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Feature Extraction Methods for Studying Surface Electromyography and Kinematic Measurements in Parkinson's Disease

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Additional information is available at the end of the chapter

1. Introduction

1.1. Parkinson's disease (PD)

Parkinson's disease is a progressive neurodegenerative disease that affects 1 % of people over 60 years of age [9]. In PD, there is a dopaminergic neuronal loss in the substantia nigra in the basal ganglia of the cerebra [48]. It has been observed that the basal ganglia has a specific effect on the temporal organization of motor cortical activity during muscle contractions. In this way, the dysfunction of the basal ganglia may lead to motor symptoms of PD. [37] The primary symptoms of PD include tremor, muscle rigidity and slowness of movements. The diagnosis is based on the presence of the primary symptoms and on the response to medication. [17, 18]. However, the diagnosis can be problematic. Clinicopathological studies from the UK and Canada have shown that the disease is diagnosed incorrectly in about 25 % of patients [48]. The pre-motor period before diagnosis may be long (5–20 years) and at the time of the diagnosis already 50–60 % of the dopaminergic neurons may be lost [22, 38].

Although there is no cure for PD, the symptoms can be relieved reasonably with medication or with the deep brain stimulation (DBS) [17]. The motor impairment, the disease progression and the efficacy of treatment are commonly evaluated subjectively using standardized rating scales such as the Unified Parkinson's disease rating scale (UPDRS) [12, 15]. No objectively measured characteristics and methods are widely used for quantifying motor symptoms of PD [2].

Several objective methods have been proposed for improving the diagnostic accuracy of PD, for enabling earlier diagnosis, and for quantifying the disease severity, progression and the efficacy of treatment. These methods include: kinematic measurements of motor tasks (e.g. finger tapping), testing of olfactory loss, imaging techniques (e.g. magnetic resonance imaging and positron emission tomography), and biochemical tests of blood and cerebrospinal fluid.

However, none of the proposed methods is widely used for PD. The validation of new methods for clinical use takes time. In order to be more sensitive than the traditional methods it is probable that a combination of several methods will be needed for PD. [2, 11, 24]

1.2. Surface electromyography and kinematic measurements in PD

Surface electromyography (EMG) and kinematic measurements are non-invasive and relatively simple and cost-effective methods for quantifying neuromuscular function and movement. Therefore, these methods may be suitable for quantifying objectively the motor impairment in PD and the effects of treatment. A few new technologies based on kinematic sensors have been recently commercialized for measuring motor symptoms of PD. The kinematic measurements provide information about human movements. However, it is possible that surface EMG provides earlier or more direct information about PD than the sole kinematic measures based on movement.

Several studies have analyzed the surface EMG and kinematic signals of PD patients in comparison to the signals of healthy subjects and aimed to correlate the most significant findings with the clinical rating scales. Differences between patients and healthy subjects have been observed in the tremor-EMG coherence [50], in the cortico-muscular coherence [37] and in the muscle activation patterns during limb movements [13, 26, 35]. In the gait characteristics, differences have been observed in the gait speed and stride length, in the arm and leg swing and in the muscle activation patterns of gait [5–7, 36, 43].

Several studies have evaluated effects of PD treatment (medication and DBS) on the basis of EMG and kinematic measurements. It has been observed that the medication and DBS may modify the tremor amplitude, regularity and frequency [4, 41, 42], movement speed [3, 8, 34, 40, 44, 49, 51, 52], joint kinetics and muscle activation during movements [55], EMG burst patterns during movement [34, 51, 52] and the cortico-muscular coherence [25, 37]. There is currently a lot of interest for characterizing EMG and kinematic signals of PD patients. However, many studies have analyzed the EMG signals of PD patients by using conventional amplitude- and spectral based methods. More information about PD could be extracted from the EMG signals by using also more modern methods of signal analysis, by analyzing sets of signal features and by analyzing the signal characteristics also on individual level.

EMG signals are impulse-like waveforms because they consist of motor unit (MU) action potentials. The level of MU synchronization is increased in PD [14, 50], which appears as an increased number of recurring spikes and bursts in the EMG signals. Therefore, there is important information about PD in the morphology of the EMG signal and in the recurring signal patterns. It has been observed that the conventional EMG signal parameters (amplitudes and the mean and median frequencies) are not effective in capturing impulse-like structures [23]. Therefore, more modern methods of signal analysis are needed for analyzing the EMG signals of PD patients.

1.3. Our approach for studying surface EMG and kinematic measurements in PD

In order to extract PD-related information from the surface EMG signals effectively, we proposed specific methods based on signal morphology, nonlinear dynamics and wavelets for analyzing the EMG signals of PD patients in [28–32]. One aim of those studies was to develop

objective methods for discriminating between PD patients and healthy subjects on the basis of surface EMG signal morphology [32] and on the basis of simultaneous EMG and acceleration (ACC) recordings during isometric [28] and dynamic muscle contractions [29]. Another aim was to develop methods based on surface EMG and kinematic measurements and analysis for quantifying effects of PD treatment (medication and DBS) on individual level. All of those studies presented an innovative approach, that combines a principal component (PC) -based method with a set of effective signal features, for analyzing the EMG and acceleration signals in PD. In the following sections 2, 3 and 4, we describe the methods that were developed and used for feature extraction and discrimination between subjects in [28–32]. All methods were tested with the measured data. In total, the measurement data from 62 PD patients and 72 healthy subjects were analyzed. The main findings of those studies are also described.

2. Analysis EMG signal morphology in PD

EMG signal is a sum of MU action potentials at a given location and therefore it is an impulse-like waveform. The EMG signals of PD patients are characterized by recurring spikes and bursts (see Figure 1) that are likely caused by the increased level of MU synchronization. Important information about PD is in the EMG signal morphology and in the recurring signal patters.

In [32], the EMG signal morphology of 25 PD patients and 22 healthy subjects was analyzed by using sample histograms and crossing rate (CR) expansions. The analyzed EMG signals were measured during the isometric contraction of biceps brachii (BB) muscles. During the task, subjects were asked to hold their elbows at a 90° angle with their palms up. The measurements were performed by using the ME6000 -biosignal monitor (Mega Electronics Ltd., Kuopio, Finland) and disposable Ag/AgCl electrodes (Medicotest, model M-00-S, Ølstykke, Denmark) in bipolar connection. The sampling rate was 1000 Hz.
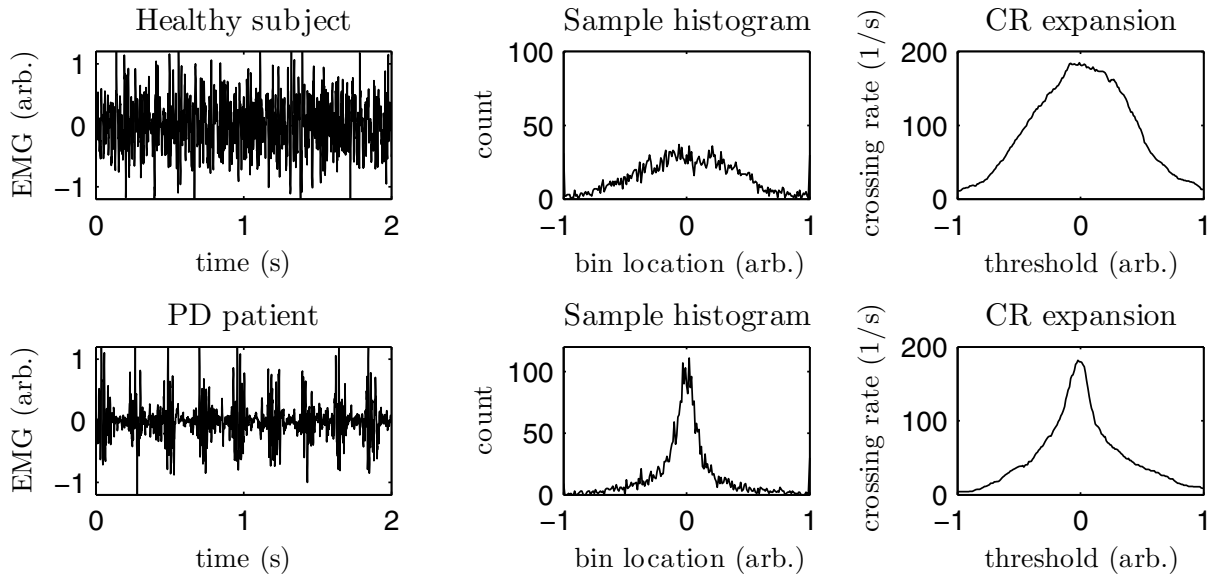
Typical EMG signals of one healthy subject and one PD patient are presented in Figure 1. One can observe that the EMG signal of the patient contains recurring EMG bursts while the EMG signal of the healthy subject does not.

2.1. Feature extraction by using sample histograms and CR expansions

Sample histograms were extracted from the scaled (between -1 and 1) EMG signals with 200 bins and the CR expansions from the scaled EMGs as the number of crossings at given threshold levels (201 threshold levels). An example of the sample histogram and the CR expansion for the healthy subject and for the PD patient are presented in Figure 1. One can observe that the sample histogram of the patient is sharper and the CR expansion narrower than those of the healthy subject.

2.2. Discrimination analysis between subjects

The calculated sample histograms and CR expansions of PD patients (with medication on) and healthy subjects were used as high-dimensional feature vectors for discrimination analysis between subjects. The PC-based approach was used for decreasing the dimensionality of the

Figure 1. EMG signals of one healthy subject (top) and one PD patient (bottom). The sample histograms and crossing rate expansions of the healthy subject and the PD patient.

feature vectors and the discriminant analysis of subjects was performed in a two-dimensional feature space.

In the PC-based approach [19], each feature vector $z_j \in \mathbb{R}^{N_p}$ is modeled with a linear model

$$z_j = H\theta_j + v_j. \tag{1}$$

In the linear model, $H = [\phi_1 \ \phi_2 \ \ldots \ \phi_K] \in \mathbb{R}^{N_p \times K}$ is the model matrix that contains the basis vectors $\phi_k \in \mathbb{R}^{N_p}$ in its columns. Vector $\theta_j \in \mathbb{R}^K$ contains the model weights and $v_j \in \mathbb{R}^{N_p}$ the model error for the j'th feature vector. The basis vectors ϕ_k are selected to be the eigenvectors of the data correlation matrix

$$R_z = \frac{1}{M} \sum_{j=1}^{M} z_j z_j^T, \tag{2}$$

where M is the total number of feature vectors and $(\cdot)^T$ denotes the transpose. Because the eigenvectors are orthonormal, the least squares solution for the model weights θ_j is of the form

$$\hat{\theta}_j = (H^T H)^{-1} H^T z_j = H^T z_j. \tag{3}$$

These weights are called the principal components. By choosing K ($K < N_p$) eigenvectors corresponding to K largest eigenvalues for modeling, the best K-dimensional orthogonal approximation for the data set is obtained. The PCs are the new uncorrelated features and they can be used for discriminating between subjects in a low-dimensional feature space.

In [32], three feature vectors were formed for each subject: one containing the EMG sample histogram, one containing the CR expansion and one containing both of them (augmented PC approach). Thus, the original dimensionality of the feature vectors was reasonably high ($N_p \geq 200$). The feature vectors of one PD patient and one healthy subject in the augmented

PC approach are illustrated in Figure 2. In addition, the correlation matrix and the three eigenvectors corresponding to the three largest eigenvalues are presented in the same figure.
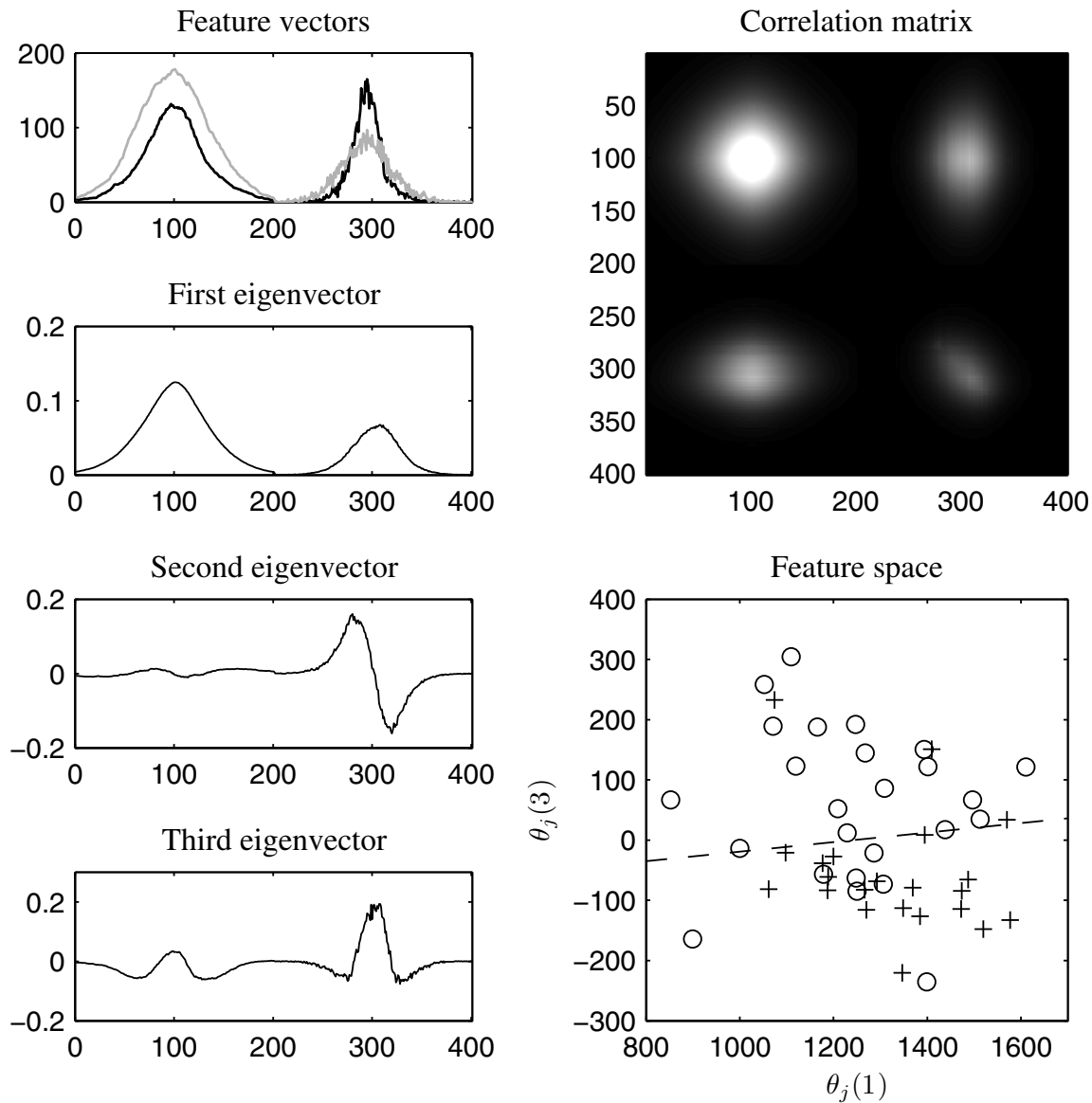
Figure 2. The feature vectors of one PD patient (black) and one healthy subject (gray) in the augmented PC approach (top left). Three eigenvectors corresponding to the three largest eigenvalues (left). The data correlation matrix (top right). The third PCs $\theta_j(3)$ with respect to the first PCs $\theta_j(1)$ of 22 healthy subjects (+) and 25 PD patients (○) (bottom right).

The correlation matrix in Figure 2 contains four white areas with high correlation. The white area in the top left corner describes correlations between the CR expansion values. The white area in the bottom right corner describes correlations between the sample histogram values. The non-diagonal white areas describe cross-correlations between the CR expansion values and the sample histogram values.

The eigenvectors in Figure 2 can be interpreted as follows:

- The first eigenvector is the best mean-square fit for the feature vectors of all subjects. Thus, it is similar to the mean of all feature vectors. Therefore, the first PC describes the amplitude of the histogram and the CR expansion with respect to the mean of all subjects.

- The second eigenvector is the best mean-square fit for the residual of the first fit. The second eigenvector describes variations in the peaks (modes) of the histograms and CR expansions of all subjects.

- The third eigenvector models variations in the heights and widths of the histograms and CR expansions in the whole data set.

The rest of the eigenvectors contain information about higher frequencies of the data and do not interest us in this case. The biggest differences between patients and healthy subjects were found in the third PC and some differences were observed in the first PC. Therefore, the discrimination between subjects was performed with respect to the third and the first PC.

2.3. Results

A linear discriminant was used in [32] for discriminating between the subjects in the two-dimensional feature space that was spanned by the third and the first PCs. The best discrimination results were obtained by using the augmented PC approach (see results in Figure 2). According to the results, 72 % of PD patients can be discriminated from 86 % of healthy subjects on the basis of EMG signal morphology.

3. Analysis of simultaneous EMG and acceleration recordings in PD

3.1. EMG and acceleration measurements

We analyzed simultaneous EMG and acceleration measurements of PD patients and healthy subjects in [28, 29] and aimed to develop methods for discriminating between the patients and the healthy subjects on the basis of the measured signals. The signals were measured during isometric contraction of BB muscles [28] and during dynamic elbow flexion-extension movements [29].

During the isometric task, the subjects were asked to hold their elbows at a 90° angle with their palms up. During the dynamic task, the subjects were asked to flex and extend their both elbows vertically and freely in two-second cycles with their palms up. Surface EMGs were registered continuously from the BB muscles and the accelerations of forearms simultaneously from the palmar side of subject's wrists. All measurements were performed by using the ME6000 -biosignal monitor (Mega Electronics Ltd., Kuopio, Finland), disposable Ag/AgCl electrodes (Medicotest, model M-00-S, Ølstykke, Denmark) in bipolar connection and tri-axial accelerometers (Meac-x, Mega Electronics Ltd., range ± 10 g). Signals were sampled with the rate of 1000 Hz. The resultant of the acceleration was used in the analysis. Low-frequency trends were removed from both signals by using the smoothness priors method [46]. The high-pass cut-off frequencies were 10 Hz for EMG and 2 Hz for acceleration.

Typical EMG and acceleration signals of one PD patient and one healthy subject during the isometric and dynamic task are presented in Figure 3. It is observed in the isometric
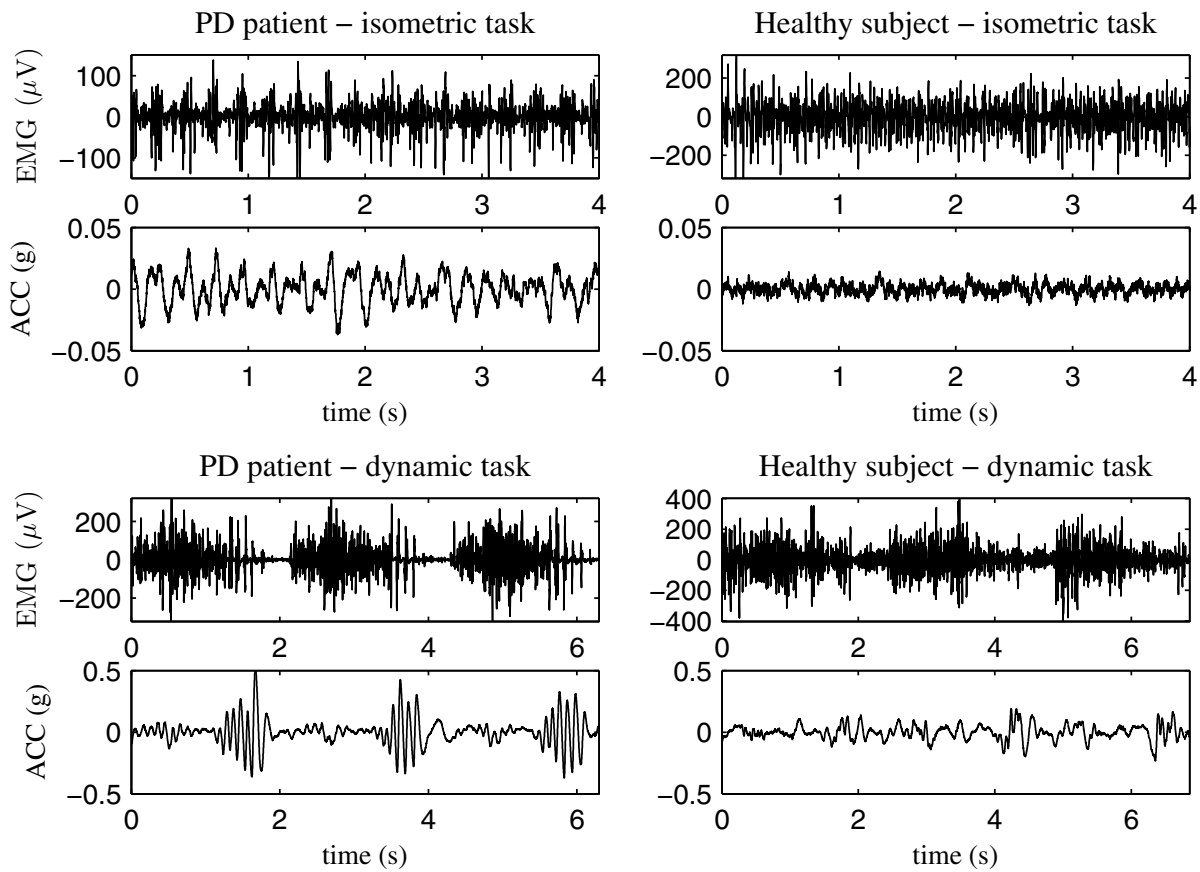
Figure 3. EMG and acceleration recordings of one PD patient (left) and one healthy subject (right) during the isometric and the dynamic task.

recording, that the EMG signal of the PD patient differs from the EMG signal of the healthy subject by containing recurring EMG bursts and the acceleration signal by containing regular high-amplitude oscillation. This oscillation is likely due to the resting and postural tremor. It is observed in the dynamic recording, that the EMG signal of the PD patient is characterized by recurring spikes and the acceleration recording by containing high-amplitude oscillation during the extension phases of the movement. The oscillation in the acceleration signal (which was high-pass-filtered with 2 Hz as cut-off frequency) is likely due to muscle rigidity and kinetic tremor (tremor that occurs during movement). In the flexion phases of the movement, the differences between the patient and the healthy subject are not as pronounced.

3.2. Feature extraction from EMG and acceleration signals

It was observed in [23] and [28, 29] that the conventional amplitude- and spectral-based EMG parameters (root mean square value and median frequency) are not effective in characterizing the EMG signals of PD patients in comparison to the signals of the healthy subjects. Therefore, we extracted a set of other PD characteristic signal features from the isometric [28] and dynamic EMG and acceleration recordings [29]. These parameters are detailed in Table 1 and they were calculated as epoch averages from the isometric EMG and acceleration signals and as time-varying from the dynamic signals.

Task type	Signal features	Notations
Isometric	sample kurtosis of EMG	k_r and k_l
	crossing rate variable of EMG	cr_r and cr_l
	correlation dimension of EMG	$D_{2,r}$ and $D_{2,l}$
	recurrence rate of EMG	$\%REC_r$ and $\%REC_l$
	sample entropy of ACC	$SampEn_r$ and $SampEn_l$
	coherence between EMG and ACC	Coh_r and Coh_l
Dynamic	recurrence rate of EMG	$\%REC_r$ and $\%REC_l$
	cross-recurrence rate of EMG	$\%REC_{r,l}$
	wavelet variable of EMG	$W_{max,r}$ and $W_{max,l}$
	cross-wavelet variable of EMG	$W_{max,rl}$
	power of ACC	$P_{acc,r}$ and $P_{acc,l}$
	sample entropy of ACC	$SampEn_r$ and $SampEn_l$

Table 1. PD characteristic signal features and their notations. The subscripts r and l in the notations stand for the side of the body.

3.2.1. Parameters of surface EMG signal morphology

In [28], we used two parameters (k and cr) for measuring the peakedness of EMG signals. The sample kurtosis was calculated as the fourth centered moment of the time series x (length N):

$$k = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu_x)^4}{\sigma_x^4},$$
(4)

where μ_x is the mean and σ_x the standard deviation (SD) of the sample values. Parameter k is higher for more peaked signals.

The parameter cr was calculated as the width/height of the CR expansion. The width of the CR expansion was defined at the level of 50 crossings/second and the height as the maximum value of the CR expansion. Parameter cr is lower for more peaked signals.

3.2.2. EMG parameters of nonlinear dynamics

In [28, 29], we used parameters of nonlinear dynamics (correlation dimension, recurrence rate and cross-recurrence rate) for analyzing the EMG signal complexity and recurring EMG patterns. In nonlinear dynamics, the original time series (EMG signal) x is used to form embedding vectors u_i

$$u_i = [x_i \; x_{i+\lambda} \; x_{i+2\lambda} \; \cdots \; x_{i+(m-1)\lambda}],$$
(5)

where λ is the delay parameter and m the embedding dimension [45]. The number of different embedding vectors is $N_m = N_e - (m-1)\lambda$ for each epoch (length N_e) of the time series x.

The correlation dimension [16] describes the complexity of the time series and it can be calculated from the embedding vectors as follows. First, the Euclidean distances between each pair of embedding vectors u_i and u_j in (5) are quantified as

$$d_e(u_i, u_j) = \sqrt{\sum_{k=0}^{m-1}|x_{i+k\lambda} - x_{j+k\lambda}|^2}.$$
(6)

The correlation sum is then calculated as

$$C^m(r) = \frac{1}{N_m^2} \sum_{i,j=1}^{N_m} \Theta(r - d_e(u_i, u_j)) \tag{7}$$

$$\Theta(s) = \begin{cases} 0, & s < 0 \\ 1, & s \geq 0, \end{cases}$$

where r is the threshold distance. The correlation dimension is formally defined as

$$D_2(m) = \lim_{r \to 0} \lim_{N_m \to \infty} \frac{\log C^m(r)}{\log r}. \tag{8}$$

Practically, D_2 is calculated as the slope of the regression curve in the log-log-representation.

Recurrence rate [53] measures the percentage of recurring patterns in the EMG signal. It can be calculated from the embedding vector distances in (6) as a percentage of distances that are below of the threshold distance r. The binary image, that contains a value 1 in the cells (i, j) where $d_e(u_i, u_j) < r$, is called the recurrence plot. The recurrence plots of one healthy subject and one PD patient are illustrated in Figure 4. One can observe that the recurrence plot of the patient contains more cells with the value 1 (white cells) than the recurrence plot of the healthy subject. It means that the EMG signal of the patient contains more recurring patterns than the EMG signal of the healthy subject. In the cross-recurrence rate, the embedding vectors in (5) are formed for two time series and the Euclidean distances in (6) are evaluated between the embedding vectors of the two different time series.
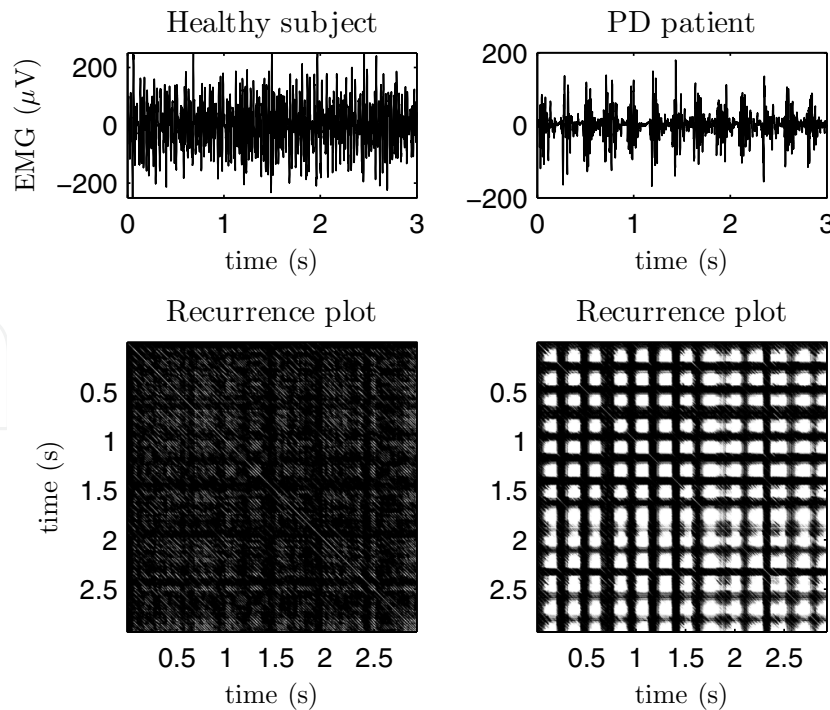
**Figure 4.** EMG signals and recurrence plots of one healthy subject and one PD patient.

3.2.3. Spectral-based parameters

In spectral analysis, the aim is to present the signal in the frequency-domain by estimating its power spectral density (PSD). The PSD estimation can be based on a Fourier transform or wavelet transform or on parametric modeling. In [28, 29], the Fourier- and wavelet-based approaches were used for analyzing the EMG and acceleration signals of PD patients and healthy subjects.

The coherence was used in [28] for quantifying similarities in the power spectra of the EMG and acceleration signals. It was calculated from the PSDs of the EMG and acceleration signals ($P_x(f)$ and $P_y(f)$) and from the cross-spectral density $P_{xy}(f)$, which were estimated by using the Welch's averaged periodogram method [54]. The magnitude-squared coherence is defined as

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_x(f)P_y(f)} \tag{9}$$

and it gives values between 0 and 1. Variable Coh was calculated as the area of the coherence spectrum above a threshold value in the frequency range 0–50 Hz. The magnitude-squared coherence estimates of one healthy subject and one PD patient are presented in Figure 5. One can observe that the area of the coherence spectrum is larger for the PD patient than for the healthy subject.
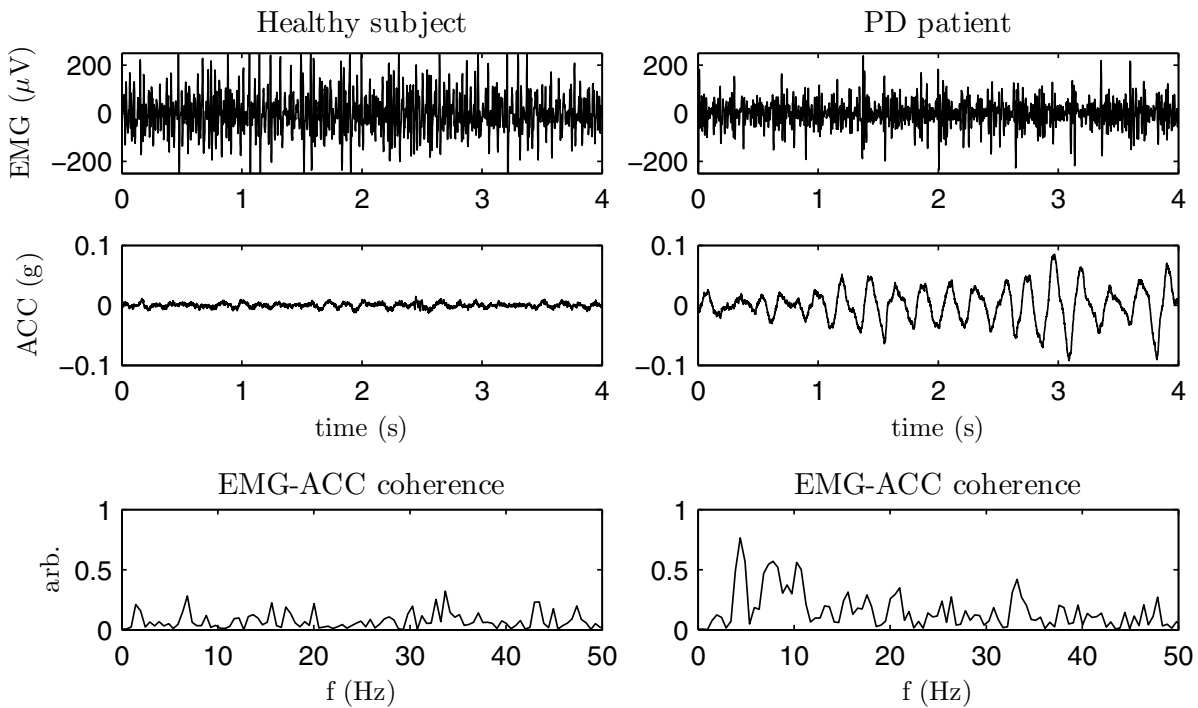
Figure 5. EMG and acceleration signals and magnitude-squared coherence estimates of one healthy subject and one PD patient.

While in Fourier approach the basis functions in the spectral decomposition are global functions, in wavelet approach [1] the functions are local. Therefore, the wavelet-based methods can be more effective than the Fourier-based method in detecting time varying features in the spectrum [10]. The basic idea in the wavelet transform is to decompose the

signal into a set of basis functions, which are obtained by scaling and shifting the wavelet function $\psi(t)$. In continuous form, the wavelet transform of the signal $x(t)$ is defined as

$$W_x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt, \tag{10}$$

where a is the scale, b is the shift, and $(\cdot)^*$ denotes the complex conjugate operator. Different kinds of wavelet functions have been defined for analysis. For discrete signals one must use discrete wavelets. The magnitude-squared wavelet transform is called the scalogram

$$P_x^W(a,b) = |W_x(a,b)W_x^*(a,b)|. \tag{11}$$

If the wavelet transforms of two signals x and y are denoted with $W_x(a,b)$ and $W_y(a,b)$, the wavelet cross-scalogram is defined as

$$P_{xy}^W(a,b) = |W_x(a,b)W_y^*(a,b)|. \tag{12}$$

In [29], the discrete Morlet wavelet was used for analysis as in many other EMG studies [10, 20, 40]. The scalograms (11) were calculated from the EMG signals of both sides of the body and the cross-scalogram (12) between the right and left side signals. The scalograms and cross-scalograms were scaled to present the percentage of energy for each wavelet coefficient as a function of time. The wavelet parameter $W_{\max}$ was calculated as the maximum energy of all wavelet coefficients from both the scalograms and the cross-scalograms as a function of time. The wavelet cross-scalograms and parameters $W_{\max,\mathrm{rl}}$ are presented for one healthy subject and one PD patient in Figure 6. One can observe that in the wavelet cross-scalogram of the patient the energy is more spread into different wavelet coefficients than in the cross-scalogram of the healthy subject. Parameter $W_{\max,\mathrm{rl}}$ is lower for the patient.

3.2.4. Acceleration signal features

Sample entropy is a parameter of nonlinear dynamics and it can be used for quantifying the regularity of acceleration signals in PD when compared to the healthy subjects. It was calculated in [28, 29] from the embedding vectors in (5) as described in [27]. In [29], the power of the acceleration signal was extracted from the dynamic acceleration recordings for quantifying kinetic tremor and rigidity during movement.

3.3. Cluster analysis of subjects

The aim in [28, 29] was to develop a method for discriminating between PD patients and healthy subjects on the basis of EMG and accelerations signal features. In total, the data from 42 PD patients and 59 healthy subjects were analyzed in [28] and the data from 49 PD patients and 59 healthy subjects were analyzed in [29].

In [28, 29], there were many parameters that could capture essential information in the measured signals. These original signal features p_j $(j = 1, 2, ..., N_p)$ (detailed in Table 1) were used to form feature vectors $z_j \in \mathbb{R}^{N_p}$ for each subject.
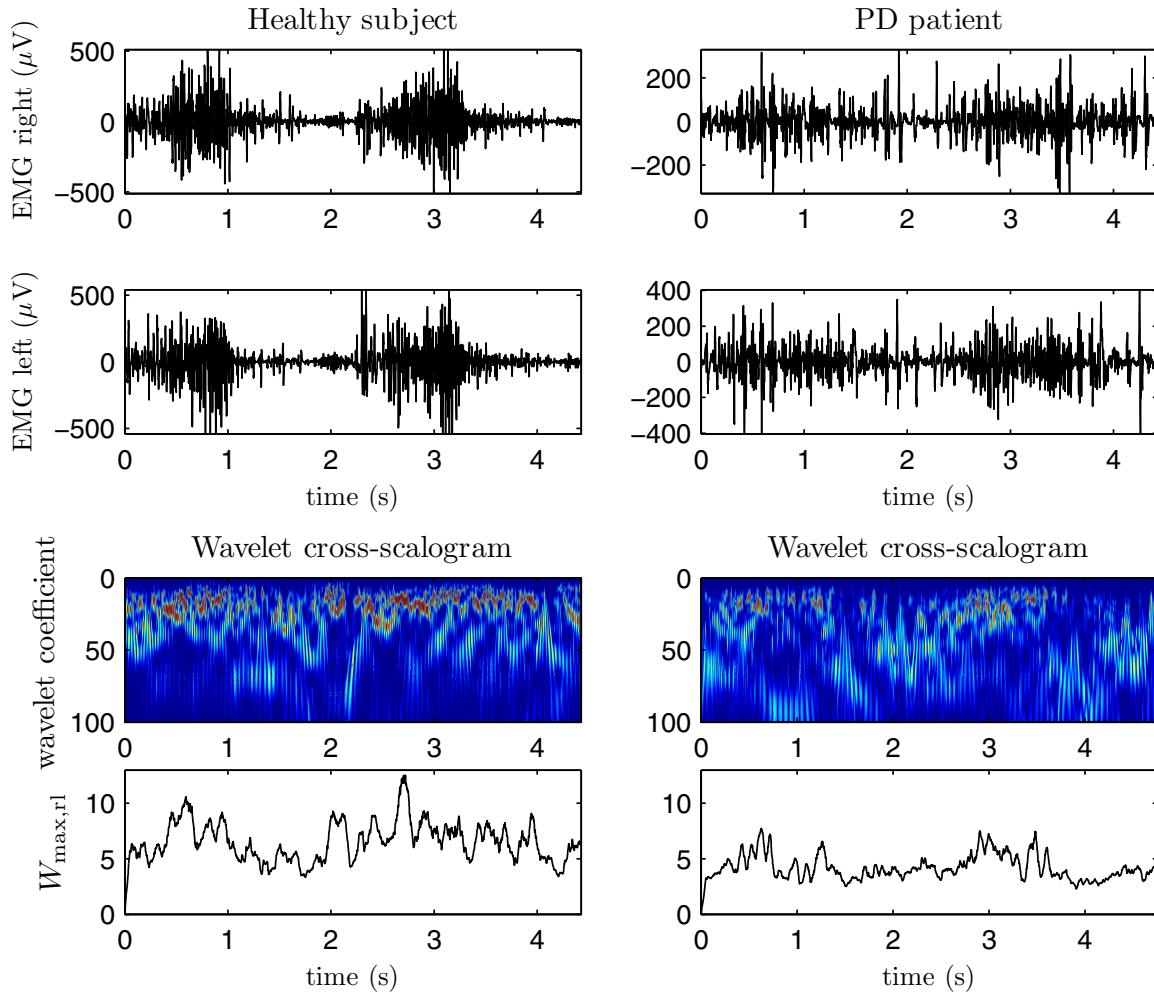
Figure 6. Right and left side EMG signals of one healthy subject and one PD patient. Wavelet cross-scalograms and $W_{\text{max,rl}}$ parameters for the healthy subject and the PD patient.

$$z_j = [p_1 \ p_2 \ldots p_{N_p}]^T \tag{13}$$

The PC-based approach [19] was used in both studies for reducing the number signal features and for transforming the original possibly correlated parameters into uncorrelated parameters.

In [28], one feature vector was formed for each healthy subject, for each patient with medication on (MED on) and for 13 patients also with medication off (MED off, no medication 24 hours before the measurement) by using the twelve EMG and acceleration parameters (six parameters from each body side) that are detailed in Table 1. The original signal parameters were normalized (to zero mean and unit SD of all subjects) before applying the PC approach. The PC approach was applied once as described in section 2.2. In [29], two feature vectors were formed for each patient and for each healthy subject of the ten EMG and acceleration parameters that are detailed in Table 1. One of the feature vectors was formed by using the mean parameter values during flexion and the other by using the mean parameter values

during extension. The signal variables were normalized and the PC approach was applied separately for the flexion and extension phases of the movement as described in section 2.2.

Cluster analysis was used in [28, 29] for grouping subjects with similar EMG and acceleration signal features into groups. This could be done by clustering the model weights (PCs) in the sum (1). An iterative k-means algorithm [47] was used for clustering the feature vectors of subjects in a two-dimensional feature space. In k-means algorithm, the only parameter given to the algorithm is the number of clusters. The algorithm begins by choosing initial estimates for each cluster center point. In each iteration step, it is determined to which cluster the feature vectors belong. The feature vector belongs to that cluster for which the squared Euclidean distance between the vector and the cluster center point in the two-dimensional feature space is minimized. The cluster center points are updated to be the mean of the feature vectors in each cluster in the two-dimensional feature space. The iteration continues until the sum of vector-to-center point distances summed over all clusters is minimized.

The validation of the clustering results was performed by using the leave-one-out method. In the method, the eigenvectors and PCs are solved for each combination of $M - 1$ feature vectors, where M means the total number of feature vectors. That is, one feature vector is left out of the group each time the eigenvectors and PCs are computed. The clustering is then performed for each combination of $M - 1$ feature vectors, and in each case, it is tested to which cluster the feature vector that was left out belongs. In [28, 29], the correct ratings of clustering were defined as the percentage (mean±SD values) of healthy subjects that belong to the healthy subject cluster and the percentage of patients that belong to the patient clusters.

3.4. Discrimination results

In [28], twelve features were extracted from the isometric EMG and acceleration signals of 59 healthy subjects and 42 PD patients. The normalized signal features (mean±SD values) for the healthy subject group and for the PD patient group are presented in Figure 7. The results show that the parameters SampEn, cr and D_2 seem to be lower and the parameters k, Coh and %REC higher for the patients than for the healthy subjects. That is, the EMGs of the patients tend to be less complex and contain more recurring patterns than the EMGs of the healthy subjects. The acceleration signals of the patients tend to be more regular and more coherent with the EMGs than the acceleration signals of the healthy subjects.

The cluster analysis of subjects was performed in a two-dimensional feature space, that was spanned by the PC sum $\theta_j(2) + \theta_j(5)$ and the first PC $\theta_j(1)$ by using the k-means algorithm. This PC sum was used, because it works better in discrimination than the single PCs. The results in Figure 7 show that 90 % of the healthy subjects belong to the cluster O_1 and 76 % of the patients in two other clusters O_2 and O_3. Seven patients with severe motor symptoms are distinguished in O_3. The ten patients in the healthy subject cluster O_1 have only little or no tremor at all in their hands. The validation by using the leave-one-out method resulted in correct discrimination rates of 90 ± 1 % for the healthy subjects and 74 ± 6 % for the patients.

In [29], ten features were extracted from the EMG and acceleration signals of 59 healthy subjects and 49 PD patients and used to form feature vectors for subjects. The normalized signal features (mean±SD values) for the healthy subject group and for the PD patient group
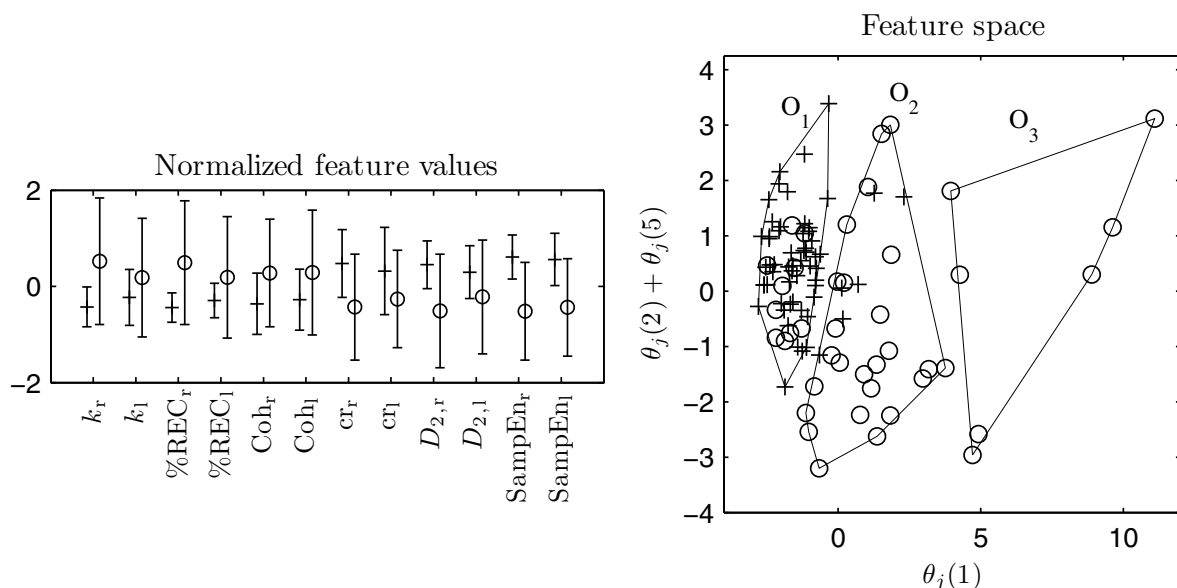
Figure 7. Mean $\pm$ SD values of normalized signal features for the patient group ($\circ$) and for the healthy subject group ($+$) (left). The cluster analysis of 42 PD patients ($\circ$) and 59 healthy subjects ($+$) in the feature space ($\theta_j(2)+\theta_j(5)$ with respect to $\theta_j(1)$). The three clusters O_1, O_2 and O_3.

in flexion and in extension are presented in Figure 8. The results show that parameters %REC and P_{acc} tend to be higher and parameters SampEn and W_{max} lower for patients than for healthy subjects both in flexion and in extension. That is, the EMGs of the patients tend to contain more recurring patterns than the EMGs of the healthy subjects and the EMG wavelet power tends to be more spread for patients. The acceleration signals of the patients tend to be of higher amplitude and more regular than the acceleration signals of the healthy subjects.

The cluster analysis of subjects was performed in a two-dimensional feature space that was spanned by the second PC and the first PC by using the k-means algorithm. The results are presented in Figure 8. According to the results, the method can discriminate 80 ± 1 % of the patient extension movements from 87 ± 1 % of the extension movements of healthy subjects, and 73 ± 1 % of the patient flexion movements from 82 ± 1 % of the flexion movements of healthy subjects. The leave-one-out method was used for validation. The patients, that could not be discriminated from the healthy subjects, had mild motor symptoms of PD.

4. PC-based approaches for quantifying effects of treatment

In addition to the discrimination analysis between subjects, the principal component -based approach can be used for quantifying the effects of treatment. In [30, 31], we aimed to develop objective methods for quantifying effects of PD treatment (DBS and medication) on the basis of surface EMG and acceleration measurements and analysis.

4.1. EMG and acceleration measurements for quantifying effects of treatment

In [30], the PC-based approach was used for quantifying the effects of DBS treatment on the basis of a set of EMG and acceleration signal features. In total, the measurement data from 13 PD patients with DBS and 13 healthy subjects were analyzed. Measurements were performed
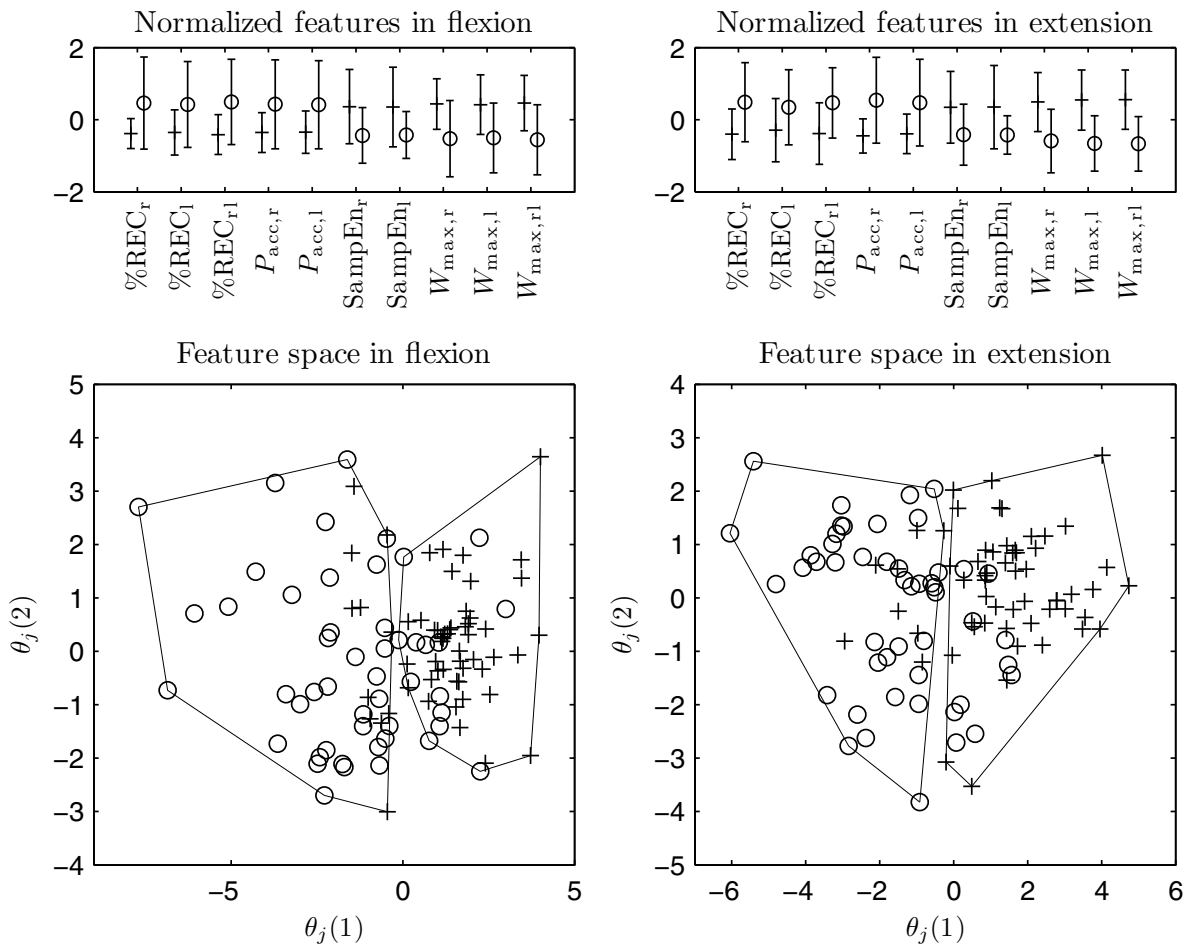
Figure 8. Mean $\pm$ SD values of normalized signal features for the patient group ($\circ$) and for the healthy subject group ($+$) in flexion and in extension (top). The cluster analysis of 49 PD patients ($\circ$) and 59 healthy subjects ($+$) in the feature space ($\theta_j(2)$ with respect to $\theta_j(1)$).

during the isometric contraction of BB muscles (see section 3.1) and they were performed once for the healthy subjects and twice for the patients: with DBS on (stimulator was turned on) and with DBS off (stimulator was turned off). Ninth order Butterworth low-pass filter with 110 Hz cutoff was used for removing the DBS artifact from the EMG signals. The low-pass filtering was performed similarly for all subjects (patients and healthy subjects). The UPDRS -motor examination was performed for each patient with DBS on and with DBS off. The measured signals of one PD patient with DBS on and off are presented in Figure 9. One can observe that the EMG signal of the patient contains recurring EMG bursts and the acceleration signal high-amplitude tremor with DBS off but not with DBS on.

In [31], the PC-based approach was used for quantifying the effects of anti-parkinsonian medication on the basis of a set of EMG and acceleration signal features. In total, the measurement data from nine PD patients were analyzed. The subjects were measured in four different medication conditions: off-medication, and two and three and four hours after taking the medication. The isometric task (described in section 3.1) was analyzed. The UPDRS -motor examination was performed for each patient in each medication condition. The EMG and acceleration signals of one PD patient in each medication condition are presented in Figure
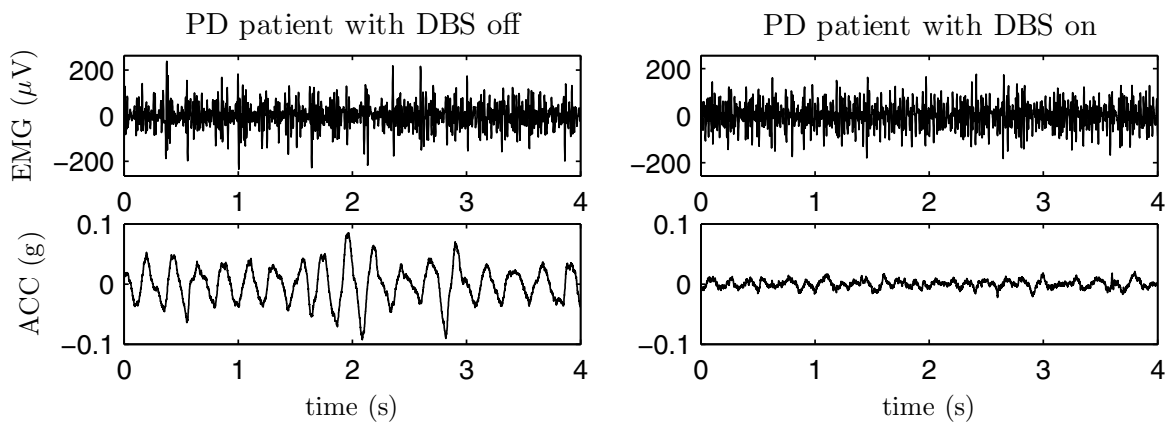
Figure 9. The EMG and acceleration signals of one PD patient with DBS on and with DBS off.

10. It is observed that the number of recurring EMG bursts and the amplitude of tremor decrease with medication and start to increase three hours after taking the medication.
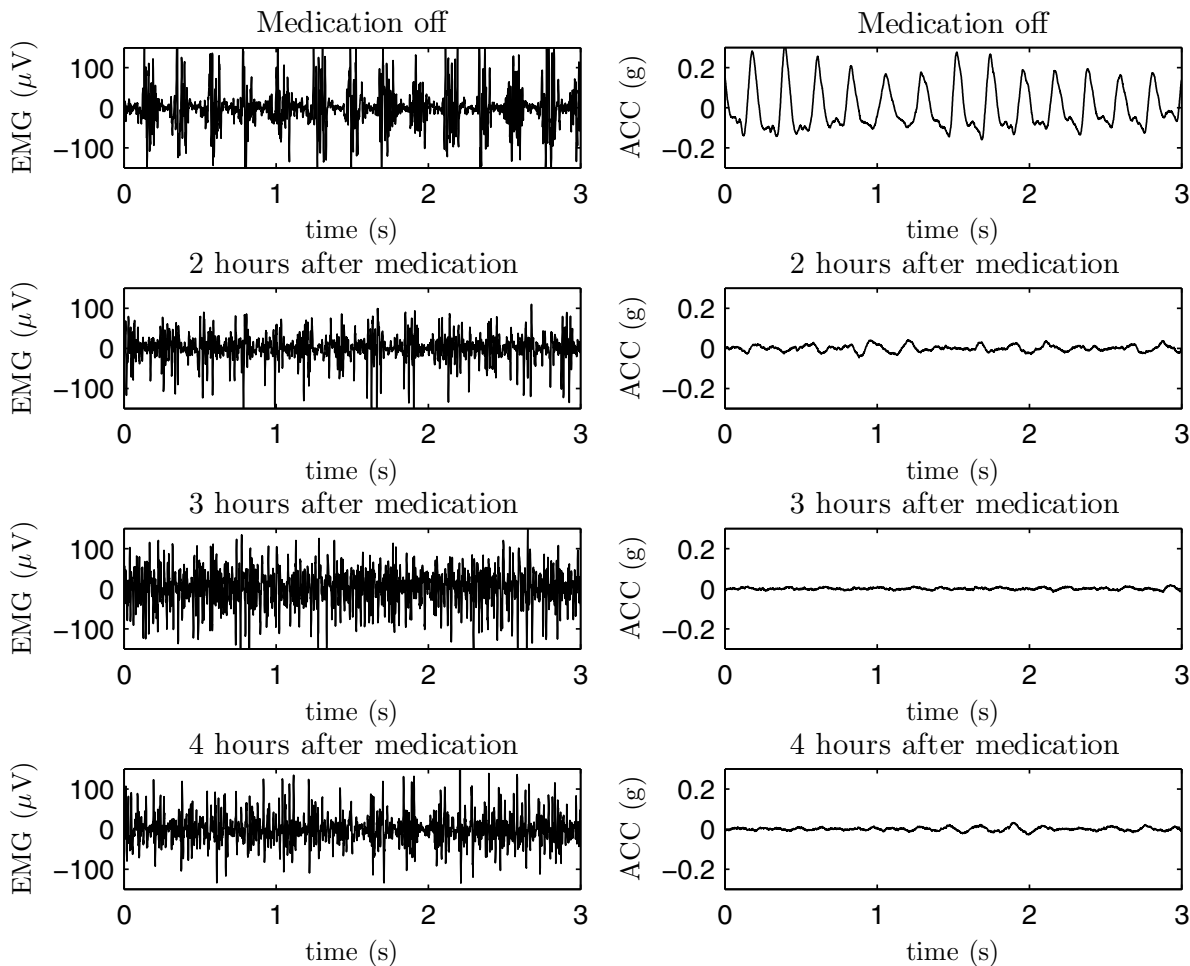
Figure 10. The EMG and acceleration signals of one PD patient in four medication conditions: with medication off, and two and three and four hours after taking the medication.

4.2. EMG and acceleration signal features for characterizing effects of treatment

Several EMG and acceleration signal features were observed to be effective in characterizing the effects of treatment on PD patients in [30, 31]. These features are detailed in Table 2.

Treatment	Signal features	Notations
DBS	correlation dimension of EMG	$D_{2,r}$ and $D_{2,l}$
	recurrence rate of EMG	$\%REC_r$ and $\%REC_l$
	root mean square amplitude of ACC	RMS_r and RMS_l
	sample entropy of ACC	$SampEn_r$ and $SampEn_l$
	coherence between EMG and ACC	Coh_r and Coh_l
Medication	sample kurtosis of EMG	k_r and k_l
	recurrence rate of EMG	$\%REC_r$ and $\%REC_l$
	root mean square amplitude of ACC	RMS_r and RMS_l
	sample entropy of ACC	$SampEn_r$ and $SampEn_l$

Table 2. PD characteristic signal features for quantifying effects of treatment. The subscripts r and l in the notations stand for the side of the body.

The parameters were calculated as described in section 3.2. The root mean square amplitude of acceleration was calculated for quantifying tremor amplitude.

## 4.3. Principal components in quantifying the effects of treatment

In [30], the ten signal features (five features from each body side) in Table 2 were normalized (to zero mean and unit SD of healthy subjects) and used to form feature vectors for subjects. One feature vector was formed for each healthy subject and two feature vectors for each patient: one with DBS on and one with DBS off. The PC approach (see section 2.2) was applied once. The eigenvectors were solved by using the feature vectors of healthy subjects. In this way, the healthy subject group formed the normal group for later comparison.

In [31], the eight signal parameters in Table 2 were normalized (to zero mean and unit SD of all patients) and used to form feature vectors for PD patients. Four feature vectors were formed for each patient (one feature vector in each medication condition). The PC approach (see section 2.2) was applied once.

4.4. Results

In [30], the group mean values of the parameters D_2 and SampEn increased and the group mean values of the parameters %REC, RMS and Coh decreased with DBS for the patient group. However, the SDs of the parameters were very high for the patient group because of its heterogeneity. Therefore, the patient measurements were studied individually. The first and the third PCs worked best in characterizing effects of DBS and differences between patients and healthy subjects. According to the results in Figure 11, 12 out of 13 patients are closer to the center point of healthy subjects with DBS on than with DBS off in the two-dimensional feature space ($\theta_3(j)$ with respect to $\theta_1(j)$). That is, the EMG and acceleration signals of PD patients are more similar with the signals of the healthy subjects with DBS on than with DBS off. The distances of the patients from the center of healthy subjects and the clinical UPDRS -motor scores are highly individual (see Table 3). It was observed in a more

detailed analysis that the method is most sensitive to PD with associated tremor. In Figure 11, one patient is farther from the healthy subjects with DBS on than with DBS off. This patient has higher tremor (acceleration signal) amplitude and regularity and less complex EMG recordings (higher %REC and lower D_2) with DBS on than with DBS off. For that patient, the measurement results contradict the subjective clinical scores.
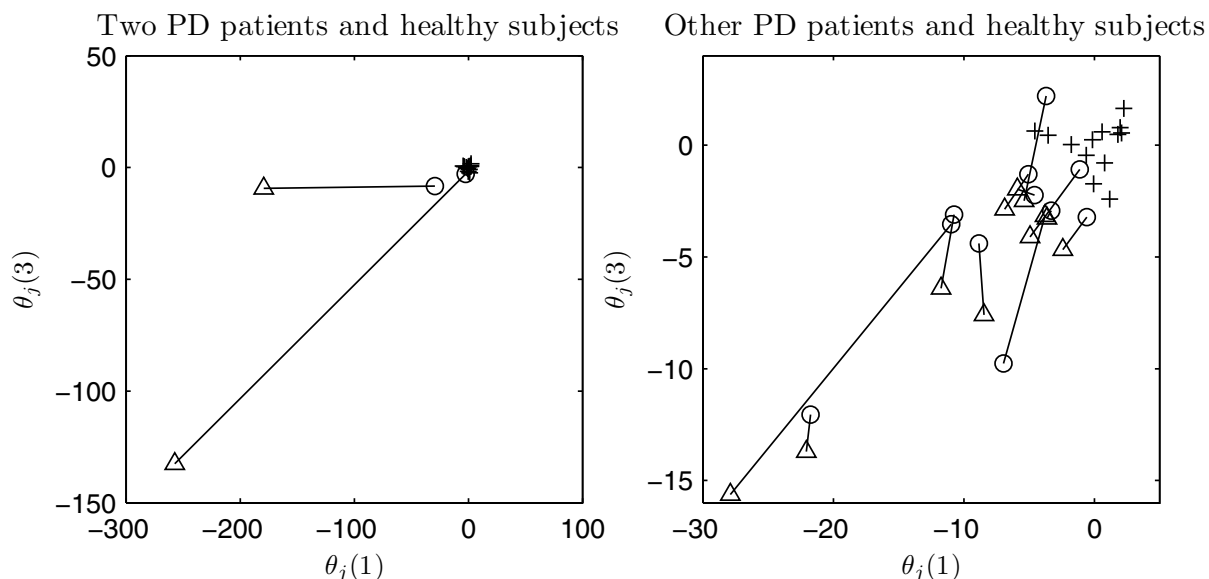
Figure 11. The third PCs $\theta_j(3)$ with respect to the first PCs $\theta_j(1)$ of 13 healthy subjects (+) and 13 PD patients with DBS on ($\circ$) and off ($\triangle$). The patients are divided into two figures, but the healthy subjects are the same in both figures. The DBS on- and off-states of each patient are connected with a line.

In [31], the first PC worked best in characterizing the effects of medication. The first PCs and the total UPDRS -motor scores in each medication condition for each patient are presented in Figure 12. One can observe that the total UPDRS -motor scores decrease (motor symptoms are relieved) with medication for all patients. Correspondingly the first PCs decrease with medication for eight out of nine patients. By examining the first eigenvector in Figure 12 one can realize that the reduction in the first PC indicates reduction in the parameters k (less spiky EMG), %REC (less recurring patterns) and RMS (lower tremor amplitude), and increase in the parameter SampEn (more complex tremor). The severity of motor symptoms (UPDRS -motor score) starts to increase 2–3 hours after medication for all patients, which indicates that the efficacy of medication starts to weaken 2–3 hours after medication. Correspondingly, the first PCs start to increase 2–3 hours after medication for seven out of nine patients. The UPDRS -motor scores and the first PCs do not start to increase at the same time for all patients, which indicates that these scores do not measure exactly the same thing.

5. Discussion

There is a need for finding objective methods for Parkinson's disease for improving the diagnostic accuracy, for enabling earlier diagnosis, and for quantifying the disease progression and the efficacy of treatment [2, 11, 24]. Surface EMG and the kinematic measurements may be potentially useful methods for quantifying the motor impairment in PD and the effects of

| Patient no.	UPDRS off	UPDRS on	Distance off	Distance on
1	56	43	26	25
2	64	48	32	12
3	59	40	7	5
4	34	14	180	30
5	71	42	289	4
6	38	31	5	12
7	47	28	6	2
8	57	33	6	4
9	43	34	13	11
10	43	24	11	10
11	44	30	6	5
12	62	38	5	4
13	43	30	5	3

Table 3. Total UPDRS -motor scores and the distances from the center of healthy subjects with DBS on and off.

treatment. However, the EMG signals of PD patients are characterized by spikes and bursts that are not effectively captured with conventional amplitude- and spectral-based parameters of EMG. Therefore, more novel methods of EMG analysis are needed for PD.

5.1. Discrimination between patients and healthy subjects

We have developed methods for discriminating between PD patients and healthy subjects on the basis of surface EMG and kinematic measurements and analysis in [28, 29, 32]. One developed approach was based on analyzing the surface EMG signal morphology [32]. One approach was based on analyzing isometric [28] and one approach on analyzing dynamic muscle contractions [29]. Principal components were used in each approach for discrimination between subjects. All methods were tested with the measured data. The obtained discrimination rates were 72 % for patients and 86 % for healthy subjects on the basis of surface EMG signal morphology, 76 % patients and 90 % for healthy subjects on the basis of isometric EMG and acceleration recordings, 73 % for patients and 82 % for healthy subjects on the basis of elbow flexion movements, and 80 % for patients and 87 % for healthy subjects on the basis of elbow extension movements. These percentages predict the sensitivities and specificities of the methods in the subject groups that were studied.

The best discrimination rates between patients and healthy subjects were obtained by analyzing the EMG and acceleration signals measured during the isometric contraction and elbow extension movements [28, 29]. In fact, it has been observed previously, that the elbow extension movements are more impaired than the flexion movements of PD patients [33]. The isometric approach was most sensitive to patients with associated tremor [28] and the dynamic approach to patients with various motor symptoms (rigidity, bradykinesia and tremor) and
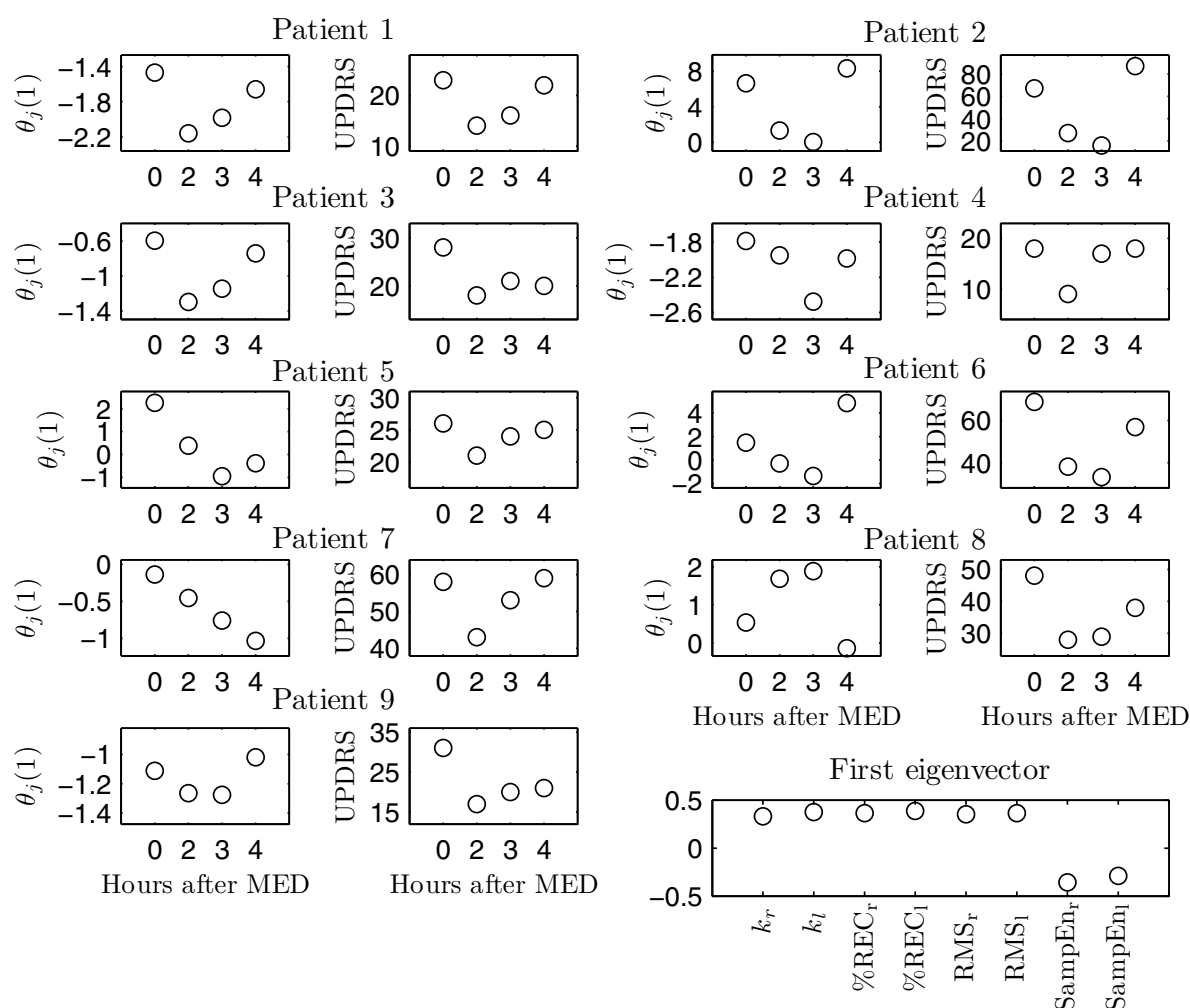
Figure 12. The first PCs ($\theta_j(1)$) and UPDRS -motor scores of nine PD patients with medication off, and two and three and hour hours after taking the medication. The first eigenvector (bottom right).

especially to patients with problems in performing movement tasks [29]. Therefore, the analysis of both kind of muscle contractions is essential when quantifying motor impairment in PD.

5.2. Quantification of the effects of treatment

In studies [30, 31], we developed methods for quantifying the effects of treatment in PD on the basis of surface EMG and kinematic measurements and analysis. The results of the study [30] show that the measured EMG and acceleration signals of 12 out of 13 PD patients were more similar with the signals of the healthy subjects with DBS on than with DBS off. This result indicates that it is possible to detect DBS-induced improvements in the neuromuscular and motor function of PD patients by using the developed analysis approach.

In [31], the EMG signals of eight out of nine PD patients changed into less spiky and the acceleration recordings into more complex after taking the medication. A reverse phenomenon in the signal characteristics was observed 3–4 hours after taking the medication for seven out of nine patients. This result indicates that it is possible to detect

medication-induced changes in the neuromuscular and motor function of PD patients by using the developed methods.

5.3. Methods of signal analysis

We extracted a large number of features from the EMG and acceleration signals of PD patients and healthy subjects in [28–32] and chose the most effective features for characterizing PD and the effects of treatment into the feature vectors for deeper analysis. The chosen EMG features were not conventional EMG parameters but they were based on nonlinear dynamics, signal morphology, wavelets and EMG-acceleration coherence. Previously, there have been only one [14] or few other studies, in which a method of nonlinear dynamics has been used for studying EMGs of PD patients. Our studies [30, 31] are the only studies that have analyzed the effects of PD treatment (DBS and medication) by using methods of nonlinear dynamics for EMG.

All of the studies [28–32] were based on an innovative way of combining the PC-based approach with the selection of feature vectors instead of analyzing the statistics of single signal parameters. The PC-based approach provided a better discrimination between the subjects by capturing essential information in the combination of variables. With the PC-based approach, it was possible to examine the effects of treatment in a feature space on an individual level.

Few things about signal quality and electrode placement should be kept in mind when analyzing the EMG signals with the proposed analysis methods. First, the EMG signal amplitude is relatively low and the signal is sensitive to noise that is coming from other electrical sources. This noise may affect the calculated signal parameters. Therefore, the noise should be eliminated already during the measurements whenever it is possible. Another thing is that sometimes a large MU is firing constantly and dominantly in the proximity of the recording electrode causing recurring impulse-like patterns into the EMG signal. In that case, a better placement of recording electrodes would be advisable.

In PD patients with DBS, the stimulator causes artifacts into the EMG signal. The DBS artifact and its filtering may affect the calculated signal parameters. Previously, the DBS artifact has been removed from the EMG signal by low-pass filtering the rectified signal with a low (20–60 Hz) cut-off frequency [21, 41, 42, 51, 52]. In our study [30], we low-pass filtered the EMG signal with the 110 Hz cut-off frequency. Our aim was to remove the DBS artifact from the EMG as effectively as possible without removing important information and to perform the filtering in the same way for all subjects in order to get comparable results.

5.4. Conclusions

In this chapter, we presented several approaches for feature extraction from surface EMG and acceleration signals and for discrimination between PD patients and healthy subjects on the basis of the extracted signal features. The presented discrimination approaches were developed in our studies [28, 29, 32]. By using the developed approaches, we could discriminate 72-80 % of PD patients from 82-90 % of healthy subjects depending on the analyzed signal features and the muscle contraction type. These percentages can be regarded as promising because it is known that the PD diagnostics can be difficult. Clinicopathological studies from the UK and Canada have shown that the disease is diagnosed incorrectly in

about 25 % of cases [48]. On the basis of our discrimination results, further research and clinical studies are suggested for evaluating the sensitivity of the developed approaches in patients with different types of PD and in patients with early stages of PD. In addition, the ability of EMG and acceleration signal features in discriminating between PD patients and other patients with similar symptoms should be studied.

In this chapter, we presented two approaches for quantifying the effects of PD treatment (medication and DBS) on the basis of the extracted EMG and acceleration signal features. The presented approaches were developed in our studies [30, 31]. By using the developed approaches, we could detect DBS- and medication-induced improvements in the neuromuscular and motor function of PD patients. This result is encouraging because the widely used method for evaluating the efficacy of PD treatment is subjective. However, the sensitivity of the developed approaches should be quantified with a larger number of PD patients.

The need for finding objective methods for PD diagnosis and for quantifying the disease progression and the efficacy of treatment is well known [2, 11, 24]. We hope that our results [28–32] can help in creating a practical method for quantifying motor impairment in PD and the effects of treatment on individual PD patients. However, in order to be more sensitive than the traditional methods, it is probable that a combination of several objective methods will be needed for PD.

5.5. Future directions

There is currently a lot of effort for determining objective methods and characteristics for PD [2, 11, 24]. One important goal of current research is to determine criteria for the pre-motor and pre-clinical phases of PD [39]. In surface EMG studies, the sensitivity of surface EMG signal features in detecting PD patients before the actual diagnosis of PD should be studied. It will be important to analyze differences in the signal characteristics between PD patients and other patients with similar symptoms. These other similar diseases form currently a significant reason for the wrong diagnosis of PD [17]. It has been observed that surface EMG and kinematic measurements can provide information about the effects of PD treatments (medication and DBS). The ability of these measurements in helping the optimal adjustment of these treatments should be evaluated.

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