Validation of Automated Mobility Assessment using a Single 3D Sensor

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Outline

- Introduction
- Proposed method
    - System design
    - Feature design
- Experiments and evaluation
- Conclusions

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  - evaluate effectiveness of rehabilitation
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  - estimate the risk of falls in elders
  - adjust medication levels for those with musculo-skeletal disorders
  - evaluate effectiveness of rehabilitation
  - sports, military application, $\cdots$
- Traditionally provide by physicians
  - restricted to cost and personnel/equipment availability
  - unable to assess more frequently
  - unable to assess at familiar places, e.g., patients' home

Automated mobility assessment

Motivation

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Goal

- design and validate an automated mobility assessment system based on signal 3D sensor
- provide study design insights in a specific context
- highlight design aspects that can be generalized to other applications


RGB data


depth data

System design

Insights into key factors for deploying an automated mobility assessment system based on cost-effective 3D sensors

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Task:

- Prefer activities exploiting the mobility of all parts of the body.
- Level of difficulty in performing activities affects the system capability.
- Better to have each task repeatedly performed.

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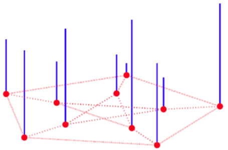
  (i.e. $A_{ij} = 1$ when a physical limb connects joint i and joint j)
- difference of 3D position at each joint between two consecutive frames $\Rightarrow$ a graph signal $\mathbf{f}_a^{(t)}(i) = \mathbf{v}_{t,i}(a)$ where $a = \{x, y, z\}$



Graph-based features

- Graph Fourier transform (GFT) can provide frequency analysis to the graph signals, which defined as

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- vectorize $C^{(t)} = [\mathbf{F}_x^{(t)}, \mathbf{F}_y^{(t)}, \mathbf{F}_z^{(t)}]$ to a row vector and concatenate into a transform coefficient matrix $\mathbf{C} \in \mathbb{R}^{(T-1)\times 45}$

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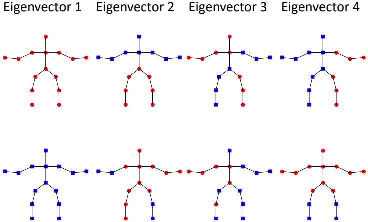
- apply pyramid pooling scheme to capture the dynamics and generate the final features

Graph-based features

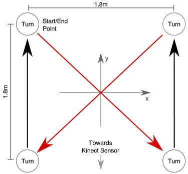
- GFT basis can capture global motion properties.
- Lead to an easier interpretation of the results compared to PCA.
- Easier to compare results across different subjects, tasks, coordinate systems or datasets since not data-dependent.



Experiments and evaluation

Experiment methodology:

- 14 subjects with Parkinsons disease
- Perform standardized tests (e.g. walking) in front of Kinect sensor
- Skeletons are extracted in real time using Microsoft Kinect SDK
- Each action is performed 5 times when medication is in effect and another 5 times after medication wears off



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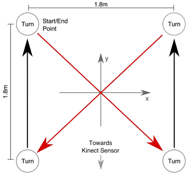

Goal:
classify between ON/OFF medication states with captured motion data

Feature performance

Table: SVM performance for various features. Accuracy is reported with the format as average accuracy (best accuracy/worst accuracy) across 14 subjects. A: Accuracy, P: Precision, R: Recall and F-M: F-measure. ALL: Gait, Angle, and Graph.

Feature	A (%)	P (%)	R (%)	F-M
Gait	63.58 (88.71/39.53)	57.26	55.40	0.51
Angle	75.30 (92.22/53.58)	75.01	74.20	0.74
Graph	82.41 (95.68/69.63)	83.04	81.93	0.82
All	84.79 (93.95/71.23)	85.43	83.38	0.84
PCA	84.66 (95.32/71.99)	85.30	84.44	0.85

Classifier performance

Table: Performance of single classifier and multiple classifiers combination. A: Accuracy, P: Precision, R: Recall, F-M: F-measure, AP: Average of Probabilities, MV: Majority Voting, S: SVM, k: k-NN, D: Decision Tree, R: Random Forest.

Classifier	A (%)	P (%)	R (%)	F-M
SVM	84.79	85.43	83.38	0.84
Random Forest	83.09	83.68	83.09	0.83
k-NN	79.24	80.16	79.24	0.79
Decision Tree	72.66	72.92	72.66	0.73
Naive Bayes	71.02	71.64	71.02	0.70
SkR (AP)	87.41	87.61	87.40	0.87
Sk (AP)	87.28	87.49	87.29	0.87
SkR (MV)	85.62	85.79	85.61	0.86
DSk (AP)	85.37	85.61	85.37	0.85
DSk (MV)	85.29	85.51	85.30	0.85

Experiments and evaluation

System performance

Table: subject-independent performance of single classifiers and multiple classifiers combination. A: Accuracy, P: Precision, R: Recall, F-M: F-measure.

Classifier	A (%)	P (%)	R (%)	F-M
Naive Bayes	60.09	60.50	60.10	0.60
Decision Tree	62.98	63.00	63.00	0.63
SVM	67.13	67.10	67.10	0.67
Random Forest	75.67	75.90	75.70	0.76
k-NN	76.86	77.10	76.90	0.77
Rk (AP)	77.32	77.50	77.30	0.77
SkR (MV)	76.92	77.00	76.90	0.77
Rk (MV)	76.59	76.70	76.60	0.77

Impact of task difficulty

Table: Performance results for three walking tasks. Accuracy is reported with the format as average accuracy (best accuracy/worst accuracy) across subjects. A, P, R and F-M denote respectively Accuracy, Precision, Recall and F-measure.

Task	A (%)	P (%)	R (%)	F-M
Count	84.79 (93.95/71.23)	85.43	83.38	0.84
Tray	82.04 (94.44/53.63)	82.19	90.00	0.85
Walk	81.04 (96.05/48.99)	81.63	87.75	0.83

Conclusions

- Propose a methodology to develop automated mobility assessment system with a single 3D sensor
- Propose graph-based feature, which achieves comparable performance while has better interpretability and robustness.
- Present an evaluation for a pilot study involving PD subjects, which supports the feasibility of using single 3D sensor to automatically assess the mobility and successfully classify the medication states.