UNSUPERVISED DOMAIN ADAPTATION FOR DEVICE-FREE HAR

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MODEL



PROBLEM

The field of human activity recognition is concerned about the model performance in crossdomain conditions. Models proposed by the researchers in past performed well when they were tested on the same subject and environment used for model training. Unfortunately, their performance suffers from acute degradation due to three main causes.

- 1. Cross-User (testing on different subjects)
- 2. Cross-Environment (testing on different environments)
- 3. A combination of both cross-user and crossenvironment.

Thus, the problem statement is the need of a robust model for HAR which would be able to achieve exceptional performance on domain shifting tasks.

BACKGROUND

In recent years, researchers have successfully recognized the human activities through commercially available WiFi (Wireless Fidelity) devices.

At the access point, one can gather the channel state information (CSI) with the help of NIC card installed. These CSI streams are sensitive to human body motions and produce abrupt changes (fluctuations) in their magnitude and phase values when a moving object is run into a transmitter and receiver pair, thus provide a ground for detecting human activities.

DEVICE-FREE SENSING

Device-Free sensing, a method of carrying information about users' behavior using commercially available WiFi devices, is gaining popularity among traditional approaches due to certain reasons.

- 1. It is a contact less sensing strategy with no need to fit any sensing equipment on the target, thus privacy is reserved.
- 2. There is no hassle to tie cumbersome devices on the object to obtain the data for sensing the motion or localization.
- 3. CSI streams are available all the time as long as WiFi devices are there in the vicinity of an AP and there is no any constraints for lightening around the area or LOS requirements.

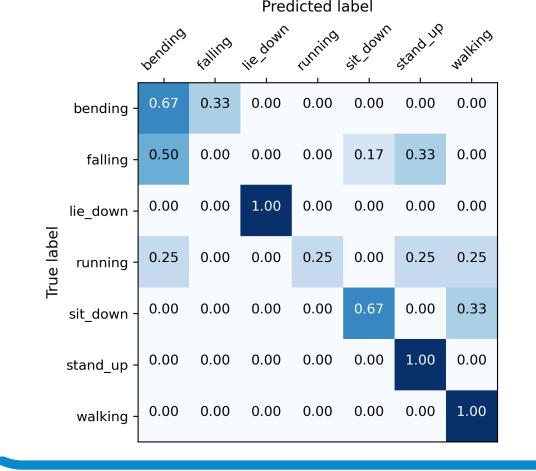
CONTRIBUTIONS

- can robustly match the source to target domain and significantly improve recognition accuracy in cross-user conditions.
- 2. We tested our model for 9 different crossuser scenarios with 3 different users involved in performing 7 different activities.
- 3. Model average simulation time for 9 different cross-user conditions is 2.66 minutes which shows that it's a light weight model
- 4. We evaluate the model performance on different training target data percentages ranging from 100% to 5% in order to analyze model's reliability on minimum training target data samples.

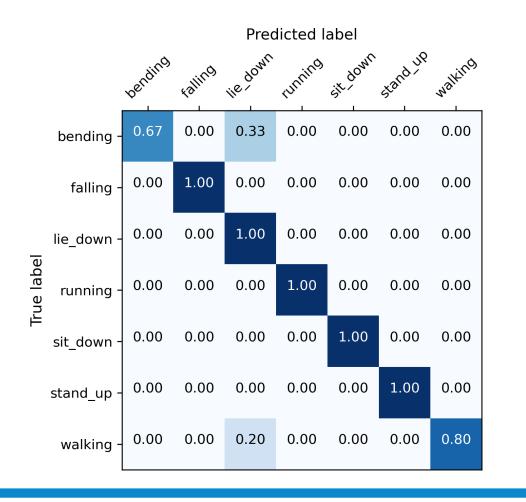
- 1. We have shown our alignment technique
- with simple model configuration.

Note: Proposed model is inspired by the work presented in [1]. Auto-Encoder Source Reconstructed Reconstruction Encoder ——— Decoder Loss (MSE) Classification Loss (Cross Entropy Loss) Step 1: Auto-encoder and Classifier Training Auto-Encoder (trained) (Reconstruction Loss Reconstructed Source of Reconstructed Data X_s Decoder Encoder -X_s) - (Reconstruction Loss of Aligned X_t) Reconstructed Target Aligner Data X_t Step 2: Auto-encoder and Aligner Training New Data Encoder Classifier Aligner Classification (trained) (trained) Step 3: Classifying activity by transforming new data via aligner





Model average recognition accuracy for non-aligned configuration using subject 2 and 3 as source domain and subject 1 as target domain is 59.3%.



Similarly, model evaluation for the same scenario with aligned configuration is 93.1% which shows the effectiveness of aligned model.

REFERENCES

- [1] Farshchian, Ali, et al. "Adversarial domain adaptation for stable brain-machine interfaces." In arXiv preprint arXiv:1810.00045 (2018).
- Fard Moshiri, Parisa, et al. "A CSI-based human activity recognition using deep learning." In Sensors 21.21 (2021):

DATASET

- 1. Dataset used in model simulation is publicly available at [2].
- 2. There are 52 subcarriers of CSI magnitudes, 20 trials taken for each experiment by 3 different subjects for 7 different activities.

FUTURE ENHANCEMENTS

- 1. Compare model performance and training time with the state-of-the-art methods.
- 2. Test model on different public datasets for cross-user and cross-environmental conditions.
- 3. Improve model performance using different loss functions such as maximum mean discrepancy loss (MMDL).