Predicting Wrist Movement Trajectory from Ipsilesional ECoG in Chronic Stroke Patients

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Abstract: Recently, there have been several approaches to utilize a Brain-Computer Interface (BCI) for chronic stroke patients. The prediction of movement trajectory based on recorded brain activity could thereby help to improve BCI-guided stroke rehabilitation or could be used for control of an assistive device, like an orthosis or a robotic arm. One problem in predicting movement trajectory in stroke patients are compensatory movements, which make it difficult to link specific brain activity to movement intention. In this paper we compare different methods for trajectory prediction and show how Canonical Correlation Analysis (CCA) can be used to predict movement trajectories. Based on the results, we argue that the resulting trajectory prediction is closer to the actual movement intention. We further show how the transformation matrices obtained by CCA can be interpreted and discuss how this interpretation might be useful to get information regarding compensatory movements in stroke and the underlying patterns of brain activity.

1 INTRODUCTION

More than 80 % of the patients surviving a stroke are affected by hemiparesis (Cramer et al., 1997) and in 30 % to 66 % of those hemiparetic stroke patients the paretic arm remains without function when measured 6 months after stroke (Kwakkel et al., 2003). Brain-Computer Interface (BCI) technology might help those patients either by using a BCI as an assistive device to compensate the missing motor function (Yanagisawa et al., 2011) or as a tool for rehabilitation.

The use of BCI for stroke rehabilitation has been particularly prominent in the last time (Buch et al., 2008; Broetz et al., 2010; Ramos-Murguialday et al., 2013; Spüler et al., 2014). In this neurorehabilitation approach, the patients' intention to move is coupled with haptic feedback given through an orthosis moving the paretic limb (Buch et al., 2008). Since the connection between the sensorimotor cortex and the peripheral muscles is disrupted by stroke, a coincident activation of the primary motor cortex and the sensory feedback loop may induce Hebbian plasticity and thus support functional recovery (Silvoni et al., 2011).

Stroke patients tend to perform compensatory movements (Cirstea and Levin, 2000), which can be a problem when using BCI feedback for stroke rehabilitation, since compensatory movements produce brain activity which is unrelated to the intended movement (Lee et al., 2009) but inadvertently influences BCI feedback. Therefore it would be beneficial if brain activity related to compensatory movements could be separated from the activity related to the intended movement and only activity related to the intended movement is feedbacked by the BCI.

In this paper we evaluate different methods for the prediction of wrist movement trajectory based on ipsilesional Electrocorticography (ECoG) data in chronic stroke patients. A special emphasis is given on the use of Canonical Correlation Analysis (CCA) for this purpose. While CCA has been previously used for SSVEP BCIs (Bin et al., 2009), c-VEP BCIs (Spüler et al., 2012), as well as general spatial filtering method for classification of evoked or event-related potentials (Spüler et al., 2013), we show in this paper how it can also be used for trajectory prediction and extraction of movement components from the trajectory data, which may help to feedback brain activity related to the true movement intention.

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2 METHODS

In this section we describe the methods we evaluated for the prediction of the movement trajectory, the evaluation process itself, as well as the ECoG data used for evaluation.

Since the use of Canonical Correlation Analysis yields some particularly interesting results, we will explain the CCA method and its application in more detail.

2.1 Canonical Correlation Analysis (CCA)

CCA is a multivariate statistical method developed by H. Hotelling (Hotelling, 1936). When having two datasets, which may have some underlying correlations, CCA can be used to find linear transformations for these two datasets, which maximize the correlation between the transformed datasets. Assuming there are two multidimensional datasets X and Y with p variables in $X = (X_1, X_2, ..., X_p)^T$ and $q \leq p$ variables in $Y = (Y_1, Y_2, ..., Y_q)^T$ and their transformed datasets $U = W_x^T X = (U_1, U_2, ..., U_q)^T$ and $V = W_y^T Y = (V_1, V_2, ..., V_q)^T$. CCA can be used to find the two transformations W_x and W_y, which maximize the canonical correlation ρ_i^* between the canonical variables U_i and V_i.

$$\rho_i^* = \frac{\mathrm{cov}(U_i, V_i)}{\sqrt{\mathrm{var}(U_i)\mathrm{var}(V_i)}} \tag{1}$$

The linear transformations W_x and W_y are selected so that their variance equals one, while they are uncorrelated to all other canonical variables.

$$\mathrm{var}(U_i) = \mathrm{var}(V_i) = 1 \tag{2}$$

$$\mathrm{cov}(U_i, V_j) = \mathrm{cov}(U_j, V_i) = 0 \text{ , } \forall i \neq j \tag{3}$$

2.1.1 CCA and Linear Regression

A traditional regression can be formulated as having a multidimensional dataset X with dimensions $n \times p$ containing n observations of p variables and another dataset Y with dimensions $n \times 1$ containing the dependent variable. A linear regression tries to model the relationship between X and Y by finding a weight vector W with dimensions $p \times 1$ so that

$$Y_i = X_i W + \varepsilon_i \tag{4}$$

with ε_i being the error term which should be minimal. Thereby one can use W to predict Y' based on the observations contained in X.

$$Y' = XW \tag{5}$$

In the case of an ordinary least squares regression, this problem is solved by finding a W that minimizes the sum of the squared differences between the predicted $Y'$and the observed Y. With $\|\cdot\|$ being the euclidean distance, the problem can be written as:

$$\min \|Y - Y'\|^2 = \|XW - Y'\|^2 \tag{6}$$

CCA can also be used to solve a regression problem. Applying CCA to X and Y, the method tries to find a transformation W_x that maximized the correlation

$$\rho = \frac{W_x^T X Y^T W_y}{\sqrt{(W_x^T X X^T W_x)(W_y^T Y Y^T W_y)}} \tag{7}$$

The results is W_x being a weight vector with dimensions $p \times 1$ and W_y being a scalar, which can be used to predict Y with

$$Y' = XW \cdot W_y{}^{-1} \tag{8}$$

Since CCA only maximizes the correlation, CCA can only be used for regression methods under the condition that X and Y have a mean of 0. If this condition holds, CCA delivers results similar to other linear regression, as we will see later in this paper. Relationships between least squares and CCA have been established earlier in the literature. (Hastie et al., 1995) found CCA to be equivalent to Fisher Linear Discriment Analysis in a binary-class case, which in turn was found to be equivalent to CCA in this case (Bishop et al., 2006). (Sun et al., 2008) showed that CCA can be formulated as least squares problem which can be used to introduce regularized CCA and sparse CCA (using L1-norm regularization).

2.1.2 CCA and Component Analysis

While we have shown the relationship between CCA and linear (least squares) regression, there is also a distinct relationship between CCA and methods for component analysis like independent component analysis (ICA) and principal component analysis (PCA).

If CCA is used with a multidimensional dataset Y, the resulting transformation matrix W_y can be used as transformation matrix that separates the dataset Y in different components (called canonical variables in the context of CCA). Due to the constraints how CCA selects W_y (see equations 2 and 3), the resulting components are uncorrelated, which is also the case for ICA and PCA. Therefore, CCA can be seen as a method that extracts components V from Y, with the components V being maximally correlated to $U = W_x^T X$.

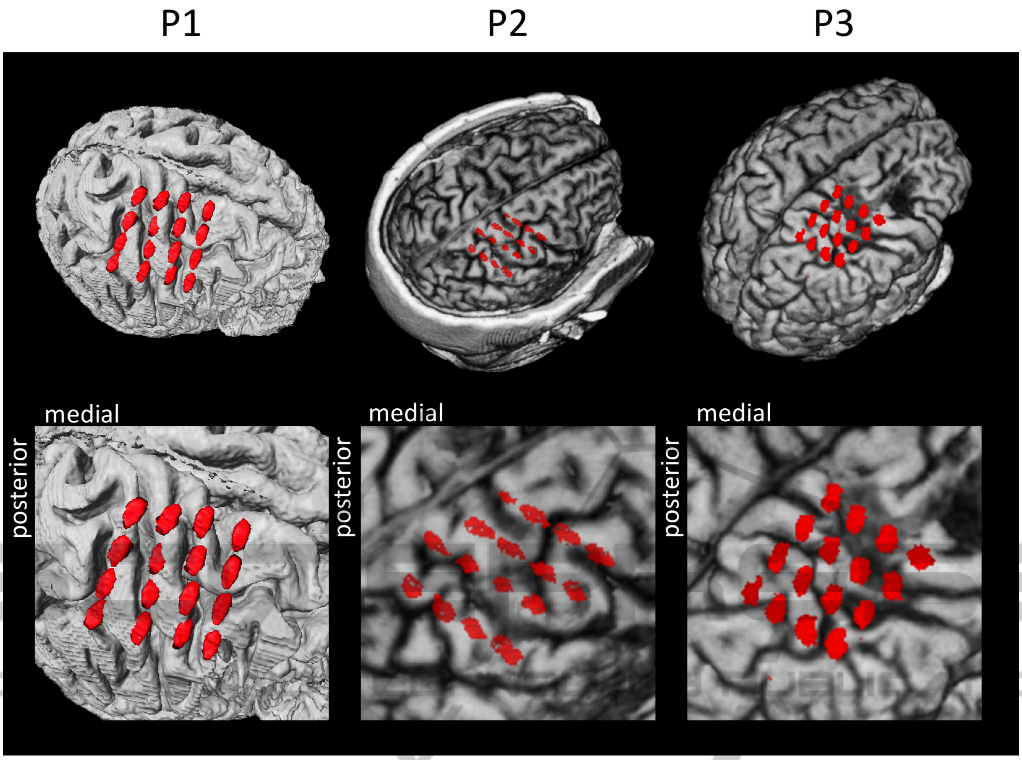

Figure 1: Locations of the epidurally implanted ECoG electrodes. Patients were implanted with 4 strips with 4 electrodes each. MRI images are reproduced from a previous publication (Walter et al., 2012).

Table 1: Demographic data for the three chronic stroke patients: Age, Sex, Fugl-Meyer Score for upper extremity (FMA, max 30), wrist (FMB, max 10), hand (FMC, max 14) and the time since insult (TSI) in month.

Patient	Age	Sex	FMA	FMB	FMC	TSI
P1	63	f	9	0	0	71
P2	56	m	19	3	1	80
P3	52	m	13	6	2	159

2.2 ECoG Data

2.2.1 Patient Description

The ECoG data used in this study was recorded from 3 patients who suffered from left-sided chronic hand-paresis due to stroke. The patients took part in a long-term investigational study for motor cortex stimulation with epidural implants concurrent to rehabilitation training to improve upper limb motor function after stroke. The study protocol was approved by the local ethics committee (Faculty of Medicine, University Hospital Tübingen) and included an initial four week evaluation period immediately after implantation of the ECoG grids to investigate patients individual cortical physiology for optimization of stimulation location and paradigms. An overview of the patients' demographic data and the Fugl-Meyer scores (Fugl-Meyer et al., 1975) for wrist movement (FMB) are shown in table 1.

Each of the 3 patients was epidurally implanted with 16 platinum disk electrodes (Medtronic, Inc.) with a diameter of 4 mm, which were arranged in 4 strips with 4 electrodes each. The strips were placed in a grid-like fashion with a center-to-center distance of 1 cm. Although technically these are 4 strips, we will refer to it as one grid. These grids were placed above the hand area of the ipsilesional motor cortex and also covered premotor and sensory areas. The location of the grids are shown in figure 1. More detailed information about the patients can be found in a previous publication (Walter et al., 2012). Data recorded during that evaluation period was used for the evaluation of the method presented in this paper.

2.2.2 Task Description

During the aforementioned evaluation period, the patients also participated in a robot-assisted stroke rehabilitation program and ECoG data was recorded during the performed exercises. Each of the patients participated in 10 to 20 sessions performed on different days in which they had to repeat wrist extension and wrist flexion several times using their paretic arm.

On average 8 minutes of wrist extension/flexion were recorded per session.

The degree to which the patients were able to perform extension/flexion varied, but movement was supported by an upper limb rehabilitation robot (Hocoma Armeo Spring), which removed gravitational effects. Further, the robot allowed movement along 7 degrees of freedom (DOF) with the angle of the 7 joints being constantly recorded.

Although the patients were instructed to do a wrist extension/flexion (needing only 1 DOF), movement along several DOF was visible due to coactivation and compensatory movements resulting from stroke. Therefore, the performed (and recorded) trajectory not matches the actual intended movement trajectory and also there is a movement trajectory present for the other DOF, where no movement was intended.

2.3 Data Processing and Feature Extraction

ECoG signals were recorded with Brainamp DC (Brain Products GmbH, Munich, Germany) amplifiers at a sampling rate of 1000 Hz and a high-pass filter at 0.16 Hz. After recording, the signal was re-referenced to the common average and a notch filter at 50 Hz was applied to filter out power line noise. To estimate the power spectrum we used the maximum entropy method (Burg, 1967) with a model order of 50. The power spectrum was estimated for each channel in the range from 1 to 500 Hz with a bin width of 4 Hz and the logarithm function was applied to each value.

To reduce dimensionality of the input space, we performed a feature selection based on R^2 values (Spüler et al., 2011) and selected the 50 features which had the highest values. In the end, those features served as input to train a model (using either a regression method or CCA) to predict movement trajectory.

2.4 Trajectory Prediction

To evaluate which method is suited best for prediction of movement trajectory, we used the following five methods:

1. **(L1 reg)** Lasso regression: Linear regression with L1 Norm regularisation using the regularisation parameter $\lambda = 0.1$.
2. **(L2 reg)** Ridge regression: Linear regression with L2 Norm regularisation using the regularisation parameter $\lambda = 0.1$.
3. **(SVR)** Support Vector Regression with a linear kernel or a radial basis function (RBF) kernel. For implementation we used LibSVM (Chang and Lin, 2011) with default kernel parameters and the hyperparameter C=1.
4. **(CCA)** Canonical Correlation Analysis for the prediction of movement components. A more detailed explanation how we applied CCA will be presented later (see section 2.4.1).
5. **(PCA + L2 reg)** Since CCA was not used to predict the actual wrist movement trajectory, but to predict movement components identified by CCA, we also used Principal Component Analysis (PCA) (Dunteman, 1989) on the recorded movement data (7 degrees of freedom) to obtain movement components that better match the movement intention of the stroke patients. The principal components with the highest variance was used for trajectory prediction by using a ridge regression as explained previously.

2.4.1 CCA to Predict Movement Components Based on ECoG Data

We have previously shown that the calculation of W_x can be seen as a linear regression, where W_x is used to predict a variable. We have also shown that the calculation of W_y can be seen as a form of component analysis, where CCA transforms the dataset Y into uncorrelated components. When both datasets X and Y are multidimensional both aspects have to be considered and the application of CCA can be seen as an extraction of components and a regression to predict those components. Both is done by CCA in one step.

When applying CCA to the ECoG data (as X) and movement trajectory data (as Y), we can use CCA to find movement components in the trajectory data and do a regression to predict those movement components based on the ECoG data. The reasoning behind this approach is that the performed (and recorded) trajectory differs from intended movement trajectory due to compensatory movements and the stroke patients not being able to properly perform the intended movement. With the extraction of trajectory components, we hope to find components which are closer to the actual intended movement trajectory. In this work we always used the first component extracted by CCA.

2.5 Performance Evaluation

To evaluate the performance of the different methods for trajectory prediction, we used a 5-fold cross-validation procedure to make sure that training and

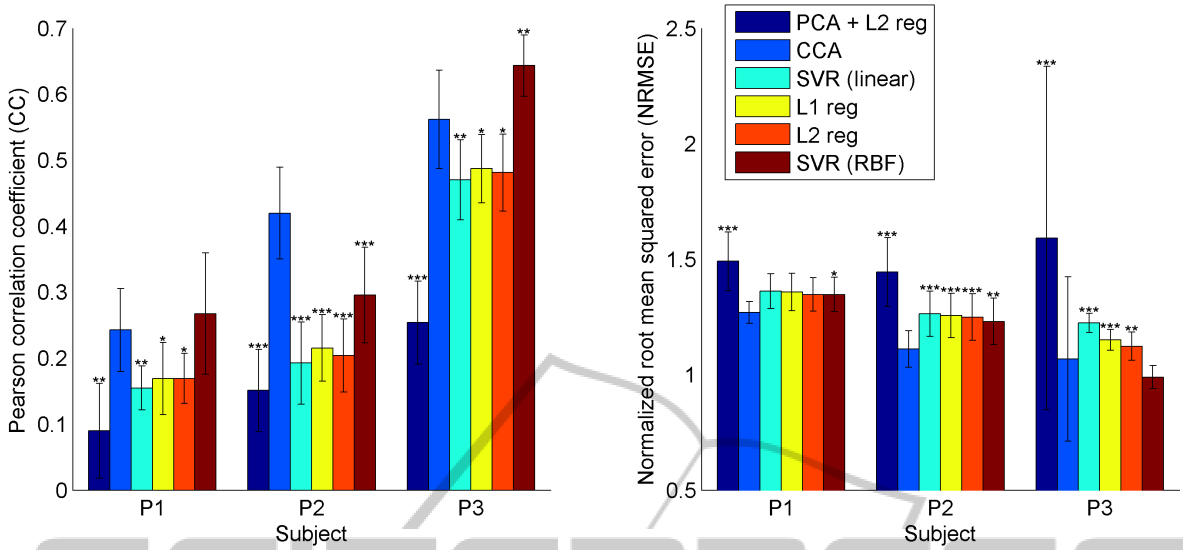

Figure 2: Performance (NRMSE and CC) for different methods for trajectory prediction averaged over all sessions for one subject. The error bars indicate the standard deviation. Asteriks denote if there is a significant difference between the method and CCA, with $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ (Wilcoxon ranksum test).

test data do not overlap. To quantify the performance of the methods, we used Pearson's correlation coefficient (CC) an the normalized root mean squared error (NRMSE), which we defined as

$$\mathrm{NRMSE} = \sqrt{\frac{\sum_{t=1}^{n}(\hat{y}_t - y_t)^2}{n}} \cdot \mathrm{var}(y)^{-1} \tag{9}$$

with y_t being the actual and $\hat{y}_t$ being the predicted value. $\mathrm{var}(y)$ denotes the variance of the actual trajectory. Since the trajectory values are different depending if PCA or CCA are used, the normalization is important to compare the RMSE between the methods.

3 RESULTS

3.1 Performance of Trajectory Prediction

On average CCA performed best with an average $CC = 0.41$ and an average $NRMSE = 1.15$. While CCA performs consistently better than the other linear methods, a Support Vector Regression (SVR) with a RBF-kernel has a significantly ($p < 0.01$) higher CC for subject P3. The results are show in figure 2 in more detailed. For each subject and method, the results are averaged over all session with the standard deviation being indicated by error bars and the significance between each of the methods and CCA being assessed by a two-sided Wilcoxon ranksum test.

3.2 Interpretation of CCA Transformation Matrices

Due to the nature of CCA, the transformation matrices W_x and W_y could be used for some neurophysiological interpretation of the data. While W_x is used to predict the movement trajectory, it shows which electrodes and which frequency ranges are important for the prediction. Thereby one can infer where (location and frequency) movement-related activity is present. W_y is used to calculate the movement components and in turn can be used to infer which joints (represented by the DOFs in our data) are active during an intended wrist movement. This could be used to gain more knowledge regarding the compensatory movement patterns of stroke patients.

Figure 3 shows the weights using a linear regression to visualize which electrodes and frequencies are used to predict the recorded wrist movement trajectory, as well as the recorded and predicted wrist movement trajectory for one exemplary session. Figure 3 also shows the R^2-values (Sheikh et al., 2003) indicating which features (electrode $\times$ frequency) correlate best with the trajectory.

Figure 4 shows the weights of the W_x and W_y (for the first movement component) when using CCA on one exemplary session. As well as the actual and predicted movement trajectory.

When comparing both figures, the activity pattern obtained by CCA (figure 4.A) is more localized than the one obtained by a linear regression (figure 3.A). Furthermore, the weights of W_y (figure 4.B) yield in-

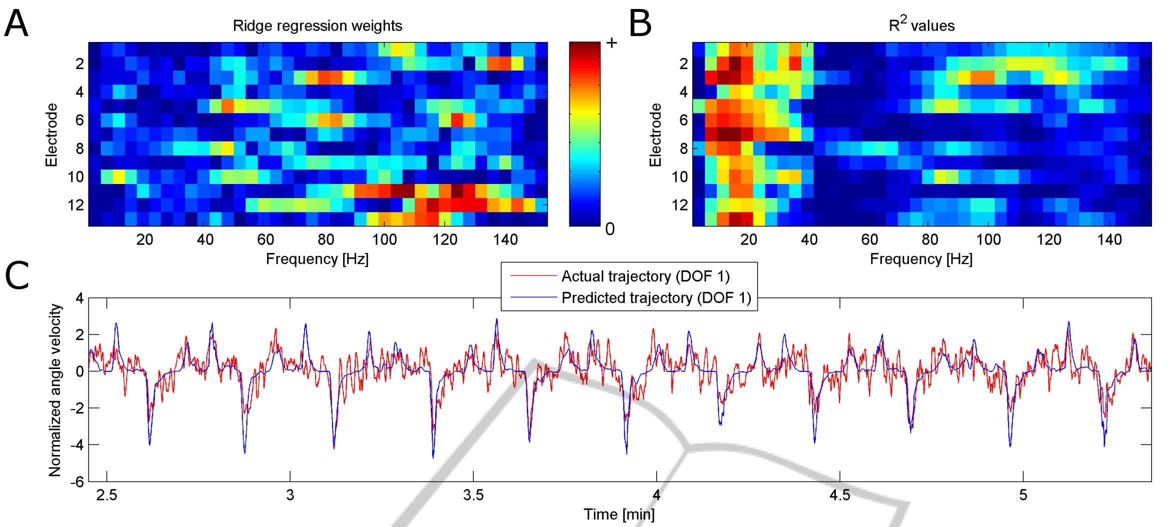

Figure 3: A: Absolute weights from ridge regression for each feature (frequency × electrode) used in trajectory prediction. B: R^2 values indicating high correlation between each feature and the trajectory C: Actual and predicted trajectory of the movement component calculated by ridge regression.

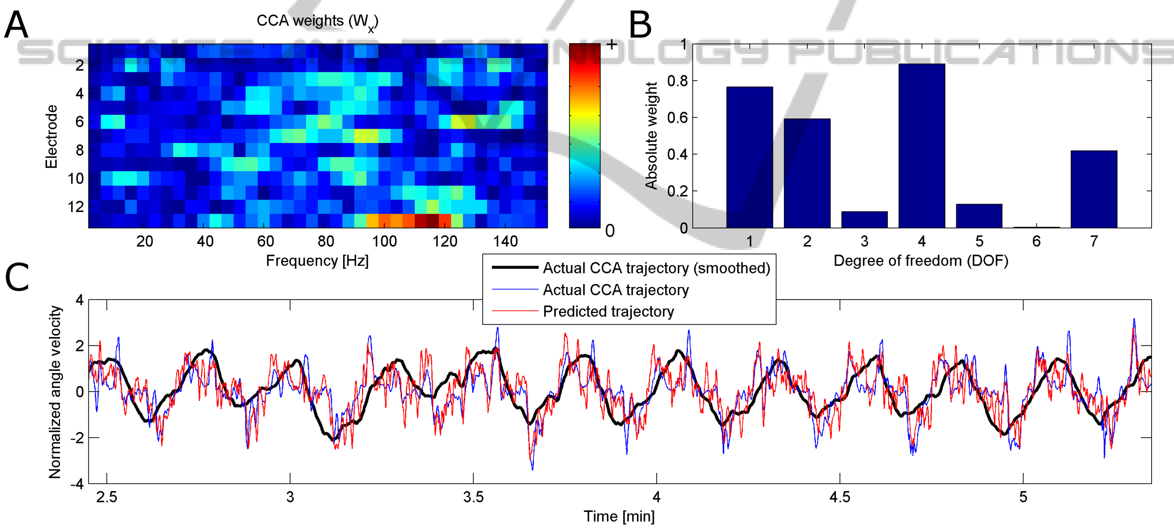

Figure 4: A: Absolute weights from CCA for each feature (frequency × electrode) used in trajectory prediction of the first movement component. B: Absolute weights for each DOF to calculate the movement component. C: Actual and predicted trajectory of the movement component calculated by CCA. The smoothed trajectory is only shown for better display purposes and was not used for trajectory prediction or performance evaluation.

formation, which DOFs are affected by the intended wrist movement, thereby showing the coactivation pattern present during the intended wrist movement.

Figure 3.C shows the actual and the predicted wrist movement trajectory using linear regression, while figure 4.C shows the predicted and actual movement trajectory obtained by CCA. When comparing the results from CCA with the results using a linear regression, the trajectory obtained by CCA seems more noisy but more natural and more representative of the true intended movement.

4 DISCUSSION

In this paper we have compared different methods for the trajectory prediction from ECoG in stroke patients. The fact that ECoG can be used for trajectory prediction was shown in several studies for subjects with an intact sensorimotor system. In (Schalk et al., 2008) average CC were approximately between 0.22 and 0.71, in (Pistohl et al., 2008) CCs between 0.3 and 0.6 were reached and performance in later studies yielded CCs in a similar range. (Nakanishi et al.,

2013) have shown that it is also possible to predict movement trajectory in stroke patients from ipsilesional ECoG. With an average CC ranging between 0.44 and 0.73 the performance obtained by Nakanishi et al. is similar to the results obtained in earlier studies with subjects without motor dysfunction. We could reproduce this finding in our work and were able to decode the trajectory with an average CC between 0.24 and 0.64 depending on the subject, which is similar to the results by (Nakanishi et al., 2013).

It should be noted that there seems to be a negative correlation between the Fugl-Meyer (FM) Score regarding wrist movement and the accuracy of wrist trajectory prediction, since the patient with the lowest FM score (indicating a high wrist motor dysfunction) had the lowest CC and vice versa. Although it seems reasonable to assume that wrist movement trajectory is harder to decode for patients whose motor system is more damaged by stroke, the current dataset (with only three patients measured) is too small to draw any significant conclusions.

Regarding the comparison of different prediction methods for wrist trajectory prediction, we found CCA and Support Vector Regression (SVR) with an RBF kernel to perform best. While CCA performed on average slightly better than SVR, the use of CCA has either advantages or disadvantages compared to SVR, depending on the point of view. While SVR predicts the trajectory of a specific joint, CCA predicts the trajectory of a component. So obviously CCA cannot be used when the aim is the prediction of a certain joint or a certain movement direction. But in case of stroke rehabilitation or orthotic control, one could also use the components predicted by CCA to give the user feedback using multiple joints at once, which would allow for a more natural feedback. This gets clearer when looking at the movement trajectories. The performed (and recorded) wrist movement trajectory looks unnatural and choppy, which is caused by hemiparesis and compensatory movements due to stroke. The movement trajectory obtained by CCA, although being more noisy, resembles much better the intended wrist extension and flexion trajectory. Thereby we argue that CCA is not only better suited for trajectory decoding than other methods, but also allows to predict the real movement intention of the patient instead of the performed and impaired movement of the stroke patient. Based on these results, one could interpret the transformation matrices to infer knowledge regarding the participation of different joints in compensatory movements and which parts of the brain signal yield information regarding the compensatory movement and the intended movement. Although we did not demonstrate this aspect of CCA in detail, we think that CCA is a potential tool in this field with possible applications beyond the use for trajectory prediction.

5 CONCLUSION

In this paper we have shown that we are able to decode wrist movement trajectory from hemiparetic chronic stroke patients based on ipsilesional ECoG recordings over their sensorimotor cortex. We have further compared different methods for trajectory prediction and could show that either SVR (with RBF kernel) or CCA are the best methods for trajectory prediction, depending on the intended application. Further we have outlined how the application of CCA could be potentially useful to infer information regarding compensatory movements, the intended movement trajectory and the underlying brain activity regarding both.

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