

Interference Detection for Mobile Monitoring Utilizing Mobility-Robust Radio Features

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Abstract—This paper proposes an interference detection method for mobile monitoring systems to detect weak wideband radio interference signals. Recently, mobile radio monitoring using mobile sensors has attracted attention as an effective technique for detecting weak interference signals. However, in mobile radio monitoring, a conventional monitoring method using absolute power values of the received signals can degrade interference detection accuracy due to signal variations caused by sensor movement.

To address this issue, the proposed method extracts mobility-robust radio features from the received signals, which are robust to sensor movement. By extracting signal duration and bandwidth as features, the proposed method is robust to variations in signal power caused by movement and is well suited for mobile monitoring systems. Simulation results show that the proposed method reliably detects weak, wideband interference signals. Under specific conditions (e.g., when utilizing signal duration for signals with 1-MHz interference bandwidth), the proposed method can detect signals that are up to 12 dB weaker than those detectable by conventional methods, achieving an almost perfect detection rate.

Index Terms—interference detection, radio features, mobile monitoring, white-box

I. INTRODUCTION

Radio interference caused by interference signals has been increasingly reported with the growing use of various wireless communication systems, radios, and electronic devices. For example, illegal radio emissions can affect the bands already in use [1]–[5]. In many countries, government-operated telecommunications regulatory agencies deploy nationwide monitoring systems to regulate unauthorized radio transmissions and confiscate non-compliant equipment. Since interference signals these days tend to be wideband and weak, it is necessary to monitor and detect not only strong interference signals but also weak ones.

Generally, received power weakens with distance from the sensor [4], making it challenging to detect weak interference signals when using fixed sensors for monitoring. As an alternative, a mobile monitoring utilizing mobile sensors mounted on moving vehicles is being considered, which can get closer to the source of interference [2]. Approaching interference signals enables them to be detected accurately before their power has attenuated. The mobile radio monitoring requires a particularly simplified system configuration due to the limited power consumption in mobile environments compared to fixed monitoring.

Conventional methods for detecting interference signals typically leverage analytical approaches based on statistical measures and signal processing techniques [2]–[9]. These methods first learn the distribution of absolute power values of licensed signals in normal states, and then detect signals that deviate from this distribution as interference [3]–[7]. The statistical methods are effective under the condition that the learned distribution remains stable and that anomalous signals exhibit behavior distinct from normal states [7]. For example, there are methods to estimate the distribution of normal states by reducing the dimensions of time-series power information and detecting interference signals [6], [7], [10]. These methods improve the detection accuracy by mapping high-dimensional data to a lower-dimensional space. Additionally, from the perspective of spectrum sharing, some methods set decision boundaries for the absolute power values to detect interference from authorized signals [3]–[5].

However, when applying conventional statistical methods to mobile monitoring with mobile sensors, learning decision boundaries at each point along a movement path requires large amount of data to ensure sufficient data density, which significantly increases time cost in mobile monitoring operation. As a potential approach to mitigate this issue, aggregating received power measurements from multiple points along the path of the movement may be considered. While it enables to enhance data density and reduce the learning burden, this approach introduces another challenge: aggregated power distribution can distort decision boundaries because the measured power in each point has a location-specific power distribution due to differing distances from the signal source. Ultimately, the distorted distribution will decrease interference detection accuracy [2].

On the other hand, many machine-learning interference detection methods have been proposed [2], [5], [11]. Time-series signals or signal spectrograms are typically learned in advance using supervised or unsupervised learning methods. For example, interference detection methods that utilize supervised learning to label features determined by the model have also been proposed, providing explainability [5]. However, in actual monitoring scenarios, it is challenging to pre-label the features because the characteristics of the interference signals are unknown.

To accurately detect unknown, weak and wideband inter-

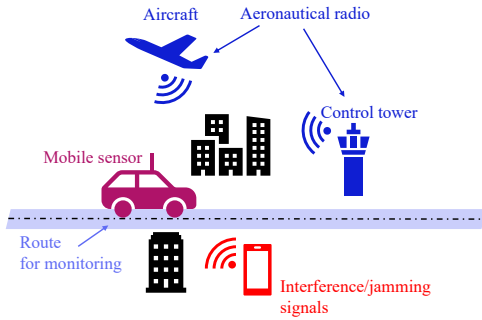


Fig. 1: Scenario for mobile monitoring in our proposal.

ference signals of approximately 1 MHz or greater bandwidth in mobile monitoring, we propose a novel detection method for mobile monitoring scenarios. The main contributions of this paper are summarized as follows:

- We extract signal duration time and bandwidth as mobility-robust radio features from received signals, rather than the absolute power values. Since these features are invariant to power variations caused by sensor movement, the proposed method detects the interference signals with high accuracy, even under the mobile monitoring environment.
- To evaluate our proposed method, we performed measurements of real aeronautical radio signals in the very high frequency (VHF) band in Tokyo.
- Under the condition that interference signals exist in VHF-band aeronautical radio signals, we demonstrate that the proposed method achieves superior true positive rate (TPR) performance compared to the conventional method, across varying interference-to-noise ratio (INR) and false alarm rate (FAR) conditions.

II. SYSTEM MODEL

We introduce the system model as the foundational background for our proposal in Fig. 1. We first introduce the mobile monitoring with mobile vehicle sensors. Unlike fixed sensors, mobile sensors can detect even weak signals by measuring while moving and approaching interference. Our work aims to monitor aeronautical radio signals and detect weak and wideband interference against aeronautical signals transmitted from aircraft and control towers while driving along predetermined routes. As a preparation for radio monitoring, the system first learns aeronautical signals as normal signal states through repeated mobile measurements. During monitoring operation, it detects interference by identifying deviations from these learned normal states.

III. PROPOSED METHOD

We propose an explainable interference detection method for mobile radio monitoring systems to identify unknown interference signals. When applying the conventional method based on absolute received power, interference detection becomes difficult because the signal distribution is distorted

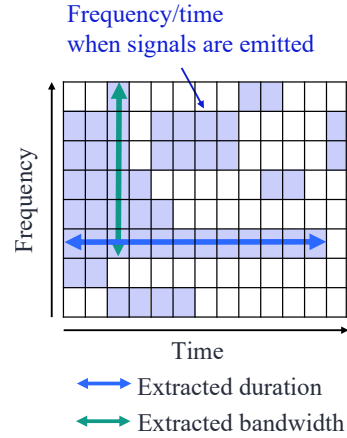


Fig. 2: Features used in the proposed method.

by sensor movement. This distortion arises from location-dependent variations in received power. In contrast, signal duration and bandwidth are less sensitive to such variations and are thus more robust to mobility. To mitigate this distortion, we leverage signal duration and bandwidth as mobility-robust features differing from aeronautical signals. Signal bandwidth is effective since aeronautical communications are narrowband, whereas interference signals tend to have wider bandwidths. Similarly, signal duration helps detect long-duration interference, while aeronautical communications are typically short. In the proposed method, feature distributions are learned in advance, and signals deviating from these distributions are detected as interference. The method does not rely on neural networks and provides a white-box interpretation of detected anomalies. Statistical representative values of duration and bandwidth are extracted for each frequency to design interpretable decision boundaries.

Fig. 2 shows the extracted features in the proposed method, where an input spectrogram is interpreted as a two-dimensional map in the time and frequency domains. For each domain, it is assessed whether the signal level exceeds the threshold for signal emission. Based on these assessments, signal duration and bandwidth are extracted. These features are derived using a single fixed time–frequency resolution (grid), eliminating the need for multiple resolutions to accommodate unknown signal characteristics. This design reduces computational complexity and power consumption while maintaining detection performance, making it well suited for simplified configurations in mobile scenarios. The proposed feature extraction relies on fixed time and frequency resolutions and may limit the detection of interference signals whose durations or bandwidths fall below these resolutions. This limitation is considered acceptable for aeronautical monitoring applications, where the primary signal characteristics can be sufficiently captured at the chosen resolutions. The resolution settings are described in detail in Section IV-A.

Fig. 3 shows the overall flow of the interference detection

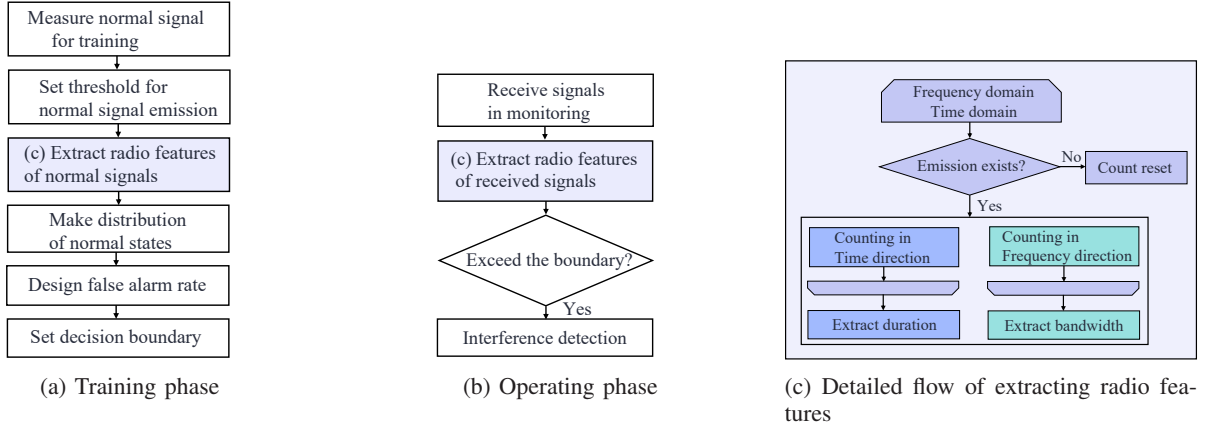


Fig. 3: Overall flowchart of the interference detection scheme utilizing our proposed method.

scheme. During the training phase, signals that can be considered as the normal states are measured over a sufficient period to capture the characteristics of the radio environment (e.g., 30 min and 60 min). Through the measurements, we establish a threshold for signal levels to distinguish between the presence and absence of normal signal emissions. Afterward, their signal duration and bandwidth are extracted as mobility-robust radio features based on the threshold. In the final step of the training phase, the detection boundaries for each radio feature are designed from the distribution of normal states based on the FAR. The training is periodically performed to account for long-term changes in the radio environment, considering factors such as license renewal cycles of regular transmitters and maintenance intervals of sensing equipment (e.g., 1 week to several months).

On the contrary, in the operating phase, we start receiving signals in monitoring. For simplicity, we simulate the received signals with interference by adding them to the signals of normal states in this work. Mobility-robust radio features are then extracted, and an interference is detected based on the learned decision boundaries. If these features exceed the boundaries, the signals are identified as interference. Feature extraction involves assessing whether signal levels in the frequency and time domains exceed a threshold. The signal duration is defined as the number of consecutive time steps exceeding the threshold for each frequency bin, while the signal bandwidth is the number of consecutive frequency bins exceeding the threshold. Both metrics reset when the signal level falls below the threshold.

IV. SIMULATION

A. Simulation condition

In this study, we compare the detection performance of interference signals between the proposed method and conventional methods through computer simulations. We first performed measurements of VHF-band aeronautical radio signals in Tokyo using a mobile sensor, recording signals for 3000 seconds while driving. These real-measured signals are

used as normal-state signals, onto which interference signals are superimposed in the simulation. Normal-state signals inherently capture variations such as multipath fading and shadowing when observed under mobility. Consequently, the model can learn these characteristics in a location-independent manner during training.

Approximately 90 % (2700 seconds) of the acquired data is used for training, and the remaining 10 % (300 seconds) is used to evaluate the existence of interference signals. We assume an interference signal with weak power and a wider bandwidth than the normal signals. Fig. 4 shows examples of the spectrum of the aeronautical signals and the interference signals at various INRs. The detailed specifications of the simulation parameters are listed in Table I. Since the specific frequencies in the VHF band cannot be disclosed, the center frequency will be represented as A MHz, and the monitored bandwidth is 20 MHz. The frequency resolution is set to 13.67 kHz, close to the bandwidth of each channel used by aeronautical radio. The time step is set to 100 ms because the duration of actual interference signals significantly impacting aeronautical radio systems is estimated to be more than 100 ms. Normal/ anomalous states are determined at each time step and frequency bin. The resolutions of time step and frequency bin represent the grid resolution in Fig. 2. The INR of the interference signal varies from -2 to 28 dB, and three patterns of interference bandwidths, 1, 0.5, and 0.25 MHz, are prepared. Additionally, five patterns of existing times of the interference signal, ranging from 4 to 7 seconds, and 10 seconds, are ready. Since the detection performance depends on the distribution of the learned radio wave features, the frequency at which the interference signal varies in nine patterns is prepared for evaluation.

B. Evaluation metrics

We evaluate the proposed method using TPR and FAR, well-known general metrics for evaluating machine-learning models [12]. We define TPR and FAR as

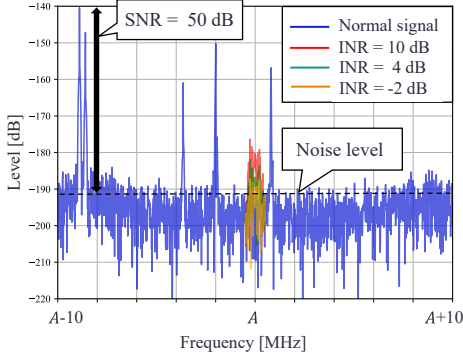


Fig. 4: Examples of relationships between aeronautical radio signals and interference signals at various INRs.

TABLE I: Simulation parameters.

Signal Processing	Value
Monitored bandwidth [MHz]	20
Sampling rate [MHz]	56
N_{FFT} [-]	4096
Δ_f [kHz]	13.67
Interference Signal	Value
Bandwidth [MHz]	1, 0.5, 0.25
Existing time of interference [s]	4, 5, 6, 7, 10
INR [dB]	-2, 4, 10, 16, 22, 28
Center frequency [MHz]	A, A $\pm$ 2, A $\pm$ 4, A $\pm$ 6, A $\pm$ 8

$$TPR = \frac{\text{Correctly detected time steps}}{\text{Interference duration}}, \quad (1)$$

$$FAR = \frac{\text{Falsely detected time steps}}{\text{Non-interference duration}}, \quad (2)$$

respectively. A time step is considered detected when at least one frequency bin is detected within the acquired bandwidth. TPR represents the proportion of time samples with frequency bins deviating from the pre-learned radio feature distribution during interference periods, and FAR denotes the proportion of such deviations during normal periods. In the evaluation, we compare the TPR of the proposed and conventional methods while keeping FAR below 0.2 %. In the ROC analysis (Section V-C), a wider FAR range (up to 10%) is considered to evaluate the trade-off between detection performance and false alarms.

V. RESULTS AND DISCUSSION

In this section, the TPR of the proposed method is evaluated against the conventional method that detects interference based on absolute power values (level-based). The level-based method is a threshold-based detector that classifies signals as interference when their absolute power deviates from the learned distribution of normal signals. Sections V-A and V-B assess TPR as a function of INR with FAR below 0.2 %. In Section V-C, we evaluate TPR as a function of FAR by fixing INR, enabling comparison of the proposed and conventional methods in distinguishing interference from normal signals.

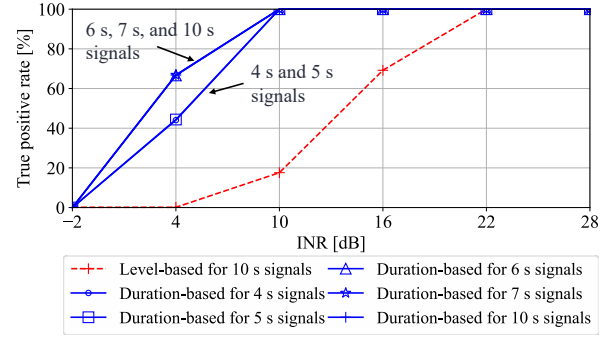


Fig. 5: TPR of proposed duration-based method and conventional method for interference signal of 1-MHz bandwidth.

A. Proposed method utilizing signal duration

First, we evaluate the detection performance of the proposed method utilizing signal durations (duration-based). Fig. 5 shows the TPR of the duration-based method and the conventional level-based method when the bandwidth of the interference signal is set to 1 MHz. The plots adopt the average TPR value obtained for each interference frequency pattern. Note that the conventional method determines normal or anomalous states at each time point, making its TPR theoretically independent of interference duration. This is confirmed by the results; therefore, only the TPR at an interference duration of 10 seconds is shown for the conventional method.

As depicted in Fig. 5 when comparing the INR for the proposed duration-based method and the conventional method to achieve the same TPR, we found that the duration-based method can detect interference signals with a smaller INR regardless of the existing time of the interference signal. For example, in Fig. 5, the duration-based method can achieve a TPR of 100 % when INR = 10 dB, whereas the conventional method can only achieve the same TPR when INR = 22 dB. This result demonstrates that interference signals from further locations can be detected, which shows high detection opportunities in mobile monitoring. On the other hand, the conventional method cannot achieve high TPR for weak (≤ 10 dB) interference signals. This can be attributed to the distortion of the power distribution caused by mobility.

B. Proposed method utilizing signal bandwidth

Next, we evaluate the detection performance of the proposed method utilizing signal bandwidth in the same way as in Section V-A. Fig. 6 shows the TPR of the proposed bandwidth-based (bw-based) method and the conventional level-based method when the bandwidth of the interference signal is set to 1 MHz, 0.5 MHz, and 0.25 MHz, respectively. The existing time of the interference signal is fixed with 10 seconds for all cases. When INR = 10 dB, in specific bandwidth conditions of the interference signal, the TPR of the bw-based method exceeds that of the conventional method by about 45 %, 85 %, and 80 %, respectively.

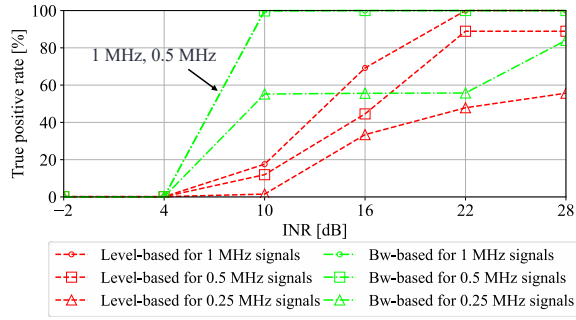


Fig. 6: TPR of proposed bandwidth-based method and conventional method.

Conversely, when $\text{INR} \leq 4$ dB, interference signals are not well detected by either method. We consider why the bw-based method cannot detect such weak interference signals as follows: Generally, received signals have sidelobes, and those of high-power signals influence other channels, especially the adjacent channels. On the contrary, when the interference signal has low power, its sidelobes do not influence the adjacent frequency band. Thus, the number of frequency bins where the interference signal exists is limited, resulting in the inability to detect weak interference signals.

C. Results of TPR against FAR

The receiver operating characteristic (ROC) curve, which is represented as TPR relative to FAR, is an indicator of performance in classifying normal and anomalous data [13]. In this study, the TPR against the FAR, as defined in Section IV-B, is used to evaluate ROC. Fig. 7 show the ROC curves of the proposed and conventional level-based methods when the existing time of the interference signal is 10 seconds and the bandwidth is 1 MHz. This study emphasizes the ROC region with FAR below 10 %, since it is crucial for practical monitoring to detect interference signals. According to the evaluation results in Fig. 7, compared to the conventional method, the proposed method maintains TPR of 100 % against FAR when the interference bandwidths are 1 MHz and $\text{INR} = 10$ dB. This indicates that the proposed method has a superior classification performance for normal signals and interference signals.

VI. CONCLUSION

In this paper, we propose an interference detection method for mobile monitoring systems that leverages mobility-robust radio features rather than absolute power to detect weak wideband interference signals. By utilizing signal duration and bandwidth as mobility-robust features, the proposed method achieves a higher TPR than the conventional level-based method. As future work, we plan to integrate the proposed method with machine-learning-based architectures to achieve higher detection accuracy. Such integration is expected to enable detection of interference signals that cannot be identified by conventional level-based methods, while the proposed

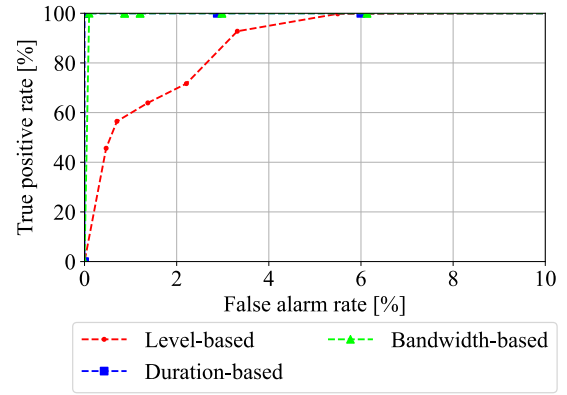


Fig. 7: ROC curves of proposed and conventional methods for interference signal with bandwidth of interference signal of 1 MHz, with INR of 10 dB.

mobility-robust feature-based method remains effective in detecting persistent interference signals based on signal duration.

REFERENCES

- [1] Y. Kang, H. Wu, Z. Zhao, Y. Li, and J. Meng, "DL-based anomaly detection at the physical-layer of cognitive radio by deep support vector data description," *IEEE Trans. Cogn. Commun. Netw.*, vol. 8, no. 4, pp. 1689–1705, 2022.
- [2] Z. Li, Z. Xiao, B. Wang, B. Y. Zhao, and H. Zheng, "Scaling deep learning models for spectrum anomaly detection," *Proc. 20th Int. Symp. Mobile Ad Hoc Networking and Computing (ACM)*, pp. 291–300, 2019.
- [3] P. Kaligineedi, M. Khabbazi, and V. K. Bhargava, "Malicious user detection in a cognitive radio cooperative sensing system," *IEEE Trans. Wireless Commun.*, vol. 9, no. 8, pp. 2488–2497, 2010.
- [4] L. Zhang, G. Ding, Q. Wu, and Z. Han, "Spectrum sensing under spectrum misuse behaviors: A multi-hypothesis test perspective," *IEEE Trans. Inf. Forensics Security*, vol. 13, no. 4, pp. 993–1007, 2017.
- [5] C. Barreyre, L. Boussouf, B. Cabon, B. Laurent, and J.-M. Loubes, "Statistical methods for outlier detection in space telemetries," *Space Operations: Inspiring Humankind's Future*, pp. 513–547, 2019.
- [6] M. Zhang, X. Li, and L. Wang, "An adaptive outlier detection and processing approach towards time series sensor data," *IEEE Access*, vol. 7, pp. 175 192–175 212, 2019.
- [7] L. Erhan, M. Ndubaku, M. Di Mauro, W. Song, M. Chen, G. Fortino, O. Bagdasar, and A. Liotta, "Smart anomaly detection in sensor systems: A multi-perspective review," *Information Fusion*, vol. 67, pp. 64–79, 2021.
- [8] M. A. Pimentel, D. A. Clifton, L. Clifton, and L. Tarassenko, "A review of novelty detection," *Signal processing*, vol. 99, pp. 215–249, 2014.
- [9] V. Hodge and J. Austin, "A survey of outlier detection methodologies," *Artificial intelligence review*, vol. 22, pp. 85–126, 2004.
- [10] H. E. Egilmez and A. Ortega, "Spectral anomaly detection using graph-based filtering for wireless sensor networks," *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1085–1089, 2014.
- [11] S. Rajendran, W. Meert, V. Lenders, and S. Pollin, "Unsupervised wireless spectrum anomaly detection with interpretable features," *IEEE Trans. Cogn. Commun. Netw.*, vol. 5, no. 3, pp. 637–647, 2019.
- [12] G. Kovács, G. Sebestyen, and A. Hangan, "Evaluation metrics for anomaly detection algorithms in time-series," *Acta Universitatis Sapientiae, Informatica*, vol. 11, no. 2, pp. 113–130, 2019.
- [13] N. Elmrabit, F. Zhou, F. Li, and H. Zhou, "Evaluation of machine learning algorithms for anomaly detection," *2020 Int. Conf. Cyber Security and Protection of Digital Services (Cyber Security)*, pp. 1–8, 2020.