Data augmentation of wearable sensor data for Parkinson's disease monitoring using convolutional neural networks

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- Published In 19th ACM International Conference on Multimodal Interaction (2017)
- 624 citation as today
- https://github.com/terryum/Data-Augmentation-For-Wearable-Sensor-Data

Challenges

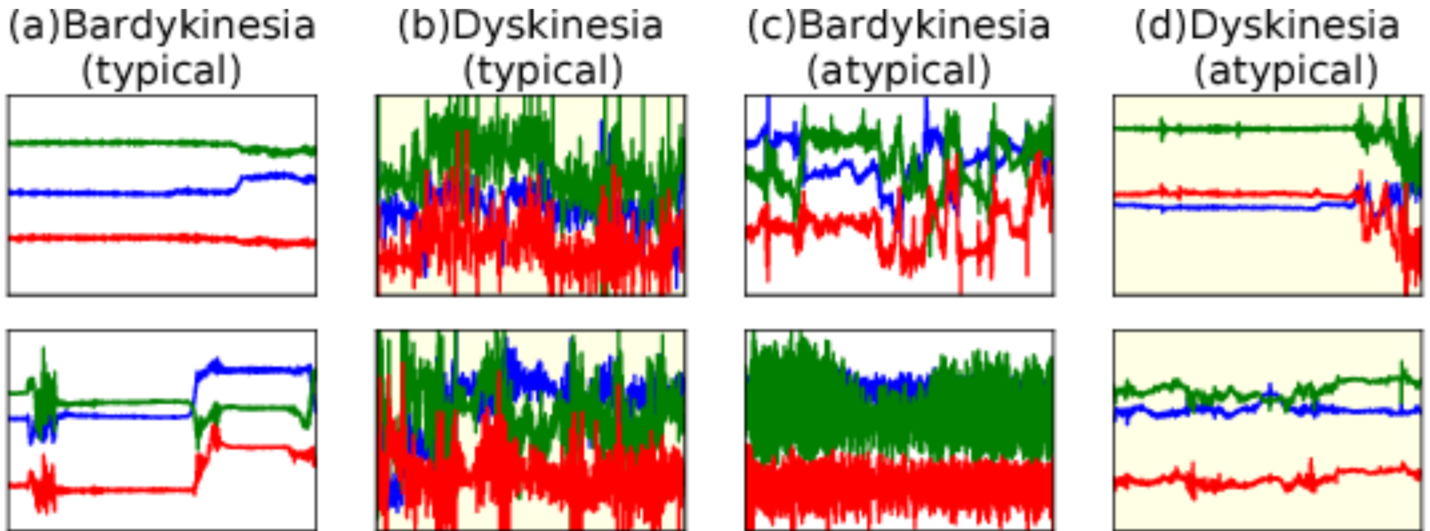
- Small medical dataset
- Noisy label
- high intra-class variability: sensor data for a single motor state of PD can vary greatly from patient to patient

Challenges in PD data

- Bradykinesia:
  - Freezing of voluntary movement, (movement speed will be decreased)
  - constant signal (less movement)
  - Atypical Bradykinesia= Bradykinesia + Tremor => *Looks like dyskinesia!!*

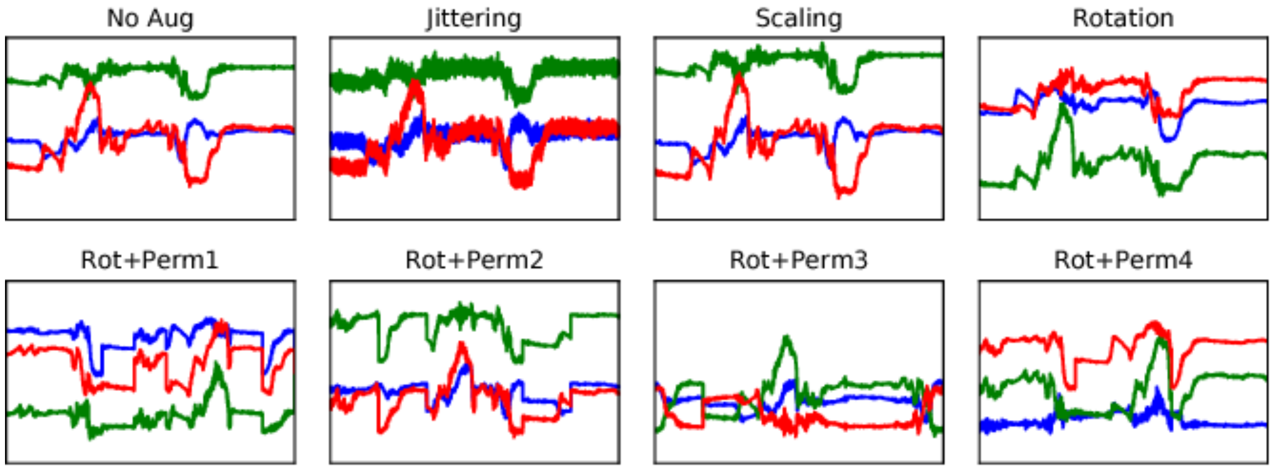
Dyskinesia:

- Extreme *involuntary* movements → fluctuation in sensor
- Atypical Dyskinesia = Dyskinesia + Voluntary suppression ➔



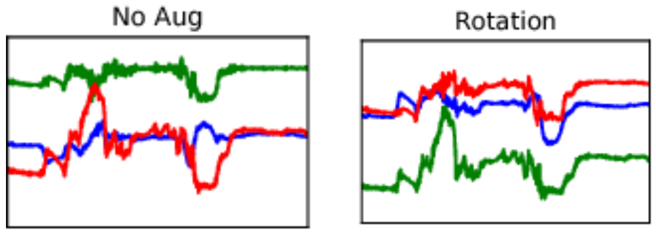
Data Augmentation

- Injecting prior knowledge
- Label preserving data augmentation for sensor is not intuitively recognizable like the image data
- Location Vs Magnitude



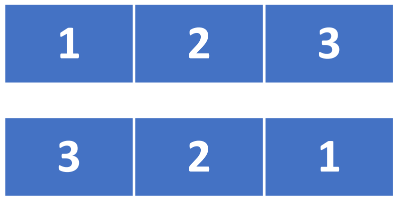
Data Augmentation (Temporal Location)

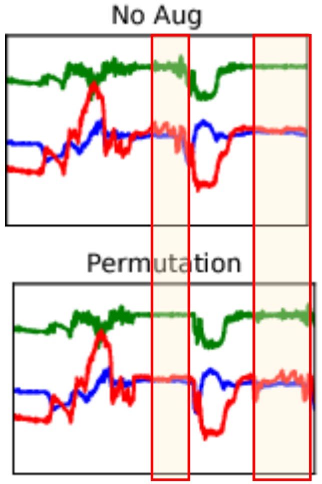
- **Rotation:** applying arbitrary rotations to the existing data, they mimic different sensor placements.
  - Changing the axes



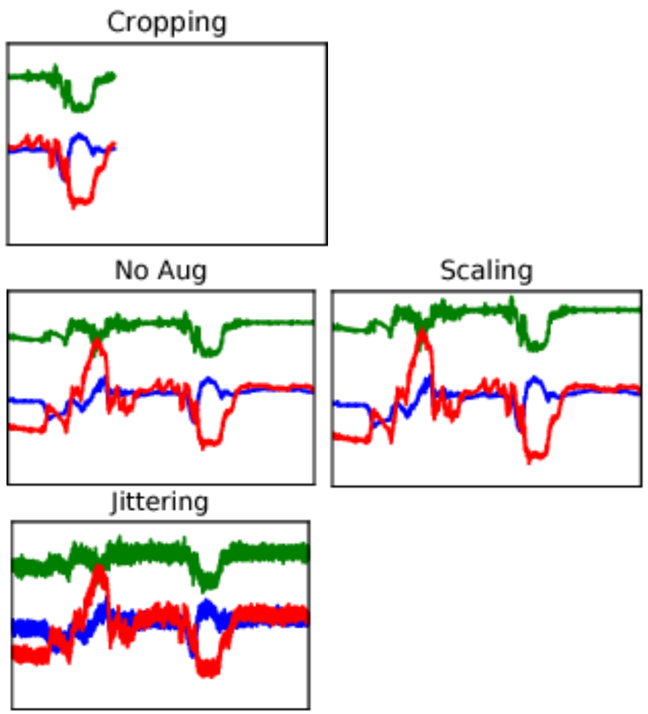
- **Permutation:**
  - Rearrange data sequence in a window = A new window!
  - Variability in the temporal location

- Slice the window data into N=3 segments
- Shuffle the n=1 segment





Data Augmentation (Magnitude)



- **Scaling:** (zoom in/out)
  - Multiplying the whole window with a random scaler
- **Jittering:** small random noise in the data
  - Simulate real world errors
- **Cropping:** (window slice)
  - Might loss important events/ capture event free region

Result

Table 1: The results of PD motor state classification with various data augmentation methods. R,P,T,M represent *Rot*, *Perm*, *TimeW*, *MagW*, respectively.

	SVM	CNN	Jitter	Scale	Crop	Rot	Perm
Train	98.82	99.92	99.78	99.84	65.77	100.0	99.33
Test	70.72	77.54	77.52	79.46	73.58	**82.62**	81.16
	MagW	TimeW	P,T	R,P	R,T	R,P,T	R,P,T,M
Train	100.0	94.67	96.63	99.08	94.70	94.43	94.20
Test	79.33	82.00	81.75	**86.76**	85.01	**86.88**	85.60

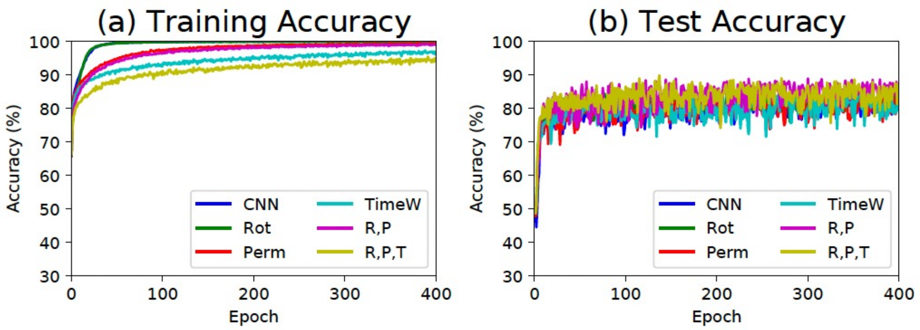


Figure 4: Training curves for *CNN*, *Rot*, *Perm*, *TimeW*, *Rot+Perm* and *Rot+Perm+TimeW* methods. The curves of *Rot+Perm+TimeW* shows slow training improvement and a better generalization performance.