Technical Paper Excerpt

In this section, we focus on analyzing the literature pertain- ing to activity detection and recognition using wireless signals. A. Human Activity Recognition Based on the relationship between activity characteristics and location, the authors in [22] develop a location-oriented activity recognition system, which can distinguish between different in-place activities, such as washing dishes and walk- ing. Wei et al. [23] consider the impact of radio frequency interference on CSI measurements and use several counter- measures to mitigate this impact to further improve the activity recognition performance. Unlike [22] and [23], Li et al. [24] propose a location-free activity recognition system, which first estimates the angle difference of arrival and then uses a trained Bidirectional Long Short-Term Memory network to complete recognition. In CARM [25], the authors propose a CSI-speed model to quantify the relation between CSI dynamics and hu- man movement speeds. Then, they build a CSI-activity model to quantify the relation between human movement speeds and activities, so as to recognize daily activities via a Hidden Markov Model. Besides activities, CSI can also be used for subtle motion detection. For example, WiCatch [26] estimates and tracks the relative AoA of hand-induced reflection and accomplishes gesture recognition via a trained support vector machine (SVM) classifier. PhaseBeat [27] provides an analysis of the CSI phase difference data with respect to its stability and periodicity, and uses root-MUSIC and fast Fourier transform (FFT) to estimate the breathing frequencies and heart rates of multiple individuals. B. Human Fall Detection The first fall detection work using commodity WiFi devices is believed to be WiFall [28]. WiFall first extracts signal features, such as normalized standard deviation and signal entropy, from CSI amplitude, through CSI aggregation, outlier removal, and singular value decomposition. Then, the SVM and Random Forests classifiers are trained to classify different human activities and achieve fall detection. Unlike WiFall, RT- Fall [29] uses the CSI phase difference over two antennas and determines the sharp power profile decline pattern of the fall in the time-frequency domain. Leveraging these observations, RTFall segments the CSI data stream and extracts features, such as median absolute deviation and signal change velocity, to train the SVM classifier for fall detection. Different from the above works, which only considers features in the time domain, FallDeFi [30] uses the short-time Fourier transform (STFT) to extract time-frequency features and the sequential forward selection algorithm to single out features that are resilient to changes in the environment. Then, these features are used to train a classifier for fall detection. Recent works Wispeed [21] and Defall [16] establish a link between the auto- correlation function of the CSI and the speed of a moving human. Through this, they can estimate the velocity of the moving human and accomplish fall detection by analyzing the change in the estimated velocity. Different from the previous work, in this paper, we establish a more accurate relationship between the phase accumulation between two adjacent CSI data packets and the velocity and acceleration of DPLC. On this basis, we propose a novel algorithm to estimate velocity and acceleration from CSI directly. At last, we evaluate the acceleration estimation performance and use the fall detection as an example to illustrate the importance of acceleration estimation in wireless sensing.