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ADAPTATION AND SELECTION TECHNIQUES BASED ON DEEP LEARNING FOR HUMAN ACTIVITY RECOGNITION USING INERTIAL SENSORS

Manuel Gil-Martín, José Antúnez-Durango and Rubén San-Segundo







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- Materials and Methods
 - Autoencoders
 - Generative Adversarial Networks
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- Human Activity Recognition (HAR)
 - Recognize different activities performed by a person
- Challenge: training and testing with different subjects (LOSO)
- Each user presents unique movement patterns not easily generalizable
- This work
 - Unsupervised learning adaptation techniques for HAR





- PAMAP2 database
 - 12 physical activities, 9 subjects
 - 3 IMUs in hand, chest and ankle
 - Accelerometer sampling at 100 Hz





- Fast Fourier Transform (FFT) of acceleration signals
 - 5.12-second windows separated by 1 second
 - 128 points represent 0-25Hz frequency range





• Deep learning architecture composed of four convolutional and two max-pooling layers as baseline



- Baseline configuration
 - Dropout layers
 - ReLU activation function
 - RMS optimizer



- Adaptation process:
 - 1. Autoencoder trained with training data.
 - Decoder replaced and encoder not trainable.
 Decoder is trained with testing data.
 - 3. Training data could be transformed to the testing domain: adapted training data.



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- Selection process:
 - value _{RMS adapted data} >= $\mu_{RMS adapted data} + \gamma * \sigma_{RMS adapted data}$

Generative Adversarial Networks (GANs)

Results

Materials and Methods

• Adaptation process:

Introduction

- 1. Discriminator is trained with testing data (real).
- 2. Random training data (fake) is processed through the generator and its output is processed through the discriminator.
- 3. GAN is trained with training data with discriminator not trainable. Generator cheats the discriminator with generated examples similar to testing data.



- value RMS adapted data $\geq \mu$ RMS adapted data + $\gamma * \sigma$ RMS adapted data
- Selection process with discriminator:
 - value discriminator output < μ discriminator output $\gamma * \sigma$ discriminator output



Discussion and conclusions



- Activity classification accuracy and confidence intervals.
 - Significant improvement and deterioration highlighted in green and red, respectively. No color when no statistical difference.

Experiment		Subject									
		101	102	103	104	105	106	107	108	109	All
Baseline	Acc (%)	86.34	87.93	85.91	89.76	87.69	85.15	92.04	87.61	96.88	87.85
	CI (±%)	1.35	1.24	1.63	1.23	1.23	1.39	1.10	1.26	4.26	0.46
Adapt. Auto.	Acc (%)	86.26	82.88	89.23	93.35	87.36	86.23	91.91	90.62	93.75	88.36
	CI (±%)	1.35	1.44	1.45	1.02	1.25	1.35	1.11	1.12	5.93	0.45
Select. Auto.	Acc (%)	86.50	87.17	88.95	91.45	88.06	85.83	92.65	92.30	87.50	89.06
	CI (±%)	1.34	1.28	1.47	1.14	1.22	1.37	1.06	1.02	8.10	0.44
Select. GAN Gen.	Acc (%)	85.58	85.84	90.38	90.15	88.39	88.04	92.04	91.69	98.44	88.94
	CI (±%)	1.38	1.33	1.38	1.21	1.20	1.27	1.10	1.06	3.04	0.44
Select. GAN Discr.	Acc (%)	87.46	88.99	87.57	84.45	89.75	86.79	93.08	90.62	96.88	88.68
	CI (±%)	1.30	1.19	1.55	1.48	1.14	1.33	1.03	1.12	4.26	0.45



- Adaptation for HAR is a very difficult task.
- Selection approaches could remove from training data the examples that differ from testing domain and improve the general performance of the system.
- Unsupervised learning adaptation approaches could pave the way for future research on domain adaptation in HAR.



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THANK YOU FOR YOUR ATTENTION

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