Rough Set Based Classifications of Parkinson's Patients Gaits

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Abstract. Motion capture (MoCap) technology becomes recently often used in neurological applications, especially for diagnosis of gait abnormalities. In this paper we present several different approaches to compute important features of gait abnormalities. This is a continuation of our previous experimental results concerning examination of Parkinson's disease (PD) with bilateral subthalamic nucleus stimulation (DBS) patient in the MoCap laboratory. At first, we calculate mean changes of the gait as effects of medication and DBS. We present these changes as phase plots suggesting different dynamics in different patients. In the second part, we apply AI approach related to application of the Rough Set Theory in order to generate decision rules for all our patients and all experiments. We have tested these rules by comparing training and test sets.

Keywords: MoCap, Deep Brain Stimulation (DBS), reducts, information table, decision rules.

1 Introduction

There were already many studies using MoCap measurements for diagnosis of human gait abnormalities related to neurological diseases as presented in references [1-4]. In these papers several different indexes were proposed and verified on experiments with neurological patients. They found that these indices might to be useful in diagnosis of neurological gait abnormalities, but different groups used different MoCap platforms and therefore algorithms for processing MoCap data were not always consistent. Also some indices were specific for patients with different neurological disorders. In our previous work, we have computed indexes for neurological gait abnormalities for PD patients with DBS [5]. We have found a strong influence of the medication and DBS on the decomposition index of knee and hip and hip and ankle. Therefore in the

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present work we have concentrated analysis on the dynamics of the hip movements during the gait. However, the present approach is different as we proposed to use not only statistical analysis of certain indexes, but also AI approach base on the rough set theory. This new approach not only summarizes actual measurements but also gives some strong predictions that might better than standard indexes [1-4], which also predict effects of different therapies for PD patients. As effects of medications and DBS are very different in different patients making predictions is very difficult task and we present here only the preliminary data.

2 Methods

Our experiments were performed on 12 Parkinson Disease (PD) patients who have undergone the surgery based on implanting Deep Brain Stimulator (DBS) for improving their motoric skills. Dr. Kwiek performed surgeries in all patients taking part in our tests on in the Dept. of Neurosurgery Medical University of Silesia (MUS) in Katowice. They were qualified for surgery and observed postoperatively in the Dept. of Neurology MUS [6,7]. Both mentioned above medical departments as well as Polish-Japanese Institute of Information Technology (PJIIT) in Bytom are collaborating, as the group of Silesian Interdisciplinary Centre for Parkinson's Disease Treatment. All experiments were performed in MoCap lab of PJIIT. PD patients performed normal walking under four experimental conditions defined by pharmacological medication and subthalamic nucleus (STN) electrical stimulation (DBS): session S1 was related to MedOFFStimOFF, session S2: MedOFFStimON, session S3: MedONStimOFF, and S4: MedONStimOFF.

In the kinematic movement recording set-up were used 10-cameras and 3D motion capture system (Vicon). The 3D position of the patient was analyzed based on 39 reflective markers (tracked at 100 FPS) placed on major body segments: 4 on Head, 5 on Torso, 14 on left and right side of upper limbs and 16 on left and right sides of lower body.

The structure of data is an important point of our analysis. It is represented in the form of information system or a decision table. We define after Pawlak [8] an information system as $S = (U, A)$, where U, A are nonempty finite sets called the *universe of objects* and the *set of attributes*, respectively. If $a \in A$ *and* $u \in U$, the value $a(u)$ is a unique element of V (where V is a value set). The *indiscernibility relation* of any subset B of A or $I(B)$, is defined [8] as follows: $(x, y) \in I(B)$ or $xI(B)y$ if and only if $a(x) = a(y)$ for every $a \in B$, where $a(x) \in V$. $I(B)$ is an equivalence relation, and $[u]_B$ is the equivalence class of u, or a *B-elementary granule*. The family of all equivalence classes of $I(B)$ will be denoted $U/I(B)$ or U/B. The block of the partition U/B containing u will be denoted by $B(u)$. Having in discernibility relation we define the notion of reduct $B \subset A$ is a reduct of information system if $IND(B) = IND(A)$ and no proper subset of B has this property. In case of decision tables decision reduct is a set $B \subset A$ of attributes such that it cannot be further reduced and $IND(B) \subset IND(d)$. Decision rule is a formula of the form $(a_{i1} = v_1) \wedge ... \wedge (a_{ik} = v_k) \Rightarrow d = v_d$, where $1 \leq i_1 < ... < i_k \leq m$, $v_i \in Va_i$. Atomic subformulas $(a_{i1} = v_1)$ are called conditions. We say that rule r is

applicable to object, or alternatively, the object matches rule, if its attribute values satisfy the rule. With the rule we can connect some numerical characteristics such as matching and support. In order to replace the original attribute a_i with new, binary attribute which tells as whether actual attribute value for an object is greater or lower than c (more in [9]), we define c as a cut. By cut for an attribute $a_i \in A$, such that Va_i is an ordered set we will denote a value $c \in Va_i$. Template of A is a propositional formula $v_i \in Va_i$. A generalized template is the formula of the form $\bigwedge(a_i \in T_i)$ where $T_i \subset Va_i$. An object satisfies (matches) a template if for every attribute a_i $(a_i = v_i)$ where $a_i \in$ A. The template is a natural way to split the original information system into two distinct sub-tables. One of those sub-tables consist of the objects that satisfy the template, the second one of all others. Decomposition tree is defined as a binary tree, whose every internal node is labeled by some template and external node (leaf) is associated with a set of objects matching all templates in a path from the root to a given leaf [10].

We will distinguish in the information system two disjoint classes of attributes: condition and decision attributes. The system S will be called a decision table $S = (U, C, D)$ where U are objects, C and D are condition and decision attributes [8].

3 Results

Recordings in four sessions: S1: MedOFFStimOFF, S2: MedOFFStimON, S3: MedONStimOFF, S4: MedONStimON were performed in all PD patients. The mean for all patients UPDRS III were improving with sessions, S1: 53+/- 4 (SE), S2: 35+/-6, S3: 22+/-3.5, S4: 18+/-3. Mean duration of three consecutive steps were similar between sessions: S1: 3.9+/- 0.2s (SE), S2: 3.6+/-1.6s, S3: 3.6+/-1.4s, S4: 3.5+/-1.2s. These values are similar to slow walk of the healthy person. In this study, we have limited our analysis to x-direction changes in the hip angles for left and right legs during three consecutive steady steps of all PD patients.

A mean of the maximum x-direction hip angles extension (swing phase) for left (L) and right (R) sides were symmetric and improved non-significantly between sessions, S1: L: 29+/-3 deg (SE), R: 29+/-3 deg (SE), S2: L:32+/-3 deg, R: 33+/-3 deg, S3: L :34+/-3 deg, R: 36+/-3 deg, S4: 35+/-4 deg R: 36+/-3 deg. We also found non-significant improvements for the x direction hip angle flexion (stand phase) between sessions. However, we have observed more significant improvements in the maximum velocity of the x-direction hip angles extension (velocity in the swing phase): S1: L: 123+/-8.5 deg/s, R: 124+/-9.5 deg/s; S2: L: 142+/-6 deg/s, R: 140+/-8.4 deg/s; S3: L: 170+/-6.5 deg/s, R: 169+/-9 deg/s; S4: L: 173+/-6 deg/s, R: 174+/-9 deg/s; and hip angle flexion speed (velocity in the stand phase): S1: L: 71+/-85 deg/s, R: 75+/-5 deg/s; S2: L: 82+/-6 deg/s, R: 93+/-6 deg/s; S3: L: 108+/-7 deg/s, R: 127+/-8 deg/s; S4: L: 120+/-9 deg/s, R: 120+/-9 deg/s.

Notice that the most significant increase in velocities was between sessions S2 and S3, so it is an effect of medications. On the basis of mean values for all our patients we can say that medication as well as DBS are improving patients' UPDRS and (hip)

movements velocities. The L-DOPA medications as well as DBS are well-established methods so one would expect such results. However, individual patients are very different and even in our small patients populations we have observed significant variability of the medication and stimulation effects. Therefore, we would like to learn, if we can group effects of medication and DBS therapies of individual patients into several categories?

We have tried two different methods; the first one was related to the dynamical system analysis and the second to the machine learning approach. In our first method, we have compared phase plots for individual patients in four sessions S1 to S4.

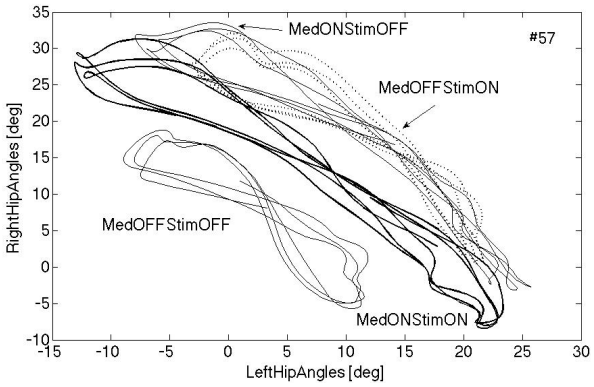

Fig. 1. Phase plots of the right against left x direction hip angles during the gait. Stimulation and medication extend trajectories and shift them up and to the right

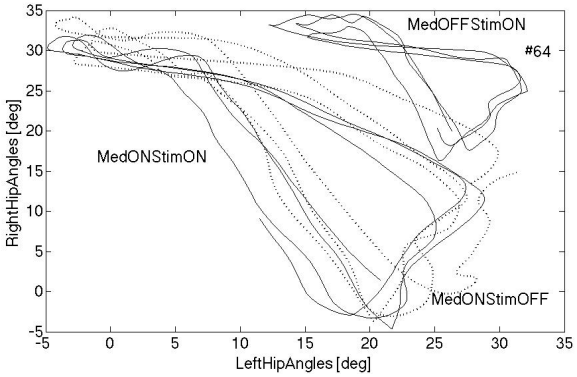

Fig. 2. Phase plots of the right against left x hip angles during walking. Notice a shift down and to the left related to the medication with extent of amplitudes and shift down as effect of DBS during MedON.

We have plotted the movement trajectories in the phase space as changes of the right hip x- angles as a function of the left hip angles changes during three steps stable walk. We have found different types of attractor changes as effect of medication and stimulations, as it is demonstrated on the following figures.

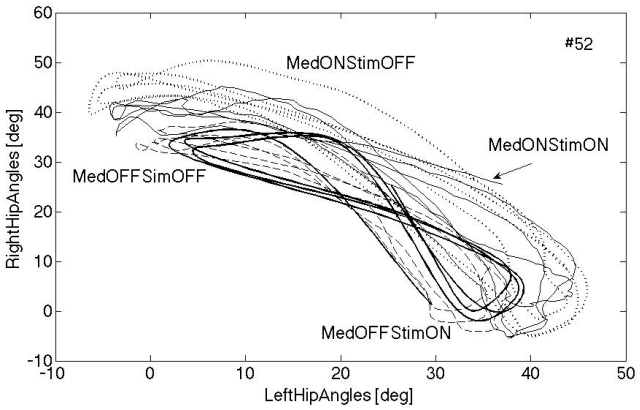

Fig. 3. Phase plots of the right against left x hip angles during walking. Notice that for this patient effects of stimulation and medications are relatively small. Stimulation alone (S2) does not introduce significant changes in comparison to the control (S1). A significant changes in trajectories' amplitude with shift up and to the right are effects of the medication (S3, S4).

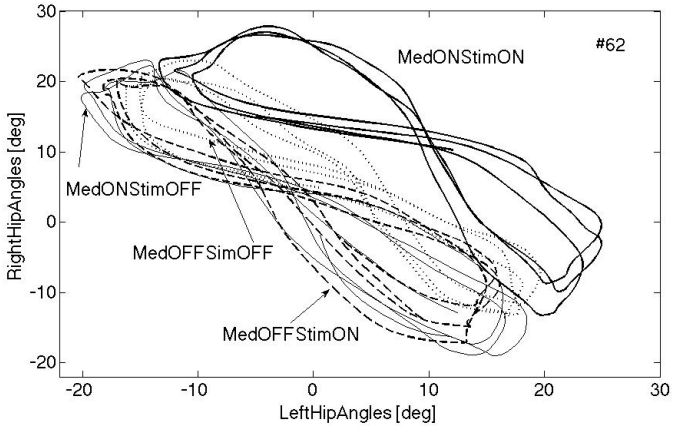

Fig. 4. Phase plots of the right against left x hip angles during walking. Notice very similar trajectories during sessions S1, S2 and S3. In contrast, interaction of medication and stimulation (S4) strongly shifts trajectories up and into the right, but without changes in amplitudes.

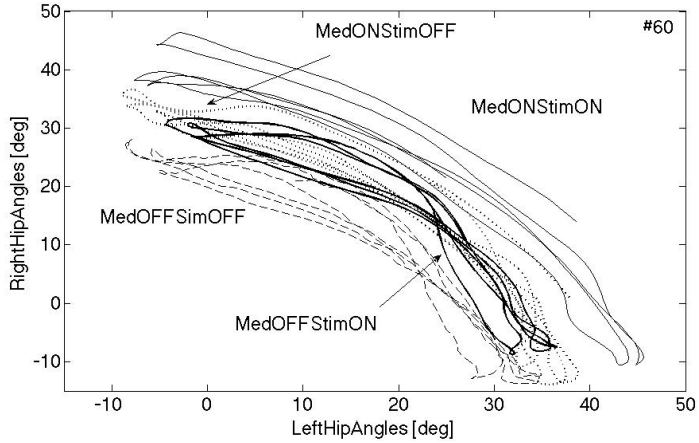

Fig. 5. Phase plots of the right against left x hip angles during walking. In comparison to the control (S1), the stimulation alone (S2) or stimulation with medication increases magnitude of trajectories. But medication alone (S3) even stronger increases the magnitude and introduce trajectories' shift down and to the left .

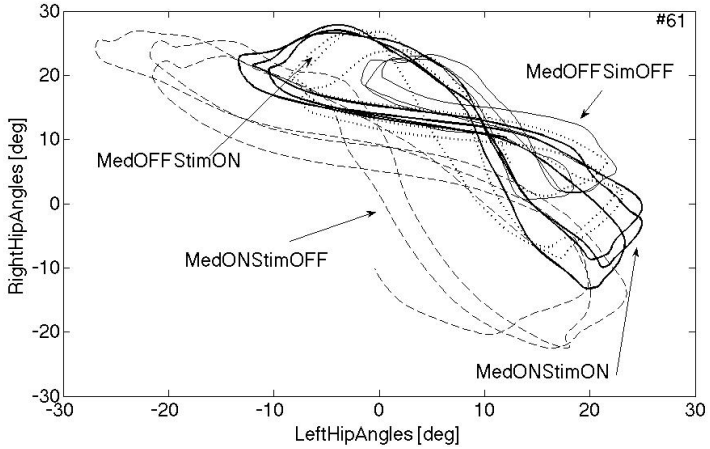

Fig. 6. Phase plots of the right against left x hip angles during walking. Notice a shift up with relatively small amplitude increase as effect of the stimulation (S2) or medication (S3) alone or both together (S4).

In summary, stimulation and medication generally increase the amplitude and shift trajectories related to PD patients walk activity. It is not mainly related to patients gait speed, as mean gait durations were similar in all sessions. These plots might give basis for the dynamical model of the gait in different sessions but as demonstrated, in different patients changes of the particular trajectory are difficult to predict, as they are effects of the system complexity and basal ganglia regulatory numerous loops interactions.

3.1 Rough System Approach

As described above we have used the RSES 2.2 (Rough System Exploration Program) [9] in order to find regularities in our data. At first our data was placed in the decision table as originally proposed by Pawlak [8]. In the row there are following attributes: P# - patient#, S# Session #, t-time, mxaL/mxaR/mnaL/mnaR – max/min Left/Right hip x-direction angles, mxVaL/mxVaR/mnVaL/mnVaR – max/min Left/Right hip x-direction velocity, and UPDRS III as measured by the neurologist in the last column. There are data from two out of 12 patients in the table below:

Table 1. A part of the decision table

P#	S#	t	mxaL	mxaR	mnaR	mnaL	mxVaL	mxVaR	mnVaL	mnVaR	UPDR
52	1	390	38.6	35.9	3.31	-0.65	1.14	1.55	-0.62	-0.65	52
52	2	390	36.2	36.0	-0.14	-2.06	1.30	1.65	-0.89	-0.85	23
52	3	330	44.8	47.9	-5.1	-3.79	2.12	2.25	-1.38	-1.58	13
52	4	400	43.5	42.9	-3.8	-3.04	1.66	1.82	-1.0	-1.21	27
53	1	320	17.7	17.0	-6.9	-6.33	1.49	1.32	-0.70	-0.80	53
53	2	305	23.2	23.3	-1.47	-2.93	1.45	1.50	-0.75	-0.94	23
53	3	290	32.6	24.3	-6.77	-13.99	1.85	1.87	-1.58	-1.79	10
53	4	320	2 6.4	20.3	-8.70	-12.81	1.51	1.59	-1.27	-1.32	8

The last column represents a decision attribute then we can write each row a decision rule as following:

('Pat'=52)&('Sess'=1) &('time'=390)& ('mxaL'=38.6)& … =>('UPDRS'=53) (1)

We read this rule as following: if for patient #52 and session S1 and time of his/her three steps 3.9 s and max hip x-direction angle equal 38.6 deg and … then his/her UPDRS III for this session is 53.

Therefore we obtain 46 decision rules directly from our measurements, as two from our 12 patients did not have all four sessions. The main purpose of our analysis is to reduce these rules and to find regularities in our data. There are many possible steps as described in [9], below we will give some examples. At first, we would like to make rules shorter and find that they apply to more than one case, e.g.:

('Pat'=60)=>('UPDRS'=9[2]) 2 (2)

('mnVaL'=-0.6756)=>('UPDRS'=32[2]) 2 (3)

it reads that Pat# 60 obtained UPDRS=9 in two sessions (eq. 2) and that min velocity of the left hip equal -0.6756 (- is related to the direction of gait) was related to UPDRS=32 in two cases (eq.3). In order to make rules more effective RSES can find optimal linear combinations of different attributes like:

*'mxVaL'*0.594+'mxVaR'*(-0.804)* (4)

*'mx_aL'*0.046+'mn_aL'*(-0.587)+'mn_aR'*0.807* (5)

and these linear combinations may be added as an additional attributes. Also we can use discretization procedure [9] that divides attributes values into non-overlapping parts:

('Pat'="(58.5,Inf)")&('Sess'="(2.5,3.5)"|"(3.5,Inf)")&('mnVaL'="(-0.9803, Inf)") => ('UPDRS'=32[3]) 3 (6)

That reads that for patients' numbers above 58.5 and in sessions S3, S4 min hip velocity is -0.9803 or above then UPDRS equals 32 in three cases (eq. 6).

As we have demonstrated above rules determining possible UPDRS are important but from patient and doctor points of view, the first message should be if the therapy (medication and/or DBS) is effective. In order to find it, we need to correlate our measurements with the session number that is related to the specific procedure. In this case the session number will be the decision attribute. In this case, we can obtain the following more general rules e.g.:

('UPDRS'=52|53|43|56|87|45|58|30|60)=>('Sess'=1[11]) 11 (7)

('UPDRS'=23|13|43|22|39|28|24|81|48|42)=>('Sess'=2[11]) 11 (8)

('time'=440|305|280|365|310)=>('Sess'=2[6]) 6 (9)

that means that session S1 (MedOFFStimOFF) is related to high UPDRS in 11 cases (eq. 7), in session S2 (MedOFFStimON) UPDRS are generally smaller in 11 patients (eq. 8) and in this session (S2) the duration of three steps is between 2.8 and 4.4 s in 6 cases (eq. 9). We can also find rules in which the duration of three steps are similar as in (eq. 10):

('time'=350)&('Pat'=56|57|62|59)=>('Sess'=4[4]) 4 (10)

Another important issue is how values of different attributes are changing in different sessions and patients. More variability is related to better attribute. Below there are two examples for: UPDRS and max hip left angles velocity.

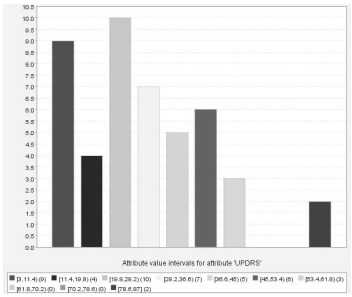

Fig. 7. Statistic for UPDRS

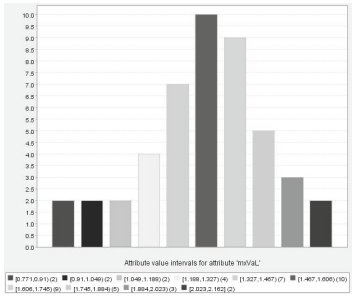

Fig. 8. Statistic for max velocity L. hip

But the main purpose of the ML approach is related to demonstration that proposed rules are enough universal to predict results from new patients on the basis of already measured patients (*test-and-train scenario* –[9]). In order to perform such test, we

have divided our data set into two parts: one 60% of our data was training set, and another 40% was set that we have tested. We have removed decision attributes from the test-set and compared them with attributes values obtained from our rules. We have used several different algorithms in order to find rules from training-set. The exhaustive algorithm [9] gave the best results described as the confusion matrix:

Table 2. Confusion matrix for different session numbers (S1-S4)

		Predicted				
		2	**3**	**4**	**1**	**ACC**
Actual	**2**	2	0	0	1	**0.66**
	3	1	0	1	2	**0.0**
	4	1	3	1	0	**0.2**
	1	0	1	1	2	**0.5**
	TPR	**0.5**	**0.0**	**0.33**	**0.4**	

TPR: True positive rates for decision classes, ACC: Accuracy for decision classes: Coverage for decision classes: 0.75, 1.0, 1.0, 0.66 and global coverage=0.8421, and global accuracy=0.3125. A global accuracy was above 30% that means that we probably need to use more rules as for example combinations of many attributes or/end extend number of measured attributes for our analysis. However problem with this approach is that its results depend on which part of our measurements was taken as training and which part was tested. In order to test in exhaustive manner or all different possibilities we have divided our experimental randomly set into 9 subsets:

Table 3. Confusion matrix for the UPDRS as the decision attribute

		Predicted					
		50,69.5	**-Inf,29.5**	**42.5,50**	**34,42.5**	**69.5,Inf**	**29.5, 34**
Actual	50, 69.5	0.67	0.0	0.0	0.0	0.0	0.0
	-Inf, 29.5	0.0	1.67	0.0	0.11	0.11	0.0
	42.5,50	0.0	0.0	0.11	0.0	0.0	0.0
	34,42.5	0.0	0.11	0.0	0.0		
	69.5, Inf	0.0	0.11	0.0	0.0	0.0	0.0
	29.5, 34	0.0	0.0	0.0	0.0	0.0	0.22
	TPR	**0.44**	**0.72**	**0.11**	**0.0**	**0.0**	**0.22**

TPR: True positive rates for decision classes, ACC: Accuracy for decision classes: 0.44, 0.72, 0.11, 0, 0, 0.22. Coverage for decision classes: 0.44, 0.602, 0.11, 0.11, 0.11, 0.167 and global coverage=0.6, and **global accuracy=0.917**. UPDRS decision classes: (50, 69.5), (-Inf, 29.5), (42.5, 50), (34, 42.5), (69.5, Inf), 29.5, 34).

4 Conclusions

We have presented comparison of the classical dynamical systems, and rough set (RS) approaches to process the MoCap data from PD patients in four different treatments. We have plotted effects of the medication and brain stimulation on individual patients gait trajectories. As these effects are strongly patient's dependent they could not give enough information to predict new patient's behavior. The RS approach is more universal as it gives general rules and predictions that cover individual patients reactions to different treatments as demonstrated for the UPDRS predictions.

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