Enhancing Initialization in Distributed HAR Systems: Leveraging CSI and RSSI for Intelligent Node Pairing

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Human Activity Recognition (HAR) using Wi-Fi Channel State Information (CSI) offers a promising pathway for unobtrusive monitoring enabling the detection and classification of physical activities from sensed data in the form of Wi-Fi signals without requiring users to wear any sensors or devices. A major challenge in current AI powered HAR solutions is the need for a central processing module, limiting scalability and real-world applicability. This has encouraged developers to lead the system's evolution toward distributed architectures, where sensing and processing are handled by multiple edge devices. A key issue in deploying distributed HAR systems is determining which transmitter-receiver pairs are best suited for accurate activity recognition in a given location. This selection is critical, as it directly affects system performance, efficiency, and scalability. This thesis focuses on improving the initialization phase of distributed CSI-based HAR systems by proposing new ideas and methods which leverage CSI data characteristics for identifying optimal device pairings across different environments. By addressing this challenge, the proposed work aims to enhance the reliability and adaptability of distributed HAR systems, leading the way for more practical and scalable real-world deployments. Improvements in the classification model have been achieved, along with promising ideas and methodologies to enhance the performance of the initialization phase, though these require further development and refinement for effective implementation.

Additional Key Words and Phrases: HAR, CSI, RSSI, CNN, Distributed AI

1 INTRODUCTION

The increasing demand for continuous, privacy-preserving human activity monitoring in different environments such as healthcare institutions or smart homes, drives interest in device-free HAR solutions.

Wi-Fi CSI sensing has emerged as a promising candidate due to its ability to detect movement through passive analysis of radio wave disturbances without the need for any wearables or devices. This makes it especially valuable for applications where user comfort and privacy are critical. CSI takes advantage of the multi-path propagation of Wi-Fi signals, where even small human movements affect the amplitude and phase of the signal, making it highly sensitive for detecting physical activities. Moreover, since the Wi-Fi infrastructure is already deployed in most indoor environments, CSI-based HAR can be implemented without additional hardware, making it cost-effective and unobtrusive [4].

However, current systems often suffer from poor scalability due to centralized computation. Centralized systems also pose serious privacy and reliability concerns, as they represent a single point of failure. A central server aggregating all activity data becomes a vulnerable target for breaches [7]. In safety-critical domains such as healthcare, where system up-time and data confidentiality are highly required, these vulnerabilities are especially concerning.

To address these limitations, many developers focused in the integration of distributed AI for HAR implementations, where edge devices such as laptops, routers, and cell phones collaboratively process and classify CSI data. These devices share partial insights, forming a multi-agent model which reaches activity and location classification by consensus. According to Jeroen Klein Brinke, numerous decision-making by consensus approaches can be applied, enabling shifting intelligence from a centralized server to a distributed architecture [2].

An issue emerges while implementing this approaches, which is determining which transmitter-receiver pairs are best suited for accurate activity recognition in a specific location. This directly impacts the system's effectiveness and scalability.

This thesis addresses the challenge of initializing distributed CSI-based HAR systems by proposing a method to automatically identify the most suitable transmitter-receiver pairs for each deployment environment. The approach leverages the rich spatial and temporal information embedded in Channel State Information (CSI) and Received Signal Strength Indicator (RSSI) data. Phase, amplitude and strength are signal characteristics that will be analyzed and processed to improve pairing decisions and optimize system performance. The aim is to develop a solution that is scalable and effective across different physical layouts, thereby laying a strong foundation for robust activity recognition without requiring manual setup.

1.1 Problem Statement

In distributed CSI-based Human Activity Recognition (HAR) systems, a critical step during initialization is the selection of optimal transmitter–receiver pairs across a set of networked edge devices. The goal is to identify those links that maximize activity recognition performance while minimizing communication overhead, and energy consumption.

1.2 Research Question

How can the initialization phase of distributed CSI-based Human Activity Recognition (HAR) systems be enhanced to automatically and efficiently identify optimal transmitter-receiver pairs by maximally exploiting the richness of CSI data?

1.3 Sub-questions (SRQs)

(1) Which model architecture, particularly in comparison to traditional approaches, can most effectively exploit the unique characteristics of CSI data, reaching the highest F1-score of edge models during the initialization phase?
(2) To what extent can RSSI data be utilized to estimate which node pairs cover an optimal sensing area and to filter out non-informative transmitter-receiver pairs, thereby narrowing

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down the set of potential sensing pairs and increasing the selection of effective pairs?

(3) To what extent can amplitude fluctuations extracted from CSI data be leveraged to evaluate a pair's transmission quality, narrowing down the set of potential sensing pairs and increasing the selection of effective pairs?

2 RELATED WORK

To identify relevant literature for this study, Google Scholar and IEEE Xplore were consulted using keywords such as "distributed AI," "federated learning," and "CSI-based human activity recognition." This search revealed three research areas of interest: centralized AI for gesture recognition using CSI, decentralized/federated learning approaches for HAR, and model training strategies in distributed systems.

Yi Zhang et al. [13] introduced the Widar framework, a Wi-Fi-based gesture recognition system leveraging AI agents trained to classify human gestures from CSI data. While their work offers valuable insights into model design and CSI signal processing, it adopts a centralized architecture. In contrast, our focus lies in refining decentralized model initialization strategies, particularly at the system's early configuration phase.

Brinke et al. [2] present one of the few studies integrating distributed AI into CSI-based HAR systems. Their work introduces various edge training strategies, Consensual, Pairwise (location-aware), and Pairwise (proximity-aware), which guide how model inferences are shared and aggregated. Our research builds directly on this foundation, specifically refining their initialization algorithm by incorporating filtering mechanisms and enhancing the classification model.

The WiFederated framework [5] offers a federated learning solution for CSI-based HAR, combining locally trained models using federated averaging. Its strength lies in its ability to generalize across environments while reducing setup effort and training repetitions. These contributions are especially relevant to our aim of improving system scalability and minimizing the initialization latency and resource consumption.

Taken together, these studies lay the groundwork for our investigation into improving model initialization in distributed HAR systems. Our work extends this literature by experimenting with CNN-based architectures for improved accuracy and exploring alternative metrics like RSSI to enhance transmitter-receiver pair selection.

3 DATA ACQUISITION

3.1 Experimental Setup

The data used in this study was collected in the e-Health House at the University of Twente, as part of previous research by Brinke et al. [2]. The environment consists of three distinct activity zones: the living room, kitchen area, and bedroom. Seven ASRock NUC BOX-1220P devices equipped with Intel AX211 NICs were strategically positioned to simulate realistic smart home setups (e.g., smart TVs, phones, or kitchen appliances).

Channel State Information (CSI) was captured using the **PicoScenes** middleware, which was run as a background system process on each

Fig. 1. Lidar scans of the apartment (e-Health House) with all nodes (n_{10},..., n_{16}. Locations where activities are performed are in yellow (L_{Bed}, L_{Living} and $L_{Kitchen}$). Note that the image labels a section as table but in this study this area will be identified as the kitchen [2].

device. The devices operated in monitor/injection mode using a 1×2 MIMO setup at a center frequency of 6.9 GHz. A packet transmission rate of 100 Hz was used, producing CSI matrices of shape $t \times 52 \times 2$ over 1-second time windows. All CSI data was encapsulated and stored in `.csi` files, which form the core of the dataset used in this study.

These `.csi` files were essential to this research, as they embed metadata from which the RSSI values can be extracted. This allows us to explore multiple signal-based estimations, including an analysis of whether RSSI can serve as a proxy for signal quality between transmitter–receiver pairs during system initialization.

Twelve participants were involved in the original study, performing a standardized set of activities, including resting, being agitated, working, and standing up, in each of the three activity zones. Activities were labeled and synchronized with the CSI data.

In this thesis, the dataset is used to develop and evaluate a refined initialization algorithm for distributed CSI-based HAR systems. Our focus is on enhancing model sensitivity and training efficiency by selectively filtering transmitter–receiver pairs using signal quality estimations, and by transitioning to CNN-based learning architectures better suited for spatial pattern extraction.

3.2 Evaluation

The primary evaluation metric used to compare different initialization approaches is the stability of the selected transmitter–receiver pairs for a given activity location. An initialization method will be considered effective if it consistently selects the same set of best performing devices across multiple runs. Conversely, an approach is considered unreliable if it frequently selects different devices under the same conditions, indicating high sensitivity to randomness or noise in the data.

4 STATE OF THE ART

An innovative approach for this initialization method focuses on measuring the sensitivity of the edge-devices. The sensitivity represents the ability of each device to detect patterns within a specific location. This section will delve into the main components of this approach as they define the bases of our initialization framework.

4.1 Multi-branch model architecture

Each device holds an artificial intelligence model architecture known as a multi-branch model. This architecture is capable of processing data through two different branches resulting in two outputs. This model is suitable for this task as the HAR system is intended to identify the activity its location [2].

4.2 Training Strategy

The sample dataset is first divided by locations, generating three smaller datasets. During initialization, each device creates a model per location and trains it for a few epochs using 15% of the corresponding dataset of that specific location and 10% for validation. Instead of evaluating final accuracy, the trend of the validation curve is computed to estimate the pair's potential to learn relevant patterns within a specific location [2].

4.3 Sensitivity calculation

The device's sensitivity is calculated using a series of equations which compare the history of the validation accuracy during the training. If the validation accuracy increases, then the learning trend will be considered positive, which is what this thesis defines as the device's sensitivity [2].

4.4 Results

Figure 2 presents a series of heatmap matrices, each corresponding to one of the three activity locations (Living Room, Bed, and Kitchen). These visualizations represent the frequency with which specific transmitter–receiver pairs are selected by the initialization algorithm across multiple runs. This facilitates the analysis of the algorithm's preferences and consistency.

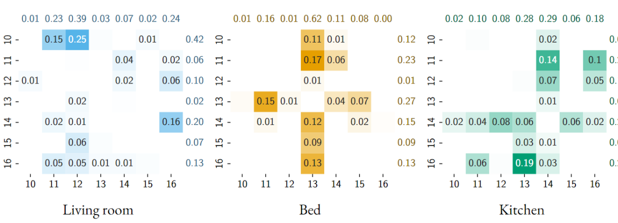

Fig. 2. Node distribution for the different rooms after the initialization phase where the entry represents how many times a receiver (row) was paired with a transmitter (column) [2].

In the living room, selection was dominated by two strong links, (n_{10}, n_{12}) and (n_{14}, n_{16}), likely due to direct signal paths because of the lack of obstacles between the devices. In the bedroom, pairings were heavily skewed towards device n_{13}, which was beside the activity zone and was involved in nearly 90% of selected pairs, highlighting the importance of proximity and signal penetration through thin barriers. In contrast, kitchen pairings were more evenly distributed, though devices positioned close to the activity area (especially n_{14} and n_{16}) were still favored. These findings suggest that spatial proximity and unobstructed signal paths significantly influence the stability and recurrence of selected pairs.

This thesis focuses on improving the consistency of the initialization algorithm by adopting the core idea of calculating sensitivity through the prediction of learning rates via stratified training and validation. The goal is to reduce variance in transmitter–receiver pair selection, ensuring the algorithm reliably converges on the most effective pairs for activity recognition.

5 METHODOLOGY

This section outlines the experimental design and techniques used to improve the initialization algorithm, with a particular focus on reducing its result variance. The methodology includes data preprocessing, model architecture design, and the implementation of filtering strategies aimed at enhancing transmission quality assessment.

5.1 Data Preparation and Preprocessing

The data used in this study was collected as described in Section 3.1. It consisted of a combination of Numpy arrays and .csi files. The Python library, Pandas, was used to preprocess the data, converting raw numpy arrays into a structured database stored in .csv and .pkl files. Reformatting the data enabled adding labels to the readings to convert them into well-defined data samples. The resulting database significantly facilitated the analysis and manipulation of the CSI data, especially in the context of training machine learning models. The software tool **Data Wrangler** was employed to visualize the data structure.

The CSI data stored in the Numpy arrays served as the samples used to train the activity classification model. All data samples contained sequences of zeros within the CSI values. Further investigation revealed that these zeros did not provide meaningful information and could potentially mislead the model during training. As a result, they were removed from the samples.

Data normalization and reshaping was applied to the remaining CSI values to ensure that all features are on a comparable scale and in the correct shape to feed the model. This step helps improve the model's learning stability and prevents features with larger numeric ranges from influencing the model's performance.

5.2 Model Architecture

Channel State Information (CSI) represents the physical characteristics of a wireless communication channel, capturing the phase and amplitude fluctuations occurring as an event unfolds in the environment, over time. Thus CSI data should be treated as time-series data, where sequential variations carry information about human activity. Consequently, models should be designed to capture and learn from these temporal dependencies.

5.2.1 Convolutional Neural Networks. A Convolutional Neural Network (CNN) is a deep learning model composed of convolutional layers that enable extracting localized patterns. CNNs are widely adopted due to their computational efficiency and capacity to learn discriminative features automatically, enabling the recognition of time-series patterns[11].

Two types of CNN architectures are commonly used in HAR systems: **1D-CNNs** and **2D-CNNs**. Although 2D-CNNs are widely used, they require reshaping or applying time-frequency transformations to CSI data, steps that may increase computational complexity, adding overhead and reducing efficiency on resource-constrained edge devices.

Why 1D-CNNs? These models convolve across the temporal dimension, preserving the structure of the signal and enabling extraction of relevant temporal features such as abrupt or periodic amplitude changes produced by human activities interfering the signal.

In contrast to 2D-CNNs, which are optimized for spatial pattern recognition, 1D-CNNs are better suited for detecting dependencies in sequential data. Moreover, their reduced complexity supports deployment in resource-constrained environments [6, 8, 9].

For this study, the proposed 1D-CNN model processes CSI data of shape (100, 52, 2), representing 100 time steps, 52 frames, and 2 channels receiving the CSI data, reshaped to (100, 104). It applies stacked 1D convolutional layers followed by batch normalization and ReLU activation.

Two models were implemented, a lightweight 1D-CNN and the activity branch of a state-of-the-art multi-branch model. The dataset was split into 80% training and 20% testing subsets. The evaluation metric used to contrast the models' performance was the **F1-score**, selected for its ability to balance precision and recall. Each model was trained and evaluated across 50 runs in different training scenarios. The effectiveness of these models will be analyzed in the Results section.

5.3 Transmitter–Receiver Pair Filtering

The initialization phase involves training and testing models for every possible transmitter–receiver pair to evaluate their sensing capacity, through the sensitivity calculation. However, it does not consider link quality degradation due to noise, low power, or physical obstacles. This study proposes improvements that exclude poor-quality links using two complementary strategies: RSSI-based and fluctuation-based filtering.

5.3.1 RSSI-based Exclusion. The Received Signal Strength Indicator (RSSI) measures the power of the received signal. This metric gives insights on how well a device can hear a signal from an access point or router.

Noise and outliers significantly degrade the accuracy of classification outcomes. In CSI data, phenomena like furniture and excessively large communication paths can introduce such noise and outliers into both amplitude and phase measurements, thereby misleading machine learning models during their training phase [12]. The noise floor sets a limit on the minimum detectable signal level, signals falling below this threshold either hinder or completely prevent a receiver from detecting and interpreting valuable patterns.

The **Signal-to-Noise Ratio (SNR)** provides a crucial metric, quantifying the strength of the desired signal relative to the background noise floor. For the signal to be considered clear, its strength must be higher than the noise floor by a significant margin [3]

Since $SNR = RSSI(dBm) - NoisePower(dBm)$ [3], high RSSI values generally correlate with lower noise impact, assuming a stable noise floor. Making RSSI a useful proxy for signal quality.

This study hypothesizes the use of RSSI to identify node pairs located within an optimal sensing area. Setting a minimum transmission power to validate the transmission's quality between a specific pair of nodes. Conversely, node pairs exhibiting excessively high RSSI values will also be excluded during the initialization phase. Strong signal strengths are typically observed between nodes in very close proximity [1], which are not suitable for area sensing purposes, as they do not contribute to effective spatial coverage.

In practice the initialization phase excludes transmitter–receiver pairs where over 30% of their frames fall outside the empirically determined optimal RSSI range of -70 dBm $< X < -55$ dBm.

RSSI values were extracted from the .csi files using the **PicoScenes** Python library. Pairs with too weak or overly strong RSSI values, often indicative of nodes too far apart or too close, were eliminated from the initialization process.

5.3.2 Fluctuation-based Exclusion. CSI data captures how signal propagates from the transmitter to the receiver, including phase and amplitude variations. CSI-based analyzes these variations to detect patterns and build up knowledge on the nature of the event occurring in the monitored area.

In the state-of-the-art initialization phase, a sensitivity calculation is implemented assessing the model's ability to recognize specific activities from CSI data. This process demands high accuracy and precision from the model to identify patterns associated to particular activity types. Drawing reliable conclusions on sensitivity from the performance of such complex learning is particularly challenging, given the limited training performed to maintain low latency during the initialization phase.

Rather than relying solely on complex multi-class activity recognition, this strategy simplifies the assessment by training a lightweight model for binary classification: detecting whether any activity is present or not. The underlying hypothesis is that node pairs incapable of identifying the presence of an activity will hardly be suitable to identify specific activities. This approach allows the initialization phase to narrow down the set of potential best sensing pairs, thereby reducing the variance of its results.

To generate "no activity" samples, CSI data was collected in the room stated in Figure 1 while being empty. These were combined with the activity dataset, relabeled into binary "activity" and "no-activity" indicators. Due to class imbalance, **class weights** were applied to penalize misclassifications of the minority class, encouraging the model to take special care identifying samples from this class.

Models were trained for each transmitter–receiver pair and ranked by their F1-scores. Pairs whose binary classifiers scored below **0.45** were excluded from candidate sensing links, as they were considered unreliable for detecting even the presence of activity.

The effects of these filtering strategies are explored in detail in the Results section.

5.4 Accuracy evaluation

The purpose of the filters is to help the initialization algorithm converge to a smaller set of potential best sensing pairs, increasing its precision. Nevertheless, it is also important to verify whether the selected pairs are truly the best sensing pairs for that specific location.

To conduct an accuracy evaluation, the node pairs will be strategically trained for each location, following the same procedure used during the initialization phase. However, instead of using only 15% of the dataset, 80% will be used to enable a more effective training

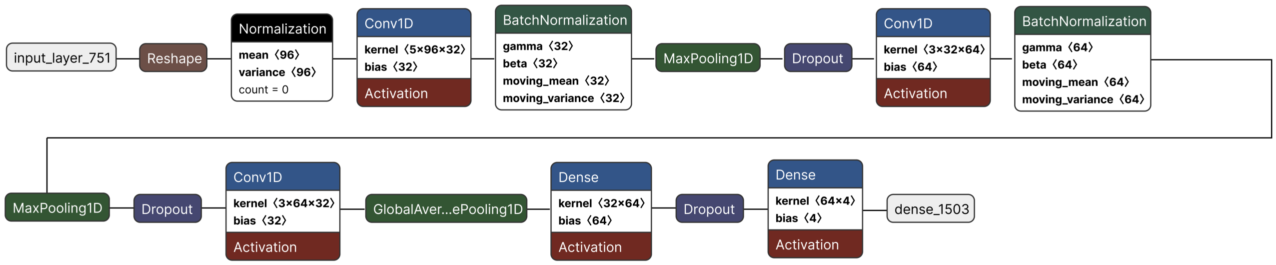

Fig. 3. Architecture of the Convolutional Neural Network (CNN) used in this study. The model consists of multiple convolutional and pooling layers for feature extraction, followed by fully connected layers for classification. Each layer is annotated with its output shape and activation function.

process. The model will pass through 50 different training iterations, attempting to overcome the impact of noise because filtering mechanisms are not being applied. By comparing the F1-scores of the resulting models, more reliable conclusions can be drawn about which node pairs are most suitable for sensing in that specific location.

In Section 6, the accuracy of the filters will be evaluated by comparing the list of selected sensing pairs to the list of best-performing pairs, identified based on model performance after more extensive training.

6 RESULTS

This section presents the outcomes of the methods introduced in the previous section. The figures represent the results gathered after conducting each experiment. In Section 7, each of these will be analyzed, providing enough background to answer the research questions.

6.1 Model Comparison

Figure 4 shows the average F1-scores achieved by the 1D-CNN and the activity recognition branch of the multi-branch model across 50 training runs.

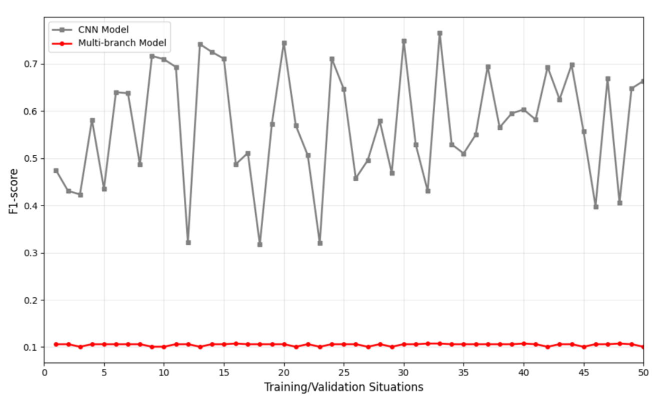

Fig. 4. F1-score reached by both models on each training situation.

Figure 5 shows the frequency with which specific transmitter–receiver pairs were selected using the 1D-CNN during the initialization process.

6.2 Impact of RSSI-based Filtering

Figure 6 shows the node pair selection after applying the RSSI-based exclusion strategy.

6.3 Impact of Fluctuation-based Filtering

Figure 7 illustrates the result of applying the fluctuation-based exclusion strategy.

6.4 Fully-trained Model's Performance

Table 1 displays the best performing pairs for each location.

Table 1. Best pairs by location, based on fully trained model performance

Location	Pair	Average F1-score
Living	(12,16)	0.77
	(16,12)	0.71
	(16,13)	0.66
	(16,11)	0.69
	(10,12)	0.65
Bed	(16,13)	0.51
	(10,13)	0.61
	(13,14)	0.62
	(13,11)	0.57
	(13,12)	0.56
Kitchen	(16,11)	0.71
	(11,16)	0.69
	(14,13)	0.61
	(16,13)	0.59
	(14,15)	0.63

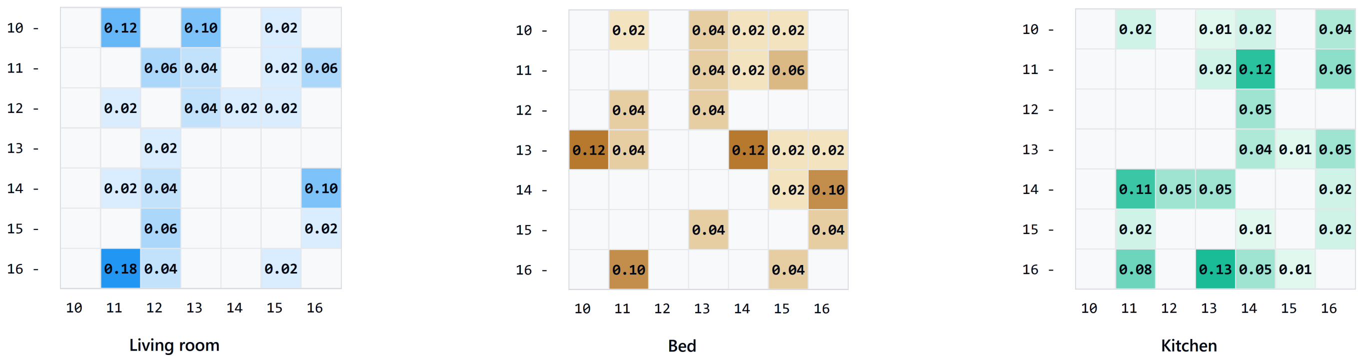

Fig. 5. Node distribution for the different rooms after CNN-based initialization. Entries represent how often a receiver (row) was paired with a transmitter (column).

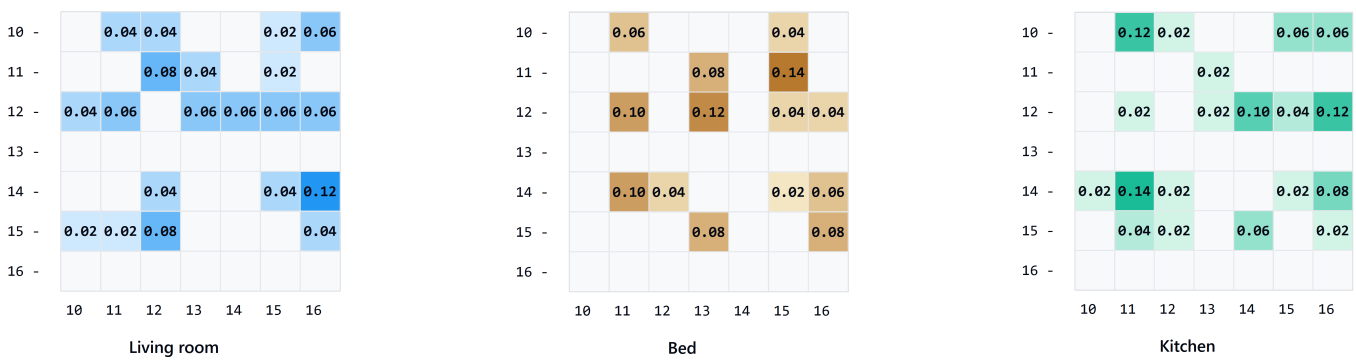

Fig. 6. Node distribution for the different rooms after CNN based initialization phase implementing filtering by RSSI, where the entry represents how many times a receiver (row) was paired with a transmitter (column).

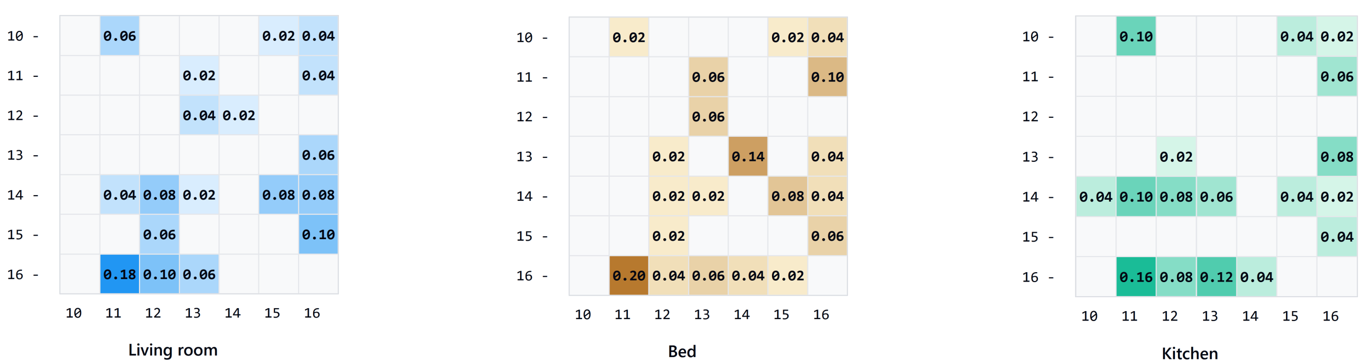

Fig. 7. Node distribution for the different rooms after CNN based initialization phase implementing fluctuation-based exclusion, where the entry represents how many times a receiver (row) was paired with a transmitter (column).

7 DISCUSSION

In Section 7 the information presented in Section 6 will be discussed. The insights obtained from the results analyzes will be taken into account to answer the research question introduced at the start of the paper.

7.1 1D-CNN for Activity Classification

The results obtained from comparing models performance address **SRQ1: Which model architecture, particularly in comparison to traditional approaches, can most effectively exploit the unique characteristics of CSI data, reaching the highest F1-score of edge models during the initialization phase?**

In terms of performance, it has been demonstrated that the 1D Convolutional Neural Network (1D-CNN) significantly outperforms the multi-branch model in activity classification, achieving a notably higher average F1-Score of 0.572 compared to 0.105. This indicated the 1D-CNN's superior capability in extracting relevant temporal patterns from CSI data.

While no major improvements in convergence are observed, some consistent patterns emerge, for example, frequent selection of (n_{11}, n_{14}) and (n_{13}, n_{16}) in the kitchen. These results also support proximity-based relevance, as seen with n_{13} being frequently paired for bed-related activities.

7.2 RSSI-based Pair Filtering

The experiment conducted to evaluate the performance of the RSSI-based filtering addresses **SRQ2: To what extent can RSSI data be utilized to estimate which node pairs cover an optimal sensing area and to filter out non-informative transmitter-receiver pairs, thereby narrowing down the set of potential sensing pairs and increasing the selection of effective pairs?**

Filtering led to a noticeable reduction in spurious pairings such as (n_{10}, n_{14}), (n_{14}, n_{12}), and (n_{16}, n_{12}), which had minimal selection frequencies. This reduces considerably the set of pairs to test for sensitivity reducing the variance of the initialization results and the algorithm's latency.

However, the filtering process also omits several high-frequency pairs that demonstrate strong performance in the fully trained model. For instance, pairs like (n_{10}, n_{13}) and (n_{13}, n_{14}), which, as Table 1 indicates, are among the most effective transmitter-receiver combinations for sensing activity on the bed, are excluded under this approach.

This highlights a conflict between what the RSSI filtering system considers an optimal sensing area and the results achieved by the trained model. To investigate the cause of this discrepancy, a deeper analysis was conducted on the RSSI values that informed the filtering mechanism. In some cases, a correlation between RSSI and physical distance was observed. Pairs such as (n_{16}, n_{13}), (n_{16}, n_{12}), and (n_{16}, n_{11}) exhibited the lowest average RSSI values, which aligns with the isolated location of n_{16}.

Nevertheless, other pairings such as (n_{13}, n_{10}) and (n_{13}, n_{12}), which are expected to have higher RSSI values due to closer proximity, displayed values similar to those of transmissions involving n_{16}.

Several factors could contribute to this inconsistency, but the most likely explanation is multipath propagation, which is widely recognized as a major limitation in RSSI-based measurements in indoor environments [10]. The approach of Masoodi et al demonstrated that using multichannel RSSI measurements can significantly improve precision in signal strength estimation [10].

This suggests that RSSI remains a promising metric for evaluating sensing quality but it requires refinement to adjust better to the complexities of indoor signal behavior.

7.3 Fluctuation-Based Pair Filtering

Lastly this section addresses **SRQ3: To what extent can amplitude fluctuations extracted from CSI data be leveraged to evaluate a pair's transmission quality, narrowing down the set of potential sensing and increasing the selection of effective pairs?**

This strategy omitted a total of 18 node pairs, which is one more compared to the RSSI-based filtering method. As shown in Figure 7, the excluded pairs do not follow a clear or consistent pattern. Both frequently and infrequently selected pairs are omitted without any evident pattern.

A major limitation of this approach is the high variance observed in the F1-scores of individual pairs across different runs. This variability makes it difficult to reliably identify the most sensitive transmitter-receiver pairs from a single training session. To obtain reliable insights on pair sensitivity, multiple training sessions using varied data samples would be required. However, this is not possible in the current setup, as it would significantly increase the model's latency.

Therefore, in its current implementation, this approach does not appear to be feasible; nevertheless, the underlying concept may still hold potential. One possible improvement could involve developing a lighter model architecture, which would allow for multiple runs in a shorter amount of time. Another direction could be the design of a mathematical method to evaluate transmission stability, for example by detecting noisy links based on the number of outliers in amplitude values. This would preserve the main idea while avoiding the need for repeated model training.

8 CONCLUSION

This thesis explores the challenge of enhancing the initialization phase of distributed CSI-based Human Activity Recognition (HAR) systems. Our primary objective was to automatically identify optimal transmitter-receiver pairs, thereby improving the consistency and reliability of the selection process.

Several promising approaches were investigated to enhance different aspects of the algorithm. Our investigation into model architectures demonstrated that a 1D Convolutional Neural Network (1D-CNN) significantly outperformed a multi-branch model in activity classification, achieving a notably higher average F1-Score of 0.572 compared to 0.105. This indicated the 1D-CNN's superior capability in extracting relevant temporal patterns from CSI data.

Later in the thesis, filtering mechanisms were investigated, starting with the RSSI-based exclusion approach. This method utilized Received Signal Strength Indicator (RSSI) values to assess signal quality. By establishing an optimal RSSI range and excluding pairs that frequently fell outside this range, the algorithm aimed to discard noisy links or those in extreme proximity, which are less suitable for area sensing.

Lastly, the focus was the fluctuation-based pair filtering. This approach involved a simpler sensitivity assessment, training lightweight models to distinguish between activity and no-activity signals. Pairs with models that did not meet a certain F1-score threshold were excluded.

While these filtering mechanisms showed promise in identifying and excluding non-informative pair links, leading to a more focused selection of candidate pairs, it was observed that they did not converge into the most sensing pairs. The core objective of achieving better accuracy for the selection of optimal pairs remains a challenge that requires further refinement of these approaches.

However, the implementation of these exclusion methods yielded a practical benefit. Filtering out suboptimal pairs before the extensive training and evaluation of the models, significantly reduced the number of models that need to be trained. This conserves computational resources and reduces the overall initialization time, offering the possibility of running the sensitivity calculation multiple times and approximating the most sensitive pairs.

In essence, while the attempts to reduce the variance in the outcome of the initialization results were not entirely successful, the proposed filtering techniques could potentially improve the process of initialization. If proper pair exclusion is implemented valuable computational time will be directed only towards potentially viable sensing pairs, thus enhancing the practical applicability and scalability of distributed HAR systems in real-world deployments.

8.1 Future work

In future work, a deeper investigation on why RSSI behaves in such an unstable way in different indoor settings should be conducted.

Gaining a better understanding of RSSI fluctuations would be critical to improving the proposed filtering system. Running specific experiments that look at how RSSI changes under different conditions could help us gain more insight into the causes of RSSI noise. Additionally, taking multichannel measurements to increase the precision of the gathered RSSI values could improve the RSSI-based filtering results. Another important step would be to implement better methods to normalize CSI, reducing environmental noise and ensuring the model focuses more on patterns caused by real human movement.

Lastly, a key issue is data imbalance, which makes it harder for the model to reliably detect activities. In this case, there was a large imbalance between the "activity" and "no-activity" data samples. To address this, more "no-activity" data samples should be collected. This can help build a better baseline of what the environment's "normal" noise looks like, allowing the model to differentiate between situations when activities are happening or not. A mathematical method could also be designed to detect samples that do not follow normal behavior. This would omit the need for training any model to detect amplitude patterns.

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