Anomaly and Event Detection in Data Streams in Practice – Gesture Recognition using WiFi

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An important aspect of data quality validation relies on and relates to the detection of anomalous data points or regions, which may represent faulty/"bad" data or events, within a set of normal/"good"/nominal data. Developing algorithmic techniques which permit the detection of events/anomalies within a nominal data stream is one of the cornerstones of data validation. This is here illustrated through gesture recognition using wireless channel state.

Data quality validation comprises numerous aspects, from detection of wrong values, duplicates and timelines issues, to the detection of complex multi-variable context-related problems. The latter is one of the most challenging aspects of data validation as it requires prior problem knowledge and advanced algorithmic strategies for the detection of faulty data. Such strategies mainly rely on the detection of statistical deviations within the data which indicate that parts of the data are governed by a different probability distribution. Although this block of the data may be considered to be faulty in some scenarios (*e.g.*, if the underline sensor is malfunctioning), it can represent rare and/or interesting events in other cases (*e.g.*, an important change on the system under measurement which may be, *e.g.*, a failure). Consequently, an important aspect of data quality validation relates to the detection of anomalous data points or regions, which may represent faulty/"bad" data or events, within a set of normal/"good"/nominal data. To this end, the development of algorithmic techniques which permit the detection of events/anomalies within a nominal data stream is one of the cornerstones of data validation.

Gesture recognition using channel state information serves as an illustration of complex data validation. The demonstrator is based on exactly the principle of event detection within a nominal data stream. Although, in the setup, the empty channel is not intuitively regarded as "good" data and the gestures as "bad", the principles of addressing the problem remain the same.

The impulse response of the channel serves as source of information for the detection of gestures. The channel impulse response can be measured through the use of the channel state information (CSI), a metric which is now available with a few commercial WiFi cards. This metric provides data about the amplitude and phase of each of the OFDM subcarriers.

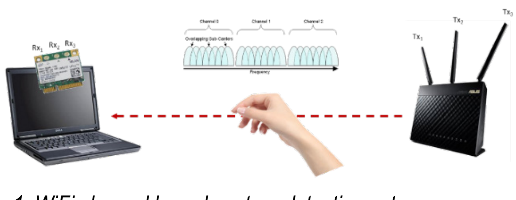

Figure 1: WiFi channel based gesture detection setup.

In the test setup, a WiFi channel is established between a laptop with Intel Link 5300 NIC and an Access Point (Asus AC1900), as shown in Figure 1. A dedicated software tool available from Intel, the "Linux 802.11n CSI Tool", is used to interface with the Network Card and read the CSI data. The Intel card is connected to 3 patch antennas in order to increase directivity and reduce the perturbations due to surrounding motion. The CSI is extracted from the ICMP echo reply packets for a selected OFDM channel of bandwidth of 20 MHz sampled over 30 equidistant subcarriers. The channel power and phase for each subcarrier and six (3 Rx and 2 Tx) of the Rx-Tx antenna pairs are registered for every ping request. The packet rate was set to 10 Hz. To this end, 6x30 CSI time-series with sampling rate of 10 Hz are recorded.

The proposed algorithmic strategy follows the principle of the Auto-Encoder (AE). An AE can be used to detect events [1], defined as data regions which are produced along a different probability distribution than the rest of the data which are considered as "normal". In our case, we define as "normal" data, the CSI of the empty channel and as "events", the CSI during a gesture.

The standard AE encoder and decoder are implemented as LSTM networks with a hidden size of 128 and sequence length of 10 (past of 1 sec). The training and validation sets consist of only data from empty channel recordings, while the test set is comprised of data from both the empty and the "with-gesture" channel. The input to the encoder is the CSI amplitude per antenna pair and subcarrier (*i.e.*, 6x30 features), and the mean spectrogram of this input. The data are first low-pass filtered with 1Hz cutoff frequency. The spectrogram is calculated for an FFT window of 50 samples (5 sec), thus with frequency resolution of 0.2 Hz. The spectrogram frequency bins are considered as additional features and are concatenated to the input.

Figure 2 shows 3 subcarriers for one Tx-Rx pair, where the gestures are marked by the red rectangles. Although we can see the channel change during the gestures, it is not evident how to distinguish this perturbation from the ones of the empty channel.

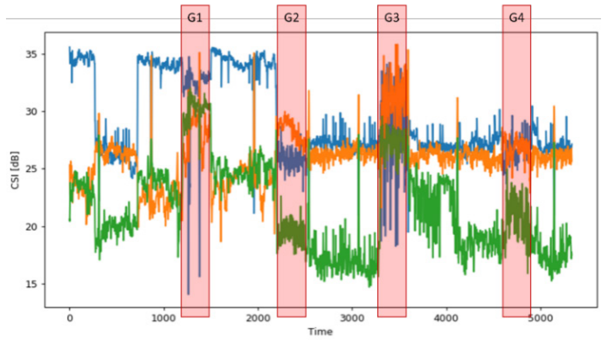

Figure 2: 3 subcarriers CSI during 4 gestures (3 possible gestures).

The mean reconstruction error could be used as way to identify gestures. However, the Mahalanobis distance and KL divergence yield a much better indication. The results demonstrate the importance of the selection of the appropriate distance metric for the accurate detection of the gestures. Most importantly, however, they demonstrate the feasibility of gesture detection even in a strongly perturbed WiFi channel. The results are promising and motivate further algorithmic investigation and improvement.

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[1] P. Malhotra, *et al.*, LSTM-based encoder-decoder for multi-sensor anomaly detection. arXiv preprint arXiv:1607.00148 (2016).