mmWave-based Human Activity Recognition

RUTGERS
WINLAB | Wireless Information Network Laboratory

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Motivations & Introduction

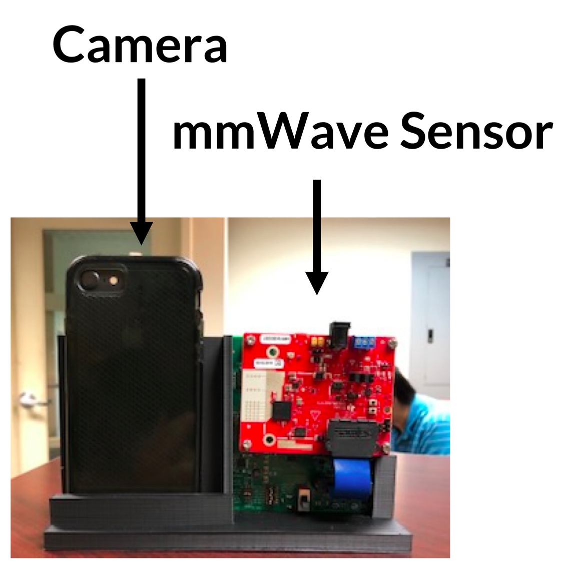
- Human Activity Recognition (HAR) has a wide range of real-world applications, such as health care and fitness tracking.
- Device-based approaches for HAR (e.g. smartwatches) have limitations due to cost and discomfort.
- Many significant efforts have recently been made to explore device-free HAR that utilizes the information collected from wireless infrastructures (e.g. WiFi signals).
- Some existing wireless sensing devices, such as cameras, can potentially leak and lead to privacy issues.

Contributions

- We proposed a hands-free system using a single mmWave sensor that can achieve HAR and create a pose estimated skeleton performing the classified activities.
- We use a single commercial off-the-shelf (COTS) radar sensor to achieve a contactless activity recognition.
- Our system works in different environments and is also possible by different people.

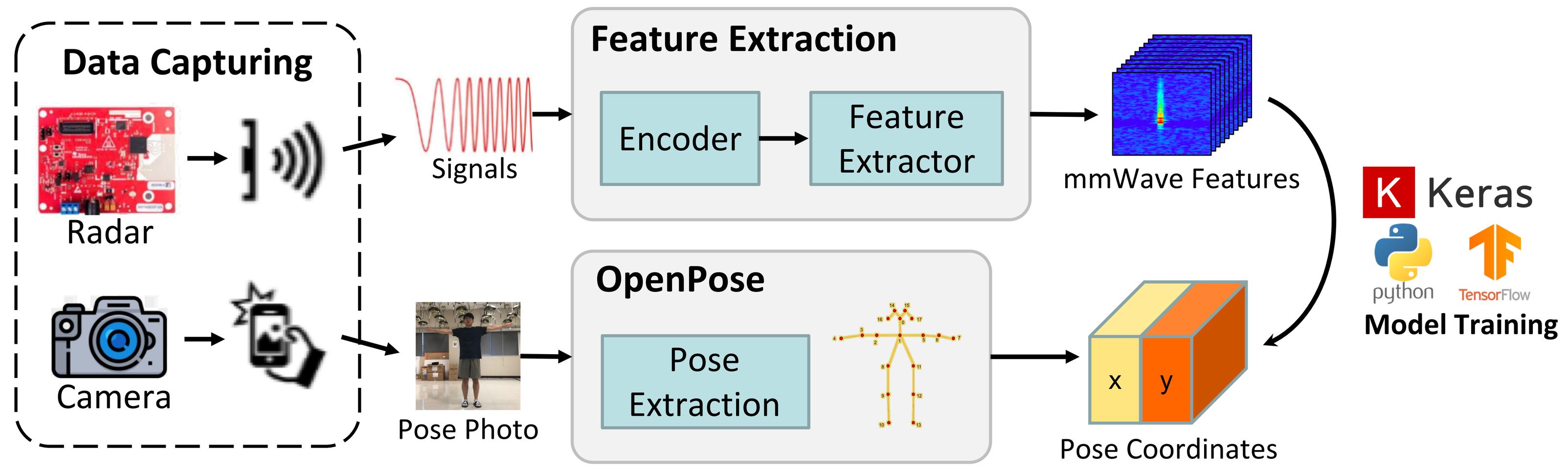
Data Collecting

- We capture both mmWave signals and picture frames while a person is performing an activity in front of the data capturing set.
- The position of the camera and mmWave sensor is fixed on a 3D-printed base.
- The camera in the data capturing set is for the ground truth.



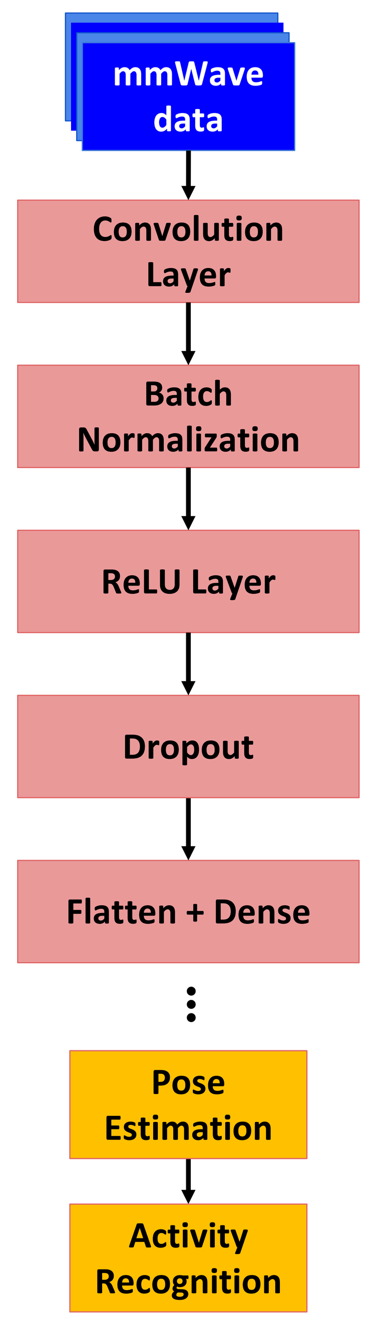
Data Capturing Set

Methodologies



System Architecture

- **mmWave Data Capturing:** The mmWave sensor triggers 150 frames over 10 seconds and captures data.
- **Camera Data Capturing:** Camera takes a picture in sync with the mmWave sensor.
- **Feature Extraction:** Process mmWave data and perform 2-D Fast Fourier Transform (FFT).
- **OpenPose:** OpenPose is an open-source project for extracting the skeleton from an image. In this project, the images are processed using OpenPose for labeling.
- **Classification Model:** Classification model is a teacher-student network composed of a Convolutional Neural Network (CNN) with the structure shown on the right. The final output of the model is an estimated human skeleton performing the classified activity.



Network Architecture

Acknowledgements

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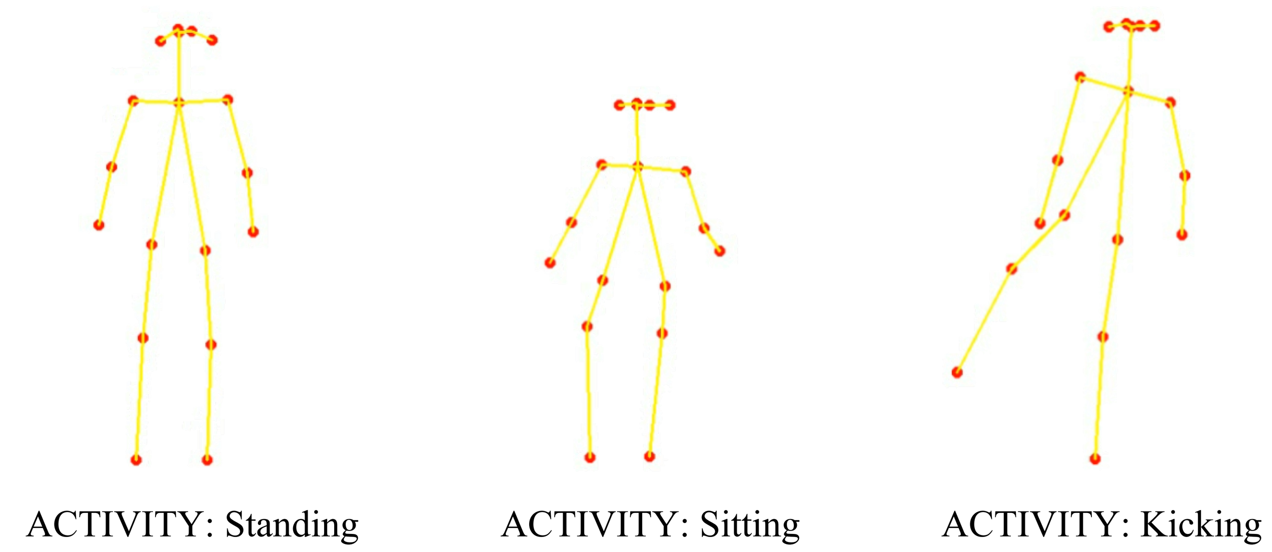
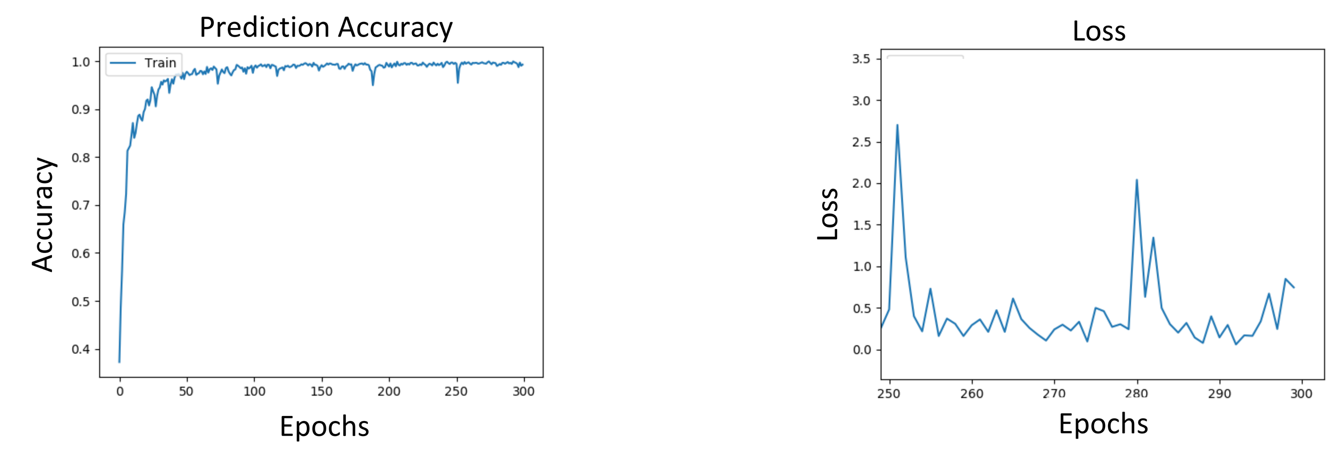
Results & Evaluation

We trained our classification models with an Adam optimizer and a total of 1200 data samples. Our current model can classify amongst three different activities: standing, stretching, kicking, and sitting down. The experiments for each activity have 450, 450, and 300 samples, respectively.



We evaluated the mean accuracy among all estimated skeleton points. As we can see from the accuracy and loss plots, we achieved 90.79% mean accuracy for pose reconstructing.



System Accuracy and Training Loss

Conclusions & Future Direction

- We proposed a hands-free Human Activity Recognition system using a mmWave sensor with signal processing and deep-learning techniques.
- Our system provides an estimated skeleton for performing the activity classification.
- We would improve the adaptability of our system and make it more robust to other potential interference.