# E2. Initial report on joint communication and localization

## Project: MAP-6G

**PROGRAMA DE UNIVERSALIZACIÓN DE INFRAESTRUCTURAS DIGITALES PARA LA COHESIÓN UNICO I+D 5G 2021**

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**Responsible**: IMDEA Networks

**Partners involved**: IMDEA Networks

## Deliverable information

**Description**: Initial specification of joint communication and localization mechanisms for ultra-low latency, reliable location services, including multi-band localization algorithms. The first version of testbed for joint localization and communication with Open Air Interface is presented and tested for its integration with mobile architectures. Also, the proposition of Deep Learning to enable intelligence in RAN has been made to enable the classification of wireless technologies but will later be used for positioning of mobile devices in a privacy preserving way. Below, we describe our work in relation to building localization algorithms and building native privacy preserving machine learning algorithms for localization.

## Localization Algorithms

### a. Activity 4: 6G algorithms for localization

**Description:** Design location algorithms and techniques to localize 6G devices as well as other objects, from cellular mobiles to low-end (IoT) categories using 6G waveforms.

A 5G New Radio testbed has been built and will be further expanded to test different 6G algorithms, waveforms and different use cases. This testbed uses a single base station but has MIMO capabilities for location and uses the open-source Open Air Interface, which is the most advanced open-source software for configuring cellular networks.

### b. Activity 5: Robust localization techniques using emerging wireless technologies

**Description:** Develop techniques that are robust to the UE environment (indoor/outdoor), leveraging multi-RAT, multi-carrier, and mm-wave technologies; Optimization of accuracy, timing, privacy, latency and energy consumption constraints.

Robust localizations are being designed by leveraging saved time-of-flight and angle-of-arrival measurements from our already built 5G testbed. Currently, we can store reference signals and channel information for offline analysis. In fact, several measurements have been made in both indoor and outdoor environments using cellular, and software defined radios as User Equipment.

## Machine Learning-based Privacy Preserving Analytics

### Activity 8: Native privacy-preserving machine learning algorithms for localization

**Description**: Design privacy-preserving machine learning-based techniques to build a network that guarantees privacy by design, and its applications for positioning mobile devices. Investigation of solutions compatible with the O-RAN Intelligent Controller for performing embedded AI/ML intelligence in the RAN

Our initial goal is to create machine learning algorithms for localization that prioritize privacy. To achieve this, we suggest utilizing Deep Learning frameworks to introduce intelligence in RAN.

At present, these frameworks allow for the classification of wireless technologies, but they will eventually be modified to enable the location tracking of mobile devices in a way that preserves privacy. Currently, we have proposed frameworks for wireless technology classification and for adaptive uplink data compression, which we will describe in more detail below.

### a. A Framework for Wireless Technology Classification using Crowdsensing Platforms

We propose a Deep Learning framework for classification of spectrum crowdsensing systems in near real-time, able to average a classification accuracy close to 94.25%. *This study has been accepted at IEEE INFOCOM 2023 conference [1].*

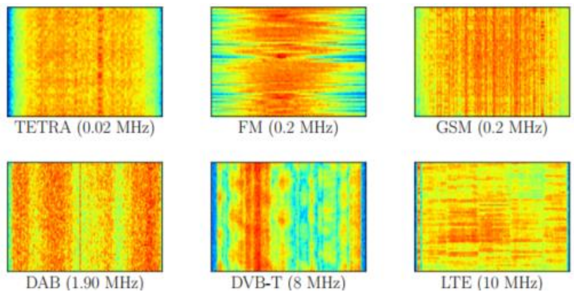



*Figure 1: Wireless technologies classified in our work*

Our framework utilizes a Long Short-Term Memory (LSTM) model as a sequence classifier. This model is lightweight and computationally inexpensive, resulting in significant savings in terms of computational and storage resources. Figure 1 displays the various technologies that are classified, along with their unique properties in terms of modulation schema and bandwidth.

Figure 2 provides a broad overview of the framework, where sensors are used to measure in-phase (I) and in-quadrature (Q) samples. These samples are then transformed into Power Spectra Density (PSD) data, which is subsequently transmitted to the backend of the crowdsensing platform for further analysis and visualization.

In our proposed framework, the transmission detection component is responsible for identifying active signals by monitoring spectrum occupancy. The data is then classified using only the portions of the spectrum where transmissions are detected. For PSD classification, an LSTM network is employed, and the model's architecture is displayed in Table 1.

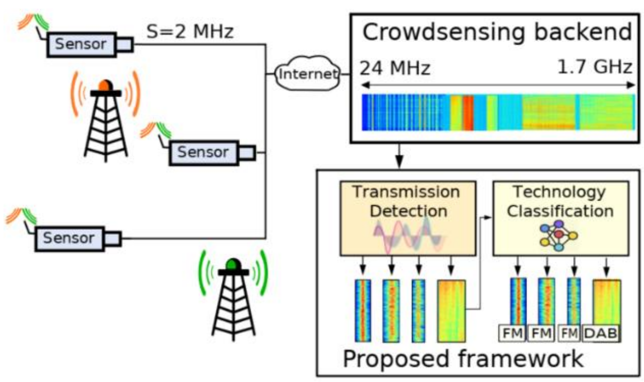



*Figure 2: Overview of the framework for wireless technology classification*

*Table 1: Model architecture where (a) is the Auto Encoder and (b) is the Classifier architecture. The line in bold represents the compressed features as input to the Classifiers.*

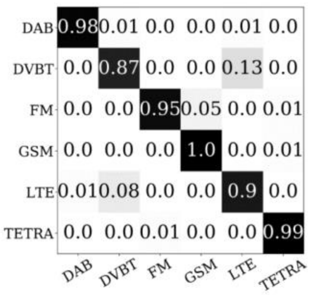
(a) AE architecture.

| Layer | Output dim. |
|---|---|
| Input | 1x32 |
| Dense/ReLu | 1x64 |
| Dense/ReLu | 1x32 |
| **Dense/ReLu** | **1x16** |
| Dense/ReLu | 1x32 |
| Dense/ReLu | 1x64 |
| Dense/ReLu | 1x34 |

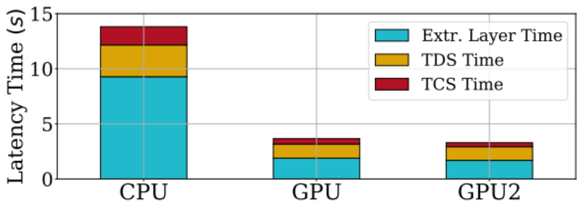
(b) Classifier architecture

| Layer | Output dim. |
|---|---|
| Input | 1x16 |
| LSTM | 1x32 |
| LSTM | 1x16 |
| Dense/ReLu | 1x16 |
| Dropout | 1x16 |
| Dense/SoftMax | 1x6 |

To train the LSTM model, we used a dataset of 134,000 PSD segments that were collected over 282 hours of sensing. The dataset was split into 80% for training and 20% for testing, with class instances being equally balanced. The model was trained and validated over 550 epochs, utilizing the Adam optimizer with a learning rate of 0.001. As demonstrated in Figure 3, our results indicate that we achieved an average classification accuracy of approximately 94.25%, with a minimal latency of 3.4 seconds.




*(a)*




*(b)*

*Figure 3: Evaluation results where: (a) LSTM confusion matrix, (b) Latency for executing the entire framework. TDS is the Transmission Detection System and TCS is the Technology Classification System*

### b. Adaptive Uplink Data Compression in Spectrum Crowdsensing Systems

FlexSpec, our proposed framework, utilizes both Deep Learning and the Walsh-Hadamard transform to compress spectrum data collected from low-cost and dispersed sensors for use in real-time applications. By utilizing PSD data, FlexSpec achieves up to 7 times greater reduction in uplink data size for signal detection while maintaining a classification accuracy of approximately 90% across different wireless technologies. *This study has been published in the IEEE/ACM Transactions on Networking Journal [2].*

Figure 4 provides an illustration of FlexSpec's various modules within a data analysis pipeline for real-time spectrum data applications. The IQ samples collected from sensors are transformed into PSD through a FFT module. An adapter, which is installed on the Edge device, assesses the application's performance by utilizing various compression ratios.

FlexSpec incorporates the adapter to facilitate the use of applications that require low latency and high computational capabilities. For applications that operate on historical data, the backend can be utilized without the adapter. A feedback loop is introduced between the adapter and the sensor to jointly determine the optimal compression coefficient k based on the current compressed data's application performance. The backend manages the infrastructure and stores compressed data for future processing.

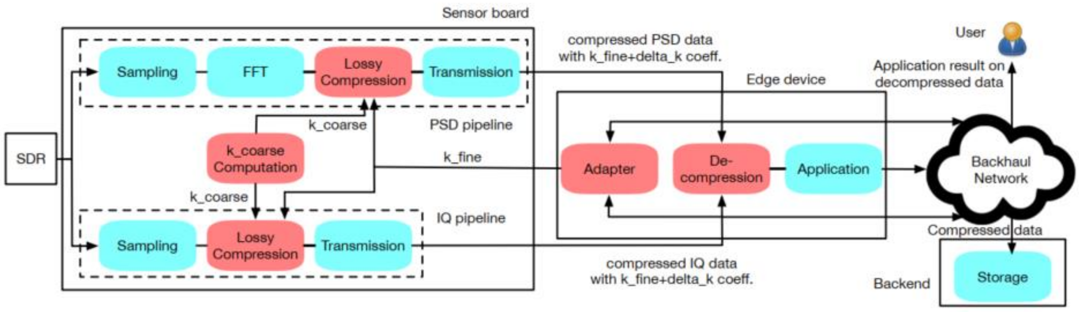



*Figure 4: Data analysis pipeline. Red blocks are added by FlexSpec's while the light blue blocks are standard spectrum crowdsensing modules. k_coarse is the initial compression coefficient while k_fine is the updated compression coefficient*

FlexSpec is implemented through a combination of C++ for the lossy compression algorithm and Python for the compression ratio adaptation scheme's logic. The performance of FlexSpec is evaluated against AirPress [4] and SparSDR [5], which are state-of-the-art crowd spectrum sensing algorithms as follows.

- Reconstruction error for PSD data

To evaluate the performance of FlexSpec's FWHT-based spectrum compression method, we use PSD data from wideband measurements covering the frequency range from 300 MHz to 4 GHz with a 100 MHz basis. The results of varying the compression ratio for FlexSpec and AirPress are shown in Figure 5 for both best- and worst-case scenarios. It can be observed that FlexSpec outperforms AirPress by up to 5 dB in both scenarios, indicating that our compression method has less information loss compared to AirPress.

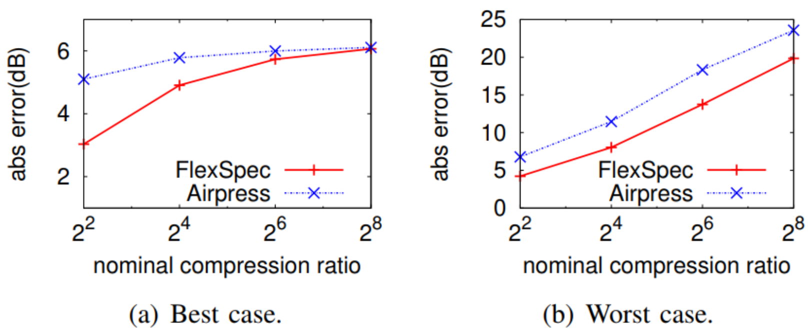
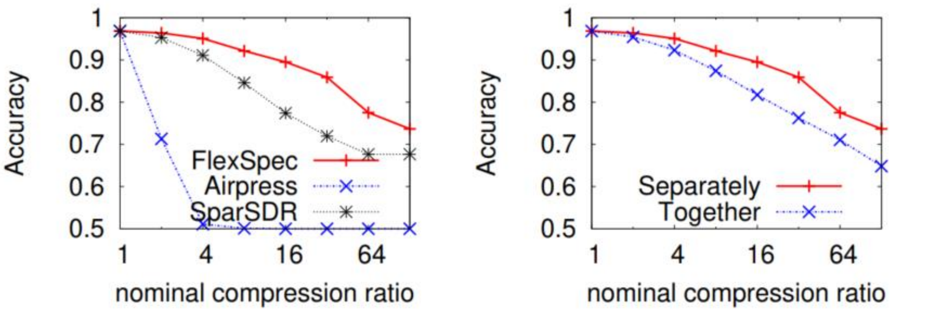



*Figure 5: Reconstruction error as a function of nominal compression ratio.*

- Signal classification based on IQ data

In order to evaluate how FlexSpec's compression algorithm affects the classification accuracy of modulation schemes and wireless technologies, we applied the compression algorithm to the training data and reconstructed the data before applying it to the deep learning model in [3]. We varied the compression ratio to see how it impacted the accuracy of the classifier.

The results in Figure 6 show that FlexSpec is able to maintain high accuracy even at higher compression ratios, while Airpress and SparSDR have much lower accuracy at similar compression ratios. This demonstrates the effectiveness of FlexSpec's compression algorithm in maintaining signal quality while reducing the data size.




(a) Comparison with baselines. (b) Apply compression on IQ readings together vs. separately.

*Figure 6: Classification accuracy results as a function of nominal compression ratio*

- Busy-Idle state

To determine whether to adjust the nominal compression ratio based on the specific application being executed on the Edge device or on the condition of the spectrum, we simulate the idle state by disconnecting the antenna from the radio receiver.

Figure 7 demonstrates the adaptive setting of the nominal compression ratio by FlexSpec, resulting in decreased backhauled data. In comparison to Airpress, which utilizes a fixed compression ratio of 8, FlexSpec can achieve a nominal compression ratio up to 10 times higher during the idle state. This, in turn, leads to up to 7 times more reduction in uplink data size for FlexSpec.

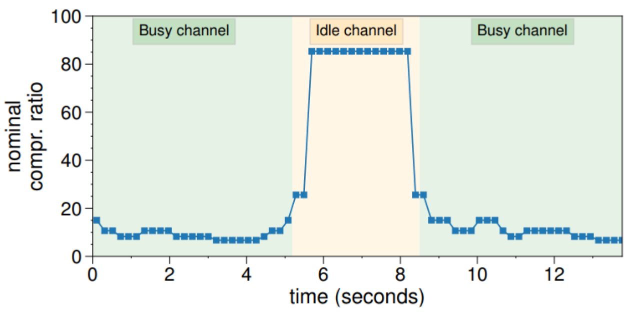



*Figure 7: Compression ratio is set adaptively in a busy-idle channel scenario. Compression ratio adapted every 200 ms*

## *References*

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2. Y. Zeng, R. Calvo-Palomino, D. Giustiniano, G. Bovet and S. Banerjee, "Adaptive Uplink Data Compression in Spectrum Crowdsensing Systems," in IEEE/ACM Transactions on Networking, doi: 10.1109/TNET.2023.3239378.

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