Supplementary Materials for "Few-Shot Open-Set Specific Emitter Identification: A Contrastive Learning Approach with False Negative Suppression"

Long Yang, Zeyu Chai, Fanggang Wang, Zhenhan Zhao, Yuchen Zhou, Jian Chen

I. Introduction

This supplementary material presents a comprehensive sensitivity analysis of the six key hyperparameters in our adaptive threshold mechanisms: q_1, q_2, p_1, p_2, α, β. These parameters control the percentile positions and margin coefficients in the calculation of adaptive thresholds in eq.(6) and eq.(10) of our work [1].

II. Experiments of Sensitivity Analysis

A. Simulation Parameters

The experiments are performed on ADS-B dataset [2] and Wi-Fi dataset [3]. For open-set testing, the ratio of known to unknown categories for ADS-B dataset and Wi-Fi dataset is 10:1 and 5:1, respectively. All experiments are conducted under the 10-shot scenario, with Monte Carlo trials repeated 100 times to ensure statistical significance.

B. Sensitivity Analysis of False Negative Suppression Parameter

In the false negative suppression mechanism, q_1 and q_2 are chosen to capture the upper tail of the distribution where false negatives are most likely to occur, while α is a conservative factor to avoid over-suppression. The theoretical foundation for parameter selection is based on statistical outlier detection principles, where we aim to identify samples in the upper tail of the similarity distribution that are likely false negatives.

Fig. 1 shows the closed-set identification accuracy on both the ADS-B and Wi-Fi datasets under different selections of q_1, q_2, and α. When q_1 is 0.75 and q_2 is 0.95, the closed-set identification accuracy on both the ADS-B and Wi-Fi datasets reach their peaks. When $q_1 < 0.75$ and $q_2 < 0.95$, the closed-set identification accuracy decreases due to excessive suppression of true negative samples. In contrast, when $q_1 > 0.75$ and $q_2 > 0.95$, the closed-set identification accuracy drops slightly because of insufficient suppression of false negative samples. The hyperparameters $q_1 \in [0.7, 0.8]$ and $q_2 \in [0.9, 1.0]$ achieve relatively high identification accuracy. It can also be observed that when α ranges from 0.5 to 0.6, the relatively high identification accuracy can be achieved on both the ADS-B and Wi-Fi datasets. When $\alpha < 0.4$, the identification accuracy decreases due to excessive suppression. In contrast, when $\alpha > 0.6$, the accuracy declines due to the fact that the conservative behavior leads to the missed detection of false negatives. Thus, $\alpha \in [0.4, 0.6]$ is a proper range for achieving a good tradeoff between excessive and insufficient suppression across different signal datasets.

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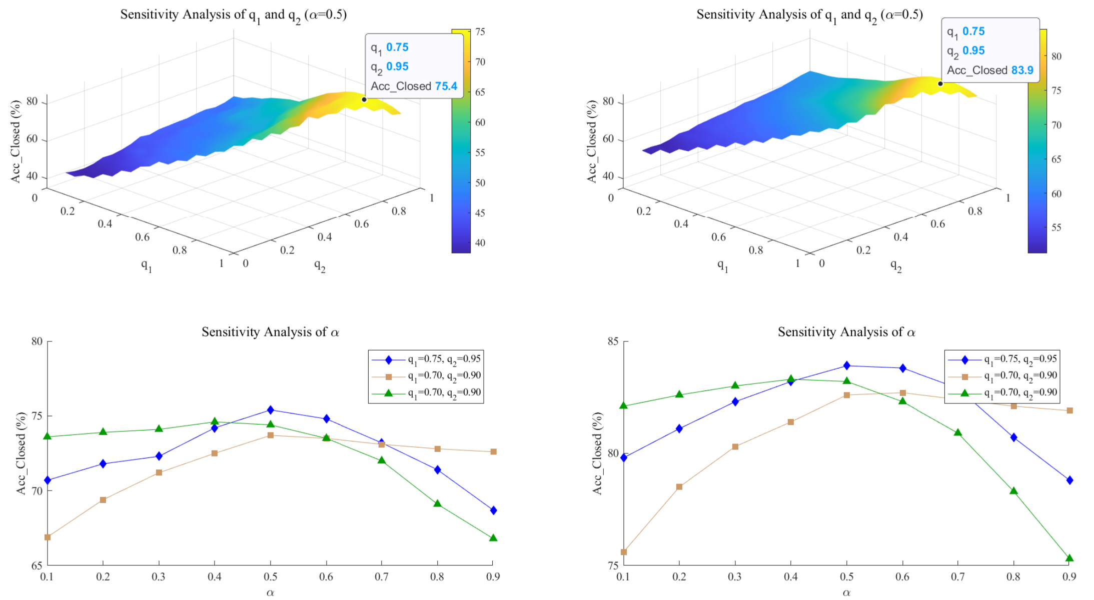
C. Sensitivity Analysis of Open-Set Identification Parameter

In the open-set identification mechanism, p_1 captures the lower bound for robust threshold calculation, while p_2 represents the typical similarity range for known emitters, with $\beta = 1.5$ providing a robust margin for unknown emitter detection. The parameter selection follows standard statistical outlier detection methodology.

Fig. 2 shows the open-set identification accuracy on both the ADS-B and Wi-Fi datasets under different selections of p_1, p_2, and β, where the open-set identification accuracy (termed "Acc_Open" in Fig. 2) is obtained from the average between the accuracy of identifying known emitters and the accuracy of identifying unknown emitters. As shown in both sub-figures of Fig. 2, the open-set accuracy reaches its maximum when p_1 is 0.25 and p_2 is 0.75 for both datasets. Further, it can also be observed that relatively high open-set accuracy can be achieved when $p_1 \in [0.2, 0.3]$ and $p_2 \in [0.6, 0.9]$. On the other hand, when β ranges from 1.4 to 1.6, the relatively high open-set identification accuracy is achieved for both the ADS-B and Wi-Fi datasets. Therefore, adopting $\beta = 1.5$ is a reasonable choice that balances the sensitivity and specificity in open-set identification.

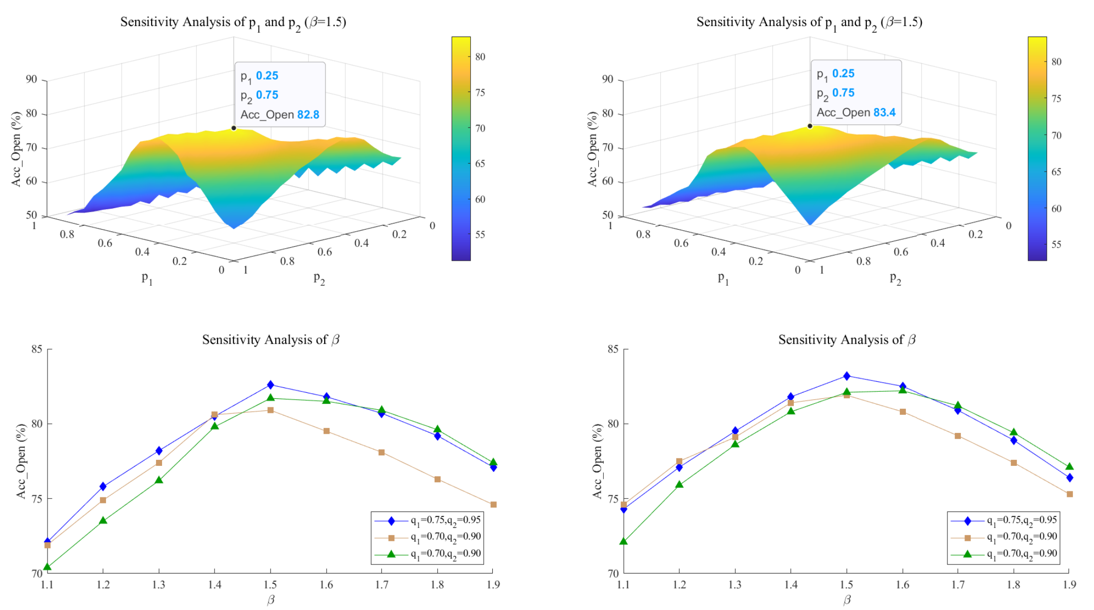
III. Conclusion

This supplementary material conducts a sensitivity analysis of six hyperparameters $\{q_1, q_2, \alpha\}$ and $\{p_1, p_2, \beta\}$ of the adaptive threshold mechanism in eq.(6) and eq.(10) of our work [1]. For the false negative suppression mechanism, the hyperparameters $q_1 \in [0.7, 0.8]$ and $q_2 \in [0.9, 1.0]$ achieve relatively high identification accuracy with strong robustness, while $\alpha \in [0.4, 0.6]$ balances excessive and insufficient suppression. For the open-set identification, it is demonstrated that the hyperparameter choice of $\{p_1 = 0.25, p_2 = 0.75, \beta = 1.5\}$ provides a good sensitivity-specificity balance in open-set identification.



(a) ADS-B (b) Wi-Fi

Fig. 1. Sensitivity Analysis of q_1, q_2 and α.



(a) ADS-B (b) Wi-Fi

Fig. 2. Sensitivity Analysis of p_1, p_2 and β.

References

[1] L. Yang, Z. Chai, F. Wang, Z. Zhao, Y. Zhou, and J. Chen, "Few-shot open-set specific emitter identification: A contrastive learning approach with false negative suppression," *submitted to IEEE Commun. Lett.*

[2] Y. Tu *et al.*, "Large-scale real-world radio signal recognition with deep learning," *Chinese Journal of Aeronautics*, vol. 35, no. 9, pp. 35–48, 2022.

[3] K. Sankhe *et al.*, "No radio left behind: Radio fingerprinting through deep learning of physical-layer hardware impairments," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 1, pp. 165–178, 2020.