In this subsection, we evaluate the parameters’ influence on the proposed algorithm’s performance.

For any dimension reduction method, the dimension of the low-dimensional subspace has a strong impact on the subspace detection performance. In the dimension reduction method based on manifold learning, the size of the local neighbourhood will also affect the algorithm’s performance. To thoroughly verify the proposed algorithm’s performance, we conducted experiments on low-dimensional subspaces with different local neighbourhood sizes and varying dimensions. For different neighbourhood sizes, the target detection AUC values obtained by the ACE target detection operator on the low-dimensional data from AVIRIS San Diego airport dataset 1 are shown in Figure 1. Figure 2 and 3 show the corresponding results obtained by using the CEM and GLRT target detection operators, respectively. In the three groups of experiments, we set the w, t, and β parameters in the proposed algorithm to the corresponding parameters to obtain better results.

|  |  |  |
| --- | --- | --- |
| (a) | (b) | (c) |

**Figure 1.** The target detection AUC value obtained by using the ACE target detection operator on the reduced dimension data from AVIRIS San Diego airport dataset 1: (a) k = 10; (b) k = 50; (c) k = 100.

|  |  |  |
| --- | --- | --- |
| (a) | (b) | (c) |

**Figure 2.** The target detection AUC value obtained using the CEM target detection operator on the reduced dimension data from AVIRIS San Diego airport dataset 1: (a) k = 10; (b) k = 50; (c) k = 100.

|  |  |  |
| --- | --- | --- |
| (a) | (b) | (c) |

**Figure 3.** The target detection AUC value obtained using the GLRT target detection operator on the reduced dimension data from AVIRIS San Diego airport dataset 1: (a) k = 10; (b) k = 50; (c) k = 100.

Figure 1 shows that in the experiments using ACE target detection operator, as the neighbourhood number k increased, the LLTSA algorithm’s performance obviously deteriorated, and the other algorithms’ performance was basically unaffected (The PCA algorithm’s performance was unaffected because it does not contain the neighbourhood number k parameter). As the dimension d of the reduced data increased, the performance of the LPP and the proposed algorithms significantly improved, and the performance of the LLTSA algorithm slightly improved. In contrast, the performance of the NPE and PCA algorithms was basically unaffected. Figure 2 shows that in the experiment using the CEM target detection operator, as the neighbourhood number k increased, the performance of the LLTSA algorithm obviously deteriorated, and the performance of the LPP and proposed algorithms was basically unaffected. As the dimension d of the reduced data increased, the performance of the LPP and the proposed algorithms significantly improved, and the performance of the NPE and LLTSA algorithms slightly improved. In contrast, the performance of the PCA algorithm was basically unaffected. Figure 3 shows that the experimental results using the GLRT and ACE target detection operators are very similar. The results of the three groups of experiments showed that the PCA algorithm’s performance is the worst, demonstrating that the linear dimension reduction algorithm is unsuitable for nonlinear data such as hyperspectral images. The low-dimensional data obtained using the LPP algorithm with different neighbourhood sizes showed better target detection performance, and the low-dimensional data obtained via the proposed algorithm has the best target detection performance.

|  |  |  |
| --- | --- | --- |
| (a) | (b) | (c) |

**Figure 4.** The target detection AUC value obtained using the ACE target detection operator on the reduced dimension data from AVIRIS San Diego airport dataset 2: (a) k = 10; (b) k = 50; (c) k = 100.

|  |  |  |
| --- | --- | --- |
| (a) | (b) | (c) |

**Figure 5.** The target detection AUC value obtained using the CEM target detection operator on the reduced dimension data from AVIRIS San Diego airport dataset 2: (a) k = 10; (b) k = 50; (c) k = 100.

|  |  |  |
| --- | --- | --- |
| (a) | (b) | (c) |

**Figure 6.** The target detection AUC value obtained using the GLRT target detection operator on the reduced dimension data from AVIRIS San Diego airport dataset 2: (a) k = 10; (b) k = 50; (c) k = 100.

Figure 4-6 show the corresponding results obtained on the AVIRIS San Diego airport dataset 2. In the three groups of experiments, we also set the w, t, and β parameters in the proposed algorithm to the corresponding parameters to obtain better results.

Figure 4 shows that in the experiments using ACE target detection operator, as the dimension d of the reduced data increases, the performance of the NPE, LPP, and proposed algorithms was basically unaffected. In contrast, the performance of the LLTSA and PCA algorithms significantly improved. Figure 5 demonstrates that in the experiments using the CEM target detection operator, as dimension d increased, the performance of the NPE and proposed algorithms was better; the performance of the LPP algorithm significantly improved, while the performance of the LLTSA and PCA algorithms slightly decreased. Figure 6 shows that the experimental phenomena using GLRT and ACE were basically the same. From the results of the three groups of experiments, for AVIRIS San Diego airport dataset 2, the neighbourhood number k hardly affected the target detection performance of the manifold learning algorithm. The performance of the NPE algorithm on AVIRIS San Diego airport dataset 2 was obviously better than that on AVIRIS San Diego airport dataset 1, which may be because AVIRIS San Diego airport dataset 2 contains less noise and the NPE algorithm is more sensitive to noise. The proposed algorithm achieves the best target detection performance on both AVIRIS San Diego airport datasets 1 and 2, demonstrating that the proposed algorithm has widespread applicability.

For different window size w and weight parameter t, Figure 7 (a) - (c) shows the target detection AUC values obtained using the ACE, CEM, and GLRT target detection operators on the low-dimensional data from AVIRIS San Diego Airport dataset 1. Figure 8 (a) - (c) shows the corresponding results obtained on AVIRIS San Diego Airport dataset 2. In the two groups of experiments, the k、β and d parameters in the proposed algorithm were set to the corresponding parameters to obtain better results.

|  |  |  |
| --- | --- | --- |
| (a) | (b) | (c) |

**Figure 7.** The target detection AUC values on AVIRIS San Diego airport dataset 1 obtained by proposed algorithm selecting different w and t parameters: (a) ACE target detection operator; (b) CEM target detection operator; (c) GLRT target detection operator.

|  |  |  |
| --- | --- | --- |
| (a) | (b) | (c) |

**Figure 8.** The target detection AUC values on AVIRIS San Diego airport dataset 2 obtained by proposed algorithm selecting different w and t parameters: (a) ACE target detection operator; (b) CEM target detection operator; (c) GLRT target detection operator.

Figure 7 shows that for AVIRIS San Diego airport dataset 1, the AUC target detection value gradually decreased as window w increased. The reason may be related to the WMF’s characteristics. When the window size w is small, the WMF can eliminate the influence of hot pixels, increasing the similarity between homogeneous pixels and improving the algorithm’s performance. However, when the window size w is large, it will inevitably contain heterogeneous pixels. The similarity between homogeneous pixels will decrease, deteriorating the algorithm’s performance. The AUC target detection value fluctuates as the weight parameter t changes. When weight parameter t is 0, the algorithm’s performance improves. For good experimental results comprehensively considering the algorithm’s running efficiency, w = 3 and t = 0 were selected. As shown in Figure 8, the AVIRIS San Diego airport dataset 2 experiment reached the same conclusion.

For different weighting parameters β, Figure 9 (a) - (c) shows the target detection AUC values obtained by the ACE, CEM, and GLRT target detection operators on the low-dimensional data from the AVIRIS San Diego airport datasets 1 and 2, respectively. In the experiments, the k, t, w, and d parameters in the proposed algorithm are all set to the corresponding parameters when better results are obtained.

|  |  |  |
| --- | --- | --- |
| (a) | (b) | (c) |

**Figure 9.** The target detection AUC values on AVIRIS San Diego airport datasets 1 and 2 obtained by proposed algorithm selecting different β parameters. (a) ACE target detection operator; (b) CEM target detection operator; (c) GLRT target detection operator.

Figure 9 shows that when β is 1, the algorithm has a better effect, so we set the value of β as 1.

Table 1-6 list the optimal target detection AUC values and corresponding parameter settings of the proposed algorithm and comparison algorithms on AVIRIS San Diego airport datasets 1 and 2, respectively. The parameters corresponding to the optimal target detection AUC value of the proposed algorithm are: t = 0, w = 3, and β = 1.

**Table 1.** Optimal target detection results on AVIRIS San Diego airport dataset 1

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dimensionality**  **reduction method** |  | **ACE detector** | | |
| **AUC** | **Dimensionality** | **k** |
| Original image |  | 0.8094 | 189 | - |
| NPE | 0.5118 | 8 | 100 |
| LPP | 0.7352 | 8 | 100 |
| LLTSA | 0.6531 | 8 | 10 |
| PCA | 0.5596 | 2 | - |
| Proposed algorithm | 0.8079 | 10 | 10 |

**Table 2.** Optimal target detection results on AVIRIS San Diego airport dataset 1

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dimensionality**  **reduction method** |  | **CEM detector** | | |
| **AUC** | **Dimensionality** | **k** |
| Original image |  | 0.8674 | 189 | - |
| NPE | 0.5832 | 10 | 50 |
| LPP | 0.8224 | 10 | 100 |
| LLTSA | 0.6133 | 8 | 10 |
| PCA | 0.4756 | 4 | - |
| Proposed algorithm | 0.8891 | 10 | 10 |

**Table 3.** Optimal target detection results on AVIRIS San Diego airport dataset 1

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dimensionality**  **reduction method** |  | **GLRT detector** | | |
| **AUC** | **Dimensionality** | **k** |
| Original image |  | 0.8094 | 189 | - |
| NPE | 0.5117 | 8 | 100 |
| LPP | 0.7378 | 8 | 100 |
| LLTSA | 0.6598 | 8 | 10 |
| PCA | 0.5316 | 6 | - |
| Proposed algorithm | 0.8170 | 10 | 10 |

**Table 4.** Optimal target detection results on AVIRIS San Diego airport dataset 2

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dimensionality**  **reduction method** |  | **ACE detector** | | |
| **AUC** | **Dimensionality** | **k** |
| Original image |  | 0.9517 | 189 | - |
| NPE | 0.9157 | 6 | 10 |
| LPP | 0.9101 | 8 | 100 |
| LLTSA | 0.8006 | 10 | 10 |
| PCA | 0.8032 | 10 | - |
| Proposed algorithm | 0.9755 | 2 | 100 |

**Table 5.** Optimal target detection results on AVIRIS San Diego airport dataset 2

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dimensionality**  **reduction method** |  | **CEM detector** | | |
| **AUC** | **Dimensionality** | **k** |
| Original image |  | 0.9669 | 189 | - |
| NPE | 0.9435 | 10 | 10 |
| LPP | 0.9447 | 4 | 100 |
| LLTSA | 0.9079 | 2 | 100 |
| PCA | 0.9131 | 2 | - |
| Proposed algorithm | 0.9779 | 6 | 100 |

**Table 6.** Optimal target detection results on AVIRIS San Diego airport dataset 2

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dimensionality**  **reduction method** |  | **GLRT detector** | | |
| **AUC** | **Dimensionality** | **k** |
| Original image |  | 0.9517 | 189 | - |
| NPE | 0.9201 | 2 | 10 |
| LPP | 0.9157 | 4 | 10 |
| LLTSA | 0.8058 | 10 | 10 |
| PCA | 0.8088 | 10 | - |
| Proposed algorithm | 0.9793 | 2 | 100 |