

RADIO FREQUENCY INTERFERENCE DETECTION IN MICROWAVE RADIOMETRY USING MULTI-DIMENSIONAL SEMI SUPERVISED LEARNING

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Radio frequency interference (RFI) in the measurements of Earth-observing radiometers is increasing over time with the increase in frequency spectrum demand for active services [1]. RFI contamination may lead to erroneous retrieval of the critical geophysical parameters in passive remote sensing missions. To overcome this problem, several detection and mitigation algorithms have been proposed and implemented with only limited success in cases of weak or noise-like interference [2]. The existing algorithms can be divided into two categories based on the number of dimensions used in the detection process, i.e., single (e.g., pulse blanking [3]) and multiple dimensions (e.g., SMAP radiometer [4]) algorithms. It should be noted that the cumulative information from the multiple dimensions is proven to be more effective than the algorithms that rely on a single dimension [5, 6]. Furthermore, the occurrence of RFI is diverse. Therefore, currently, there is no labeled baseline dataset is available for RFI-contaminated data. Taking these into consideration, in this work, we have proposed the one class support vector machine algorithm (OCSVM) to use the information from RFI-free measurements alone. Furthermore, we have performed an extensive feature analysis to differentiate between the RFI-contaminated and RFI-free measurements.

We have performed the experiments on simulated radiometer measurements where the RFI-free measurements are considered as normally distributed. The interference signal is assumed to be pulsed sinusoidal. Since the RFI is additive, we have added the interference signal to RFI-free measurements to create the RFI contaminated measurements. The baseband radiometer measurements in the presence of the RFI are mathematically described in Eq. (1).

$$x_C(t) = x_N(t) + \sum_{i=1}^N A_i \sin(2\pi f_i t + \phi_i) \text{rect}\left(\frac{t - t_0}{\omega_i}\right). \quad (1)$$

The first term in Eq. (1) denotes the normally distributed white Gaussian noise with zero-mean and the standard deviation σ , and the second term denotes the pulsed sinusoidal interference signal. The undetermined parameters in the interference source are the amplitude (A_i), frequency (f_i), and the duty cycle ($d_i = \frac{\omega_i}{T}$). The distribution of these parameters is considered uniform in the respective ranges. For instance, the amplitude is distributed in the minimum and the maximum ranges corresponds to the variation of the INR from -20 dB to 10 dB. The frequency is uniformly distributed with in the bandwidth of the digital backend of the PALS radiometer which is ranging from 15 to 35 MHz. The phase of the interference signal is uniformly varied from zero to 2π . Finally, the width of the pulse envelope is varied in such a way that the DC of the pulse is uniformly distributed between 1% to 100% . The starting time of the pulse at each integration time is varied randomly across the integration time ranging from zero to 2π which corresponds to the variation in the integration time ranging from zero to $350 \mu\text{s}$. The goal is to evaluate the performance of the proposed detection algorithm against the INR of the multi-source RFI model.

Each measurement is described by a vector of thirty-one features extracted in time (i.e., mean, variance, power, peak to peak distance, median, average over absolute value of first differences, average over time series differences, mean of the auto-correlation coefficient, distance, Ljung-Box (LB) test), spectral (i.e., power spectral maximum, centroid shift, spectral spread, spectral entropy, spectral skewness, spectral kurtosis, spectral crest, spectral flatness, spectral flux), and statistical (i.e., Jarque-Bera (JB), Lilliefors (L), Anderson-Darling (AD) tests, skewness (m_3), kurtosis (m_4), 5 to 10 standard moments ($m_5 - m_{10}$), and inter quantile range (IQR)) domains. Dataset is constructed using 400 numbers of measurement vectors belonging to each RFI-contaminated and RFI-free classes. Features are ranked based on the summation of false alarms and misdetections such that a lower value of the summation indicates that the feature is more discriminant than the feature with a higher value. Features with higher discriminating ability are selected to construct the proposed algorithm.

For given dataset, the OCSVM finds the hyper-plane that separates the given RFI-free measurements from the origin of the training data in a higher dimensional feature space. The OCSVM model is trained using the RFI-free measurements in the dataset such that the optimal decision boundary away from the origin of the RFI free measurements is computed. The reported values for performance metrics are five-fold cross validated. Finally, the performance of the proposed approach in each fold is evaluated using the accuracy, precision, and recall metrics and averaged over the number of folds. Finally, we have compared the performance of the OCSVM with the traditional RFI detection algorithms such as kurtosis detection, pulse blanking, and kurtosis detection or pulse blanking (we will refer this algorithm as “OR algorithm”). Here, both kurtosis detection and pulse blanking algorithms are implemented by thresholding in such a way that kurtosis and power values deviates from mean by three standard deviations are detected as RFI-contaminated. OR algorithm is implemented by combining the detection outputs of kurtosis detection and pulse blanking by logical OR operation.

Fig. 1 (a) shows the receiver operating characteristics (RoC) of the OCSVM with two features (dashed line) and additionally introduced features using our feature selection algorithm (solid line) as a function of INR. Fig. 1 (b) shows the RoC of the kurtosis detection (dashed line) and pulse blanking (solid line) as a function of INR. From the figure, it can be observed that when the $\text{INR} < -25$ dB, OCSVM and pulse blanking act similar to a random classifier. Similarly, kurtosis detection acts as a random classifier for $\text{INR} < -5$ dB.

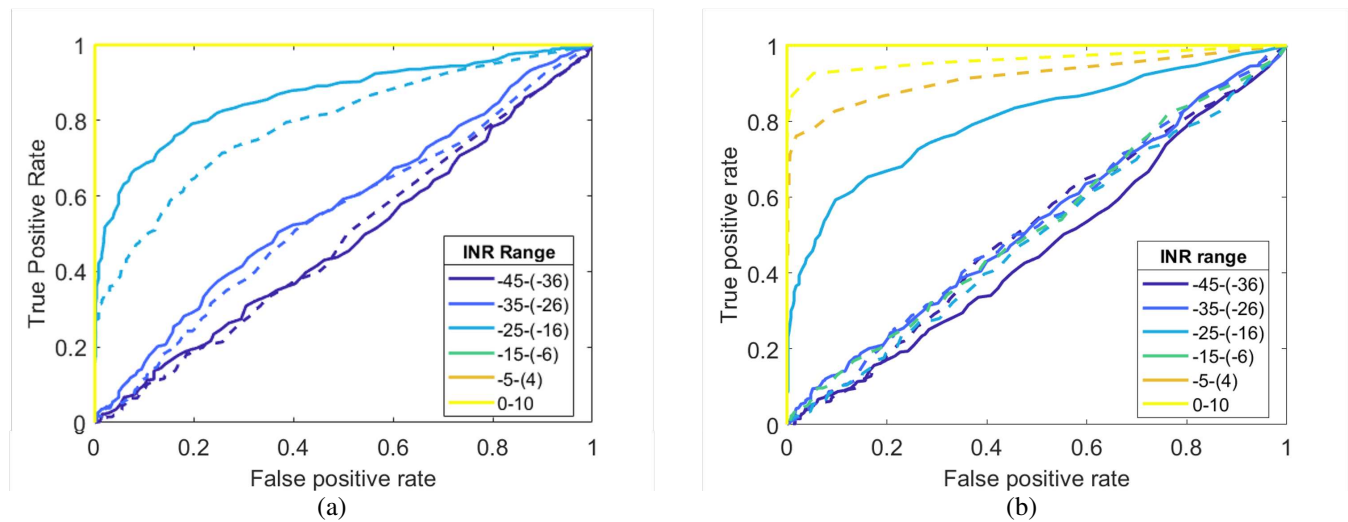


Fig. 1. RoC of the OCSVM (a) and the traditional RFI detection algorithms (b) as a function of INR.

For the RFI cases with INR ranges from -25 dB to -16 dB increasing the number of informative features increases the overall performance. When the INR of the RFI is ranging from -25 dB to -16 dB, OCSVM detects more RFI-contaminated measurements than the OR method. The results demonstrate a significant improvements over existing RFI detection techniques, especially, for RFI contaminated cases with low INR. As future work, we plan to extend this study to include different types of RFI signals so that new features providing a better representation of a dynamic RFI environment can be identified.

1. REFERENCES

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