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Decoding Intra-Limb and Inter-Limb Kinematics During Treadmill Walking From Scalp Electroencephalographic (EEG) Signals

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Abstract

Brain-machine interface (BMI) research has largely been focused on the upper limb. Although restoration of gait function has been a long-standing focus of rehabilitation research, surprisingly very little has been done to decode the cortical neural networks involved in the guidance and control of bipedal locomotion. A notable exception is the work by Nicolelis' group at Duke University that decoded gait kinematics from chronic recordings from ensembles of neurons in primary sensorimotor areas in rhesus monkeys. Recently, we showed that gait kinematics from the ankle, knee, and hip joints during human treadmill walking can be inferred from the electroencephalogram (EEG) with decoding accuracies comparable to those using intracortical recordings. Here we show that both intra- and inter-limb kinematics from human treadmill walking can be achieved with high accuracy from as few as 12 electrodes using scalp EEG. Interestingly, forward and backward predictors from EEG signals lagging or leading the kinematics, respectively, showed different spatial distributions suggesting distinct neural networks for feedforward and feedback control of gait. Of interest is that average decoding accuracy across subjects and decoding modes was $\sim 0.68 \pm 0.08$, supporting the feasibility of EEG-based BMI systems for restoration of walking in patients with paralysis.

Keywords

Biological system modeling; brain-computer interfaces (BMIs); decoding; neural prosthesis

I. Introduction

In 2009, approximately 1.9% of the U.S. population reported some form of paralysis [1], which affects the movement capabilities and the quality of life of about 6 million people. Moreover, the socio-economic burden imposed on patients, relatives, and caregivers is enormous. For example, it is estimated that a spinal cord injury (SCI) patient with a high tetraplegia (C1–C4) injury at 25 years of age would have a lifetime care cost of ~\$3 million [1]. Since locomotion deficits are commonly associated with spinal cord injury [2], [3], limb loss [4], brain injury, and neurodegenerative diseases [5], [6], there is a need to investigate new potential therapies to restore gait function in such patients.

Development of novel interventions, which has been a longstanding focus of rehabilitation research worldwide, could then improve the quality of life of patients with paralysis while reducing the care costs to society. Given the substantial number of people affected, surprisingly, little is known about the organization of motor circuits for bipedal locomotion in humans [7]. Although central pattern generators for locomotion are important in the control of walking, supraspinal networks, including the brainstem, cerebellum, and cortex, must be critical as result of the additional demands imposed by bipedal walking in humans [7]–[11]. This view is supported by neuroimaging studies showing that rhythmic foot or leg movements recruit primary motor cortex [12]–[15], whereas electrophysiological investigations have shown electrocortical potentials related to lower limb movements [16], and greater involvement of human cortex during steady-speed normal locomotion than previously thought [16], [17]. Studies using functional near-infrared spectroscopy (fNIRS) have shown involvement of frontal, premotor and supplementary motor areas during walking [18]–[21], EEG investigations have shown electrocortical activity coupled to gait cycle phase during treadmill walking [17], and functional magnetic resonance imaging (fMRI) studies show that treadmill exercise alters brain activation of paretic leg movements in stroke patients, evoking new connections at the subcortical and cerebellar levels [13]. These brain activation changes are associated with improved walking function after treadmill training, which also positively affects spatial-temporal gait parameters during over-ground walking [22]. Using transcranial magnetic stimulation (TMS) we found that brief exposures to treadmill walking altered corticospinal excitability to lower extremities in chronic stroke survivors [23]. Together these findings suggest a potential for long- and short-term CNS plasticity in the control of gait, but they do not provide a comprehensive picture of the brain's role in bipedal gait, as neither imaging nor TMS reveals direct information on the time course of cortical control during gait. Most importantly, these studies indicate an important role for cortical areas in the generation of bipedal locomotion; however, we still do not understand how the brain regulates motor output in anticipation of key events such as foot placement at landing, weight acceptance, and push-off into swing phase [17]. Nor do we know how cortical control adapts to generate compensatory movements in response to asymmetries imposed on the system due to brain injury.

Recently, Nicolelis *et al.* demonstrated that primary sensory-motor cortex carries information about bipedal locomotion [24]. They showed that chronic recordings from ensembles of cortical neurons in primary motor (M1) and primary somatosensory (S1) cortices can be used to predict the kinematics of treadmill bipedal walking in rhesus macaques. These results support the feasibility of BMI systems to restore locomotion. However, an important challenge of that study is its invasiveness. Electrodes implanted directly in the cortex might pose a serious risk for the patient, and may result in complications due to loss of signal integrity. Invasive methods could also reduce the spectrum of patients that could use the technology such as pediatric populations or the elderly. Alternatively, it may be possible to use noninvasive scalp EEG to decode gait parameters in humans. Recently, our laboratory showed that the critical information needed to decode the kinematics from upper and lower limbs is available in the amplitude modulation of EEG signals in the lower frequencies (0.1–4 Hz; namely, the delta band) [25]–[28]. Relevant to the present study is our demonstration of the feasibility of decoding linear and angular kinematics of one leg in human treadmill walking from scalp EEG signals [25]. Here, we extend our initial study to demonstrate that scalp EEG can be used to infer the angular joint position and velocity of the hip, knee, and ankle joints as well as the intra- and inter-limb coordination patterns of the reconstructed left and right-leg trajectories with as few as 12 electrodes. Additionally, we designed forward (causal) and backward (noncausal) neural decoders to predict gait kinematics from EEG signals that lagged or led the limbs' motion, respectively. This allowed us to examine the cortical contributions to walking of feedforward and feedback network processes. We made the assumption that

training decoders to predict kinematics based only on the past history of the scalp EEG effectively discounts the role of refference (i.e., neural responses to feedforward commands given in the far past) as predictors of future performance. This approach was adopted as [9], [11], [29] reported that a significant amount of cortical activity during walking appears to be generated by sensory afferent feedback, which suggests a significant role for long loop feedback mechanisms. In summary, the ultimate goal of this research is to design a noninvasive neural interface capable of controlling a lower-limb powered prosthesis or exoskeleton to restore gait in patients with gait disabilities.

II. Methods

A. Study Participants and Procedures

The methods follow those reported in [25]. Six healthy adults aged 18–45 (three male, three female) with no history of neurological disease or lower limb pathology and free of injury participated in the study after giving informed consent. The study was conducted with approved protocols from the Institutional Review Boards at the University of Maryland—College Park, the University of Maryland—Baltimore, and the Baltimore VA Research and Development Committee. Participants were first asked to walk on a treadmill, to establish their comfortable speed during a 5-min familiarization period that preceded the beginning of the recordings. Next, a 2-min rest period (baseline) while standing on the treadmill was followed by 5-min of precision walking, when subjects were instructed to walk on the treadmill at their comfortable speed while receiving real time visual feedback (30 frames/s) of their lower limbs through a video monitor in front of them. Subjects were told to avoid stepping on the white stripe (2-in wide) glued diagonally on the treadmill's belt by using the monitor's video to keep track of foot placement relative to the white stripe. This increased the attentional demands during treadmill walking [6], a condition that can be considered to mimic walking in a novel environment or under novel conditions (e.g., after a stroke). The precision walking paradigm puts us a step closer to the actual application where patients have impaired or complete gait dysfunction and therefore would need to rely purely or significantly on effortful attentive conscious control of gait.

B. Limb Movement and EEG Recordings

The 3-D joint kinematics of the hip, knee, and ankle joints were recorded using an infrared optical motion capture system (Optotrak, Northern Digital, Waterloo, ON, Canada, 100 Hz) with foot switch data (Koningsberg Instrumentation, Pasadena, CA, 100 Hz). Precision manufactured 5-cm-diameter disks (Innovative Sports Training, Chicago, IL), each embedded with three infrared diodes that formed an equilateral triangle (~ 3 cm sides), were affixed with adhesive and secured with foam wrap at the second sacral vertebra (S-2) and on the thigh, shank, and foot segments of each lower limb. A segmental model of the lower limbs was then determined by digitizing joint centers for the hip, knee and ankle joints of each limb. Gait kinematics were derived from the model using motion analysis software (Motion Monitor, Innovative Sports Training, Chicago, IL) and exported as ASCII files containing time histories of joint angular positions and joint angular velocities for the hip, knee and ankle joints of both legs. Whole scalp 60-channel EEG (Neuroscan Synamps2 RT, Compumedics USA, Charlotte, NC) and electro-ocular activity were recorded (sampling rate of 500 Hz; band-pass filtered from 0.1 to 100 Hz; right ear lobe (A2) was used as a reference) and time-locked with the movement kinematics using the footswitch signals.

C. Signal Preprocessing

All the data analysis, decoder design and cross-validation procedures were performed offline using custom software written in MATLAB (Mathworks Inc., Natick, MA). Twelve electrodes covering most brain areas involved during locomotion were used for decoding:

pre-frontal (F3, Fz, F4), motor (C3, Cz, C4), parietal (P3, Pz, P4), and occipital (O1, Oz, O2). These 12 electrodes based on the standard 10–20 positioning of electrodes, were chosen to minimize the number of electrodes while eliminating the computational and time expenses involved in electrode selection, both of which will simplify clinical application. Signals from each EEG electrode were decimated by a factor of 5 (to 100 Hz), then filtered with a zero-phase, third-order, band-pass Butterworth filter (0.1–2 Hz) and standardized by subtracting their mean and dividing by their standard deviation [25], [27]. Kinematic data were filtered with a zero-phase, third-order, band-pass Butterworth filter (0.1–3 Hz), as this frequency range accounted for 90% of the signal power.

D. Decoding Method

Time-embedded forward (10 taps or lags plus the tap at time “0”, corresponding to 100 ms in the past with respect to the limb kinematics) or backward (10 taps looking ahead plus the tap at time “0”, corresponding to 100 ms ahead of the limb kinematics) linear Wiener filter [24]–[28], [30] were independently designed, optimized, and cross-validated for each extracted gait parameter. The forward linear model was given by

$$y(t) = a + \sum_{n=1}^N \sum_{k=0}^L b_{nk} S_n(t-k) + \varepsilon(t) \quad (1)$$

where $y(t)$ is the predicted gait parameter time series representing the angular kinematics ($\theta, d\theta/dt$), for the hip, knee, and ankle joints; L and N are the number of lags and the number of electrodes, respectively; $S_n(t-k)$ is the standardized voltage measured at EEG electrode n at lag time k ; a and b are weights obtained through multiple linear regression and $\varepsilon(t)$ is the residual error. The parameters of the model were calculated using the standard generalized linear model (GLM) functions in MATLAB under the Gaussian distribution using the linear *link* function. The backward model differs from the forward in the sign of standardized voltage, which is $S_n(t+k)$, as we take samples (taps) of the EEG in the future with respect to the kinematics.

E. Model Performance Metrics

In order to assess and compare the predictive power of each decoder (neural decoders were trained independently for each subject, and each decoded parameter), a five-fold cross validation procedure (i.e., 1 set of test data that was not used to train the decoder) was employed for testing purposes. That is, the data recorded during the 5 min of the walking task were divided into five segments (1 min each). Four segments were used for training, while the remaining segment was used for testing the model. This procedure was repeated for all the possible combinations. The Pearson correlation coefficient (r) was calculated between the known measured signal and the predicted decoder's output as follows:

$$r(x, \hat{x}) = \frac{\text{cov}(x, \hat{x})}{(\sigma_x \sigma_{\hat{x}})} \quad (2)$$

where x is the actual measured parameter, $\hat{x}$ is the prediction of that parameter, and σ_x and $\sigma_{\hat{x}}$ are the standard deviations of x and $\hat{x}$, respectively.

The (signal to noise ratio) was calculated according to [24] as

$$\text{SNR}(x, \hat{x}) = 10 \log_{10} (\text{Var}(x) / \text{MSE}(\hat{x})) \quad (3)$$

where the variance of the actual measured parameter (signal x) was calculated by subtracting out the mean of the signal, then squaring and averaging the amplitude. The noise was the

difference, or error, between the predicted ($\hat{x}$) and actual (x) measured signal. The mean squared error was calculated by squaring the difference, then averaging to get the MSE, or the power of the noise. The ratio between $var(x)$ and $MSE(\hat{x})$ was converted into a decibel (dB) scale.

A $SNR = 0$ means that the signal and the noise are equally present in the reconstructed kinematic parameter. A $SNR < 0$ (poor prediction) indicates a noisy reconstruction, while a $SNR > 0$ (good prediction) indicates a high-quality reconstruction of the signal.

F. Scalp Maps

To visualize the relative contributions of scalp regions to the reconstruction of the joint angle (ϕ) and the angular velocity ($d\phi/dt$) of the hip, knee and ankle joints, in both the forward and backward conditions, the squared correlation (i.e., variance) values for each sensor at each lag were calculated. This led to 11 values for the forward (−100 to 0 ms in increments of 10 ms) and 11 values for the backward (0 to +100 ms, in increments of 10 ms). The 11 values of each sensor were then averaged, leading to one value for each sensor. The size of each sensor plotted in the scalp map represents the value of the average: the higher average the larger the circumference of the sensor. In order to better visualize the differences of the sensors for the same angular parameter of the same joint between backward and forward (i.e., angular velocity of the left leg in the backward and forward conditions) in terms of contribution of the single sensors to the decoding, the following steps have been taken. First, the sensors were assigned a value between 1 and 12, where 12 indicated the sensor with the highest average. Then, the absolute value of the difference between sensors decoded in the backward mode and in the forward mode was calculated. A value equivalent to “0” showed that that particular sensor had the same importance in the decoding process, while a value > 0 means that differences in that particular sensor were observed between backward and forward mode. These values were then plotted on the scalp map. The *topoplot* function of EEGLAB [31] was used to plot the correlation values.

G. Phase Coordination

The inter- and intra-limb phase coordination was examined by using the Hilbert transform [32]. Each of the five folds of the actual and the predicted kinematic angular parameter was filtered with a third-order, band-pass Butterworth filter (0.1–3 Hz), then standardized and finally transformed to the following vector:

$$V_m(t) = v(t) + iv'(t) \quad (4)$$

where $v(t)$ is the real part of the m -fold that corresponds to the actual or predicted trajectory, while $v'(t)$ is the imaginary part calculated with the Hilbert transform

$$v'(t) = \frac{1}{\pi} PV \int_{-\infty}^{+\infty} \frac{v(\tau)}{(t - \tau)} d\tau \quad (5)$$

where PV is the Cauchy principal value.

The analytical phase was then calculated by taking the arctangent of the vector

$$phase(t) = \arctan\left(\frac{v'(t)}{v(t)}\right). \quad (6)$$

The phase values of the five folds were then averaged, leading to two averages, one for the actual and one for the predicted trajectory. This was done for both the left and the right

limbs. The last step was to calculate the root mean square (rms) values. For the intra limb coordination, the rms value was calculated between the angular velocity and the joint angle of the following pairs of parameters: ankle–knee, ankle–hip, and knee–hip of the same limb (right or left). For the inter limb coordination, the rms value was calculated between the same parameters of the left and right, i.e., the angular velocity of the left and right ankle.

III. Results

A. Decoding Accuracy

Both left and right leg angular kinematics were decoded with high decoding accuracy (r) and values from the neural activity acquired from a sparse array of 12 scalp EEG electrodes. Fig. 1 shows an example of the measured (black) and the reconstructed (gray) kinematics using the forward decoder for the best subject (S4) in terms of decoding accuracy, while Fig. 2 reports the mean $r(\pm std)$ and SNR($\pm std$) values for each subject for each limb (left and right) and for each decoding mode (forward and backward) and the mean across the six subjects. Table I reports the mean and standard deviation of the r and values for each individual gait parameter for the best subject (S4) for both the forward and backward decoders. In the worst-case scenario, the mean r and SNR values for S4 were approximately 0.6 and 2 dB, respectively, for the forward and backward decoders. SNR values are extremely important when paired with r -values. In fact, r -values only report similarities in the pattern between recorded and reconstructed signals, but fail to take into account differences in amplitude. This leads to a lack of information about the accuracy in predicting, for instance, the magnitude of the angular velocity. SNR values carry this information and proved to be a powerful metric to evaluate the quality of the decoded trajectories. Fig. 3 shows the relation between r (y axis) and SNR (x axis) values for the mean of each subject for the left and right limbs for data decoded in the past and in the future. The absence of SNR values < 0 and the fact that SNR values increase as r -values increase confirms the quality of our decoding results.

B. Intra- and Inter-Limb Coordination

In order to test if the coordination between right and left limbs decoded with forward and backward decoders was preserved in the reconstructed trajectories, the actual and predicted trajectories from both limbs (right and left) have been standardized with respect to the mean and standard deviation and then plotted in 2-D space. Fig. 4 depicts the inter-limb phasing for the best-decoded subject (S4) with the forward mode. The x-axis represents the left limb, while the y-axis the right limb. Predicted trajectories (gray) matched qualitatively the coordinative pattern of the measured trajectories across all the joints and parameters, except for the angular velocity and joint angle of the ankle, which were the least accurate. We also computed the Hilbert transform and the rms values were used as described in Section II. Intra-limb coordination was tested in the right and left limbs by taking the difference in phase of the actual and predicted trajectories between the following pairs: ankle–knee, ankle–hip, and knee–hip for the same angular parameter. Inter-limb coordination was tested by taking the difference in phase of the actual and predicted trajectories between the following pairs: ankle (left)–ankle (right), knee (left)–knee (right), and hip (left)–hip (right) for the same angular kinematic parameter. Fig. 5 shows boxplots for each pair of rms values for the forward mode. Results are depicted for the lower quartile, median, and upper quartile values (outliers are represented with + sign). Anova statistical analysis applied to each pair (i.e., joint angle of the right and left knee) of the rms values showed no significant difference ($p > 0.05$) for all the pairs, except for the inter-limb phase of the joint angle of the hip.

C. Scalp Map Analysis

The topography of the mean squared correlation (i.e., variance) values of the sensors across all the lags for the best subject (S4) for the backward and forward decoders along with the difference between sensors is plotted in Fig. 6. These scalp maps represent the individual contribution (i.e., variance accounted for) of electrodes to decoding, that is, the spatial distribution of the EEG information about walking contained at each electrode site. Given the fact that only 12 sensors have been used for the analysis, no interpolation was adopted and the contribution of each electrode is represented by the size of the circumference of the black circles surrounding each of them. In the forward mode [Fig. 6(a)], the angular velocity of the ankle and of the knee in both legs recruits mainly the most frontal electrodes (F3, Fz, and F4), while the angular velocity of the hip mainly recruits electrodes Cz and C4. For the joint angle, the most frontal and occipital electrodes have an important role in the ankle decoding for both legs. For the knee, electrodes Fz, Cz, and C4 show high activity in both legs, while in the hip joint similarities between the two limbs are observed in electrodes Cz and C4. Occipital electrodes also contribute, albeit to a lower extent, to decoding.

Parietal electrodes (P3, Pz, P4) played a minor or nonsignificant role in the decoding process, with the exception of the joint angle of the ankle and hip of the right limb. In the backward mode [Fig. 6(b)], the angular velocity of both limbs of the knee and hip mainly recruits frontal and motor electrodes, while in the ankle the F3 had a major role in the left limb and O1 and Oz showed a major contribution in the right limb. Significant contribution from the parietal electrodes have been observed only in the right and left knee. Regarding the joint angles, the frontal electrodes play a major role across all the joints, except for the right ankle. Motor and parietal electrodes showed significant contributions, with the exception of the right hip. The contribution of occipital electrodes (O1 and Oz) is evident only in the left ankle and knee and in the right hip. Differences in terms of contribution to decoding for each electrode is shown in Fig. 6(c). Significant differences have been observed in the angular velocity of the left ankle, knee and hip and in the joint angle of the right ankle, knee and hip.

D. Decoding Accuracy Was Not Affected or Corrupted by Eye, Mechanical, or EMG Artifacts

One of the main concerns in the BMI field is the presence of mechanical and electromyographic (EMG) artifacts and the potential contribution of the eyes to the decoding process. We addressed the issue of potential mechanical artifacts introduced by motion of the EEG cap wires to the recording amplifiers (due in turn to movement of the subject) in our previous report [25] by using the phase locking value (PLV) [33], [34]. We worked under the assumption that if the motion of the EEG wires corrupted in some way the measured EEG signals, this problem should have been observed in all the electrodes as the wires were bundled in a single connector. Results from that study, which used a higher electrode count, supports the notion that no mechanical artifact affected our decoding. In fact, in a recent study on the removal of movement artifact from high-density EEG recorded during walking and running [16], it was reported that “in both walking conditions (0.8 m/s and 1.25 m/s), gait-related artifact removed from the EEG signals was minimal.” In the present study, subjects walked at a pace lower than 0.8 m/s (the highest one was 2.4 km/h $\approx$ 0.66 m/s), supporting our claim that no artifacts played a significant role in our decoding analysis.

The potential contribution of the movement of the eyes to decoding was also addressed in our previous studies [25], [28]. In those studies, the decoding process was carried out by adding the standardized vertical electrooculogram (VEOG) activity to the optimal set of electrodes used for decoding. The r -values and the regression weights were calculated in this

new condition. We compared the r -values with and without the VEOG electrode by calculating the difference in percent and divided the absolute value of the regression weights of the eye-electrode by the sum of the absolute value of all the regression weights of the best fold. No significant differences, between the two sets of weights and r -values were found, suggesting that the role of eye-artifacts in the decoding process was negligible. Regarding the presence of muscle artifacts, it has been shown in [35] that EMG and ocular artifacts do generally occur mainly at frequencies higher than 8 Hz, which is four times higher than our frequency cutoff of 2 Hz used for reconstruction. Moreover, it has been demonstrated that facial EMG artifacts are localized to prefrontal and temporal electrodes [35], and thus, we did not include electrodes spanning those scalp areas in the present analysis.

IV. Discussion

The feasibility of decoding kinematic parameters (linear and angular) recorded during human treadmill walking using EEG was recently shown by our group [25]. However, in that study scalp EEG signals were used to infer the motion of a single limb (right) with as few as 16 electrodes and only the forward mode was investigated. Here, we extend our results to both legs, for forward and backward decoders, and their coordinative dynamics using a sparse electrode array consisting of only 12 scalp electrodes.

The results of the decoding show that high r and SNR values can be achieved in both limbs by using such a limited number of electrodes for both modes. What is particularly encouraging is the fact that SNR values were all > 0 . In fact, we believe that SNR values paired with r -values could be a better indicator of the performance of a decoder than r values alone. Correlation values provide information about the pattern of two signals, but are insensitive to their amplitude. As shown in Fig. 3, the SNR values (x-axis) increase as the r values increase. This is a sign that our decoders are capable of reliably inferring not only the phase, but also the magnitude of the angular kinematic parameters for both limbs. This result is even more remarkable if we consider the fact that values reported are the mean of the five-fold cross validation. This is to indicate that our decoders are robust: whether in the backward or in the forward mode, extremely low standard deviations values were found for both the r and the SNR values (reported in Table I). Furthermore, the similarities between forward and backward decoding accuracies support the hypothesis that both efferent and afferent cortical activity generated during locomotion can be predicted from scalp EEG [9], [11].

The scalp map analysis confirmed our results reported in our previous study [25], that is, human walking is sub-served by a complex, distributed but sparse cortical network, in which different scalp areas over anterior, right lateral and right anterior-occipital scalp areas seem to equally contribute to the decoding, at least at the macro-scale of EEG. Here we found that this sparse network that encoded right-side lower limb kinematics is mirrored in the case of the left leg kinematics. The scalp map analysis also revealed that the complex neural networks underlying the forward (efferent) and backward (feedback) signals are different, even though the correlation values reported were similar. This suggests that our methods are able to decode to some extent independent cortical contributions of feedforward and feedback processes during walking. This assumed that training decoders to predict kinematics based only on the past history of the scalp EEG effectively discounts the role of reafference (i.e., neural responses to feedforward commands given in the far past) as predictors of future performance. Ultimately, this notion would need to be examined in de-afferented patients, or in protocols based on motor imagery, as during imaginary movement the feedback from the spinal cord is unlikely to be present. Nevertheless, in the case of applications to patients with paralysis, it would not matter whether feedforward/afferent signals are decoded as long as they are useful to generate BMI commands. Moreover,

signals in these patients would be much “cleaner” particularly if sensory feedback is abolished due to the lesion. That different decoders were optimized for forward and backward predicting models, suggest different spatially distributed networks are being recruited. Understanding what part of the EEG is responsible for feedforward and backward control will help us to figure out which temporal features should be used for BMI.

Our examination of the inter- and intra-limb coordination patterns showed that the relative phasing is well preserved in the predicted trajectories even though the decoders were calibrated independently. The knee and the hip joints showed the best coordinative pattern, while the ankle showed the poorest relationships. This is in agreement with the r and SNR values reported in Table I, where the worst decoding accuracies were observed in the ankle. We note, however, that the accuracy of ankle decoding could be improved with more electrodes strategically placed on the scalp as we have shown previously for decoding of the kinematics of a single lower-limb extremity [25]. In order to quantify the intra- and inter-limb phase coordination, a phase analysis using the Hilbert transform [32] was applied to the left and right limbs. With exception for the inter limb phase of the joint angle of the hip, all the other predicted trajectories did not show any significant difference, confirming once again the robustness of the decoders. This is indeed an important result, as the preservation of the phase is one of the key factors in controlling a prosthetic leg.

V. Conclusion

The main result of this study is that low-density scalp EEG can be used to reconstruct the angular kinematics as well as the intra- and inter-limb coordination dynamics during human bipedal locomotion during treadmill walking. We showed that with as few as 12 sensors we obtained decoding accuracies comparable to methods based on intra-cortical invasive recordings [24] in both the backward and the forward decoder models. Interestingly, the cortical mappings for the forward and backward decoding suggest different cortical contributions to feedforward and feedback mechanisms during walking. These results support the feasibility of using noninvasive scalp EEG to develop BMI systems for restoration of bipedal locomotion.

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Biography

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Larry W. Forrester received the A.B. degree in psychology from Duke University, Durham, NC, in 1972, the M.A. degree in physical education from Wake Forest University, Winston-Salem, NC, in 1984, and the Ph.D. degree from the University of Maryland, College Park, in 1997. He completed a postdoctoral fellowship training in stroke rehabilitation at the Baltimore Veterans Affairs Medical Center (VAMC), Baltimore, MD, in 1999.

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Jose L. Contreras-Vidal (M'88–SM'08) received the Engineer's degree in electronics and communications from the Instituto Tecnológico y de Estudios Superiores de Monterrey (ITESM), Monterrey, Mexico, in 1987, the M.S. degree in electrical engineering from the University of Colorado, Boulder, in 1990, and the Ph.D. degree in cognitive and neural systems at Boston University, Boston, MA, in 1994.

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Prof. Contreras-Vidal is a member of the Society for Neuroscience, President-Elect of the International Graphonomics Society, a 2006 City of Paris Senior Research Scholar, a fellow of the International Brain Research Organization-Institut National de la Sante et de la Recherche Medicale (IBRO-INSERM) in 2000, a Human Frontier Science Fellow (1995), NIH Motor Function, Speech and Rehabilitation Study panelist (2006–2010). He was the Chair of the 15th IGS Conference in Cancun, Mexico, June 12–15, 2011.

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Fig. 1.

Reconstructed right and left leg kinematics from EEG for the “best” (S4) subject in the forward mode (8 out of a 60 s walking session are shown in this example). Rows represent ankle, knee, and hip joints. Each column represents comparison of reconstructed (gray) and actual (black) measured angular kinematic trajectories for joint angle and angular velocity time series with 12 electrodes. The stick figure shows the real movements at the time 1, 3, 5, and 7 s.

Fig. 2.

Decoding accuracy (r) and SNR values $\pm$ std for the six subjects. Mean of the right (black) and left (white) limbs for each subject is shown for the (a) forward and (b) backward decoders.

Fig. 3. Comparison of decoding accuracy (r) versus SNR (dB) between past (black) and future (gray) of the mean of the right and left limbs for the current study ($N = 6$). Each circle represents the mean across all parameters for each limb for each subject.

Fig. 4.

Standardized predicted (gray) and actual (black) trajectories of the ankle, knee, and hip joint angle for the best subject (S4) in the forward mode. X and Y axes represent, respectively, the standardized joint angle (or angular velocity) of the left and right limbs. Rows represent ankle, knee, and hip joints, while each column represents comparison of reconstructed and actual measured angular kinematic trajectories. Before being standardized, the predicted trajectory has been filtered with a zero-phase, third-order, band-pass Butterworth filter (0.1–3 Hz) before being plotted for comparison to the 3 Hz filtered measured data.

Fig. 5.

Inter- and intra-limb phase relation for kinematics decoded with the forward decoders. Each column reports the results for a distinct parameter (angular velocity and joint angle). Row (a) shows the results for the inter limb phase, while rows (b) and (c) show, respectively, the results for the left intra-limb and right intra-limb coordination. Y-axis reports the rms value. Keys: (A) stands for ankle actual, A(P) for ankle predicted, K(A) for knee actual, K(P) for knee predicted, H(A) for hip actual, H(P) for hip predicted, AK(A) for ankle–knee actual, AK(P) for ankle–knee predicted, AH(A) for ankle–hip actual, AH(P) for ankle–hip predicted, KH(A) for knee–hip actual and KH(P) for knee–hip predicted.

Fig. 6. Spatial distribution of decoding accuracies across sensors for the “best” (S4) subject. Scalp maps represent the mean spatial distribution of across electrodes across all lags for each parameter resulting from the training of the linear model for the forward prediction (a) and the backward prediction (b) Differences at each sensor across the two predictions are shown in (c).

TABLE I

DECODING RESULTS FOR THE BEST SUBJECT (S4)

	Left		Right		Left		Right	
	<i>r</i>	<i>SNR</i>	<i>r</i>	<i>SNR</i>	<i>r</i>	<i>SNR</i>	<i>r</i>	<i>SNR</i>
Ankle	0.66 (.05)	2.5 (.52)	0.78 (.02)	4.15 (.57)	0.65 (.04)	2.44 (.45)	0.78 (.02)	4.13 (.53)
$d\phi/dt$	0.66 (.13)	2.75 (1.2)	0.83 (.02)	5.13 (.61)	0.66 (.14)	2.66 (1.1)	0.84 (.01)	5.39 (.56)
ϕ								
Knee								
$d\phi/dt$	0.86 (.02)	5.9 (.71)	0.87 (.01)	6.16 (.35)	0.86 (.02)	5.9 (.71)	0.86 (.01)	5.79 (.23)
ϕ	0.80 (.05)	4.47 (1.1)	0.85 (.03)	5.67 (.85)	0.82 (.04)	4.95 (1.1)	0.83 (.04)	5.17 (.96)
Hip								
$d\phi/dt$	0.75 (.05)	3.57 (.87)	0.82 (.03)	4.89 (.7)	0.75 (.05)	3.67 (.86)	0.80 (.04)	4.59 (.79)
ϕ	0.80 (.05)	4.55 (1.0)	0.83 (.04)	5.11 (1.0)	0.84 (.04)	5.36 (1.1)	0.84 (.04)	5.60 (1.1)

Correlation coefficient (*r*) and *SNR* (dB) for the predictions of the angular velocity and joint angle for all the 3 joints. The numbers represent the mean (standard deviation).