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

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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 equations (6) and (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 accuracies 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 accuracy on both the ADS-B and Wi-Fi datasets reach their peaks. A low setting of q_1 and q_2 leads to excessive suppression of true negative samples, resulting in a certain degree of decrease in identification accuracy. In contrast, a high setting leads to insufficient suppression of false negative samples, causing a slight drop in identification accuracy. The parameter q_1 within the range of 0.7-0.8 and q_2 within 0.9-1.0 achieve relatively high identification accuracies, demonstrating high robustness.

The identification accuracy reaches its maximum when α is around 0.5–0.6 for both the ADS-B and Wi-Fi datasets. A smaller α leads to aggressive suppression, causing the accuracy to drop. In contrast, a larger α results in conservative behavior that may miss false negatives, as evidenced by the accuracy decline. The trend validates that $\alpha = 0.5 - 0.6$ is the optimal range, balancing between excessive and insufficient suppression across different signal datasets.

C. Sensitivity Analysis of Open-Set Identification Parameter

In the open-set identification mechanism, p_2 represents the typical similarity range for known emitters, while p_1 captures the lower bound for robust threshold calculation, 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 accuracies on both the ADS-B and Wi-Fi datasets under different selections of p_1, p_2, and β. The open-set accuracy "Acc_Open" denotes the average of the accuracy of identifying known emitters and the accuracy of identifying unknown emitters. The open-set accuracy reaches its maximum when p_1 is 0.25 and p_2 is 0.75. A low setting of p_1 makes the threshold too aggressive, leading to false unknown classifications, while a high setting of p_1 makes the threshold too conservative, failing to detect unknown emitters. The parameter p_2 shows hight robustness across a wide range. $p_2 = 0.75$ provides sufficient spread information while maintaining stability.

The open-set identification accuracy reaches its maximum when β is around 1.4–1.6 for both the ADS-B and Wi-Fi datasets. Setting β to 1.5 provides an optimal balance between sensitivity and specificity in outlier detection.

III. Conclusion

This supplementary material conducts a sensitivity analysis of six hyperparameters(q_1, q_2, p_1, p_2, α, β) in our adaptive threshold mechanism. For false negative suppression mechanism, q_1 within 0.7–0.8 and q_2 within 0.9–1.0 achieve relatively high identification accuracies with strong robustness, α within 0.5–0.6 balances excessive and insufficient suppression. For open-set identification, the selected values

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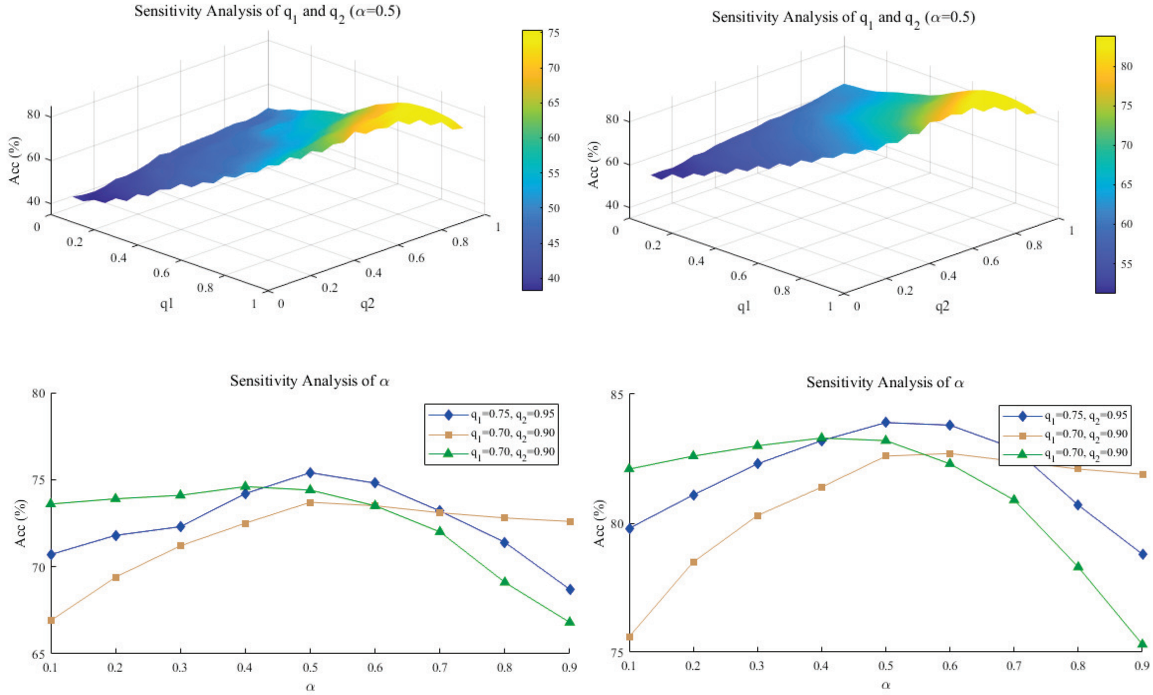
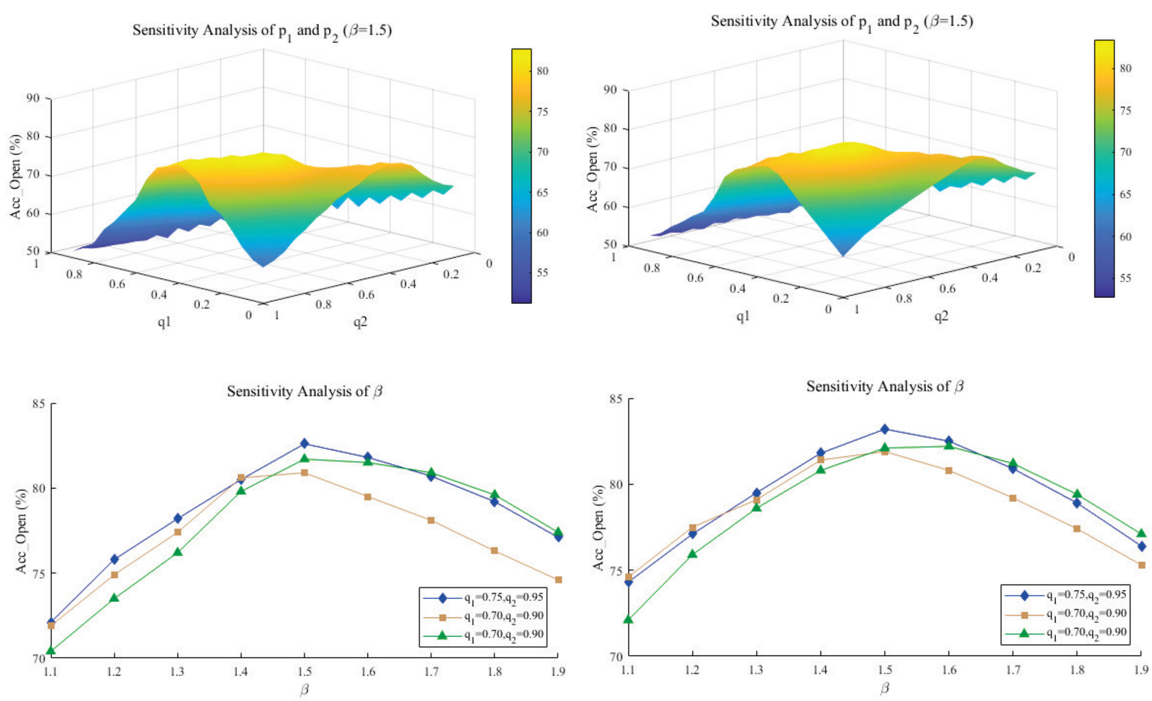


(a) ADS-B (b) Wi-Fi

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.

$p_1 = 0.25, p_2 = 0.75, \beta = 1.5$ effectively harmonize sensitivity and specificity, where $p_1 = 0.25$ avoids over-aggressive or conservative thresholds, $p_2 = 0.75$ ensures spread information stability, and $\beta = 1.5$ provides a robust margin for unknown emitter detection.

References

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