Topic: Human Pose Estimation Using Radar Raw Data

3D human pose estimation (HPE) is the process of identifying and monitoring human body parts or key joints (such as head, elbows, and knees) in a three-dimensional environment [1]. HPE is used to understand human activity and analyzing motion, with a wide range of applications including rehabilitation, professional sports, augmented/virtual reality, and autonomous driving [1].

To predict the 2D/3D human skeleton, camera images are typically used to estimate body keypoints [2]. However, this vision-based HPE is dependent on lighting and may raise privacy issues [2]. In order to address these limitations, frequency modulated continuous wave (FMCW) radar offers a solution that is robust to lighting conditions, preserves personal privacy, and is available as a low-cost, single-chip component [3, 4]. To overcome the difficulty of interpreting FMCW mmWave sensor data [5], the raw sensor data is preprocessed, to represent a scene via intensity-based spatial heat maps, range-Doppler maps, or target lists/point clouds [6]. Even then, HPE is a non trivial task and machine learning (ML) algorithms help to recognize patterns to predict specific poses [5]. Therefore, existing radar-based HPE algorithms typically use ML to infer human pose. Besides the specific ML algorithms, the main difference is the form of the radar input data on which the models are trained. Due to the complex structure of raw radar data [5], the first radar based HPE ML models were trained on highly preprocessed training data. The most common first level of radar signal processing is to extract range and velocity (Doppler) via Fourier Transforms (FT) used in many HPE algorithms [2, 3, 7, 8, 9]. The next higher preprocessing level, is radar point clouds [6, 10], which are typically generated using a constant false alarm rate (CFAR) algorithm [11] in conjunction with the FT-processed data. However, these preprocessing steps result in loss of detail information [4]. In particular, CFAR algorithms can miss radar targets due to incorrect parameter settings [12] or low signal-to-noise ratio (SNR) [13]. To address these shortcomings, [4] used the following new approach: HPE directly based on raw mmWave radar data.

In order to evaluate whether lower levels of radar data preprocessing improve HPE performance, this research aims to develop ML models based on raw radar data and evaluate them against existing approaches. Specifically, in a first step, the raw radar data of the mmRadPose dataset [10] will be FT-preprocessed and used to develop ML models for HPE. Each resulting model will then be evaluated against existing models based on the same level of preprocessing, such as HuPR [2], using 4D FT radar data (range, Doppler, azimuth, elevation), and then against models based on higher levels of radar data preprocessing, such as PointnetPoseRNN [10], which uses radar point clouds for prediction. In a second step, to evaluate the unprocessed radar data of the mmRadPose dataset, the developed models will be trained and evaluated on the HuPR [2] dataset. Consequently, the research question of this thesis is how different preprocessing levels of raw radar data affect the performance of HPE ML models.

In the light of that objective, this work consists of the following parts:

- Literature review of existing radar-based HPE methods to obtain models for performance evaluation and as a basis for developing raw radar data based HPE ML model.
- Definition of the raw radar data format conducted in [10] and its addition to the mmRadPose [10] dataset.
- Development of ML models which predict human pose based on FT-preprocessed raw radar data from the mmRadPose [10] dataset.
- Evaluation of the developed ML models against other radar HPE algorithms based on the same level of preprocessed radar data, such as HuPR [2] and Cubelearn [4] and then against models based on higher level preprocessed raw radar data, such as the radar point cloud based PointnetPoseRNN [10].
- Evaluation of the unprocessed radar data of the mmRadPose [10] dataset by training and evaluating the developed ML model on the HuPR [2] dataset.

The thesis must contain a detailed description of all developed and used algorithms as well as a profound result evaluation and discussion. The implemented code has to be documented and provided. An extended research on literature, existing patents and related work in the corresponding areas has to be performed.

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