Interference Detection, Classification and Cancellation from Space,

Executive Summary Report

ESA Contract No. 4000125820

1. Introduction

This document has been prepared by Harp Technologies Oy as the outcome of the European Space Agency's (ESA) "Interference Detection, Classification and Cancellation from Space" (IDS) activity. This document is the Executive Summary Report and summarizes the work performed during the activity, results, and conclusions.

Intentional and unintentional electromagnetic transmission can interfere with various space-borne receiving systems. Generally, such occasions are called Radio Frequency Interferences (RFI). Reports of RFI problems can be found from all space application domains that use radio receiving systems: Satellite navigation services (such as the Galileo service), telecommunications, Earth Observation, or satellite telemetry, tracking and commanding services.

In this activity a Matlab-based simulator (called IDS Simulator) environment has been developed. The simulator is capable in simulating various RFI detection, isolation, characterization, classification and localization (DISCCL) algorithms in generic scenarios, where user can set up and configure many aspects of RFI transmitters, satellites, satellite receivers and the DISCCL algorithms themselves. To be concise, the two ultimate aims of this activity were:

1) To develop a simulator tool that makes various RFI threat scenarios available with wide variety of realistically tunable parameters, and
2) To study the performance of selected DISCCL algorithms and their sensitivity to selected system parameters.

The generic scenario established by the IDS Simulator is depicted in Figure 1. It illustrates the main components that can be set up with the simulator. They are:

- Transmitters on the Earth (or even in space). The user can determine many aspects of transmitters, including their position and dynamics, signal waveforms, temporal behaviour, and antenna characteristics. Transmitters can be designated to Galileo uplinks or RFIs.
- Satellites in user-defined (keplerian or two-line-element defined) orbits. Satellites can be equipped with receivers with detailed characteristics on a component level, different antennas, and various errors related to, e.g., satellite attitude, receiver gain characteristics and clock errors.
- Signal propagation between transmitters and satellite receiving systems.
- DISCCL algorithms for detection, isolation, characterization, classification and localization. Various algorithms can be enabled, used in combinations, and their parametrization can be tuned. The DISCCL algorithms available in the simulator are listed in Table 1.

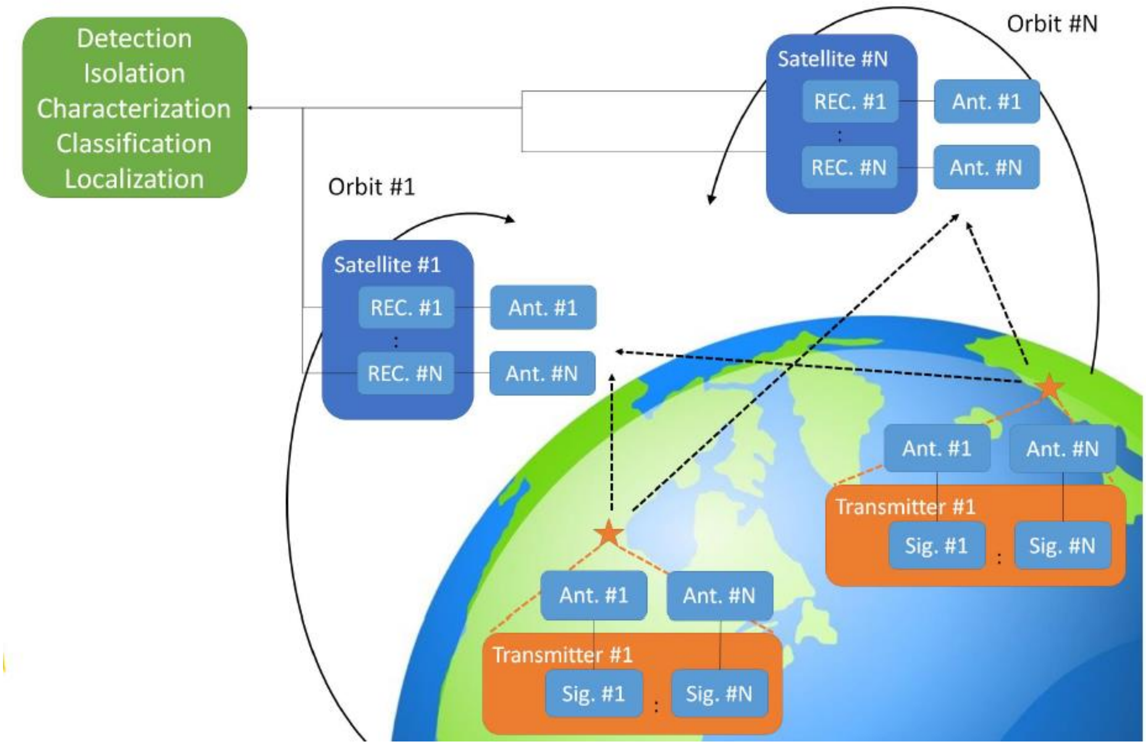


Figure 1. Overall scenario of the IDS Simulator.

Table 1. DISCCL algorithms studied or included in the IDS simulator.

Algorithm class	Technique	
Detection	Energy detector	Gaussianity detector
	Power Spectral Density detector	Space-domain detector
Isolation	Short-Time Fourier Transform (STFT)	
	Fourier Synchro-Squeezed Transform (FSST)	
	Single-channel Quadratic Time-Frequency Domain (SQTFD)	
	Multi-channel Quadratic Time-Frequency Domain (MQTFD)	
	Independent Component Analysis (ICA)	
	Convolutive ICA (CICA)	
Characterization	Mean frequency	Pulse width
	Occupied bandwidth	Duty cycle
	Spectral kurtosis	
Classification	Feature based pattern recognition by State Vector Machine (SVM) classification	
	Recurrent Neural Network (RNN) (using Matlab's Deep Learning Toolbox)	
	Convolutive Neural Network (CNN) (using Matlab's Deep Learning Toolbox)	
Localization	Time-Difference of Arrival (TDOA) using Cross Ambiguity Function (CAF)	TDOA & FDOA (Frequency Difference of Arrival) using CAF
	MUSIC (Multiple Signal Characterization)	

2. Detection Algorithms

The IDS simulator provides four types of detection algorithms: Energy Detector is based on power estimation of the radio channel, Power Spectral Density Detector is based on spectral analysis of the radio channel power, Gaussianity Detectors are based on analysis of signal's amplitude distribution, and Space-domain Detector is based on covariance analysis of signals from multiple receiver channels.

In the activity the detectors, their parametrization and calibration were studied and their performance was tested against typical RFI signal waveforms. The main figure-of-merit in their assessment was Probability of Positive Detection at given False Alarm Rate (FAR).

Figure 2 shows an exemplary result of detectors performance simulation. In this case detectors were tested with a certain telecommunication waveform (Direct Sequence Spread Spectrum Quadrature Phase Shift Keying, DSSS QPSK). The figure shown the Probability of Detection for each detector as a function of Signal to Noise (SNR) ratio (a.k.a, in this case, Interference to Noise Ratio, INR).

Simulator can also be used to perform Receiver Operating Characteristics (ROC) analysis, where POD is studied as a function of FAR for a particular signal level. Such analysis is also shown in Figure 2.

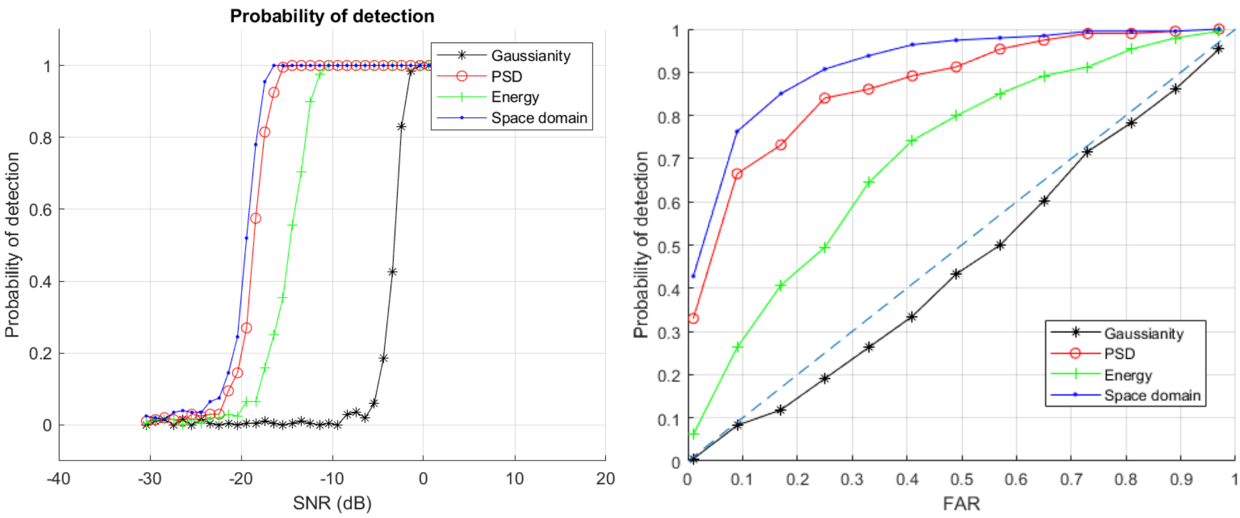


Figure 2. Exemplary result of detection analyses with IDS Simulator. LEFT: Probability of detection as a function of SNR for the four detectors when a DSSS QPSK signal is used as RFI. RIGHT: ROC analysis of the detectors in a case where SNR of the RFI is -20 dB.

About the RFI detectors we can generally conclude that the performance of different algorithms is highly dictated by computing power available in the practical system. Algorithms that analyse the spectrum of the radio channel with high frequency resolution (such as PSD) can perform clearly better than time domain detectors. On the other hand, time domain detectors can also be sufficiently accurate and they are FAR less resource hungry than detectors based on spectral analysis.

3. Isolation Algorithms

The IDS simulator provides six isolation algorithms: Four of them are based on linear or non-linear Time-Frequency Domain analyses (FTFT, FSST, SQTFD, and MQTFD, see Table 1). In addition, two versions of ICA, which is based on iterative solving of the signal mixing matrix from multiple antennas, is provided.

In the activity the isolators and their parametrization were studied and their performance was tested against typical RFI signal waveforms and their combinations. The main figure-of-merit in their assessment was so-called scale-independent error metric, which is an amplitude insensitive measure of similarity between the input signal component and isolated signal component.

Figure 3 shows an exemplary result of MQTFD isolator performance simulation. In this case isolator was tested with using a combination of four signals as input (DSSS QPSK, Linear Frequency Modulated (LFM) signal, Non-linear LFM signal (NLFM), and Frequency Hopping Spread Spectrum (FHSS) signal). Spectrograms of individual components of this input signal is shown in Figure 3, left figure. The input signal is subjected to MQTFD isolation process, output of which is presented in Figure 3, right figure. From the result we see good qualitative performance of the isolator, but also some mixing especially between NLFM and FHSS signals.

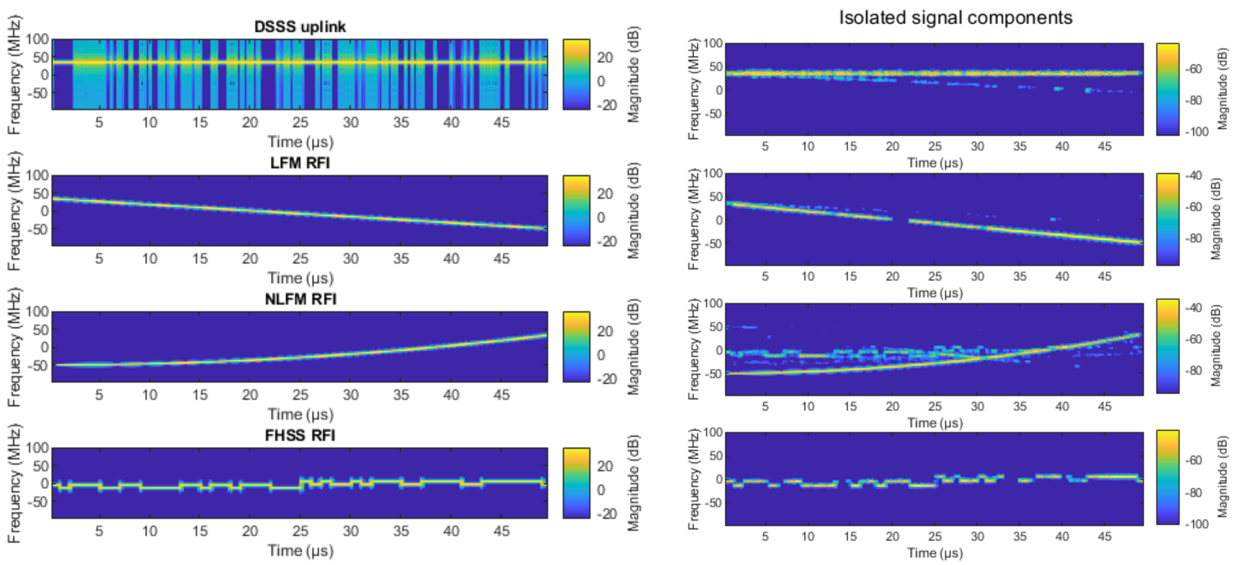


Figure 3. Exemplary result of isolation analyses with IDS Simulator. LEFT: Four components of the input signal. RIGHT: Resulting output components given by the MQTFD isolator for the input signal.

About the RFI isolator we can generally conclude that the performance of multichannel algorithms (MQTFD and ICA) are clearly (obviously) better than single channel algorithms. For the benefit of single channel algorithms, which essentially use image processing methodologies to detect certain shapes in time-frequency domain, we want to state that such algorithms (and tools for them) will be most likely developed fast in the future due to development of computer vision and AI based algorithms for various applications.

4. Characterization and Classification Algorithms

IDS simulator provides five characterization algorithms: Three of them can be applied to any signal (mean frequency, occupied bandwidth and spectral kurtosis), and two are more specific for pulsed signals (pulse width and duty cycle).

In the activity the characterization routines were selected from consolidated source (Matlab's Signal Processing toolbox) and they can be used to support other algorithms (classification and localization) that can benefit from a priori knowledge of the measured signal properties. For example, localization algorithm MUSIC requires an estimate for the frequency of the RFI signal and characterization process can give an estimate for that.

Figure 4 shows exemplary results of characterization simulations. In this case the mean frequency and occupied bandwidth algorithms were tested with various waveforms as a function of SNR.

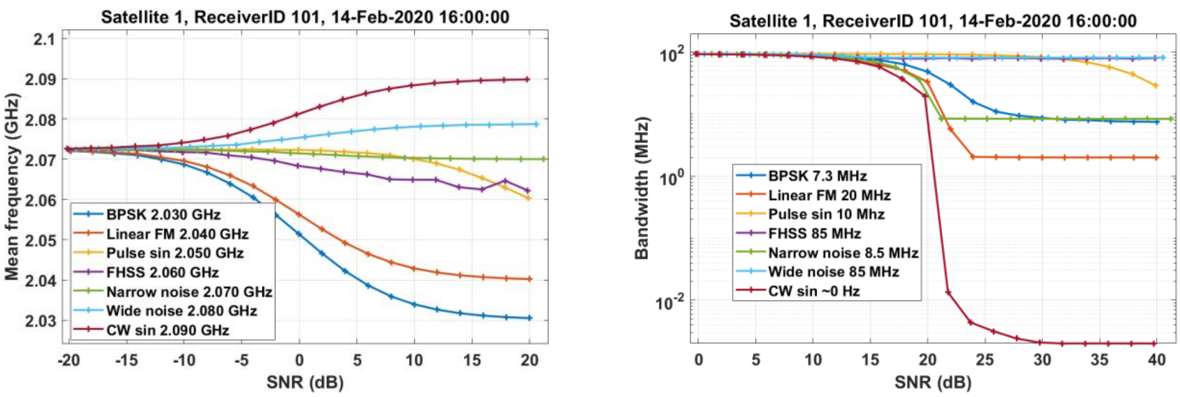


Figure 4. Exemplary results of characterization analyses with IDS Simulator. Results of mean frequency (LEFT) and occupied bandwidth (RIGHT) characterization of various waveforms (with true values of the parameters indicated in the legend) as a function of SNR.

Three classification algorithms that are based on machine learning (or artificial intelligence) techniques were tested with IDS Simulator: a feature based pattern recognition by State Vector Machine (SVM) classification, and two classifications based on neural networks: Recurrent Neural Network (RNN) and Convolutive Neural Network (CNN).

In the activity the classifiers, their operation and parametrization were studied and their performance was tested against typical RFI signal waveforms. The main figure-of-merit in their assessment was probability of correct classification (PoCC) and so-called confusion matrix, which explains the result of classification.

All tested algorithms, as typical machine learning algorithms, include variety of tunable parameters and degrees of freedoms e.g. in their architecture, cost function definition, and teaching processes. In addition, the teaching set utilized during the teaching process affects the end result. For example, in the definition of SVM classifier we studied the use of: 1) three SVM architectures (multi-class, one-against-one, and one-against-all), 3) three different features that describe the input signal and feed the classifier, 3) three kernel functions that define class boundaries, 4) effect of the size of the training set, 5) effect of signal preprocessing (frequency normalization), and 6) effect of noise in the teaching process.

Figure 5 shows examples of classification results of two test cases. First, we show a confusion matrix for a SVM classifier when testing the classifier with 200 randomized signals in each class. The classifier has been taught using 2000 randomized and labelled signal samples from each class. The average probability of correct classification of the 1400 test signals (7*200) is 89 %.

We also show the performance of the same classifier as a function of INR for a single RFI in each class (Figure 5, right figure). In this case we see that some algorithms get correctly classified close to 0 dB SNR, but some (FHSS and Narrowband noise) gets never correctly classified. We also learned that the threshold INRs for correct PoCC can vary significantly depending on actual parameters of the signal.

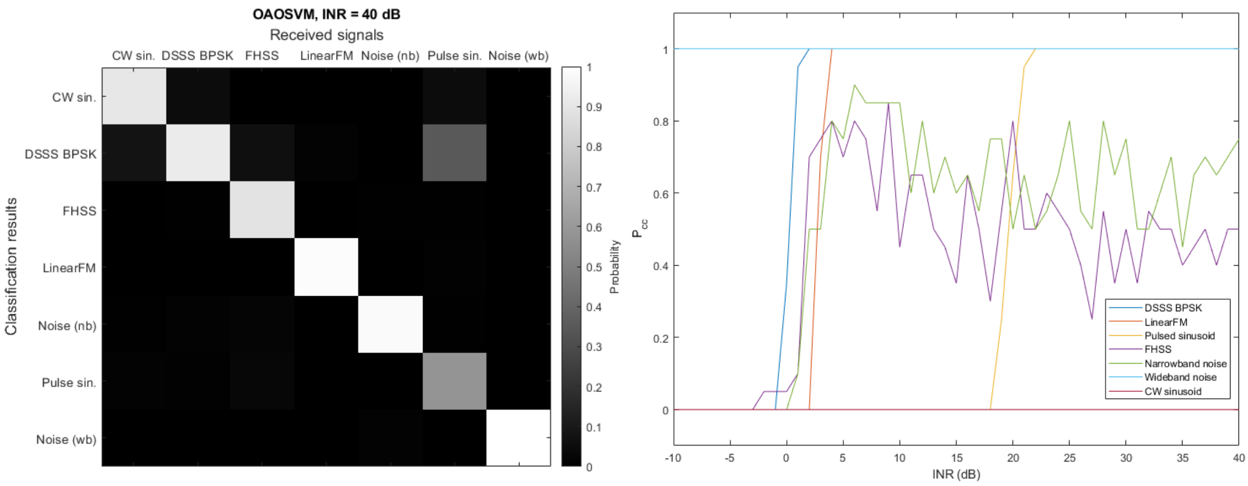


Figure 5. Exemplary classification results from IDS Simulator. LEFT: Performance of a SVM classifier when 1400 test signals in 7 classes are classified. RIGHT: PoCC as a function of INR for single exemplary signal waveforms.

Also neural network based classifiers were tested. For their testing we used networks built with Matlabs Deep Learning toolbox. Also with them a wide variety of tunable parameters exists. For example, we studied influence of the teaching set size to the performance. Results summarized in Table 2 suggest that CNN seem to require larger teaching set than RNN algorithm, whose performance wasn't degraded significantly even when the number of signals in the teaching set was reduced to 3500 signals from 14000 signals.

Table 2. PoCC for the CNN and RNN wrt. training set size. Two PoCC values are shown in each cell: the first value in the case of INR = 40 dB, and the second value for the case INR = 20 dB.

Classifier type\Tr. set s.	**3500**	**7000**	**14000 (reference)**
CNN	0.881/0.369	0.922/0.379	0.968/0.494
RNN	0.978/0.686	0.984/0.663	0.989/0.681

Due to large variety of degrees of freedom with the classification algorithms, we conclude that making much general comments on their relative abilities is difficult. However, the following things is concluded from this study comparison:

- SMV seem to work somewhat better at lower INR levels than neural networks. (With the ideal signal the performance is only PoCC = 90 %.) ;
- CW and pulsed signals seem to be the ones that are most difficult to classify by all classifiers;
- DSSS BPSK seem to be better classified by SVM algorithms than by Neural Networks;
- The RNN seem to perform clearly better than CNN when INR is lower;
- SVM seem to perform best close to INR = 0 dB conditions.
- The RNN performs better than CNN when small amount of teaching signals is available.

Comparison of the probability of correct classification as a function of signal SNR for the reference classifier architectures used in the study (SVM, RNN, CNN) is presented in Figure 6. As an overall conclusion we state that classificaiton algorithms include a plethora of implementation variations, and this space is only scratched in this study. With the simulator, performance of these could be studied further.

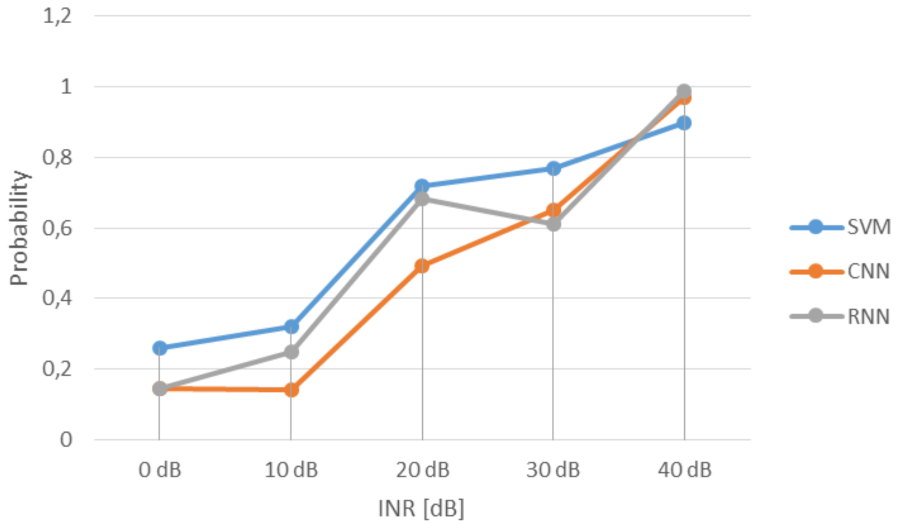


Figure 6. Performance comparison of the three classifier types (SVM, CNN, and RNN). The figure shows average PoCC across the all signal types as a function signal INR.

5. Localization Algorithms

The IDS simulator provides three localization algorithms: MUSIC is based on receiving multiple signals coherently of a single satellite. TDOA and TDOA&FDOA are based on determination of time and frequency differences from signals that are measured typically on different satellites.

In the activity the localization algorithms and their parametrization were studied and their performance was tested against typical RFI signal waveforms. The main figure-of-merit in their assessment is geolocation error (that can be characterized with systematic (bias) component and deviation).

Figure 7 presents an exemplary performance assessment of the MUSIC algorithm. The scenario includes a satellite on Medium Earth Orbit (MEO) and an RFI (located at (0,0) in lat,lon). The satellite is equipped with a hexagonal antenna array that resembles the SAR (Search and Rescue) antennas of the Galileo service satellites. The satellite propagates in orbit for 4 hours during which localization measurements is done at 19 location, and 50 times in each location. The resulting 50 localizations from one time moment are shown in Figure 7, top right figure. If averaged over time, the geolocation accuracy is approximately 1 km. The figure show also averaged (over 50 samples) accuracy for all 19 time moments (bottom left), and localization accuracy for various waveforms as a function of Interference signal to Noise Ratio (ISNR) (bottom right).

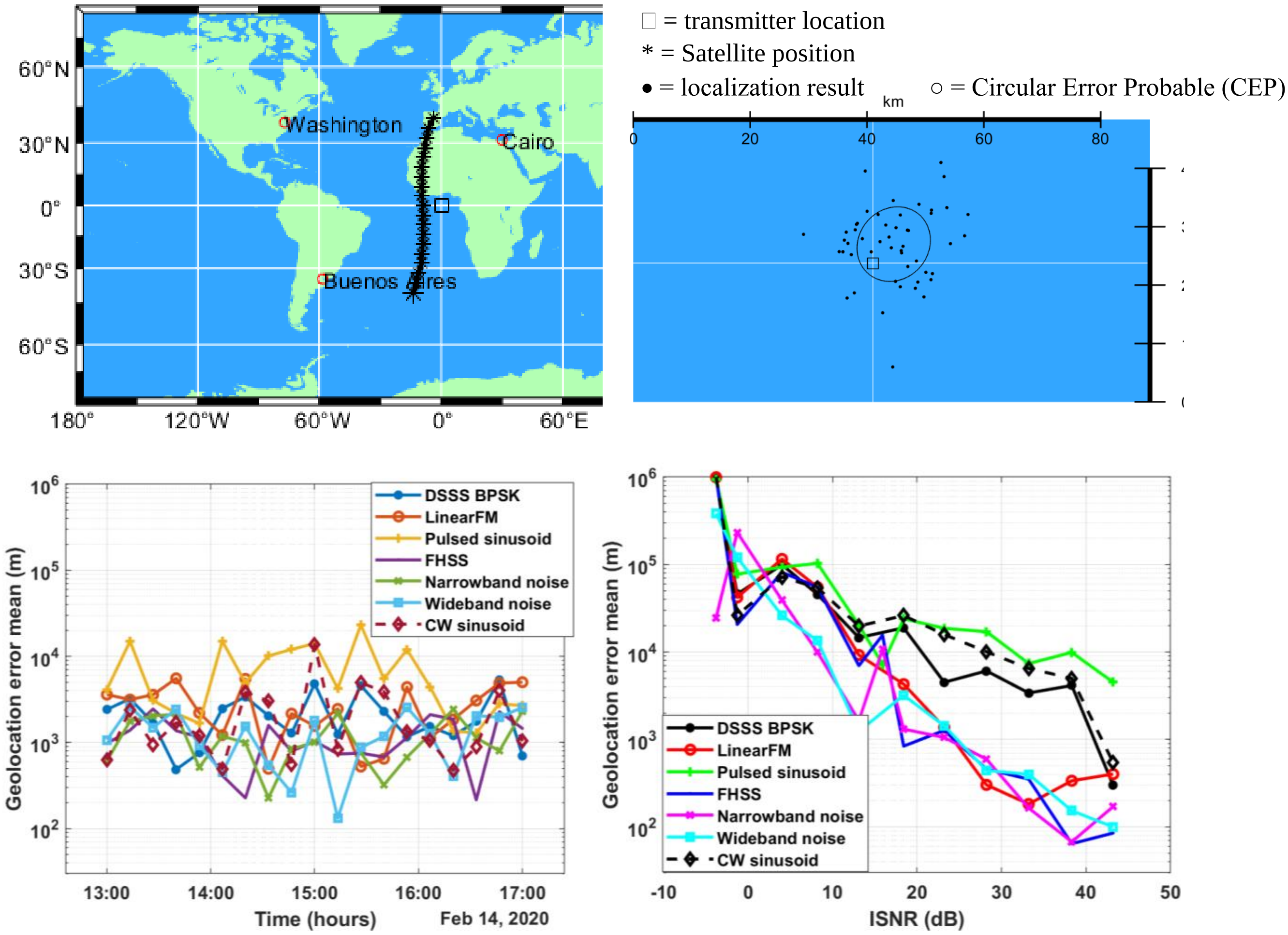


Figure 7. Exemplary result of MUSIC localization performance analyses with IDS Simulator. TOP LEFT: Scenario used in the simulation. Asterisks show the satellite track and the square the location of RFI. TOP RIGHT: Localization results from a single time moment (dots). BOTTOM LEFT: Localization accuracy for each time moment of the scenario for various waveforms. BOTTOM RIGHT: Accuracy of localization as a function of ISNR for various waveforms.

Figure 8 presents a performance assessment of the TDOA algorithm. The scenario included a triangular constellation of three satellites on Low Earth Orbits (LEO) and an RFI. The satellites are equipped with isotropic antennas. The satellite propagates in orbit for 20 minutes during which localization measurements is done at 10 location, and 20 times in each location. The figures in the bottom row show the average localization accuracy from 5 time moments (during which the RFI is visible to satellites), and localization accuracy for various waveforms as a function of Interference signal to Noise Ratio (ISNR). In that result the ideal performance (<100 m accuracy) above certain ISNR achieved since no other error sources (besides noise) is present in the simulation.

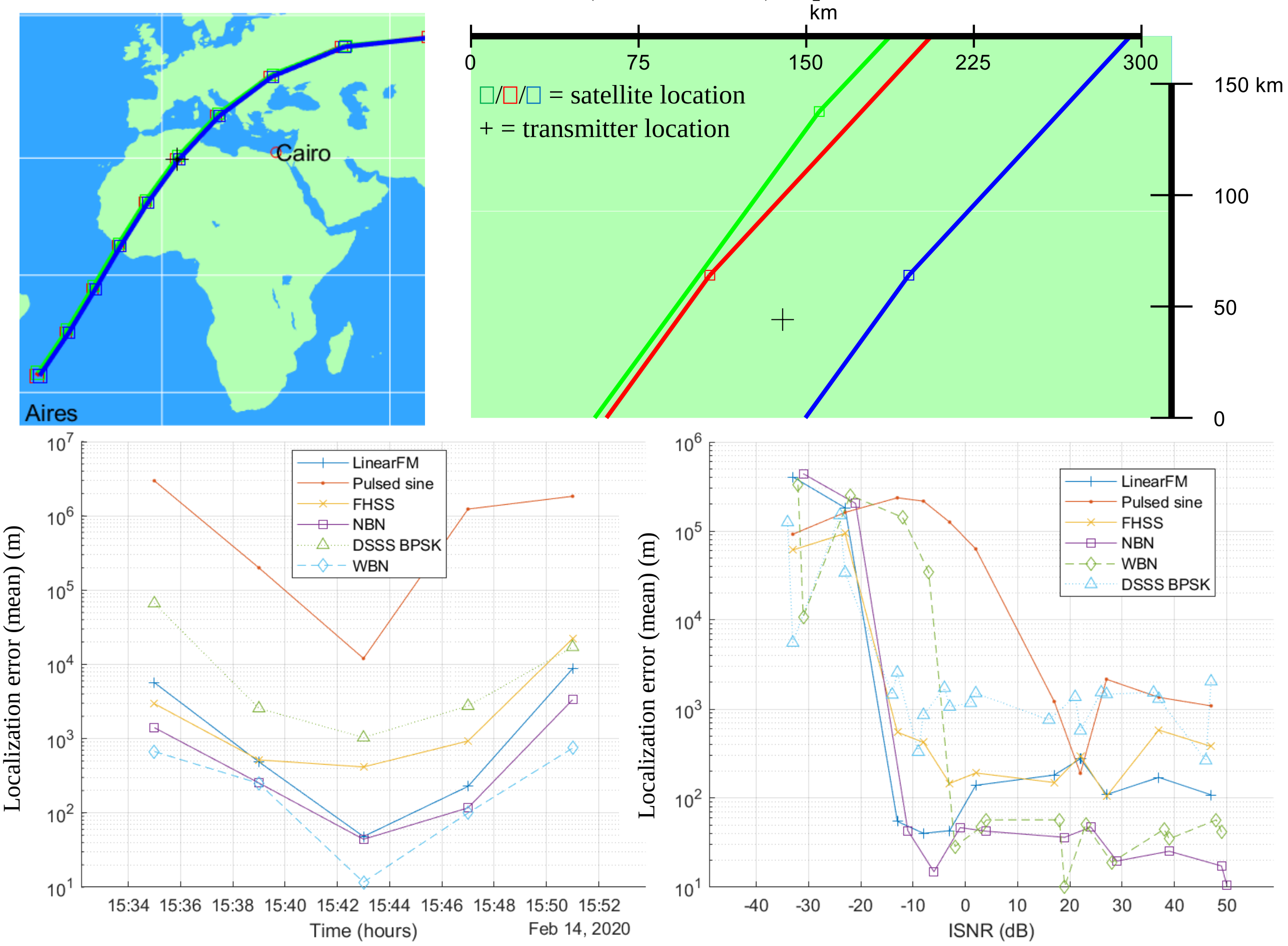
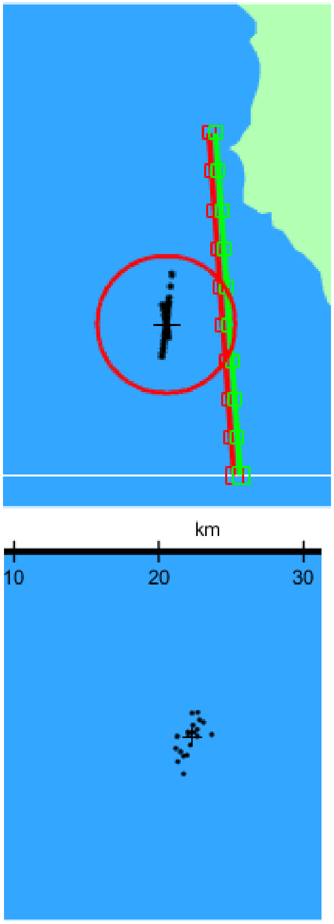
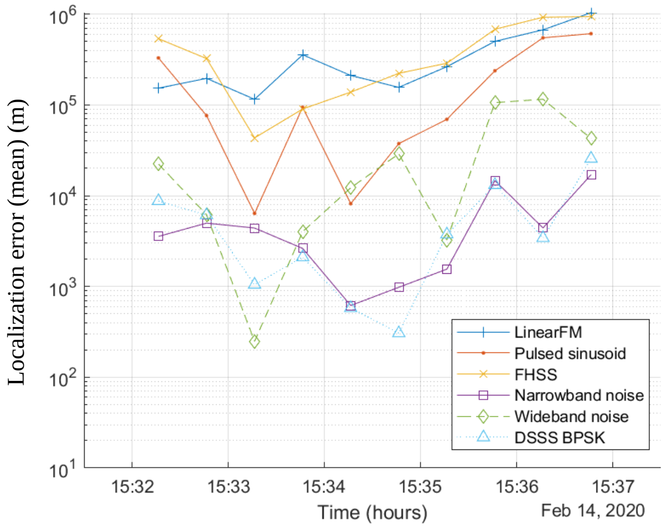


Figure 8. Exemplary performance analyses results of TDOA with IDS Simulator. TOP LEFT: Tracks of the three satellites used in the simulation. TOP RIGHT: Detail of the satellite positions (squares) close to the RFI source ("+"-sign). BOTTOM LEFT: Localization accuracy (mean over the 20 samples) for each time moment of the scenario for various waveforms. BOTTOM RIGHT: Localization accuracy as a function of ISNR for various waveforms.

Finally, we show a performance analysis of TDOA&FDOA algorithm in Figure 9. The scenario includes now a constellation of two satellites on LEO and an RFI. The satellites propagates in orbit for 5 minutes during which localization measurements is done at 10 location, and 20 times in each location. The figure shows the average localization accuracy on the map and as a function of time.

Figure 9 also demonstrates the performance when a pixel aggregation algorithm (here, Least-Mean Square, LMS algorithm) is applied for a number of measurements separated in time. Whereas the top right figure show the accuracies for single time moment localizations, the bottom right table summarizes the accuracies when measurements from only three time moments are aggregated. In this scenario the localization accuracy of most signals gets to a level of 1-2 km and remains quite constant to the negative SNR levels, before the localization fails to give any results.





Localization accuracy of TDOA&FDOA [km]

SNR (dB)	LFM	Pulsed	FHSS	NBN	WBN	DSSS BPSK
26	1.2	3.0	8.0	1.5	1.9	1.3
16	1.2	1.6	2.4	1.8	1.8	2.4
6	1.7	-	0.0	1.5	1.6	1.6
-4	2.0	-	11.8	1.2	1.1	1.9
-13	1.6	-	12.2	1.3	-	3.7
-24	-	-	-	-	-	-

Figure 9. Exemplary result of TDOA&FDOA localization performance analyses with IDS Simulator. TOP LEFT: Tracks of the two satellites used in the simulation and all localization results from the 10 time moments for NBN signal. TOP RIGHT: Localization accuracy for each time moment of the scenario for various waveforms. BOTTOM LEFT: 20 localisation repetitions of the scenario using LMS pixel aggregation (data from all 10 points was aggregated). BOTTOM RIGHT: Localization accuracies of TDOA&FDOA as a function of SNR for various waveforms. In this test only three time points were used for pixel aggregation.

From more detailed analysis (see the Final Report) we learned that the limited frequency domain accuracy and peak recognition accuracy are the most significant practical aspects that limit the accuracy of localization algorithms based on Cross-Ambiguity Function (CAF) peak searching. Aggregation multiple measurements improves the performance even if just a few time moments.

The above examples were done in somewhat different scenarios to study the behaviour of individual algorithms. In order to compare their performance against each other, we used a three-satellite LEO scenario shown in Figure 10. In this case we simulated L-band (Galileo E1 signal band) receiving systems and four specific transmitter types (representing different E1 band RFI threats). We used three approaches to localize the transmitters:

1) Localization based on data from three satellites and TDOA
2) Localization based on data from two satellites and TDOA&FDOA

3) Localization based on an antenna array on one of the satellites and using MUSIC. For the array, we consider an "L"-shaped array of five antennas, where distance between elements is 0.5*lambda.

Localization result of the four transmitters (having an effective radiated isotropic power, EIRP) are shown in Figure 11 of 5 dBW.

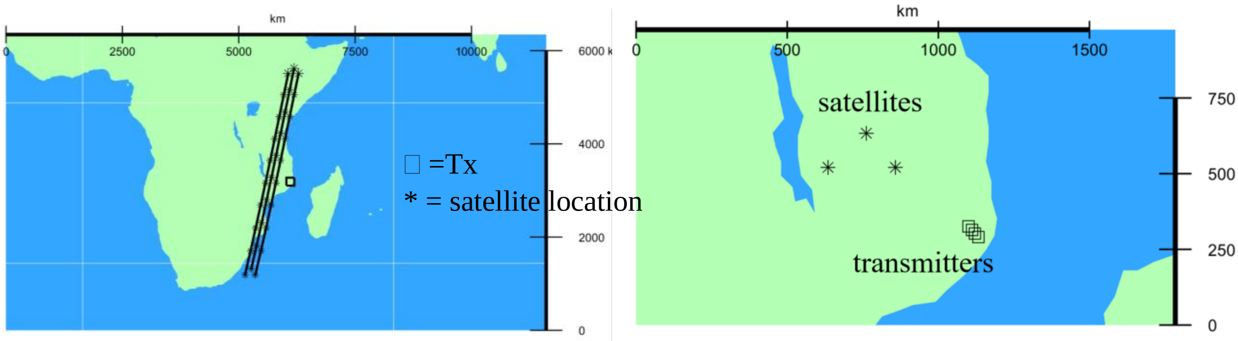


Figure 10. LEO-scenario to compare the performance of localization algorithms. Overview (left) and detail during the fifth time moment (right).

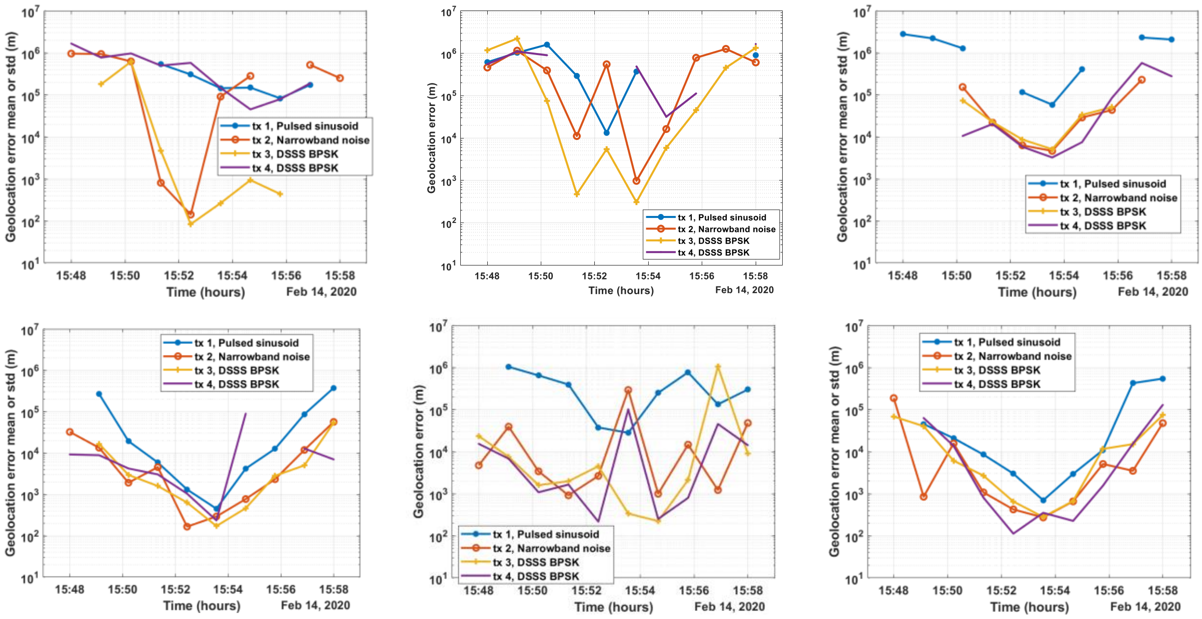


Figure 11. Localization accuracies of the four specific E1-band threats from a satellite triplet and TDOA (left column), tandem satellite and TDOA&FDOA (middle column), and single satellite and MUSIC (right column). The top row results are obtained when TX EIRP is 5 dBW, and the bottom row results are obtained when TX EIRP is 25 dBW.

Some notes from this test (more detailed analysis in Final Report) are that the TDOA algorithm gives the most accurate and stable results in this scenario. TDOA&FDOA is not much worse, but its performance is more distracted by geometry and noise variations. With LMS aggregation the best accuracies when EIRP power was 5 dBW were 0.3 km for TX-3 signal (1 MHZ BPSK) with TDOA, and 0.5 km with TDOA&FDOA. Localization of other transmitters with that transmit power was not exactly successful. The MUSIC method gave also rather consistent localization results with 5-10 km accuracies for many signal types.

6. End-to-End Demonstrations and Promising Concepts

In a practical RFI counteraction strategy several DISCCL algorithms are needed. Detection may be needed to trigger other operations, isolation can be needed to separate signals prior to classification, etc. IDS Simulator makes such chain processing possible as well. Figure 12 shows an example of an analysis where influence of isolation algorithm (STFT) to the classification accuracy is demonstrated. From the result we see how classification of LFM signal gets more difficult when a QPSK signal intrudes the classification (the left figure). The isolation algorithm applied prior to classification significantly improves the correct classification thresholds. (It is noted that classification of pure LFM also improves due to SFTF since it acts as additional bandpass filter).

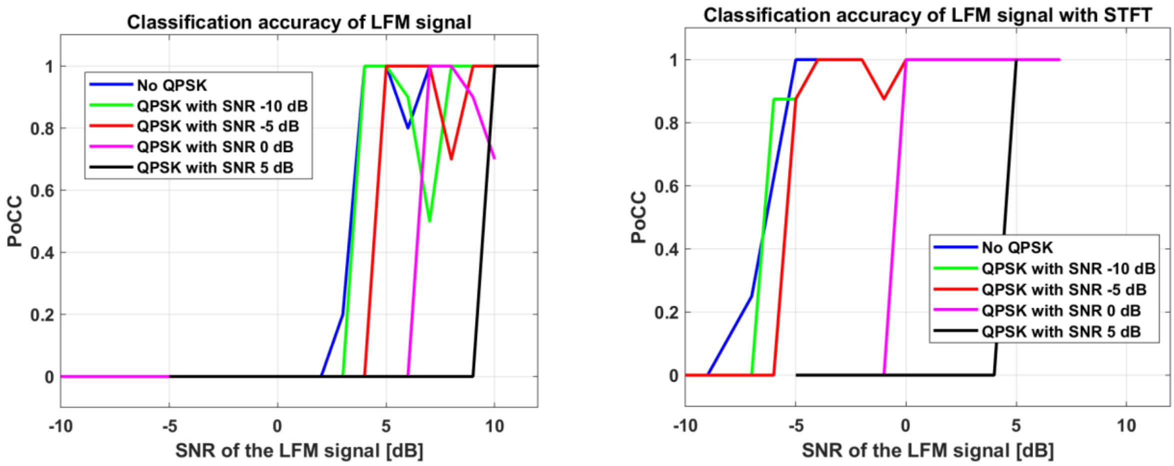


Figure 12. PoCC of an LFM signal in the presence of QPSK signal. LEFT: Result without isolation, RIGHT: Result with STFT isolation.

Another example of a processing chain is shown in Figure 13, where we show how a mean frequency characterization improves MUSIC localization. The left figure shows the localization error when information of the centre frequency of the RFI don't exists, and this frequency changes in the scale of tens of MHz. The accuracy is in the order of 10-30 km. If a characterization algorithm is used prior to localization, the result improves as presented in the right figure, to the scale of 0.5-1 km. This result signifies the importance of characterization with certain algorithms.

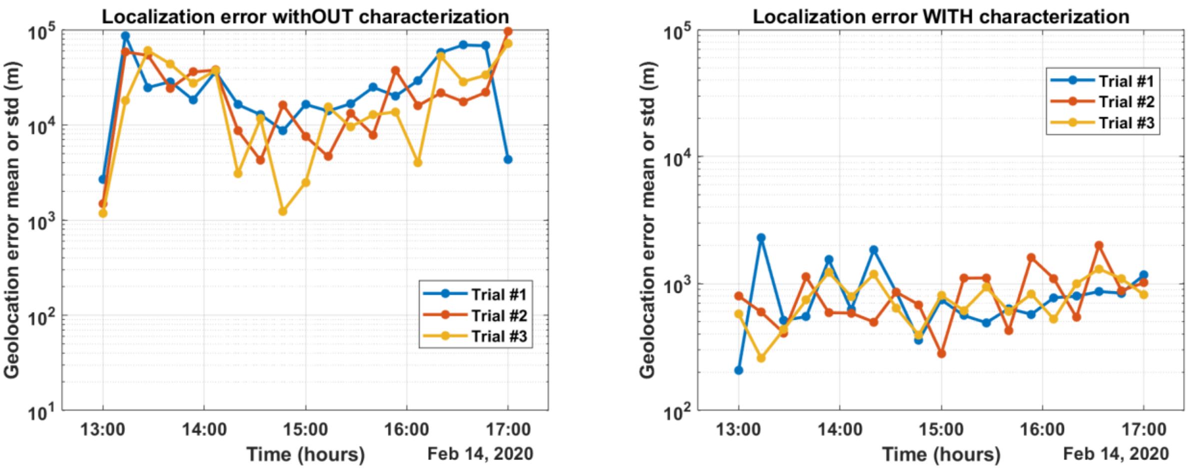


Figure 13. Localization accuracy of MUSIC when LEFT: not using and RIGHT: using the mean frequency characterization. Both figures include results from three tests with different realization of centre frequency errors (which is in the scale of tens of MHz).

In the final part of the activity promising RFI counteraction techniques and concepts were identified. In that respect the following was concluded:

- Many high-performing detection, isolation, classification and characterization algorithms are based on spectral analysis. Such detectors require implementation of real-time Fast Fourier Transform (FFT) of variable sizes to the Digital Signal Processing (DSP) part of the sensor. Having DSP cores capable in various FFT operations would be beneficial to many algorithms. These cores would facilitate efficient on-board detection (PSD), isolation (time-frequency-based), characterization (mean frequency, bandwidth, spectral kurtosis) and classification (feature-based SVM and NN) algorithms. At least the following operational concepts would be supported by FFT cores:
    - Usage of spectral analysis based detection algorithms real time on-board to efficiently trigger any successive operations (signal sample saving, or other RFI counteractions).
    - Usage of real-time on-board signal characterization, such as centre frequency estimation (or SNR estimation, which was not among the algorithms studied in this activity)
    - Usage of real time on-board isolation algorithms based on spectral analysis;
    - Usage of real time on-board classification based on spectral features;

  In addition, such capability would facilitate a variety of additional signal analysis methods (not covered in this study).
- Any single detection algorithm has no good overall performance. The higher the spectral (or temporal) resolution, the better is the detection capability. However, there is a trade-off to be made between computational complexity and platform resources. Therefore, computationally friendly algorithm combinations may be most cost-effective. Certain combination of time and coarse spectral resolution RFI sensor might be a cost-effective solution. E.g., a gaussianity detector in combination with low resolution spectral detectors would be effective for real time detection.
- Performance of ridge detection isolation algorithms have fundamental limitations due to their simplicity.
- In classification, Neural Networks algorithms offer a wide framework for machine learning. There exists a variety of different architectures, and a variety of their parametrization. Development of algorithms, tools, optimized circuits and processing environments for their utilization has strong market pull, as many applications benefit from their use. This commercialization will result in libraries and datasets which could be exploited in signal classification. Commercial applications don't typically employ the most resource hungry technology. Therefore, applications where small and medium scale processing capability is needed is foreseen to develop much. Such development is seen, e.g., in the ML-based drone navigation, autonomous cars, etc.

  In RFI context this could be exploited by demonstrating real time on-board classification features that can be achieved with small processing platforms.
- In localization the localization methods based on multi-satellite measurements, i.e., the TDOA(&FDOA) seem to be the most promising concepts. They utilize the formation flying or larger constellations, which will be more common in the future. It is noted that

commercial companies with small satellites are providing such data products in US, and similar activities are under development in Europe. It is noted also that the best operational concept to perform localization with the method is to post process the data on-ground (see the next point). Therefore, the method is not usable use cases where real-time localization or AOA information of the emitter would be needed (e.g., adaptive null-steering filters).

- High-accuracy localization requires accurate modelling of satellite path and location, digital elevation model of the Earth, etc. Therefore, the high-accuracy localization is best to perform on ground processing stations. However, when processing power and inter-satellite communication will be developed enough in the future, also multi-satellite localization in real time become possible.

Based on the above points we concluded three promising RFI sensing technology concepts to be developed further:

1. **Concept #1: RFI signal detector using time and frequency domain detectors in parallel on a small satellite suitable platform**. In this concept a RFI receiver is performing spectrum monitoring on certain frequency bands of interest. The hardware we propose would consists of a digital signal processing unit that has many RFI detection algorithms parallel for high sensitivity detection. According to this study (and others), no single algorithm can perform well against all RFI signal types. A flexible DSP unit would enable usage of several algorithms and reconfiguration possibilities. Such DSP unit could work as individual payload with an RF fron-end (e.g., an SDR), or as an added functionality of other radio receiver systems (such as scientific radio receivers). Characteristic features of the DSP unit would be: Availability of several complementing RFI algorithms operating in time/polarization/spectrum domain.
2. **Concept #2: RFI signal sensor to support emitter TDOA&FDOA localization in a formation flying.** This concept mission would consists of several (e.g., 3-4) satellites so that TDOA&FDOA localization becomes possible. The concept would detect RFI's synchronously with the satellite swarm, and deliver the necessary signal samples to ground for accurate localization. The payload would support either real time detection, or would work synchronously according to specified plan (mission level trade-off is needed). The signal samples would be down-linked and detection and localization performed on ground.
3. **Concept #3: Real-time signal detection and classification from resource-friendly computing platform.** This concept would aim to fast (real-time) on-board signal classification that could be needed in future mega-constellations (tens of thousands of satellites), where no data down-link is possible. Such functionality could be used for Space Situational Awareness (SSA), optimization of radio channel use for telecommunications, or for RFI monitoring. For the purpose we propose to develop a resource friendly DSP unit that would focus on real-time classification (rather than to detection as in Concept #1). The concept would feature a DSP unit that is specialized to certain operations required in classification (such as tensor calculation for neural networks).

7. Final Conclusions

In this Executive Summary Report we described the IDS Simulator tool and some DISCCL algorithm performance analysis done with it. We conclude by stating that IDS Simulator is a highly tunable simulator tool for RFI scenario and DISCCL algorithm analysis. Using the simulator we have studied characteristics of a number of various algorithms. About the performance analysis of DISCCL algorithms we conclude that the simulator was used to test altogether 21 DISCCL algorithms, and some of them had several variants. From the algorithm study we make some high level conclusions notes:

- About the RFI detectors we state conclude that the performance of detection algorithms is highly dictated by computing power available in a practical system. Algorithms that analyse the spectrum of the radio channel with high frequency resolution can perform clearly better than time domain detectors. On the other hand, time domain detectors can also be sufficiently accurate and they are FAR less resource hungry than detectors based on spectral analysis.
- For signal isolation we tested time-frequency analysis-based methods, which essentially are image processing methodologies to detect certain shapes in that domain. Such algorithms will be developed fast in the future due to computer vision and Artificial Intelligence (AI) based applications. Simulator also provides a novel Independent Component Analysis (ICA) method, which can have benefits in certain scenarios.
- For RFI characterization we used a set of well-known and consolidated signal characterization methods. They are mostly used as a tool for other DISCCL algorithms, such as localization and classification.
- For classification we tested three machine learning methods: State Vector Machines, Recurrent and Convolutive Neural Networks (RNN and CNN). As an overall conclusion we state that especially these artificial intelligence algorithms include a plethora of implementation variations, and this space is only scratched in this study. With the simulator, performance of these could be studied further.
- For localization we implemented well-known TDOA, FDOA&TDOA and MUSIC algorithms. Also these algorithms have been developed over years and variants of them can be found. In a practical receiver system measuring RFI system data can be accumulated over time to perform more accurate localization with, e.g., the LMS algorithm. With such accumulation very high accuracies down to tens of meters can be demonstrated. Such simulations can be carried out with the presented simulator.

For algorithms in each category, we summary the key performance findings and conclusions in Table 3.

Finally, we conclude that IDS simulator is a highly tunable simulator for RFI scenario and DISCCL algorithm analysis. It can be used to demonstrate and study various effects in RFI receiving scenarios. The performance analysis done in this activity is only a scratch of the multi-dimensional parameter space that can be reached with the simulator.

Table 3. Conclusions of DISCCL algorithms.

Algorithm	Summary of the Performance
Detection	- The studied detectors start to reliably detect the test signals when Interference to Noise Ratio is between -25 dB - 0 dB. - The detector based on spectral analysis (PSD) and multiple receivers (space domain) have typically the best performance, its detection threshold varying between -25 dB and -10 dB depending on the test signal. - Performance of the space domain detector was rather constant to all RFI types. It requires multiple receivers to operate, but when such are available in the system it can be a powerful detector. - The time domain detector (gaussianity) has to poorest performance. Its detection threshold typically varies between -10 and 0 dB, except for noise signals, which cannot be detected with the tested gaussianity detectors. - Presence of the uplink typically degrades the detection performance by 5 – 15 dB. However, presence of uplink seem to enhance the performance of gaussianity detector. - For the studied specific cases (1: Galileo Uplink threat, 2: RFI targets from LEO, 3: LEO constellation) we can conclude that PSD was able to detect the Galileo Uplink threat (threat #1) with TX EIPR power > 40 dBW. Also other detectors performed adequately against the threat. For Threat Scenario #2 the PSD and energy detectors were starting to detect RFIs with EIRP power of > -10 dBW, making them barely sensitive enough for the applications. - Based on the experiences it is recommended to focus in spectral analysis based detectors in future developments.
Isolation	- The single channel isolation algorithms based on time-frequency domain analyses and ridge detection was found to be quite primitive in their isolation capabilities – They get easily confused when two signals overlap in spectral domain and spectrally hopping signals are also difficult for them. - The ridge-detection algorithm use a heuristic parameter for signal band-width. They would benefit from signal characterization activities combined with isolation. - The multi-channel algorithms (MQTFD and ICA) were more capable in separating complex waveforms. - The performance of isolation algorithms was measured with scale-independent error metric that equals to 1 for completely different signals and 0 to equal signals. Based on the error metric, ICA provided the most stable isolation performance and achieved error metric < 0.5 when INR increased > 9-20 dB.
Characterization	- Tested characterization algorithms were based on spectral analysis (mean-freq, bandwidth, and spectral kurtosis) or amplitude histograms. - Centre-frequency algorithm reaches <10 % error level when INR increases above 5 – 10 dB. The bandwidth estimation requires >20 dB INR for the similar error level. - The centre-frequency is an important input e.g. to MUSIC. - It was found that characterization methods to estimate INR would be important from operational point of view. They were not studied in the frame of this activity.
Classification	- The studied classification algorithms (SVM and neural networks) are based on machine learning. They are characterized by a great degrees of freedom in their architecture, teaching and weighting process. This makes it impossible to make general conclusions of their applicability based on this study only.

	- SVM seemed to perform slightly better in low-INR conditions (INR 10-20 dB) than neural networks. With the studied classes, it reached 75 % correct classification with INR was 20 dB. At the same INR, RNN had 70 % and CNN 50 % correct classification presentage. - RNN performs slightly better when limited number of teaching signals are used to train the network. Overall, teaching set and its representativeness is important for the performance. - In the technology survey it was found that a lot of development is happening with neural networks, much because computer vision applications. Therefore, they seem to be developing fast and they seem to be flexible machine learning approach.
Localization	- MUSIC algorithm is based on usage of antenna array. The larger the array, the better the localization accuracy. In this test we considered rather small (40 cm) hexagon array with six antennas. - MUSIC accuracy depends on INR. From MEO, with 10 dB INR only noise signals were possible to localize with <25 km accuracy. With 20 dB INR the accuracy was < 8 km and with 40 dB < 1 km. From LEO, km-scale accuracy was achieved with 10 dB SNR, and 10-km-scale with -10 dB SNR. - MUSIC uses an estimate for the RFIs centre frequency. If such is not available, the localization accuracy may be increased to hundreds of kilometres. With the simple mean-frequency estimation the accuracies of < 1 km were achieved. - MUSIC is an AOA-algorithm, thus it is directly sensitive to errors in platform attitude. Sub-degree accuracy is needed from LEO to keep localization error < 10 km. - With TDOA sub-km scale accuracies are achieved in clearly lower INR than with MUSIC. The sub-km scale was achieved with -10 dB INR for the best cases. - With TDOA&FDOA the localization performance was rather binary, meaning that whenever the localization algorithm converged, the localization accuracy was in 1-2 km-scale. - With both TDOA&FDOA and TDOA aggregation of multiple measurements with LMS method greatly improves the localization accuracy. Already with few measurements (say, 5-10 measurements) the accuracy was improved significantly. The pure TDOA seemed somewhat more accurate in the final performance testing of the specific test cases, resulting in 100-500 meter accuracies, whereas TDOA&FDOA resulted in 500-1000 meter accuracies - For the studied specific cases (1: Galileo Uplink threat, 2: RFI targets from LEO, 3: LEO constellation) we can conclude that MUSIC array was able to localization of the threat to ~10 km accuracy, if 90 dBW EIRP power is assumed. If EIRP power of 60 dB is assumed to localization is very unlikely. For Threat Scenario #2 The km-scale accuracies are achieved when TX EIRP reaches 0 dB, which is clearly higher than the targeted power range (-25 - -5 dBW). Thus, sensitivity improvements of the receiver are needed if localization of such targets are pursued.