

The effectiveness of applied treatment in Parkinson disease based on feature selection of motion activities

Streszczenie. W pracy zaprezentowano analizę skuteczności stymulacji prądowej jądra niskowzgórzowego oraz leczenia farmakologicznego w chorobie Parkinsona. W tym celu badano właściwości dyskryminacyjne, charakterystycznych cech ruchu. Dla danych kinematycznych przeprowadzono ekstrakcję, a następnie selekcję cech. Zastosowano ranking atrybutów bazujący na entropii i zachłanne przeszukiwanie wspinaczkowe z oceną średniej odległości wewnątrzgrupowej. Uzyskane wyniki wykazują większy wpływ stymulacji prądowej na badane czynności ruchowe. (**Skuteczność leczenia w chorobie Parkinsona na podstawie selekcji charakterystycznych cech ruchu**).

Abstract. The analysis of effectiveness of deep brain stimulation and pharmacological treatment in Parkinson disease is presented. It is based on an examination of discriminative properties of distinctive motion features. The feature extraction and selection of kinematical motion data is carried out. The attribute ranking with entropy based attribute evaluation and greedy hill climbing search with assessment of an average inner class dissimilarity are applied. The obtained results show that deep brain stimulation has greater impact on investigated motion activities.

Słowa kluczowe: choroba Parkinsona, pomiar ruchu, selekcja cech, ekstrakcja cech, nadzorowane uczenie maszynowe

Keywords: Parkinson diseases, motion capture, feature selection, feature extraction, supervised machine learning

Introduction

Parkinson's disease (PD) is a chronic progressive disease, which belongs to the group of motor system disorders. The dysfunction of movement are caused by the loss of dopamine-producing brain cells in the substantia nigra, a region located in the midbrain. Nowadays only symptomatic methods of treatment have been applied, because the reason of cells destruction in substantia nigra is not known. The main motor features of PD are: tremor in hands, arms, legs, jaw and face, rigidity of the limbs and trunk, bradykinesia, impaired balance and coordination. The primary pharmacological drug is L-dopa, a specific amino acid, which after reaching the brain, is converted into dopamine. Fundamental pharmacological medication with L-dopa is successful for first years, but later the progression of neurodegeneration as well as dopaminergic treatment itself results in motor complications. There is an alternative symptomatic treatment for advanced PD patients using Deep Brain Stimulation (DBS). DBS of the subthalamic nucleus (STN) has become an established therapy for patient with PD, it is an effective and safe method of symptomatic treatment of PD patients, who are medically resistant to pharmacotherapy [1][2]. The objective assessment of the treatment carried out by clinicians is based mainly on the Unified Parkinson's Disease Rating Scale (UPDRS). The motor part of UPDRS consist of 14 points, which evaluate different motor skills based on discrete scale in range of 0-4, where 0 means normal ability to move.

In this study we compare and demonstrate possibilities of the developed multi-featured MOCAP measurement system on medical examination data of the Parkinson Disease patient who has undergone the surgery based on implanting Deep Brain Stimulator for improving his motoric skills. The patients taking part in this research were operated on in the Department of Neurosurgery Medical University of Silesia in Katowice[8][9][10]. All measurements were done in multimodal Human Motion Laboratory of Polish – Japanese Institute of Information Technology (P JWSTK) in Bytom, Poland. The laboratory allows to acquire motion data through simultaneous and synchronous measurement and recording of motion kinematics, muscle potentials by electromyography, ground reaction forces and video streams in high definition format

Data were collected from PD patients during four experimental conditions called sessions, defined by pharmacological medication and subthalamic nucleus electrical stimulation: Session1: StimOFF/MedOFF, Session2: StimON/MedOFF, Session3: StimOFF/MedON and Session4: StimON/MedON.

Experimental scenario includes seven tasks and has been planned based on criteria taking into consideration in motor examination part of UPDRS scale. In the described work data from Task 2 and Task 4 are used. Task 2 contains gait measurements, performed across a straight line with different speed. In Task 4, a pull test is carried out. A participant is standing erect on the platform with feet no more than shoulder width apart and is pulled back. It allows to asses the ability to recovery on his own and evaluate the postural stability..

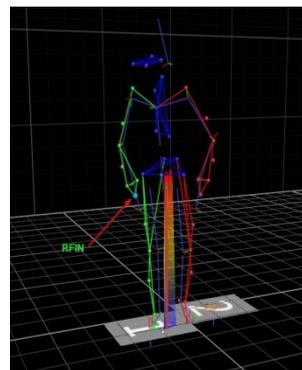


Fig. 1 Markers tracked by 10-camera, 3D motion capture system (Vicon).

In Fig. 1 locations of 39 attached markers on a human body, tracked by the motion capture cameras are presented. The assumed skeleton model, reconstructed on the basis of markers positions contains 24 segments with rotations coded by Euler angles. There are also global rotation and translation data included in the kinematical frame description, which results in 78 dimensional pose space. What is more, muscle potentials of the lower body parts are captured by 16 electrodes of EMG subsystem and ground reaction forces are measured by two plates as shown in Fig. 1.

In Fig. 2 a rotation data of left femur and head segments of selected gait are presented. The directions rx, ry and rz are defined in local coordinate system and are different for both segments. The gait cycles corresponding to two adjacent steps can be detected on the basis of femur rotation data analysis. In Fig. 2 example data captured by GRF and EMG subsystems are visualized. .

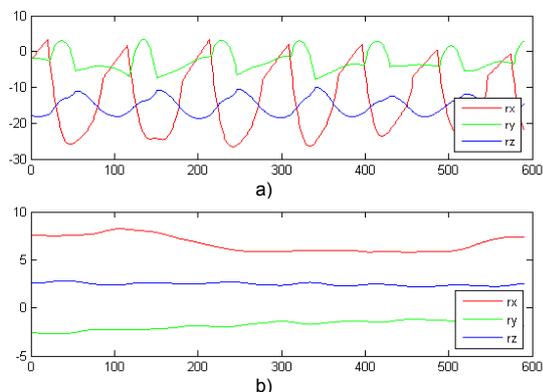


Fig. 2 Rotation data of selected gait. a) femur segment, b) head segment

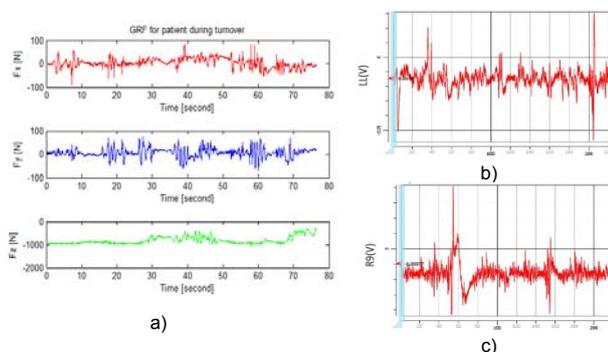


Fig. 3 Ground reaction forces during turnover and muscle potential data of selected gait a) ground reaction forces, b) rectus femoris of left leg muscle potentials, c) rectus femoris of right leg muscle potentials

Related Work

Motion capture (MOCAP) technology used for measurement and analysis of human movement, has been developed very fast in recent years. Multi-modal systems (among other contributions) are very promising tool to improve treatments and diagnostics in such area of medicine as orthopedics, neurology, physical therapy and the neurosurgery, thanks to the fact that MOCAP systems allow for precise measurements of geometric and kinematic features of consecutive stages of human movement. It synchronizes multimodal measurements of motion and matches them with a whole range of clinical data. Interesting research concerning analysis of human gait abnormalities related to diagnosis of neurological diseases based on motion capture data were presented in references [3-6]. MOCAP system, allows to compute temporal and spatial measurements and joint angular displacements of the limbs during movement. As a results of various studies related to a disturbances of gait, over a dozen quantitative measures describing way of walking were defined. Such parameters as speed, length of step, its variability and symmetry were used to diagnosed the effect of bilateral posteroventral pallidotomy on the walking patterns of patients with PD [3]. In other studies, some more complex measures as Phase Coordination Index (PCI) or Decomposition Indices (DI) were used to find differences between PD and SWEEDs (scans without evidence of

dopaminergic deficits) Patients [4]. The first one reflects temporal accuracy and consistency of step timing, while DI is define as percentage of stance phase when one joint is moving while the other is not, calculated for hip-knee, hip-ankle, and knee-ankle pairs. Walking measures illustrating asymmetry of arm swing, trunk rotation and stride time [5] were used to improve the diagnosis of early stages of Parkinson disease [6]. Based on the literature review of the aforementioned publications, several indices describing gait have been implemented and calculated for data from PD Patients collected in PJWSTK, in Bytom. These parameters were calculated for left and right side separately. Based on the results, it was found that the left and right components of these indices have some additional diagnostic value, because they allow for detecting which body side is more affected by the disease. Results of this study have been already published [7]. The other research involved the analysis of resting tremor, which is the one of the most important motor symptoms of Parkinson disease for diagnosis and treatment. Based on data collected in PJWSTK a system for analysis of tremor in PD patients during standing have been developed. Trajectory of marker located on wrist has been used to calculate several parameters as mean and max amplitude Fourier spectra of 3D signals, for right and left side, in two frequency range 4-6 [Hz] (typical Parkinsonian tremor [12]) and 3-7 [Hz]. The results show that, there are statistical differences between session with and without treatment [11].

In [13] the motion capture is used to asses gait abnormalities associated with coxarthrosis – a degenerative diseases of a hip joint. The kinematical data is reduced by principle component analysis and Fourier coefficients of 3D gait trajectories are calculated. Obtained gait descriptors are further classified by supervised machine learning.

Feature extraction and selection

Most often used approach of motion data classification in medical applications is based on the extracted features of motion time sequences. There are different kind of feature set proposed in the literature. They can directly reflect interpretable characteristics as described in previous section phase coordination index, decomposition or asymmetry indexes. In our previous works on human identification [14],[15],[16] and assessment of gait abnormalities [13] we proposed and applied statistical, timeline, histogram and Fourier transform features sets. In the statistical set there are mean values and variances of each pose attribute and in the histogram based one, we build separate histogram for each attribute.

The Fourier feature set contains coefficients of a frequency domain into which motion data is transformed. To reduce number of features low pass filtering is carried out. It takes into consideration only first twenty components with the lowest frequencies.

In timeline feature extraction approach motion is divided into specified number of intervals which are described by their average values of every pose attribute.

The feature extraction usually gives great number of different features. For instance in case of Fourier extraction approach, for the pose description containing 75 attributes we obtain 3000 separate features. In most cases only small parts of the whole feature set are discriminative from the point of view of given classification or diagnostics task and the remaining parts contain only noise. Thus feature selection which determines most valuable subset of features could be carried out.

In most simple case feature rankings with separate assessment of every attribute by some kind of quality index are calculated. In such a case the subset consists of top

ranked attributes. The attribute can be evaluated by entropy based measures. The entropy H of the random variable X is the measure of the uncertainty of the data. There is no uncertainty if we have only a single variable value and the highest uncertainty occurs when the values are distributed uniformly, because in such situation guessing the variable is most difficult. To evaluate the entropy we usually calculate the average information of the values, where the information is estimated by the logarithm of the i -value probability p_i :

$$(1) \quad H(X) = -\sum_{i=1}^n p_i \log p_i$$

We can calculate entropy of the class $H(C)$ and entropy of the class with respect to the given attribute values $H(C|A_1, A_2, \dots, A_k)$

$$(2) \quad H(C|A) = H(C|A_1, A_2, \dots, A_k) = \sum_{i=1}^k p(A_i)H(C|A_i)$$

If the entropy of the class is greater than entropy of the class attribute with respect to the attribute values, it means that attribute explains the class - the uncertainties of the class for the known attribute values is lower.

To rank the attributes the difference between entropies of the class and entropy in respect to the attribute values is usually calculated. What is more, further it can be normalized by the entropy of the evaluated attribute. Such a measures are called information gain (IG) and gain ratio (GR) [17].

$$(3) \quad IG(A) = H(C) - H(C|A) \quad GR = \frac{H(C) - H(C|A)}{H(A)}$$

The assumption that single attributes reveal their distinction properties is very often naïve. In many cases attributes contain discriminative data only if considered with others. In such a case attribute rankings are insufficient, the evaluation of whole feature subset has to be carried out.

There are two crucial challenges of such a feature selection. It is the proper search method and the way feature subsets are evaluated. It is unworkable to examine all possible subset combinations in a finite time by exhaustive search, because the problem is NP complete. Thus, any search strategy has to be assumed. In greedy hill climbing search, we start with the best evaluated attribute and in the subsequent iterations determine the one to include which causes the subset to obtain best evaluation score. To reduce the risk of hill climbing termination in local extreme, more than one non improving node usually is considered.

In genetic search strategy [17] candidate solutions represented feature subsets are coded by binary strings. The subsequent generations of feature subsets are inherited from previous ones with usage of basic genetic operators as selection, crossover and mutation.

To evaluate discriminative properties of feature subset the ratio between an average distance in the whole motion set and an average inner class distance can be calculated:

$$(4) \quad RBID = \frac{\sum_{c_1 \in C} \sum_{i_1 \in c_1} \sum_{c_2 \in C} \sum_{i_2 \in c_2} d(i_1, i_2)}{n^2 \cdot \sum_{c \in C} \frac{\sum_{i_1 \in c} \sum_{i_2 \in c} d(i_1, i_2)}{n_c^2}}$$

where C is set of all classes, n is number of classes and i_1 and i_2 are instances of class c_1 and c_2 respectively.

Results and conclusions

In the experiment we examine two activities: typical gait and pull test. From the pose description the translation data are removed. It makes the analysis independent on activity location, the obtained results relies only on the joint movements. For the motion data sequences containing

Euler angles of joint rotations Fourier transform is calculated and feature extraction is carried out.

The final step is associated with feature selection. The greedy hill climbing search and subset evaluation by ratio based on inner class dissimilarity (RBID) are used. What is more the attributes rankings with InfoGain measure are calculated.

We defined two types of train sets used in features selection called Stimulation ON and Medication ON. The first one contains activities of Session 1 and Session 2, the second of Session 1 and Session 3, as described in the first section. It means that train set Stimulation ON compares activities of PD patients without any treatment and with stimulation enabled, which are considered to be class values. In fact it allows to assess effectiveness of deep brain stimulation on PD patients activities. Similar train set Medication ON allows to analyze influence of pharmacological medication on PD activities.

Motion type	Stimulation ON	Medication ON
Typical gait	9400%	5500%
Pull Test	1300%	850%

Table 1 The impact of stimulation and medication on the selected motion activities

In Tab. 1 the obtained results of greedy hill climbing selection are presented. The table contains RBID values for the selected features sets. The differences between considered motion classes are significant and the stimulation for both activities has a greater impact on them – there are greater RBID values in case of Stimulation ON train sets. Greedy search usually finds only a few most significant features. For instance, in the case of typical gait and stimulation enabled they are associated with the following joints: left humerus, thorax, left foot, lower neck, right foot, upper neck, left shoulder, lower back, right radius and head.

Stimulation ON		Medication ON	
Rfoot	144	Lhand	131
Lhumerus	133	Rfoot	112
Thorax	133	Upperback	112
Rfemur	132	Rhand	108
Lowerback	129	Thorax	108
Lfoot	126	rhumerus	104
lhand	120	lowerback	100
Upperback	118	lfemur	100
Lfemur	115	lshoulder	99
Lshoulder	107	rshoulder	92
Lshoulder	98	rfemur	89

Table 2 Rankings of aggregated InfoGain values for ten most significant joints, typical gait activity

Stimulation ON		Medication ON	
Rhumerus	106	lfemur	70
Lfemur	88	lhumerus	52
Lhumerus	85	rshoulder	50
Lfoot	77	lfoot	42
Lhand	75	rfoot	43
Rhand	74	rhand	42
Rfoot	74	rfemur	38
lshoulder	55	lshoulder	35
Rfemur	49	rhumerus	28
rtibia:	43	upperneck	27
Ltibia	32	head	26

Table 3 Rankings of aggregated InfoGain values for ten most significant joints, pull test activity

In Tables 2 and 3 top ten, aggregated rankings determined by InfoGain measure are shown. In aggregation

the total score of all attributes associated with the specified joint is calculated.

The results are consistent with the previous observations - once again stimulation makes the joints movements to be more distinctive, the total scores of Stimulation On train sets are greater, for both considered activities.

In the work we evaluate the influence of treatment applied in PD on two motion activities. It is based on the analysis of extracted motion descriptors and their discriminative abilities. The final conclusion says that stimulation has greater impact on motion capture data. What is more, we are able to point joints which are affected most by applied treatment.

However the only feature selection is insufficient to judge ultimately which differences are more important in PD treatment.

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REFERENCES

- [1] Rodriguez-Oroz MC, Obeso JA, Lang AE et al. *Bilateral deep brain stimulation in Parkinson's disease: a multicentre study with 4 years follow-up*. Brain (2005); 128:2240-2249.
- [2] Kenney C., Simpson R., Hunter C., Ondo W., Almaguer M., Davidson A., Jankovic J. *Short-term and long-term safety of deep brain stimulation in the treatment of movement disorders*. Neurosurg (2007); 106:621-625.
- [3] Siegel, K.L.; Metma L.V. *Effects of Bilateral Posteroventral Pallidotomy on Gait of Subjects With Parkinson Disease*. Neurology (2000). VOL 57.
- [3] M. Hong, J. Perlmutter, and G. Earhart. *A kinematic and electromyographic analysis of turning in people with Parkinson disease*. Neurorehabilitation and neural repair, (2009), 23(2):166.
- [4] Mian O. S., Schneider S. A., Schwingenschuh P., Bhatia K. P., Day DPhil B. L., *Comparison with Parkinson's disease patients and healthy controls*. Gait in SWEDDs patients: (2009)
- [5] Zifchock RA, Davis I, Higginson J, Royer T. The symmetry angle: a novel, robust method of quantifying asymmetry. Gait Posture; (2007) 27(4):622-7.
- [6] Lewek MD, Poole R, Johnson J, Halawa O, Huang X. Arm swing magnitude and asymmetry during gait in the early stages of Parkinson's disease. Gait Posture. (2010); 31:256-260.
- [7] Stawarz M., Kwiek S., Polański A., Janik Ł., Boczarska-Jedynak M., Przybyszewski A., Wojciechowski K., *Algorithms for computing indexes of neurological gait abnormalities in patients after DBS surgery for Parkinson Disease based on motion capture data*, Machine Graphics & Vision (2012) (in press).
- [8] Kwiek S. J., Boczarska M., Świat M., Kłodowska-Duda G., Kukier W., Ślusarczyk W., Antonowicz-Olewicz A., Szajkowski S., Suszyński K., Bażowski P., Opala G., *Deep brain stimulation for Parkinson's disease. Experience of Silesian Interdisciplinary Centre for Parkinson's disease treatment in Katowice, 39 Zjazd Polskiego Towarzystwa Neurochirurgów i Sekcji Pielgniarskiej PTNCh z udziałem Greckiego Towarzystwa Neurochirurgicznego*. Mikołajki, Poland, (2010), pp. 85-86.
- [9] Kwiek S. J., Kłodowska-Duda G., Wójcikiewicz T., Ślusarczyk W., Kukier W., Bażowski P., Zymon-Zagórska A., Buszta H., Konopka M., Giec-Lorenz A., Opala G. *Stereotactic stimulation and ablative procedures for therapy of movement disorders. Own experience.. Acta Neurochir.* (2006) Vol.148 No.10, p.42.
- [10] Kwiek S.J. , Kłodowska-Duda G., Wójcikiewicz T., Ślusarczyk W., Kukier W., Bażowski P., Zymon-Zagórska A., Buszta H., Konopka M. , Kie ltyka A., Opala G. *Simultaneous targeting and stimulation of STN and VIM in tremor predominant PD patients*. Pro's and cons. Acta Neurochir. (2003); Vol.148 No.10, p.36.
- [11] Stawarz M., Polański A., Kwiek S., Boczarska-Jedynak M., Janik Ł., Przybyszewski, A., Wojciechowski K.; *A system for Analysis of Tremor In Patients with Parkinson's Disease Based on Motion Capture Data*. L. Bolc, R. Tadeusiewicz, L.J. Chmielewski; (2012), Computer Vision and Graphics: Proc. LNCS Vol. 6374, ICCVG.
- [12] Findley LJ, Gresty MA & Halmagyi GM Tremor, the cogwheel phenomenon and clonus in Parkinson's disease. J Neurol Neurosurg Psychiatry, (1981), 44, 534–546.
- [13] Switonski, A., Mucha, R., Danowski, D., Mucha, M., Cieslar,G., Wojciechowski, K., Sieron, A., *Diagnosis of the motion pathologies based on a reduced kinematical data of a gait* Electrical Review, (2011), Vol. 87, Issue 12 B, 2011, p. 173-176
- [14] Switonski, A., Mucha, R., Danowski, D., Mucha, M., Cieslar,G., Wojciechowski, K., Sieron, A., *Human identification based on a kinematical data of a gait*, Electrical Review, (2011), Vol. 87, Issue 12 B, p. 169-172
- [15] Świtoński A., Polański A., Wojciechowski K., *Human Identification Based on Gait Paths*,ACIVS Lecture Notes in Computer Science, (2011), Vol. 6915 LNCS, 2011, p. 531-542
- [16] Switonski A., Polanski A., Wojciechowski K.: *Human Identification Based on the Reduced Kinematic Data of the Gait*, International Symposium on Image And Signal Processing and Analysis, Dubrownik (2011), p. 650-655
- [17] Witten I., Frank E.: *Data Mining: Practical Machine Learning Tools and Techniques*, Morgan Kaufmann, (2005)

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