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学术论文

Implicit Detection of Parkinson’s Disease from Everyday Activities
基于日常行为感知的帕金森病隐式检测

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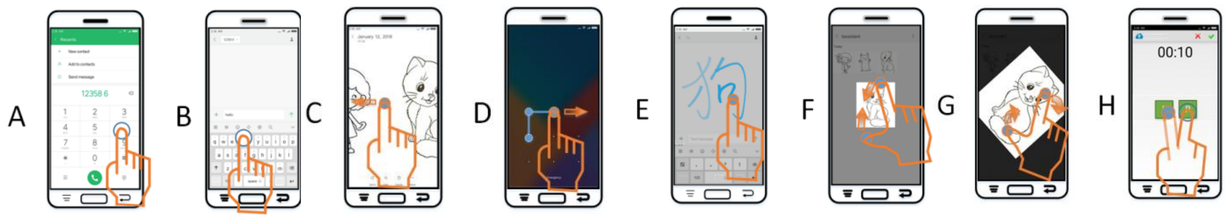
Background

- **Parkinson’s Disease (PD)**
  - one of the most common neurological diseases (8-18 per 100,000 persons)
  - motor impairment symptoms include tremor, bradykinesia, postural instability, rigidity, etc.
  - traditional clinical evaluations (e.g., standardized test) rely heavily on practitioners’ expertise and cannot guarantee early interventions
- **Existing Approaches**
  - using accelerometers or commodity device such as smartphones to develop fine-grained motor tracking tools
  - a common limitation of prior work is that they require subjects’ explicit and active participation while it is difficult to sustain users’ motivation, especially when the symptoms are not evident

Hypothesis

- The design rationale is that the PD motor symptoms (e.g., bradykinesia, tremor) could affect hand and finger performance while interacting with smartphones.
- We hypothesize that we can build a machine learning model that can distinguish PD patients from the healthy subjects implicitly.
- The term *“implicit”* means that our approach can evaluate and monitor PD as a side effect during everyday tasks.



A: dial numbers; B: type text messages; C: swipe screen; D: draw graphical password; E: handwrite characters; F: zoom in/out pictures; G: rotate pictures; H: alternating finger tapping.

Figure 1: Common smartphone interactions explored in this study.

Experiment

- 20 PD subjects *vs.* 22 age-matched healthy controls at Peking Union Medical College Hospital
- We collected the interaction activity data when participants performed a variety of touch gestures with a smartphone.
- The interaction activity data, including screen pixel positions, screen pressure values, accelerometer outputs, and their corresponding timestamps, were collected.

Gesture Type	Interaction Task	Gesture Features	Pressure Features	Accelerometer Features
Static Gestures	Dialing phone numbers	mean and standard deviation of inter-tap dwelling time, time between press and release, screen distance between press and release	mean, standard deviation, and derivative of screen pressure	mean, standard deviation, and derivative of the output from x/y/z axis
	Typing text messages			
One-Finger Manipulation Gestures	Swiping left or right	mean, standard deviation, and derivative of finger movement speed		
	Drawing graphical passwords			
	Handwriting Chinese characters			
Two-Finger Manipulation Gestures	Zooming in/out pictures	mean, standard deviation, and derivative of finger movement speed (for each of the two fingers)		
	Rotating pictures			
Sensor-Enhanced Alternating Finger Tapping (AFT)		mean and standard deviation of inter-tap dwelling time, time between press and release, screen distance between press and release		

Figure 2: Tasks and the corresponding features explored in the study.

Findings

Finding 1: Detection accuracy based on sensor-enhanced AFT (H’) is significantly higher than tap counting (H).

Finding 2: Detection accuracies based on drawing graphical password (D) and handwriting Chinese characters (E) are significant higher than tap counting (H).

Finding 3: There is no significant difference between detection accuracies based on everyday interaction tasks and the sensor-enhanced AFT (H’).

Finding 4: The detection accuracies of using pressure features (81.0%) and accelerometer features (83.3%) are higher than using gesture features (69.0%) while the significance is marginal.

Finding 5: The overall classification accuracy is 88.1% (with 90.0%/86.4% sensitivity/specificity) for AdaBoost algorithm.

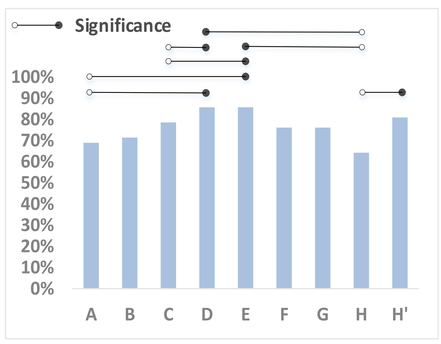


Figure 3. Classification accuracies corresponding to different interaction tasks.

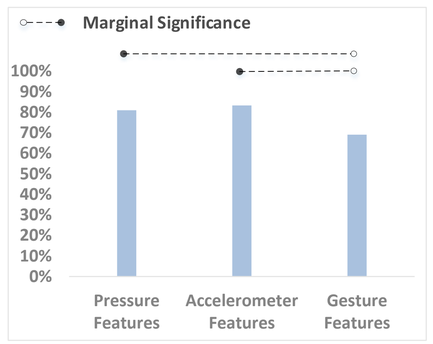


Figure 4. Classification accuracies of using different feature sets.

Conclusion

- We demonstrate the feasibility of implicit detection of PD motor impairment by analyzing users’ smartphone interaction activities when they perform a variety of everyday tasks.
- The detection happens implicitly and passively without interfering with the normal use of smartphones.