mmWave-based Human Activity Recognition

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Motivations & Introduction

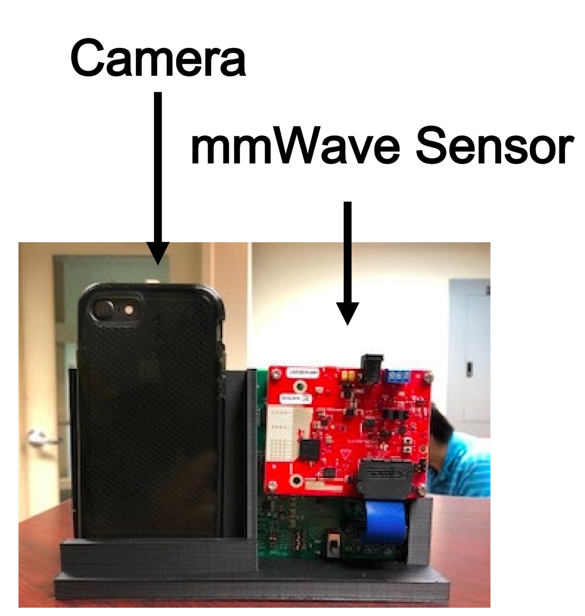
- Human Activity Recognition (HAR) has a wide range of real-world applications, such as health care and fitness tracking.
- Device-based approaches for HAR (e.g. smartwatches) have limitations due to cost and discomfort.
- Some existing solutions using cameras can potentially leak and lead to privacy 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.

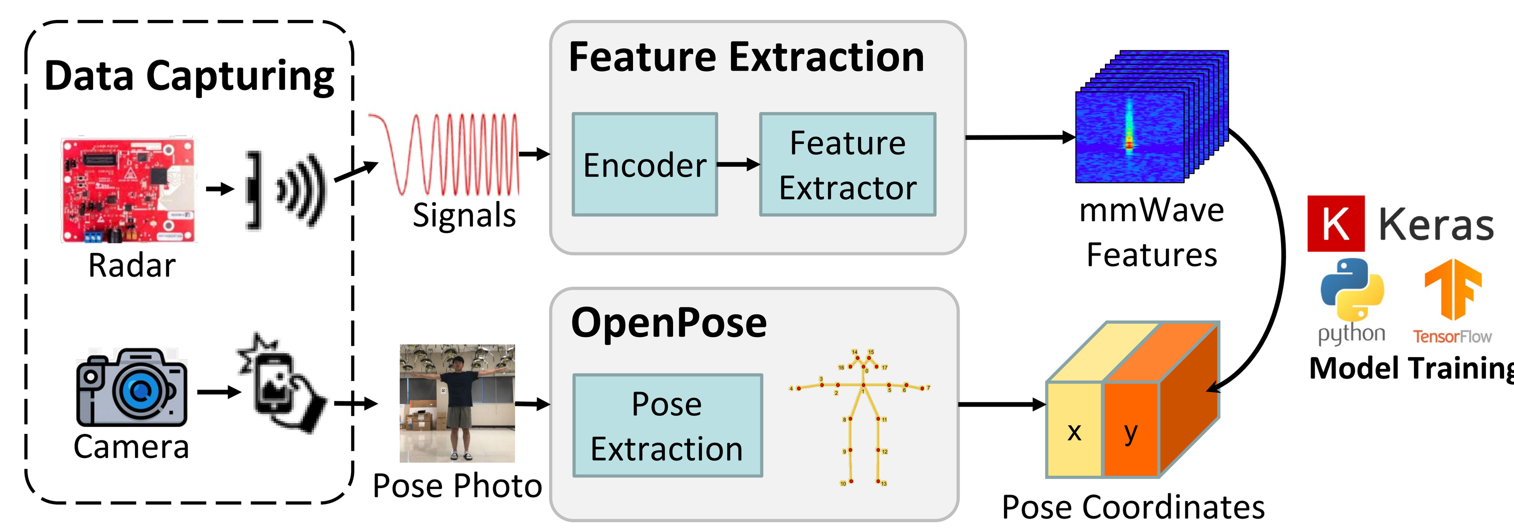
Data Collecting

- 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 is for recording the ground truth.



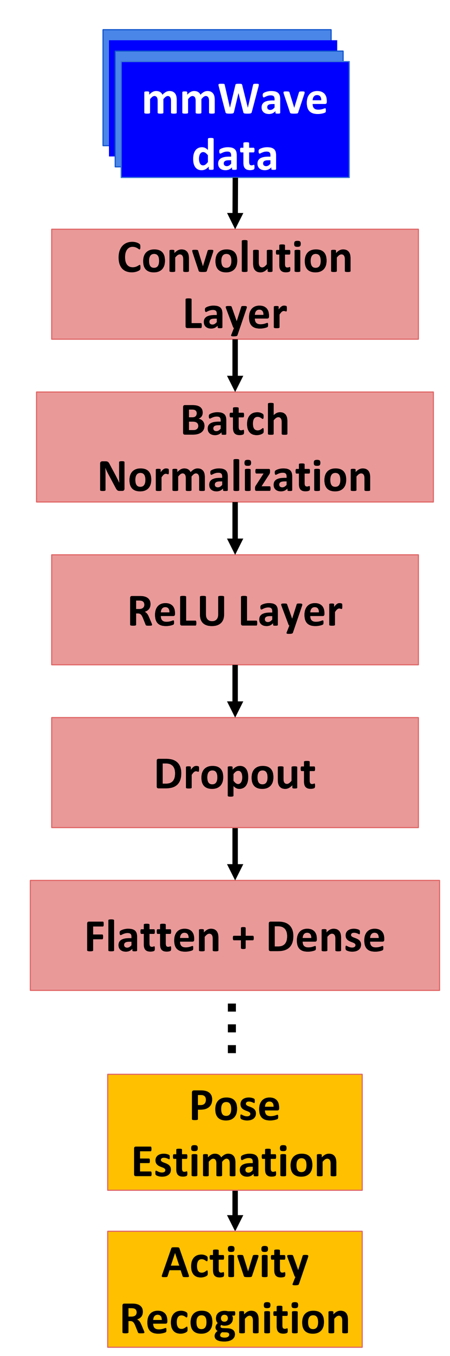
Data Capturing Set

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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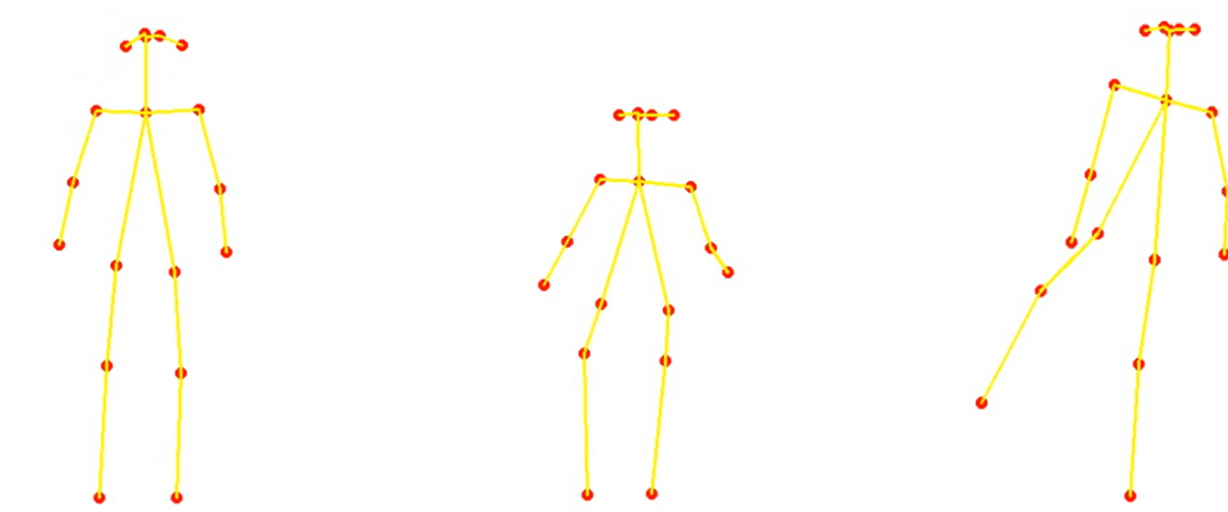
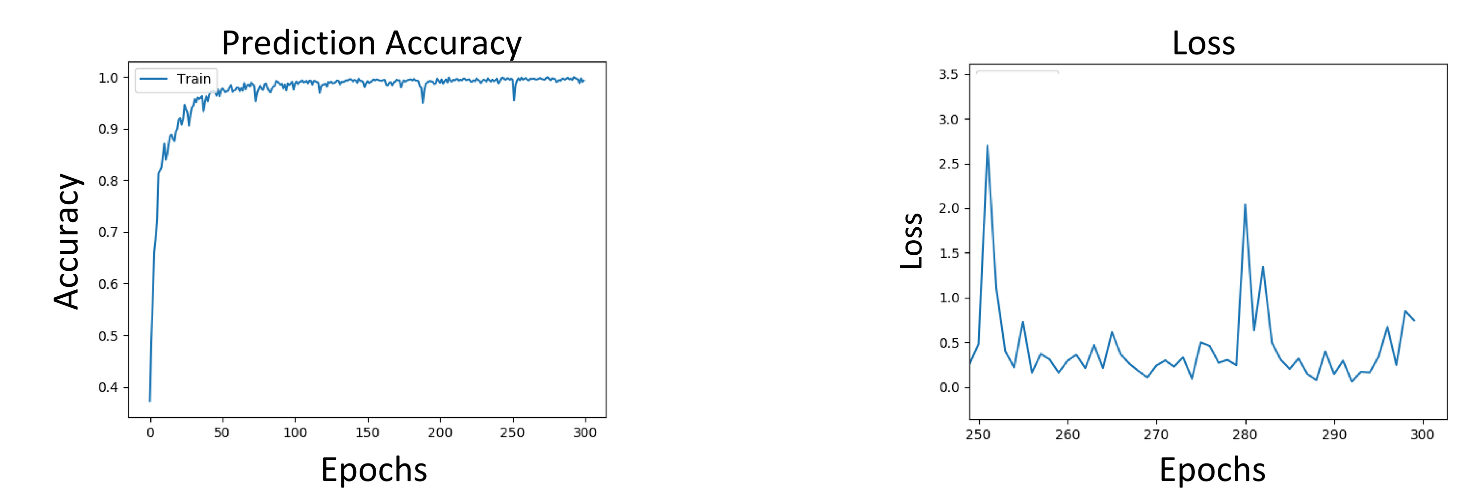
Results & Evaluation

The classification model is trained 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.



ACTIVITY: Standing ACTIVITY: Sitting ACTIVITY: Kicking

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 Directions

- 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.