Decoding of velocities and positions of 3D arm movement from EEG*

Patrick Ofner[1] and Gernot R. Müller-Putz[1]

Abstract— A brain-computer interface (BCI) can be used to control a limb neuroprosthesis with motor imaginations (MI) to restore limb functionality of paralyzed persons. However, existing BCIs lack a natural control and need a considerable amount of training time or use invasively recorded biosignals. We show that it is possible to decode velocities and positions of executed arm movements from electroencephalography signals using a new paradigm without external targets. This is a step towards a non-invasive BCI which uses natural MI. Furthermore, training time will be reduced, because it is not necessary to learn new mental strategies.

I. INTRODUCTION

A brain-computer interface (BCI) [1] measures biosignals originating in the brain and uses them to control devices. One important application of a BCI is the restoration of upper limb functionality of paralyzed persons [2]. The ideal solution is to detect natural movement imaginations in a non-invasive way and continuously control an arm neuroprosthesis. Here, natural means that the actually imagined arm movement (in a certain direction with a certain speed) is also executed by the arm neuroprosthesis. Thus, there exists a direct-link between motor imagination (MI) and arm neuroprosthesis movement. In this work, we assume that an arm neuroprosthesis capable of executing natural movements exists and face the problem of detecting natural movements.

Sensorimotor rhythms (SMR) [3] based BCIs detect power modulations in certain frequency bands in electroencephalography (EEG) signals [4] induced by MI. In [5] imaginations of foot movements were used for closing and opening the right hand of a patient with tetraplegia. The switching between different phases of the lateral grasp with left hand MI was shown in [2]. SMR based BCIs have the advantage of operating non-invasively, but MIs are artificially assigned to neuroprosthesis movements. Thus, MIs are not natural.

Gratifyingly, there are evidences that low frequency signals measured from cortex carry valuable information regarding arm movement trajectories. It was shown in [6] that it is possible to decode two-dimensional movement trajectories when controlling a joystick. Signals were recorded with electrocorticography (ECoG). A low frequency time-domain signal was found which correlates with movement trajectories. This signal component was referenced as local motor potential (LMP). In [7] it was shown that the arm movement

direction of subjects performing a center-out task can be decoded from ECoG. Decoding information was carried by movement-related potentials as well as spectral amplitude modulations in low frequencies ($< 2\,\text{Hz}$) and in the high gamma band. [8] successfully decoded arm movement trajectories from subjects using low frequency components from ECoG signals. There, subjects performed two-dimensional movements to random targets.

[9] proofed that three-dimensional executed arm movements can also be decoded from EEG, probably paving the way to a new generation of BCIs which decode non-invasively natural arm movement imaginations. In [9] low-pass filtered ($< 1\,\text{Hz}$) signals were used to decode arm velocities during a center-out reaching task. It is probable that these low frequency components measured from EEG are the same as those measured from the ECoG, although yet a proof remains.

In this work we were basing on the approach from [9] and investigated if it is possible to decode arm movements from EEG (velocities and positions) using a new paradigm without external targets.

II. METHODOLOGY

A. Subjects

Five healthy right-handed subjects (3 females) participated in the experiment. Subjects s1, s2 and s3 had prior experience with BCI measurements. Subjects were seated in an armchair with their left forearm fully supported by the armrest.

B. Paradigm

Subjects moved their right arm continuously and self-chosen in front of the body in all three dimensions. We call this a continuous and self-chosen movement task. The hand was closed and the thumb was on the upside. Subjects were instructed to perform natural, round (not jaggy) and in speed varying arm movements when a trial started. To suppress eye movements, subjects were asked to fixate their gaze on a cross presented on a screen in front of them. Further restrictions were not imposed. We recorded ten trials, each lasted $65\,\text{s}$. For further analysis, we only used the last $60\,\text{s}$ of a trial to exclude movement onset effects. Thus, in total we obtained $10\,\text{min}$ movement data from each subject. The start of a trial was indicated by a short beep tone. Breaks were inserted between trials with a subject specific duration (usually around $1\,\text{min}$) to avoid fatigue of arm and shoulder muscles. No feedback was provided.

[1]Both authors are with the Institute of Knowledge Discovery, Graz University of Technology, Krenngasse 37, 8010 Graz, Austria.
Correspondence to Patrick Ofner (patrick.ofner@tugraz.at)

C. Signal recording

Forty-nine Ag/AgCl electrodes spread over sensorimotor and frontal areas were used to record EEG signals from the scalp. Three electrooculography (EOG) electrodes were positioned above the nasion, and below the outer canthi of the eye. Reference was placed on the left ear, ground on the right ear. All electrode impedances were below $5\,k\Omega$. After band-pass filtering between $0.01\,Hz$ and $200\,Hz$ with an eighth-order Chebyshev filter and applying a notch filter at $50\,Hz$, signals were sampled with $512\,Hz$ using four g.USBamp amplifiers (g.tec, Graz, Austria). x/y/z coordinates of the right hand of the subjects were tracked with the Kinect sensor device (Microsoft, Redmond, USA) using the OpenNI framework (http://www.openni.org) and the NiTE middleware (PrimeSense, Tel-Aviv, Israel). We rotated the coordinate system so that the x-axis was going from right to left, the y-axis from down to up and the z-axis from front to back relative to the subject. EEG, EOG and hand positions were recorded with a customized TOBI Signal Server [10] and Matlab (MathWorks, Massachusetts, USA). After recording, we removed linear trends from raw EEG signals per trial. We filtered signals with a $100\,Hz$ zero-phase, fourth order, low-pass Butterworth filter and down sampled to $256\,Hz$ to reduce computational effort.

D. Decoder

1) Velocity: The velocity decoder was originally described in [9] and is only summarized here. It transforms EEG signals into instantaneous velocity signals of the (right) hand. In a preprocessing step, we low-pass filtered with a fifth-order Butterworth filter with a cutoff frequency of $1\,Hz$. Then, we calculated time differences of the filtered signals and normalized to a mean value of 0 and a standard deviation of 1. The resulting signals are referenced as $S_n[t]$, where n is the EEG channel number and t is the time step. The actual decoder comprises three linear models:

$$v_x = a_x + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nkx} S_n[t - kT] \qquad (1)$$

$$v_y = a_y + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nky} S_n[t - kT] \qquad (2)$$

$$v_z = a_z + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nkz} S_n[t - kT] \qquad (3)$$

v_i is the velocity of the hand in the i-th dimension, N is the number of EEG channels, L is the number of time lags used for decoding. T is the interval between two time lags and was set to $11.7\,ms$, which is 3 times the smallest time step when using a sampling rate of $256\,Hz$. a_i and b_{nki} are the weights of the linear models. The weights were found with multiple linear regressions. As dependent variables we used $1\,Hz$ low-pass filtered and differentiated measured x/y/z coordinates of the hand.

2) Position: Here we present an adaption of the velocity decoder which decodes *directly* hand positions of executed movements from EEG. The differentiation of the position yields the velocity. Thus, one can suppose removing the differentiation step in the velocity decoder described above would give us the actual position of the hand. We found that frequencies below $0.5\,Hz$ negatively influence correlations. Therefore, instead of just removing the differentiation, we replaced the low-pass filter and the differentiation with a band-pass filter with cutoff frequencies at $0.5\,Hz$ and $2\,Hz$. The output of the three linear models is now the position of the hand. To compute the model weights with multiple linear regressions, the band-pass filtered ($0.5\,Hz$ - $2\,Hz$) measured coordinates of the hand were used as dependent variables.

E. Analysis

To assess the quality of the velocity decoder we calculated for each subject Pearson correlation coefficients (r) between decoded x/y/z velocities and $1\,Hz$ low-pass filtered measured x/y/z velocities from the Kinect. We used a 30-fold cross-validation, that means we tested against $20\,s$ of data. For the position decoder, measured hand positions were band-pass filtered from 0.5 to $2\,Hz$ and correlated with the decoded positions. To exclude a possible decoding of eye movements instead of brain activity, we also decoded velocities and positions from EOG.

Each channel at each time lag has three weights (b_{nkx}, b_{nky}, b_{nkz}, corresponding to the x/y/z coordinates). These weights form a vector contributing (weighted with the EEG signal) to the final velocity or position, respectively. To assess the contribution from each channel at each time lag, we computed the euclidean norm over these weight-vectors and averaged over cross-validation folds.

III. RESULTS

A. Velocity Decoder

For each subject, the mean value and standard deviation of r over all 30 cross-validation folds, when decoding velocity from EEG, are shown in Table I. The mean value and standard deviation of r over all subjects in x, y and z axis are 0.70/0.77/0.62 $\pm$ 0.13/0.11/0.15. Decoding from normally distributed random data yield maximal absolute r values of 0.03/0.12/0.07. Table II shows r when decoding from EOG. Here, the mean value and standard deviation of r over all subjects are 0.35/0.33/0.23 $\pm$ 0.22/0.20/0.16.

TABLE I

SUBJECTS MEAN VALUES AND STANDARD DEVIATIONS OF r OVER CROSS-VALIDATION FOLDS WHEN DECODING VELOCITY FROM EEG

	s1	s2	s3	s4	s5
v_x	0.53±0.09	0.71±0.08	0.79±0.07	0.74±0.11	0.73±0.10
v_y	0.84±0.06	0.78±0.09	0.71±0.09	0.78±0.09	0.71±0.13
v_z	0.71±0.08	0.54±0.16	0.67±0.06	0.50±0.16	0.67±0.12

A common weight pattern between equivalent time lags was not found across subjects. Subjects show basically at least a contribution from premotor/supplementary motor area or primary motor/sensory area. All subjects show contribution peaks at time lags 35 ms and 82 ms and a high contribution plateau between. The same contribution distribution over

	s1	s2	s3	s4	s5
v_x	0.27±0.17	0.46±0.17	0.15±0.18	0.44±0.20	0.42±0.19
v_y	0.42±0.12	0.28±0.18	0.13±0.14	0.48±0.18	0.33±0.18
v_z	0.25±0.17	0.17±0.16	0.20±0.14	0.18±0.16	0.33±0.15

time lags can be observed when decoding from random data drawn from the standard normal distribution. Exemplarily, Fig. 1 shows the contribution of each EEG channel at each time lag averaged over cross-validation folds for subject s3.
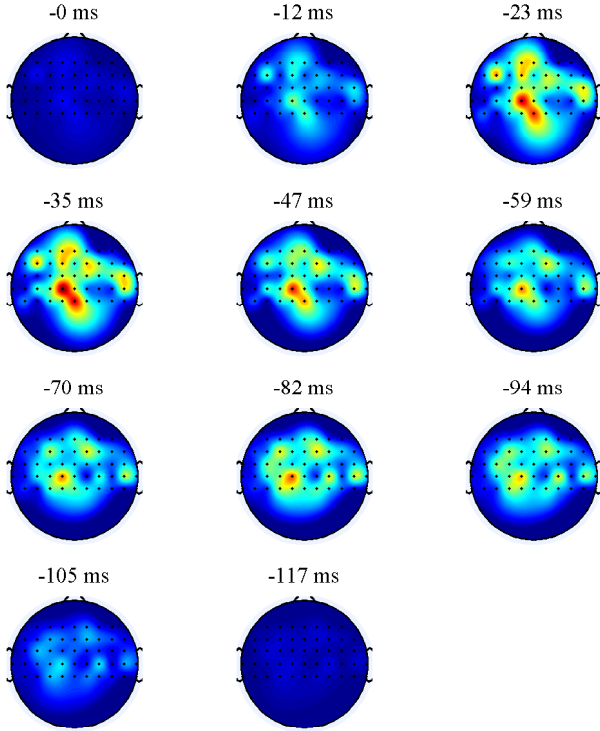

Fig. 1. Velocity decoder: Qualitative contribution of each channel at each time lag for s3. The largest contribution is colored red, the smallest blue.

An example of decoded and low-pass filtered measured velocities for subject s3 are shown in Fig. 2. The decoder was tested on run 1 and trained on runs 2 to 10.

B. Position Decoder

For each subject, the mean value and standard deviation of r over all 30 cross-validation folds, when decoding position from EEG, are shown in Table III. The mean value and standard deviation of r over all subjects in x, y and z axes are 0.70/0.78/0.62 ± 0.12/0.09/0.14. Decoding from normally distributed random data yield maximal absolute r values of 0.01/0.07/0.04. Table IV shows r when decoding from EOG. Here, the mean value and standard deviation of r over all subjects are 0.33/0.32/0.22 ± 0.22/0.19/0.14.

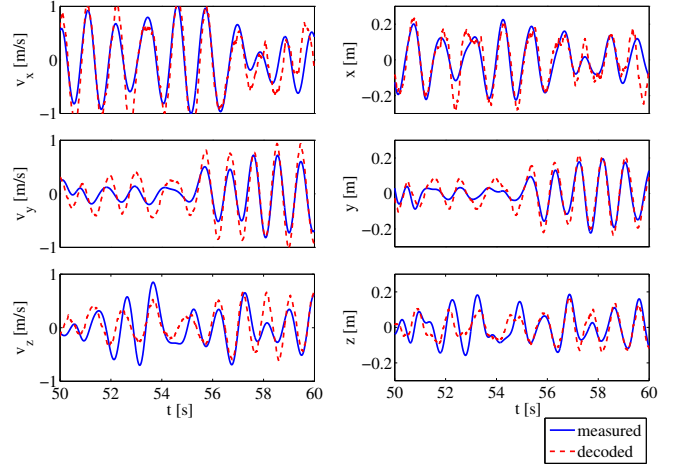A common weight pattern between equivalent time lags was not found across subjects. Contributions from the 105 ms

Fig. 2. Decoder example: Measured and decoded velocities (left) and positions (right) from subject 3 in the time domain.

	s1	s2	s3	s4	s5
x	0.52±0.08	0.71±0.06	0.79±0.08	0.75±0.09	0.73±0.10
y	0.84±0.04	0.81±0.05	0.73±0.08	0.80±0.09	0.74±0.11
z	0.71±0.08	0.54±0.16	0.66±0.07	0.54±0.17	0.64±0.11

time lag were similar to contributions from the 35 ms time lag of the velocity decoder. All subjects show contributions peaks at time lags 12 ms and 105 ms and low contributions otherwise. The same contribution distribution can be observed when decoding from normally distributed random data. Exemplarily, Fig. 3 shows the contributions for subject s3.

An example of decoded and band-pass filtered measured positions for subject 3 are shown in Fig. 2.

IV. DISCUSSION

In this paper we proofed that velocity and position decoding from executed arm movements in three dimensions without external targets is possible from EEG. r values were reasonable high. In [9] r values for x/y/z-axes were 0.19/0.38/0.32, which are two to almost four times smaller than correlations measured in this work. The coordinate systems were comparable, only the x and z axes were inverted. Reasons for this discrepancy could be that we did not presented targets – movements were self-chosen – and we omitted the first 5 s of runs to exclude possible existing

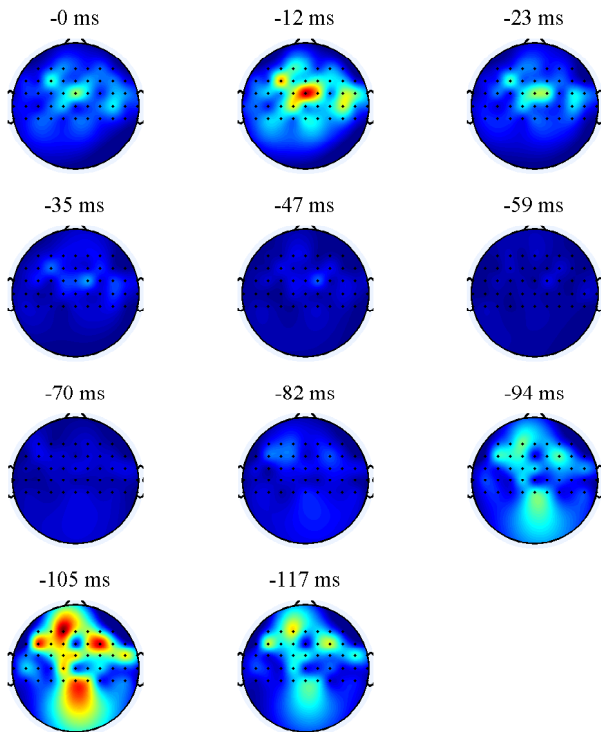|	s1	s2	s3	s4	s5
x	0.23±0.13	0.45±0.17	0.10±0.21	0.43±0.15	0.42±0.18
y	0.40±0.12	0.27±0.15	0.11±0.13	0.49±0.17	0.32±0.16
z	0.22±0.14	0.20±0.16	0.17±0.12	0.23±0.13	0.31±0.14

Fig. 3. Position decoder: Qualitative contribution of each channel at each time lag for s3. The largest contribution is colored red, the smallest blue.

tuned to the head properties of a person (e.g. geometry, conductivity), each person would have an individual weight pattern. If there is more than one area on the cortex coding velocity/position information, the weight pattern differences between subjects would be even more distinct. Subjects show basically at least a contribution from premotor/supplementary motor area or primary motor/sensory area. This is similar to [9] where high contributions from precentral gyrus, postcentral gyrus, and inferior parietal lobule were found, and to [11] where premotor, posterior parietal and occipital areas showed the largest contributions (using low frequency signals for decoding). Interestingly, the contribution course over time lags can also be obtained when decoding from random data. Thus, the contribution course over time lags has to be attributed to general properties of the multiple linear regression.

A non-invasive position decoding could be the basis to control an arm neuroprosthesis in a natural manner. The position of the hand is controlled by the user with natural MI, and inverse kinematics is used to move the joints of the arm neuroprosthesis in their proper position. Furthermore, the training time will be formidable reduced, because it is not necessary to learn new mental strategies.

movement onset effects. However, in the center-out reaching task used in [9] it is likely that movements were completed within 5 s. In [11] similar low r values (0.37/0.24 for x/y-axes) were obtained when decoding hand velocities from EEG during a drawing task restricted to left/right/up/down movements. Movement trajectories were self-chosen as in our work. However, because of the restriction to only four movement directions, it is obvious that executed movements were jerky and not continuous. Thus, it is possible that our relative high correlations are due to continuous movements (instead of "stop-and-go" movements).

The risk that our promising results are due to eye activity can be neglected, because the gaze of subjects was controlled, and decoding from EOG yield lower correlations than decoding from EEG. However, it is interesting that EOG based correlations were not close to 0. One reason could be that subjects moved their eyes correlated with movements over a short period of time. Another explanation is that we measured brain activity even perhaps at EOG electrodes. Low frequency biosignals are conducted better over the head than high frequency biosignals. Thus, low frequency EEG components are widespread over the scalp, and therefore even EOG electrodes could contain decodable movement information.

A common weight pattern between equivalent time lags was not observable across subjects. Weights probably include a spatial filter – in addition to the actual decoder part – to reduce the signal-to-noise ratio of the measured velocity/position coding sources. If this spatial filter is highly

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