A discrete classification was performed using Linear Discriminant Analysis (LDA) implemented in MatLab with the function *classify* of the Statistical Toolbox. The five minutes of labeled EEG data for each subject was split into five equal parts of 60 seconds. Four of those parts were used for training while the remaining was used for testing. We used 5-fold cross validation.

F. Electrode Selection

Aiming to build a universal system (i.e. valid for every user) and to reduce the complexity of our algorithm, we performed an analysis to detect which electrodes contained useful information about the gait process. We used genetic algorithm implemented in MatLab as *ga*, to find the set of

TABLE I

AVERAGE DECODING ACCURACY OF THE CLASSIFICATION FOR THE BEST SET OF ELECTRODES AND THE SET OF THE 15 MOST OCCURRING ELECTRODES

Subject	Decoding accuracy I (%)	Decoding accuracy II (%)
1	92.91	87.69
2	90.73	85.30
3	96.65	93.83
4	96.30	91.30
5	91.97	89.03
Total average	93.71	89.42

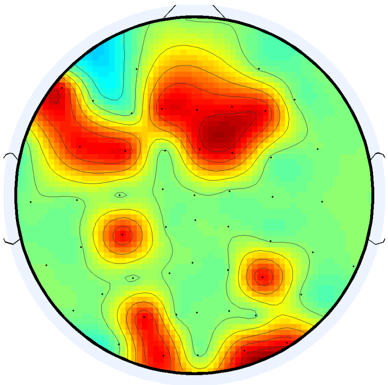

Fig. 1. Heat map of scalp showing areas involved in decoding process.

electrodes that minimizes the classifications error for each subject.

We then analyzed these best sets to obtain the set of 15 electrodes with the highest occurrence among all the best sets of all subjects.

III. RESULTS

In Table I, the *Decoding accuracy I* was calculated as the average values of accuracy after running 5-fold cross validation, using the best set of electrodes for each subject. The *Decoding accuracy II* was calculated as the averaged values of accuracy after running 5-fold cross validation, using the common set of 15 electrodes found as explained in II-F.

In Fig. 1 a heat map showing the position of the 15 most occurring electrodes was computed in order to show what areas of the scalp are more involved in the decoding of the human gait.

IV. DISCUSSION

In [1], Contreras-Vidal and colleagues have shown the feasibility of continuous decoding to describe the human gait, obtaining a correlation coefficient of $r \simeq 0.68$ using as few as 12 electrodes and the same data as the work reported in this paper.

In this paper we show that a discrete classification between the classes *Stance* and *Swing* can be performed with an average decoding accuracy of 93.71% using the best set of electrodes for each subject.

The decoding accuracy of our discrete classification cannot be directly compared to the correlation coefficient for continuous decoding given in [1], because the discrete classifier only gives the present phase of the subject during the gait process and does not contain all of the gait information, while continuous decoding describes the gait process in more detail. The discrete classification approach greatly simplifies the rather complex task of walking, which leads to some loss in degrees of freedom. However, gains in precision with an almost negligible mis-classification percentage for some subjects. We believe that with the discrete method based on classes, a gait descriptor function that uses only that information as input (and probably some subject dependent parameters) could describe the whole gait process. Even if not possible, this method could be a great complement to the already existing methods of continuous decoding, for example adding some extra information about the foot making contact with or leaving the floor.

V. CONCLUSION

This paper shows the feasibility of decoding human gait using a novel discrete approach based in two classes. We believe that this division of the human gait into classes could lead to a complete human gait descriptor. We show that discrete decoding with as few as 15-electrodes is possible with an average accuracy of 89.42% varying from 85.30% to 91.30%. This little variance in the values, indicates that our algorithm is robust. Future studies should analyze and design the gait descriptor mentioned before and how the proposed discrete classifier could help improving already existing methods. Also improvements could be made of this classifier by dividing the gait process into more classes. Applying this approach to subjects that suffered from stroke would be an interesting direction for future work.

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