Monitoring Human Performance with Wearable Accelerometers

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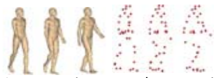
Motivation



- Parkinson's Disease(PD): A progressive neurodegenerative movement disorder affecting 3% of the population over 65 years
- Periodic assessment of motor impairments is very crucial ; currently used human observer-based assessments are **subjective** and inadequate for spotting **mild symptoms**
- Motion capture systems: Becoming more portable/affordable for clinical use and give very precise motion information of the whole body

Project goal: Use motion capture data for **quantitative analysis** of motor symptoms in PD

Dataset

- Participants: 4 PD patients (3 male, 1 female) and 2 healthy controls. All the PD patients had Deep Brain Stimulator (DBS) implanted (age ranged from 51 to 67 years)
- Patients were off-drugs for 12 hours and then went through various motors tests on and off stimulator. The UPDRS motor components tested were: action tremor, tremor at rest, hand movement, leg agility, gait and postural stability
- Used a Vicon motion capture (Mocap) system with 16 infrared cameras (sampling at 120 Hz) to capture body movements during each test. UPRDS scores (0 to 4 range) were assigned by trained professional: 0-2 → *mild* symptoms and 3-4 → *severe* symptoms

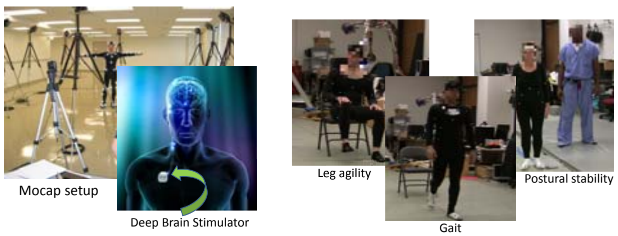


Figure 1: Experimental Setup and Data Collection Method.

Features

- Marker trajectories were high-pass filtered (4 Hz cut-off)
- Maximum amplitude variations after high-pass filtering (tremor effect). Ratio of the total signal energy with energy content beyond 4Hz
- Frequency domain entropy. Compute the features on the variations of the hand-normal **n**, knee height variations (for leg agility)
- Center of Mass (COM) variations, body angle variance (postural stability); mean speed, mean step width (gait)

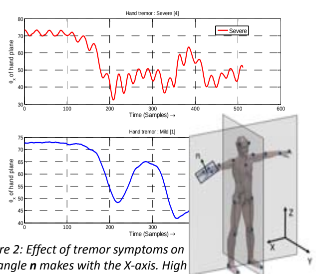
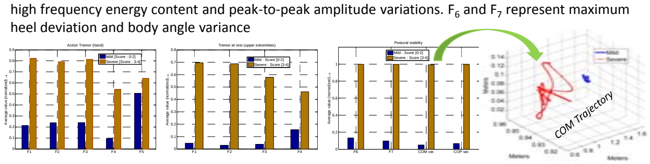


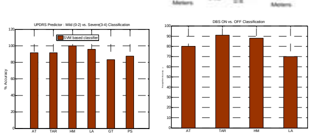
*Figure 2: Effect of tremor symptoms on the angle **n** makes with the X-axis. High frequency variations are prominent*

Mild vs. Severe Symptom Classification

- We demonstrate the quantitative differences between mild and severe symptoms for different features across various motor tasks (below). F_1 through F_5 represents various features associated with high frequency energy content and peak-to-peak amplitude variations. F_6 and F_7 represent maximum heel deviation and body angle variance



- We used a Support Vector Machine (SVM) for discriminating mild (score 0-2) vs. severe (score 3-4) symptoms as well as ON vs. OFF DBS states across various motor tasks
- Each classifier went through a leave one out cross-validation test (classification results are shown here)



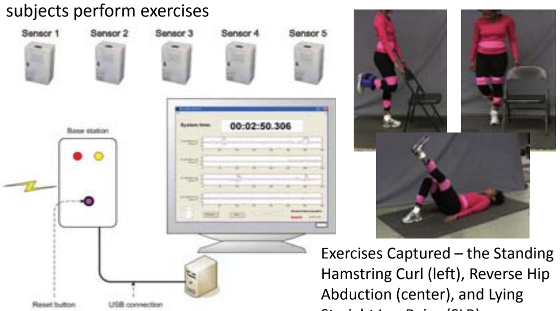
- AT: Action tremor, TAR: Tremor at Rest, HM: Hand Mov, LA: Leg agility, GT: Gait, PS: Postural stability

Motivation

More than 20 million Americans suffer from knee osteoarthritis (OA), a degenerative disease that causes joint pain, weakening of quadriceps muscles and restrictions in mobility[1]. This poster describes methods for assessment of exercise quality using body-worn accelerometers for the development of an in-home rehabilitative device that will recognize errors in patient exercise performance, provide feedback on performance, and motivate the patient to continue the prescribed exercise regimen.

System set up and data capture

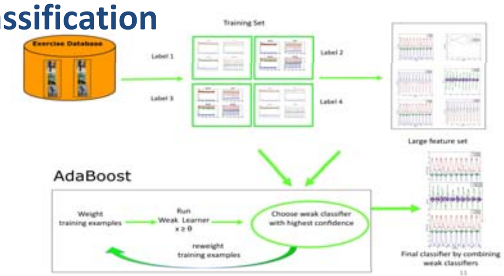
Five accelerometers placed on the legs and waist track movement while subjects perform exercises



Wireless Data Acquisition System

Exercises Captured – the Standing Hamstring Curl (left), Reverse Hip Abduction (center), and Lying Straight Leg Raise (SLR).

Classification



Results

Within Subject

Exercise	L	TPR	TNR	S
SHC	1 Performing fast	0.59	0.95	5
	2 Thighs not parallel	0.83	0.91	7
	3 Trunk bent forward	0.86	0.95	3
RHA	1 Performing fast	0.99	0.94	6
	2 Trunk bent towards working leg	0.87	0.99	4
	3 Over tilting hip up	0.99	0.73	6
	4 Bringing working leg knee up	0.75	1.00	4
SLR	1 Performing fast	0.74	0.79	4
	2 Returning foot to floor	0.98	0.61	6
	3 Knee not fully extended	0.93	0.94	3
	4 Overshooting	0.84	0.84	7

Table 1: Shown are the true positive (TPR) and true negative (TNR) rates for each label. *S* is the number of subjects included.

Across Subjects

Exercise	L	TPR	TNR	N
SHC	1 Performing fast	0.74	0.98	50
	2 Thighs not parallel	0.95	0.87	306
	3 Trunk bent forward	0.89	0.97	72
RHA	1 Performing fast	0.97	0.83	300
	2 Trunk bent towards working leg	0.82	0.96	79
	3 Over tilting hip up	0.96	0.76	318
	4 Bringing working leg knee up	0.64	0.99	80
SLR	1 Performing fast	0.91	0.97	115
	2 Returning foot to floor	0.98	0.72	331
	3 Knee not fully extended	0.77	0.98	103
	4 Overshooting	0.75	0.88	182

Table 2: *N* is the number of examples of the error included in the training set.

Leave One Subject Out

Exercise	L	TPR	TNR	N
SHC	1 Performing fast	0.32	0.94	5
	2 Thighs not parallel	0.78	0.29	7
	3 Trunk bent forward	0.28	0.99	3
RHA	1 Performing fast	0.86	0.15	6
	2 Trunk bent towards working leg	0.18	0.84	4
	3 Over tilting hip up	0.63	0.25	6
	4 Bringing working leg knee up	0.06	0.91	4
SLR	1 Performing fast	0.50	0.96	4
	2 Returning foot to floor	0.67	0.02	6
	3 Knee not fully extended	0	0.84	3
	4 Overshooting	0.66	0.91	7

Table 3: *N* is the number of examples of the error included in the training set.

Summary

The system obtains an average TPR of above 70% for most labels of the standing hamstring curl, reverse hip abduction and straight leg raise. Generalization to new subjects is less successful, in part because our small subject pool does not encompass all common variations of the errors.

Current work

- Previous tasks for monitoring human performance from accelerometers were formulated as classification problems.
- Currently, we are investigating algorithms to solve two problems for classification of time series from accelerometer data:

1) The difference between the two time-series classes (e.g. older adults with risk of falling or not, or assessment of quality exercise) is not necessarily exhibited throughout the entire duration of the time series. The global statistics often cannot distinguish well these two types signals. Moreover, although temporal signals might exhibit repeated discriminative patterns/templates, the locations, length and number of the occurrences are not known. Based on our recent work on jointly localization and classification[5], we plan to extend our algorithm to automatically select the temporal segments in a weakly supervised manner that are more discriminative between two medical conditions. See figure 6.

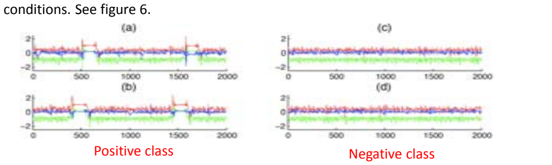


Figure 6: What distinguishes the signals on the left from the ones on the right? Can we automatically discover it?

Preliminary results on CMU-MMAC dataset

CMU-MMAC dataset contains accelerometer measures of human subjects performing tasks involved in preparing and cooking five different recipes: brownie, scrambled egg, pizza, salad, and sandwich. This dataset is challenging because it was captured in an unstructured environment and the subjects were minimally instructed. How a recipe was cooked varied greatly from one subject to another. Moreover, the course of food preparation and recipe cooking contains a series of actions, and most of them are not repetitive. Many actions such as walking, opening the fridge, and turning on the oven are common for most recipes. More discriminative actions such as opening a brownie bag or cracking an egg are often buried in a long chain of actions. In our preliminiary experiments, we found that localizing the discriminative patterns leads to improvement in classification performance, as shown in the results below.

	Brownie	Egg	Pizza	Salad	Sandwich
Brownie	68.8	6.2	6.2	0.0	18.8
Egg	25.0	31.2	12.5	12.5	18.8
Pizza	11.8	5.9	47.1	17.6	17.6
Salad	5.9	11.8	23.5	35.3	23.5
Sandwich	0.0	7.1	0.0	14.3	78.6

Average accuracy
- Ours: 52.2%
- SVM: 42.4%
- Random: 20%

2) Previous work on classifying human motion from accelerometers has emphasized types of features and classifiers and little attention has been paid to the choice of positive and negative training samples (that has large impact in the final detection/classification performance). In our recent work on facial event detection [6], we have shown an average improvement of 15% of area under the ROC by optimally selecting the positive and negative samples in the time series. Following this work, we plan to extend our algorithm for sample selection in time series to our problems for human performance monitoring from accelerometer data.

Acknowledgments and references

Data collected through the Claude Pepper Older Americans Independence Center at the University of Pittsburgh by Jennifer Brach Sokol and Dave McGurl.

[1] Hausdorff JM, Rios DA, Edelber HK. Gait variability and fall risk in community–living older adults: a 1–year prospective study. Archives of Physical Medicine and Rehabilitation, 2001.

[2] Hornbrook MC, Stevens VJ, Wingfield DJ, Hollis JF, Greenlick MR, Ory MG. Preventing falls among community–dwelling older persons: results from a randomized trial. The Gerontologist, 1994.

[3] Centers for Disease Control and Prevention, National Center for Injury Prevention and Control. Web-based Injury Statistics Query and Reporting System (WISQARS) [online]. 2005- cited 2009 Nov 12. Available from URL: www.cdc.gov/ncipc/wisqars.

[4] Menz, HB., Lord, SR., Fitzpatrick, RC. Acceleration patterns of the head and pelvis when walking on level and irregular surfaces. Gait Posture 18: 35 46, 2003

[5] Nguyen, M., Torresani, L, De la Torre F., and Rother C. Weakly supervised discriminative localization and classification: a joint learning process. International Conference on Computer Vision 2009.

[6] Zhu Y., De la Torre F., and Cohn J. Dynamic Cascades with Bidirectional bootstrapping for Spontaneous Facial Action Unit Detection. IEEE Transaction on Affective Computing, 2011.

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