HATRNet: Human Activity/Transition Recognition using Deep Neural Networks

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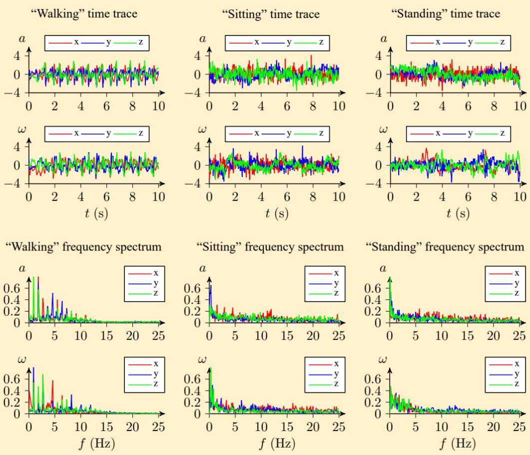
BACKGROUND and MOTIVATION

- Human Activity Recognition has great potential for customized healthcare
- Smartphones incorporate sensors (accelerometer, gyroscope etc.)
- Sensor data can be used to classify human activities and transitions

- Improvements compared to state of the art:
  1. Advanced preprocessing including data augmentation
  2. End-to-end deep learning solution (no feature extraction)
  3. Improved architecture enabling accurate classification of transitions

1. DATASET

- SBHAR dataset of 6 activities and 6 postural transitions from the Galaxy SII
- 3-axial linear acceleration and 3-axial angular velocities traces at 50 Hz
- Augmented to 3,640 examples with no feature selection (beyond FFT)

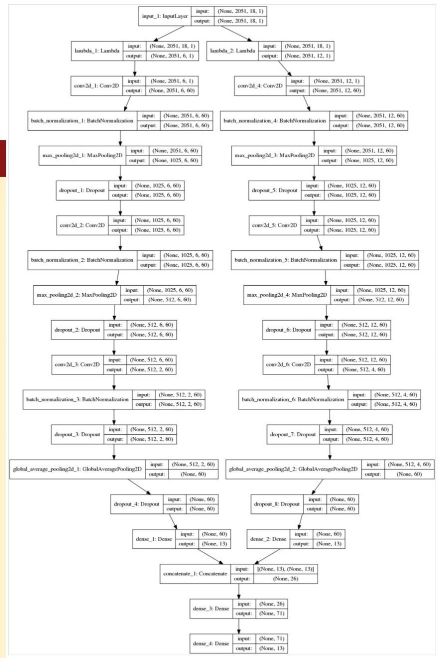


FUTURE WORK

- Model ensembling using data representations from sequence models
- Implement the model on a smartphone for real-time inference
- Incorporate frequency and phase traces into the sequence model

2. NEURAL NETWORK ARCHITECTURE

Siamese (non-weight sharing) CNN



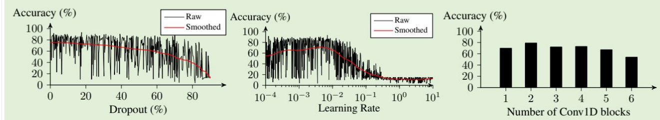
Siamese (non-weight sharing) CNN

- Left subnetwork takes time traces as input (6 zero-padded channels)
- Right subnetwork takes frequency and phase traces as input (12 interpolated channels)
- Late sensor fusion employed for encoded, efficient feature extraction
- Conv1D filter size: 1x14 Conv2D filter size: 3x42 Filter #: 60 learning rate: 0.0026

Sequence (LSTM) Model

- Takes time traces as input (6 channels of variable length)
- Two LSTM layers (128 to 32 output channels)

Random Coarse- to Fine-grain Hyperparameter Search



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3. RESULTS and DISCUSSION

Literature comparison (grouped postural transitions):

SVM, 561 features extracted [1]

	WA	WU	WD	SI	ST	LD	PT
WA	1834	64	5	3	2	0	1
WU	10	1743	51	5	5	0	16
WD	0	2	1671	1	7	0	1
SI	0	0	0	1875	**94**	6	3
ST	0	2	0	**109**	2049	0	1
LD	0	0	0	1	0	2148	2
PT	0	1	2	0	0	0	1036

CNN (2.5 second traces) [2]

	WA	WU	WD	SI	ST	LD
WA	487	0	9	0	0	0
WU	2	468	0	0	0	1
WD	0	0	420	0	0	0
SI	0	2	0	443	**46**	0
ST	0	0	0	**16**	516	0
LD	0	0	0	0	0	537

HATRNet Results (ungrouped postural transitions):

Siamese (non-weight sharing) CNN

	WA	WU	WD	SI	ST	LD	ST-SI	SI-ST	SI-L	L-SI	ST-L	L-ST
WA	21	0	1	0	0	0	0	0	0	0	0	0
WU	0	36	0	0	0	0	1	0	0	0	0	0
WD	0	0	33	0	0	0	0	0	0	0	0	0
SI	0	0	0	20	**0**	0	0	0	0	0	0	0
ST	0	0	0	**2**	27	0	0	0	0	0	0	0
LD	0	0	0	0	0	26	0	0	0	0	0	0
ST-SI	0	0	0	0	0	0	19	0	0	0	0	0
SI-ST	0	0	0	0	0	0	0	10	0	0	0	0
SI-L	0	0	0	0	0	0	0	0	11	0	0	0
L-SI	0	0	0	0	0	0	0	0	0	15	0	2
ST-L	0	0	0	0	0	0	1	0	1	0	10	0
L-ST	0	0	0	0	0	0	0	0	0	0	0	7

WA: Walking, WU: Walking-Upstairs, WD: Walking-Downstairs, SI: Sitting, ST: Standing, LD: Laying-Down, PT: Postural Transition, ST-SI: Stand-to-Sit, SI-ST: Sit-to-Stand, SI-L: Sit-to-Lie, L-SI: Lie-to-Sit, ST-L: Stand-to-Lie, L-ST: Lie-to-Stand

Architecture Comparison:

	CNN1	CNN2	LSTM	SVM [1]	Perceptionnet (CNN) [2]
Number of categories	12	7	12	7	6
Error Rate	3.29 %	0.82 %	18.11 %	3.22 %	2.75 %