

View-angle Invariant Object Monitoring Without Image Registration Xin Zhang^{1,2}, Chunlei Huo^{1,2}, Chunhong Pan^{1,2}

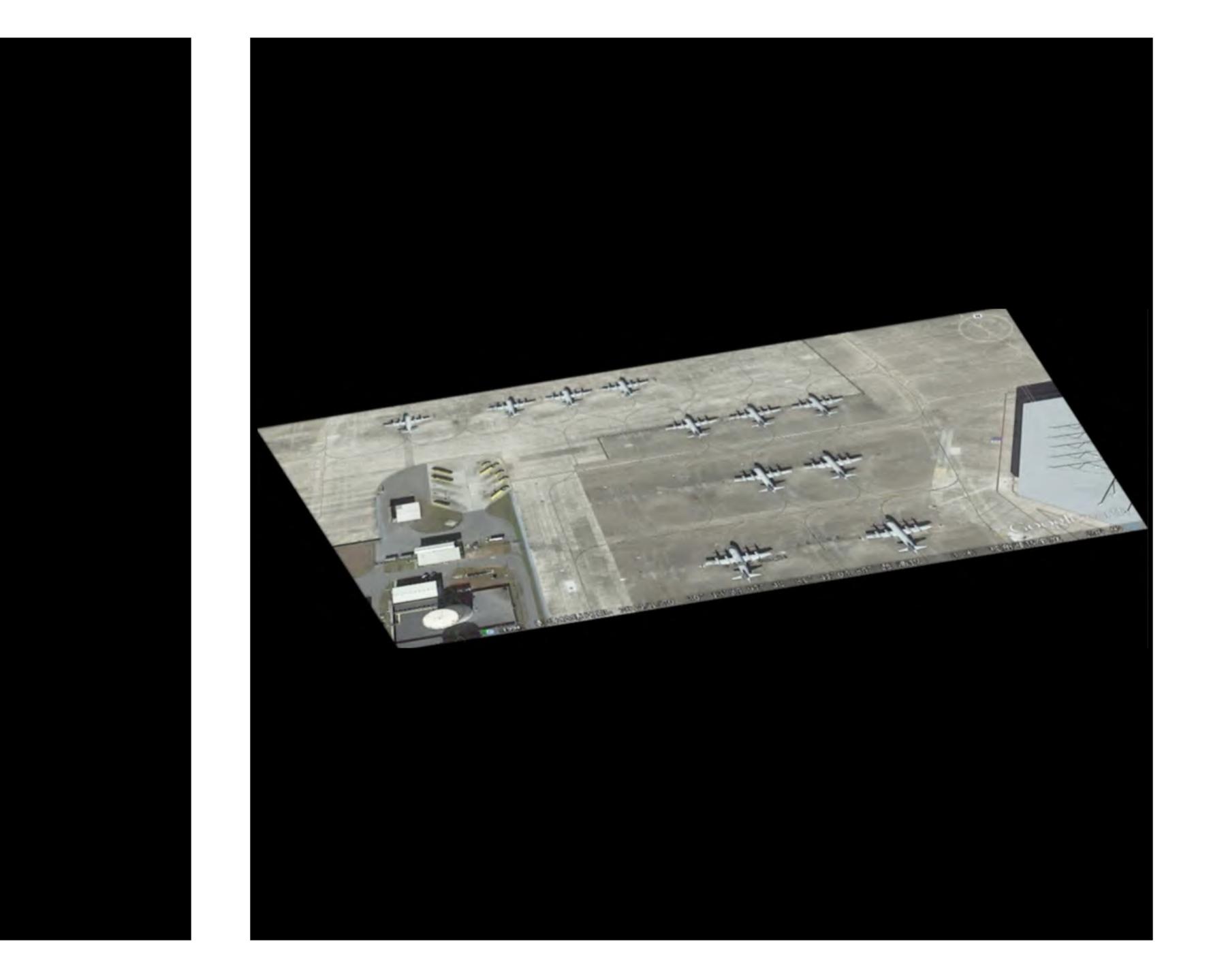
1. NLPR, Institute of Automation, Chinese Academy of Sciences 2. School of Artificial Intelligence, University of Chinese Academy of Sciences.



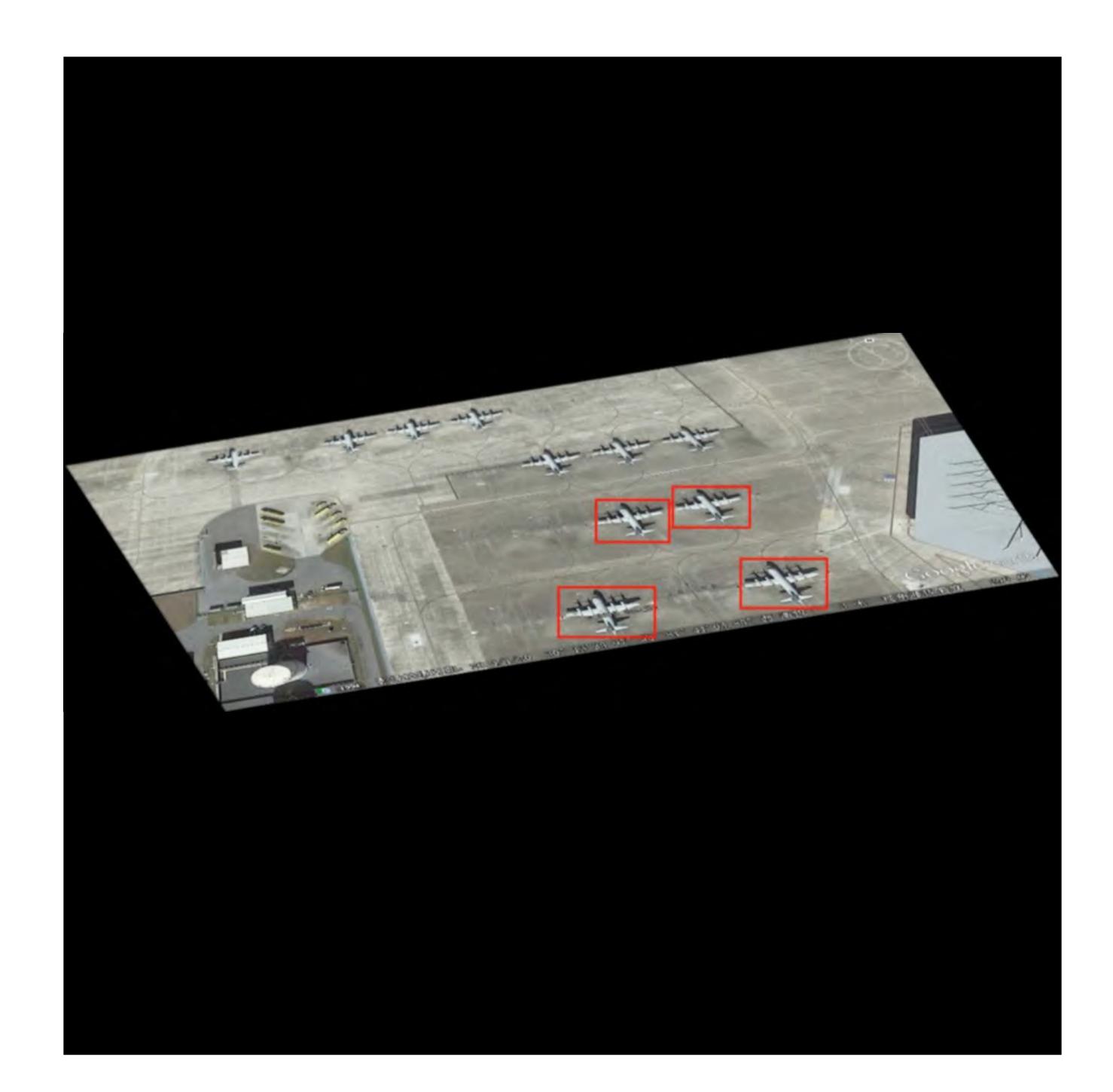
Introduction



Input: Multi-temporal remote sensing images of different times in the same area.



Ouput: The result of object monitoring.



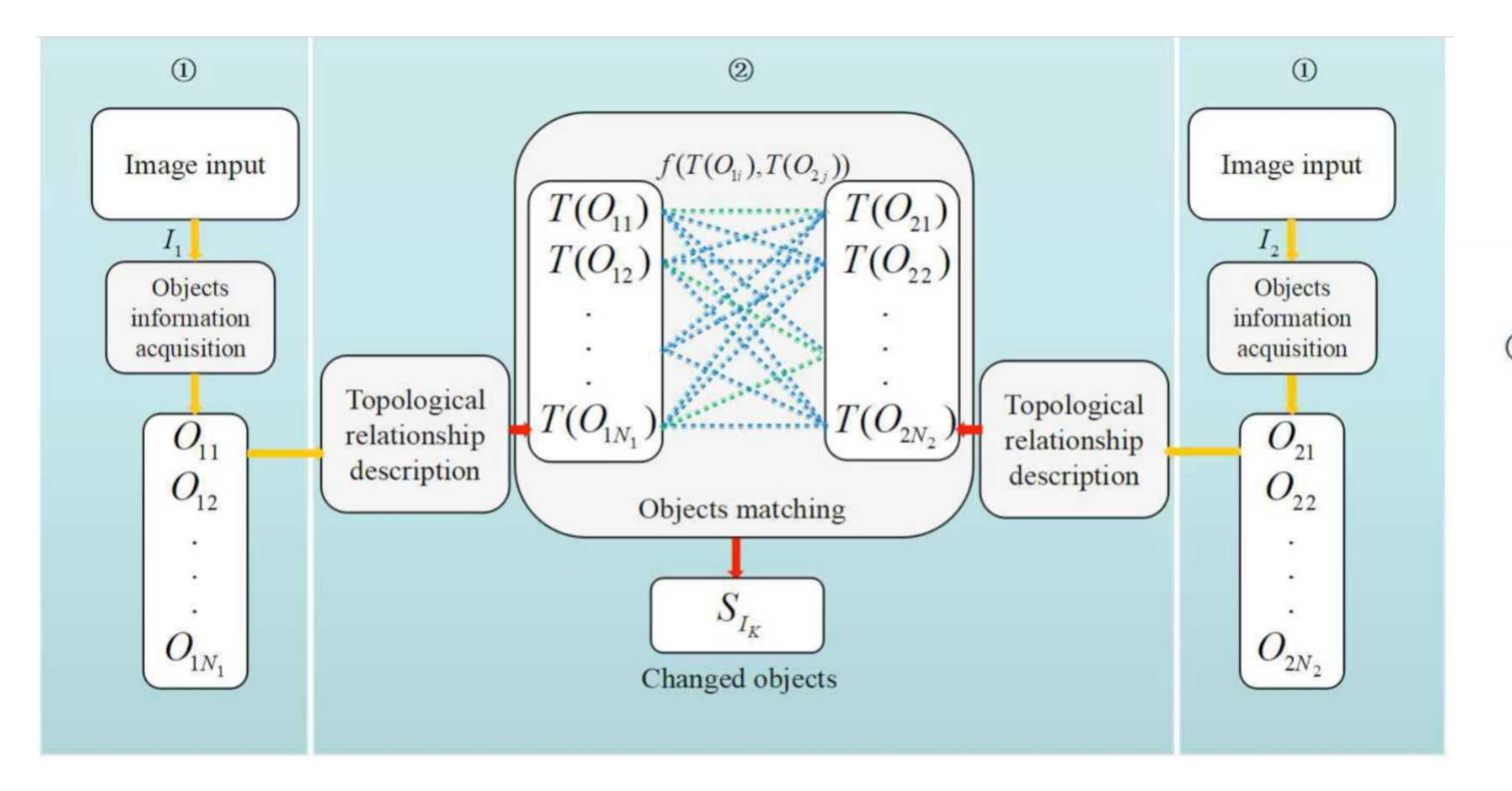
Introduction

Limitations of the traditional change detection methods:

• The traditional change detection performance depends highly on the accuracy of image registration. • The results obtained by the current change detection algorithm are pixel-level changes, it is lack of rich semantic information of the changed objects.

 $I_{change}(p_i) = S(\tilde{I}_1(p_i), \tilde{I}_2(p_i)) \in \{0, 1\}$

The framework of object monitoring Decoupling the object-level change detection task into two sub-tasks: objects information acquisition and matching.



1 Affine invariant object detection

(2) Robust point matching

Match Unmatched

and matching.

1. The framework of object monitoring Different from traditional change detection methods, we innovatively decouple the object-level change detection task into two sub-tasks: objects information acquisition

$$C_{I_1}(i) = \sum_{j=1}^{N_2} f(T(O_{1i}), T(O_2))$$
$$C_{I_2}(j) = \sum_{i=1}^{N_1} f(T(O_{1i}), T(O_2))$$

 $S_{I_K} = \{O_{Kl} \mid C_{I_K}(l) = 0, l = 1, 2, \dots, N_K\}, K = 1, 2$

$(2_i)) \in \{0, 1\}, i = 1, 2, \dots, N_1$

$(2_i)) \in \{0, 1\}, j = 1, 2, \ldots, N_2$

- - longitude and latitude. inclination parameter t.

Latitude $\theta \longrightarrow \text{Inclination } t$

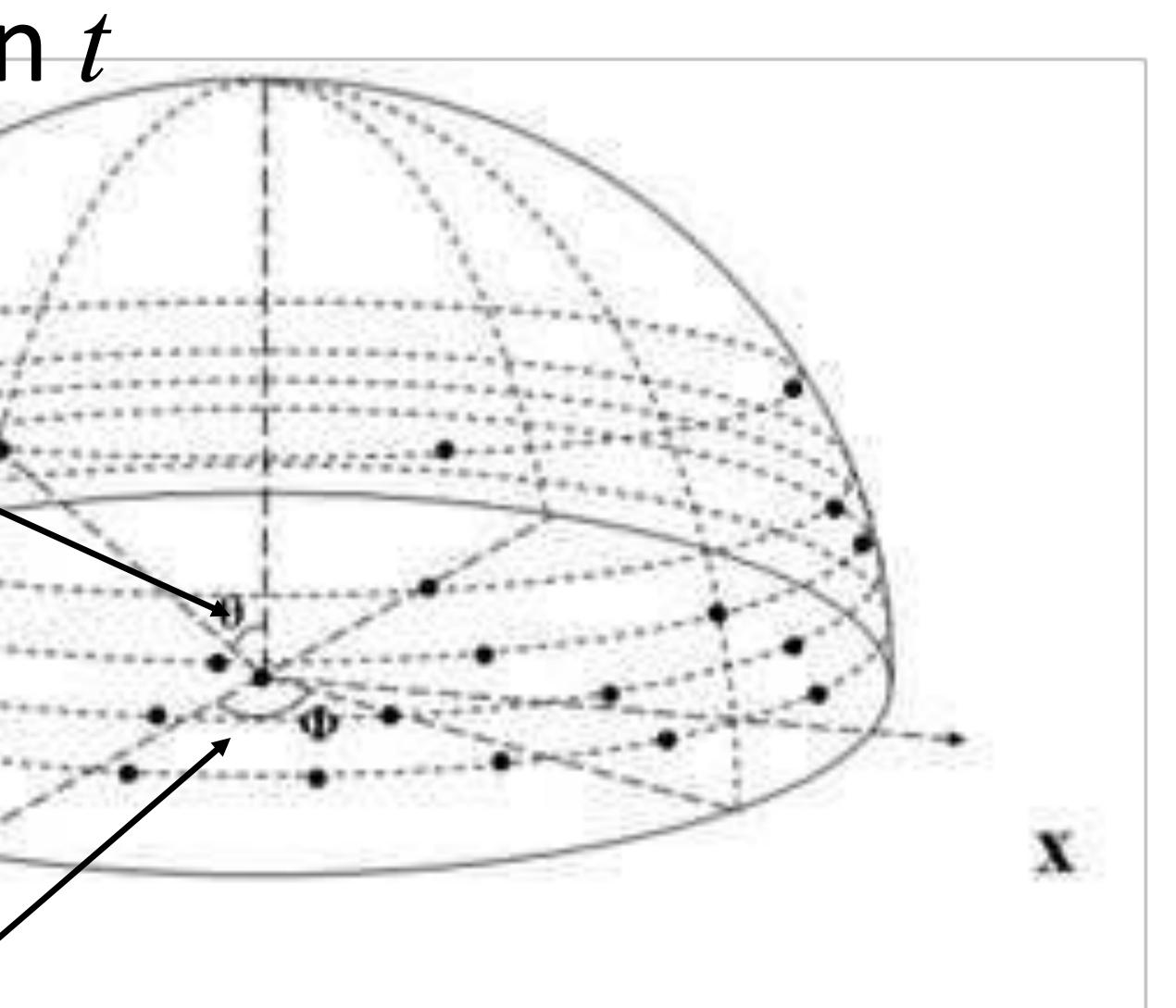
 $t=\sqrt{2}, \ \theta=45$

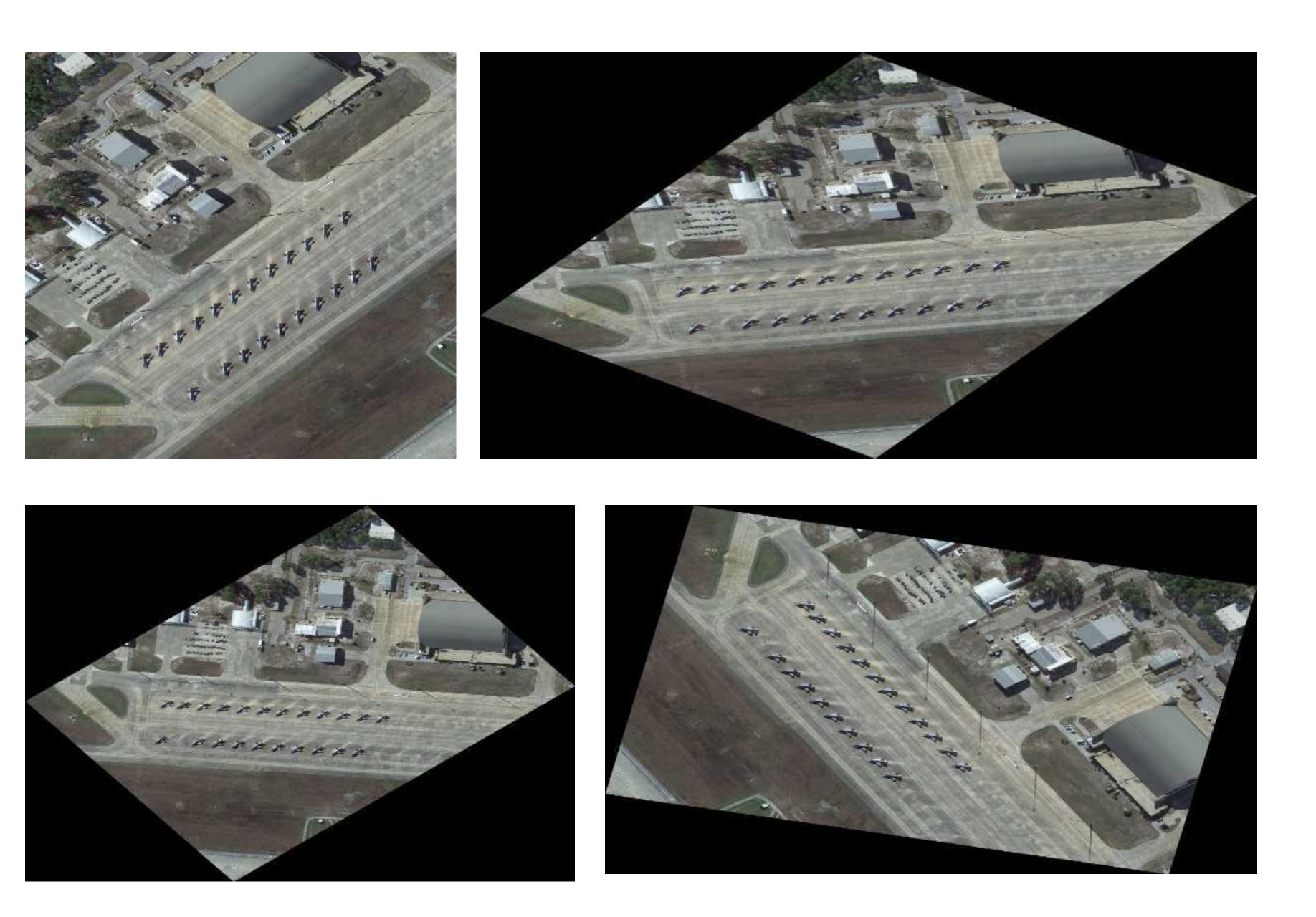
 $t=2, \theta=60^{\circ}$

 $t = 2 \sqrt{2}, \quad \theta = 70^{\circ}$ $t = 4, \quad \theta = 75^{\circ}$

 $t=2\sqrt{2}, \ \theta=80^{\circ}$

2. Affine Invariant Object Detection • Multi-view images are generated by simulating the position of the camera, including - Each training image is rotated by the longitude parameter Φ and tilted by the

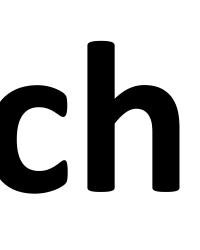


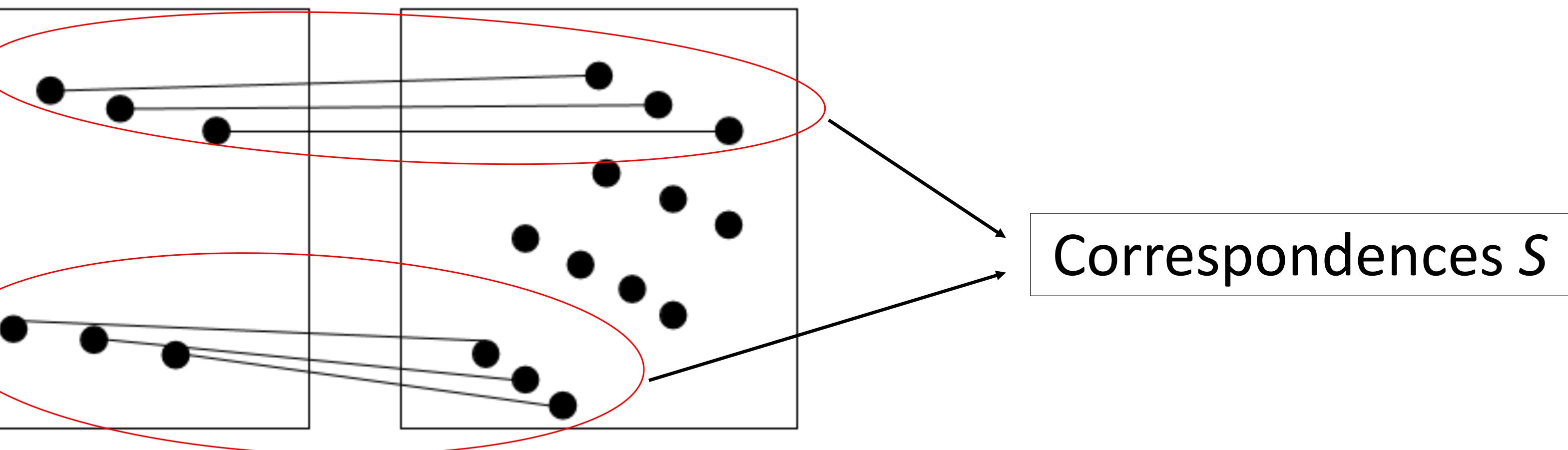


3. Robust Point Matching

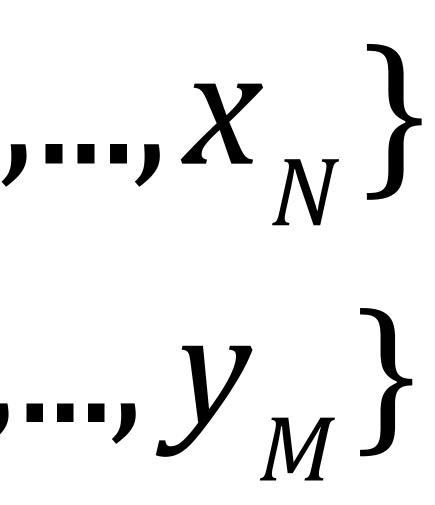


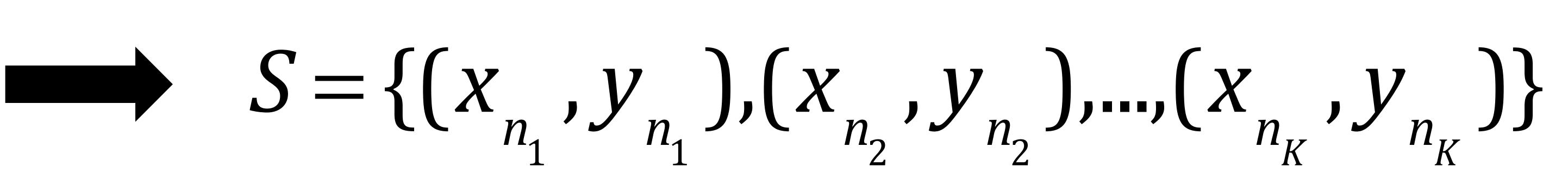
 $X = \{X_1, X_2, ..., X_N\}$ $Y = \{y_1, y_2, ..., y_M\}$





Model point set Y Target point set X

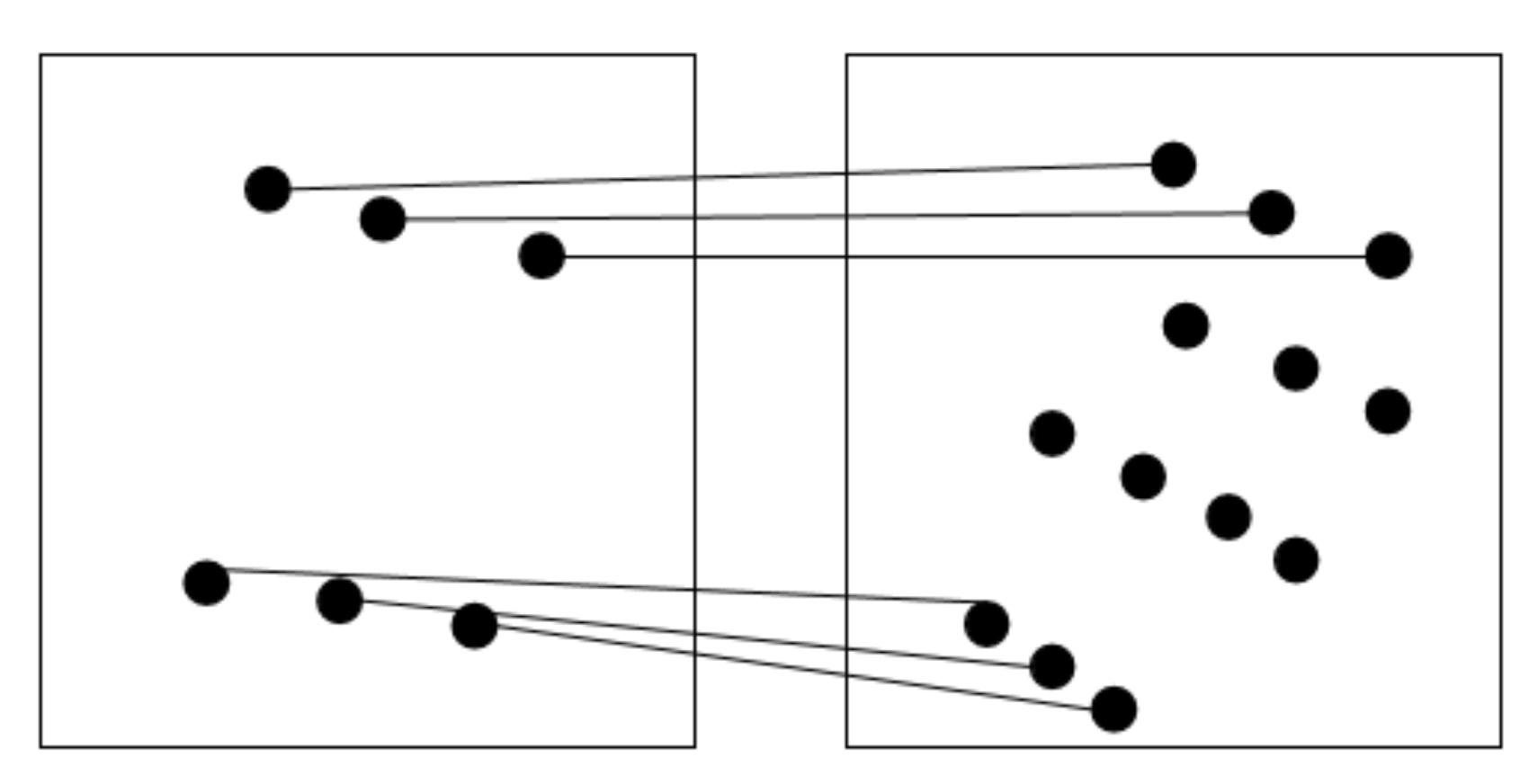




3. Robust Point Matching

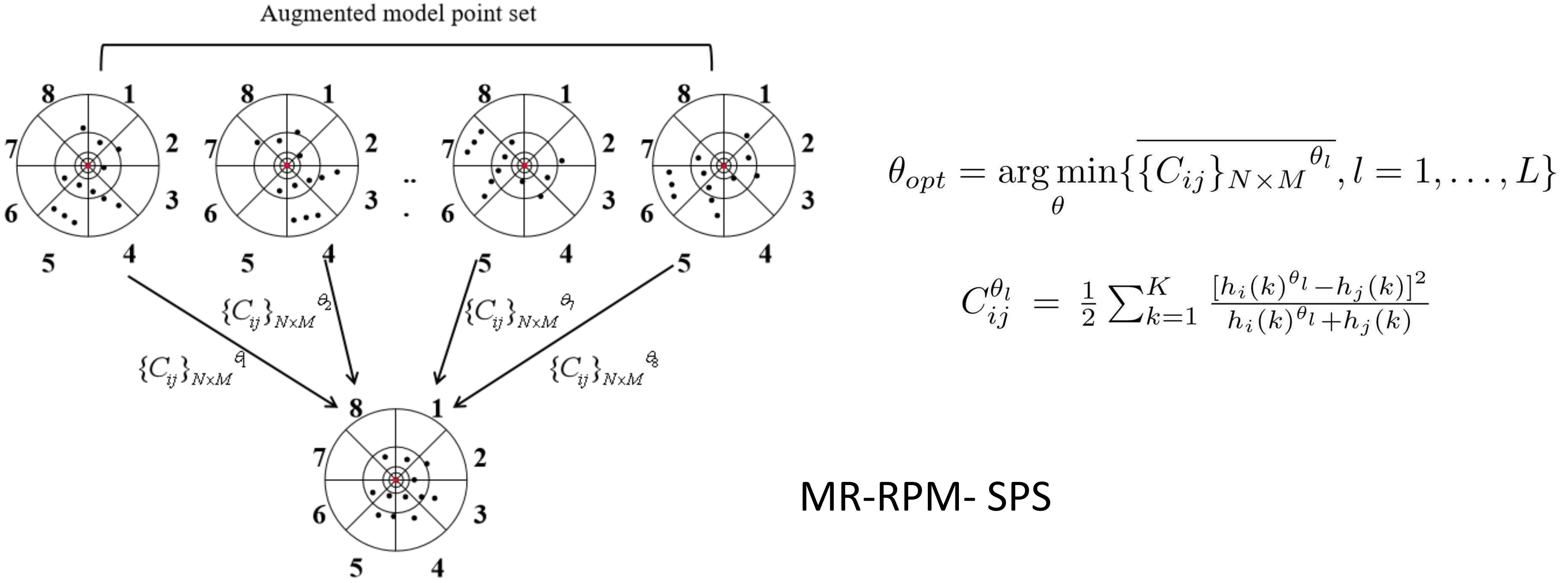
[1] Jiayi Ma, Jia Wu, Ji Zhao, Junjun Jiang, Huabing Zhou, and Quan Z Sheng, "Nonrigid point set registration with robust transformation learning under manifold regularization," IEEE Transactions on Neural Networks, pp. 1–14, 2018. [2] Serge Belongie, Jitendra Malik, and J Puzicha, "Shape context: A new descriptor for shape matching and object recognition," pp. 831–837, 2000.

• MR-RPM[1] consider shape context [2] algorithm as topological relationship descriptor. By calculating the neighborhood distribution of each point, the point can be encoded. If there is a group of point pair in the two point sets whose context encoding distance is very close, we can assume that this two points have a high probability of matching. • Since objects contained in the images may be fewer and the topological relationship between small point sets is weak!



3. Robust Point Matching

sets matching.



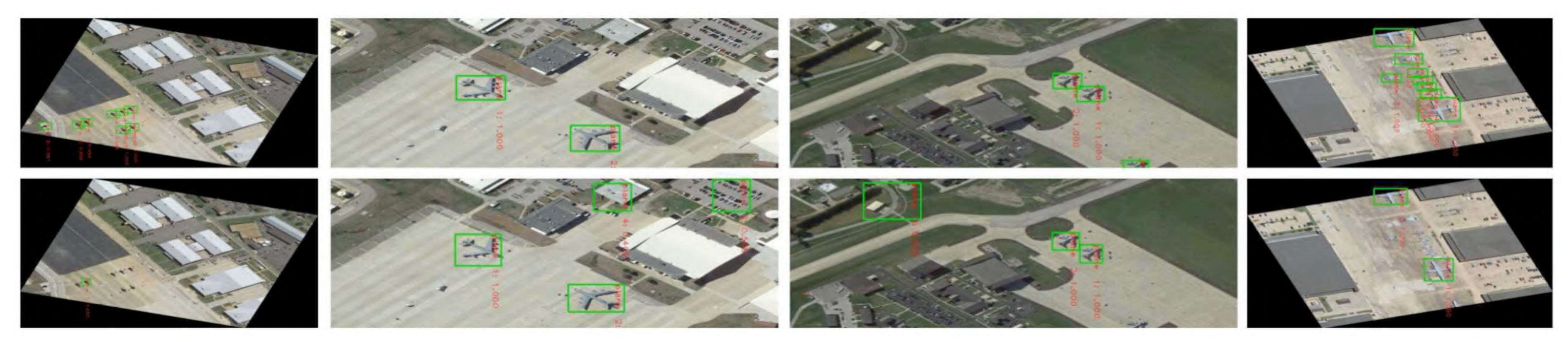
• An improved shape context algorithm is presented to deal with small point

Target point set

- - 700 high resolution remote sensing images containing planes are used to generate
 - multi-view images. Each image generates 43 images with different view angles.
 - Each of the models is trained for 602000 iterations using 1 Nvidia Titan Xp (12GB) GPU.
 - 3000 test images are generated by 300 remote sensing images through the affine transformation.

1. Experiment on Object detection

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Aifronn

FRCNN



Method	AP^{50}
FRCNN AiFRCNN	97.43 99.48

AP^{60}	AP^{70}
96.59	92.25
98.69	92.59

Approach

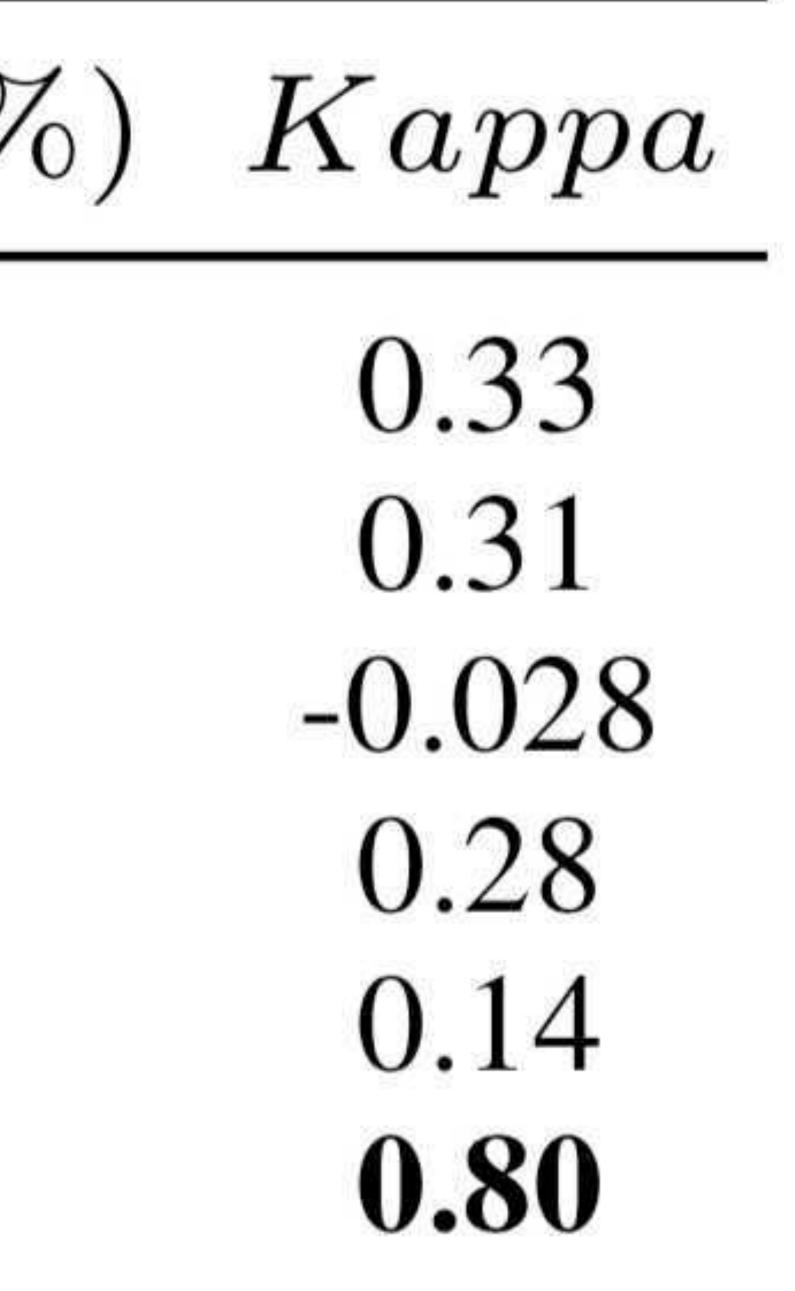
Registration-based approach DNN-based approach MSER+ASIFT AiFRCNN+CPD AiFRCNN+MR-RPM AiFRCNN+MR-RPM-SPS



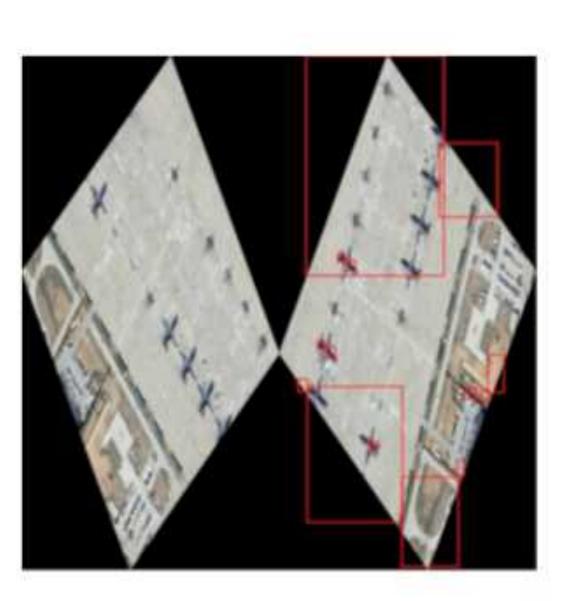
2. Experiments on Change Detection

26.1537.343.87 23.2227.716.74

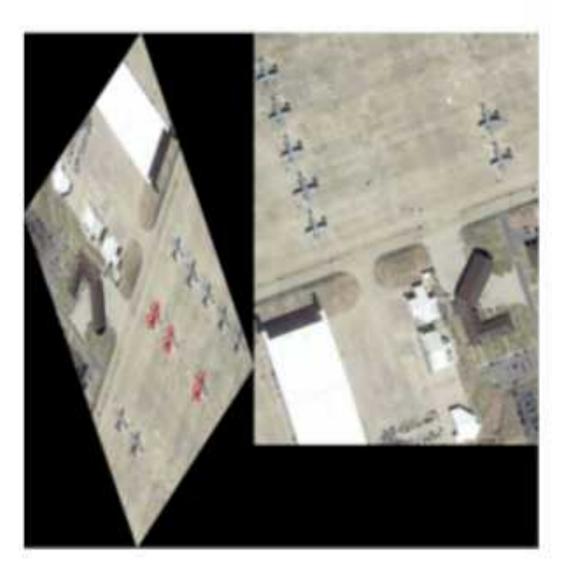
FDR(%) MDR(%) PCC(%) Kappa39.55 69.5 23.0266.3051.2759.2 48.8268.53 58.2762.4490.86 14.17



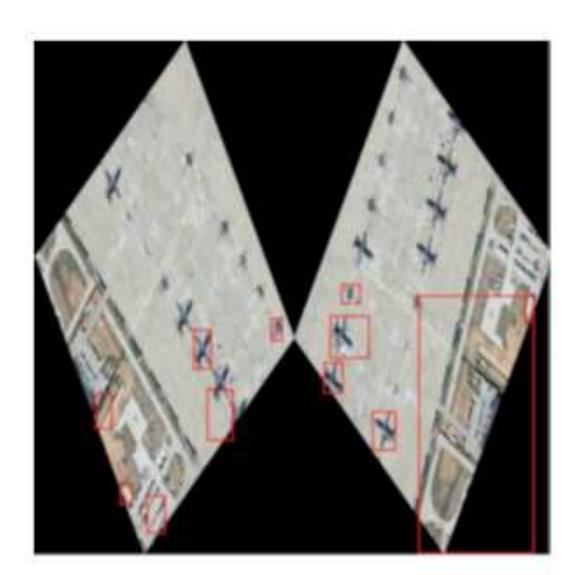
2. Experiments on Change Detection



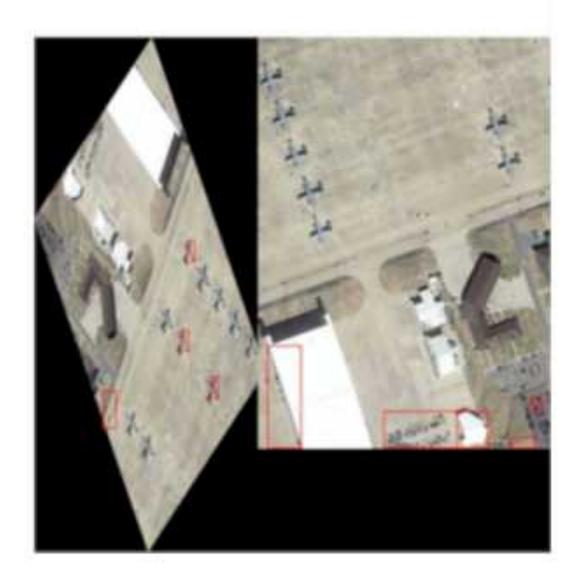




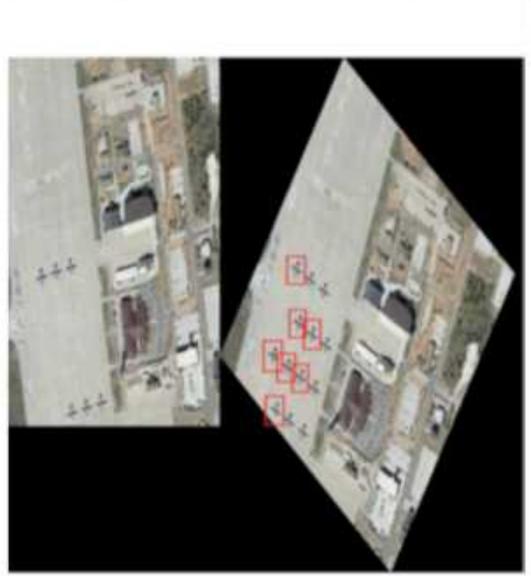


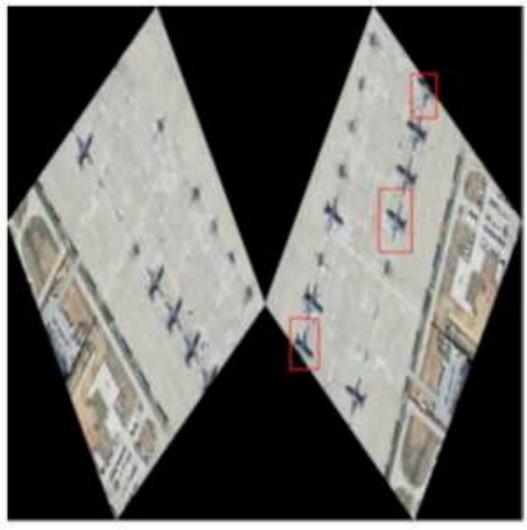


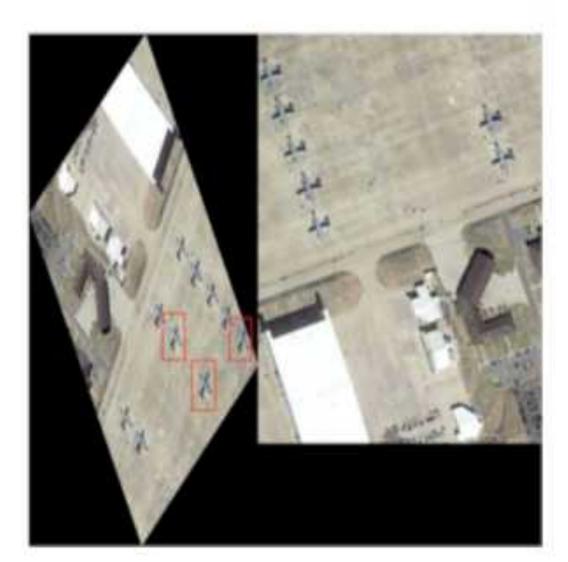


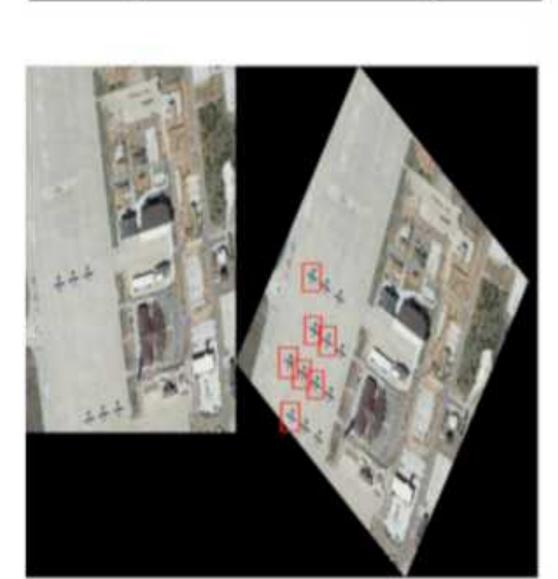


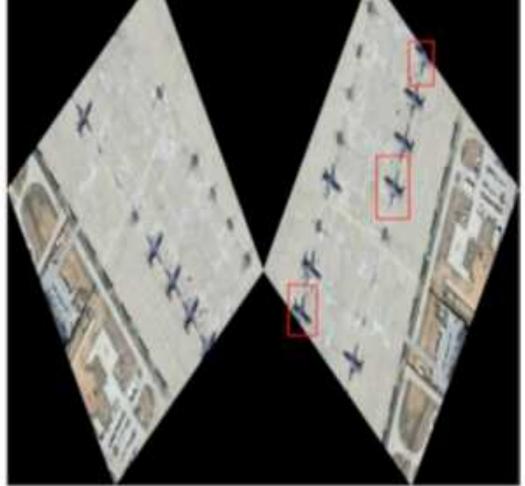


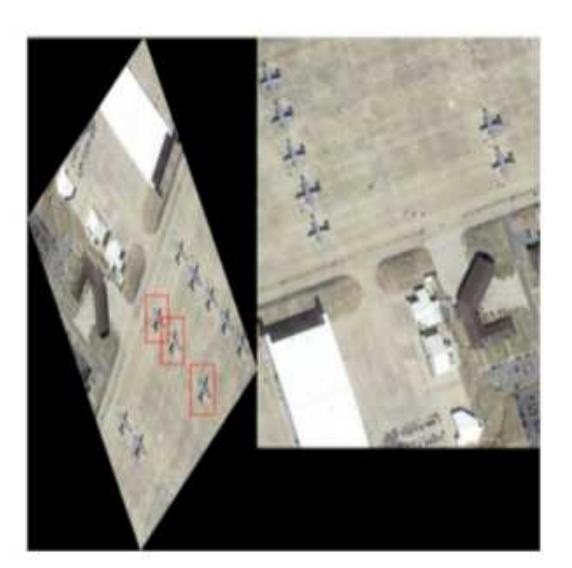




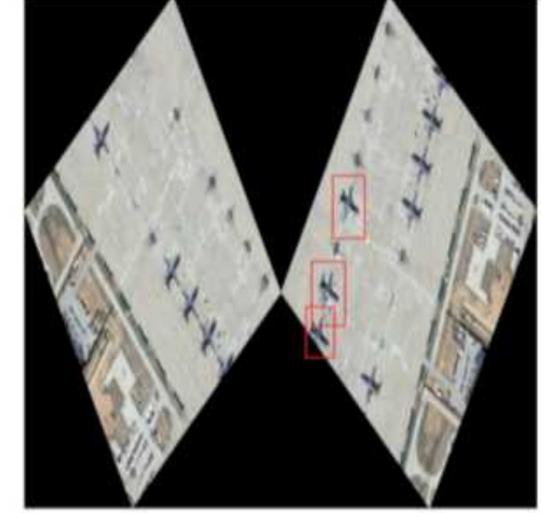




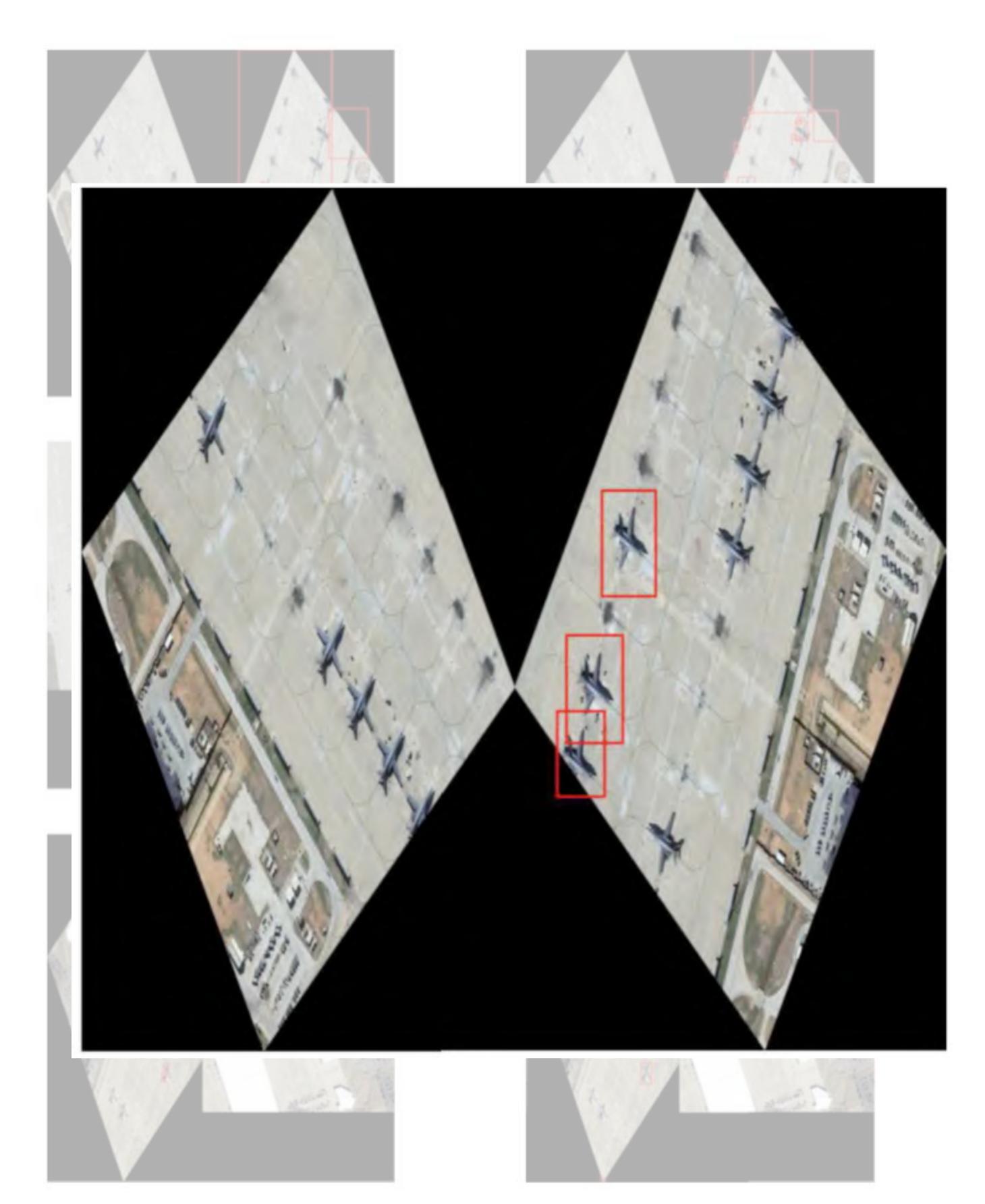


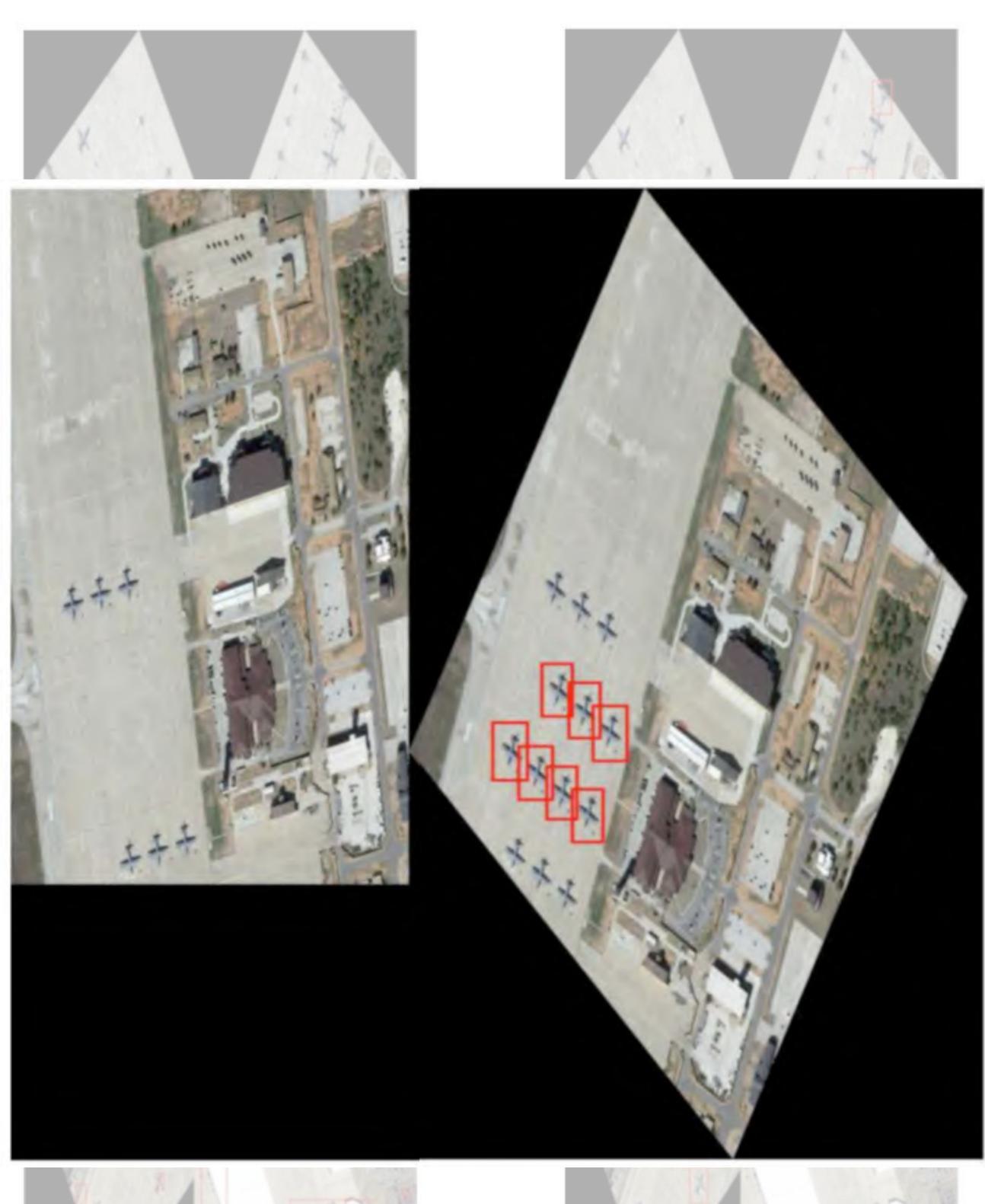


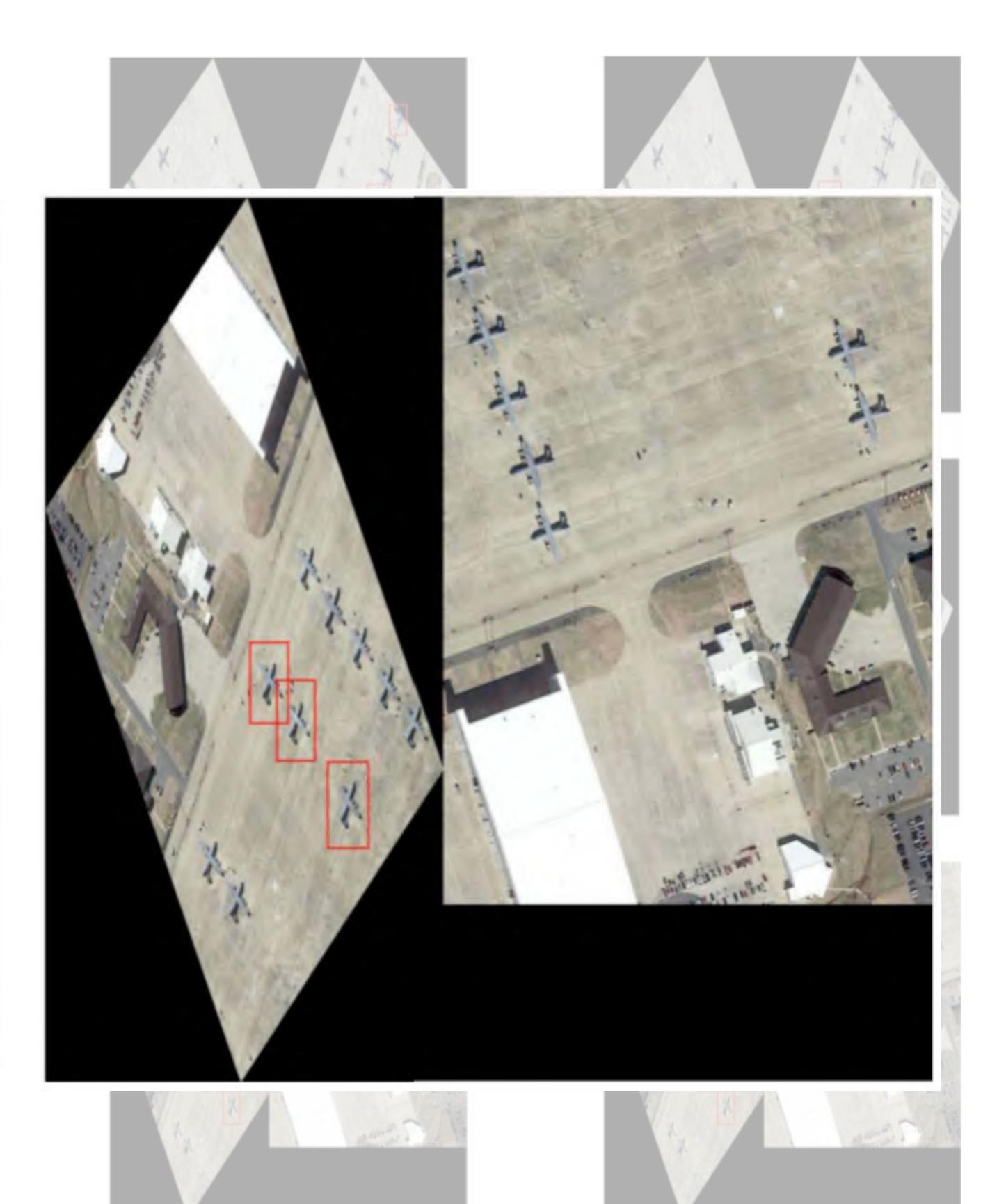




2. Experiments on Change Detection

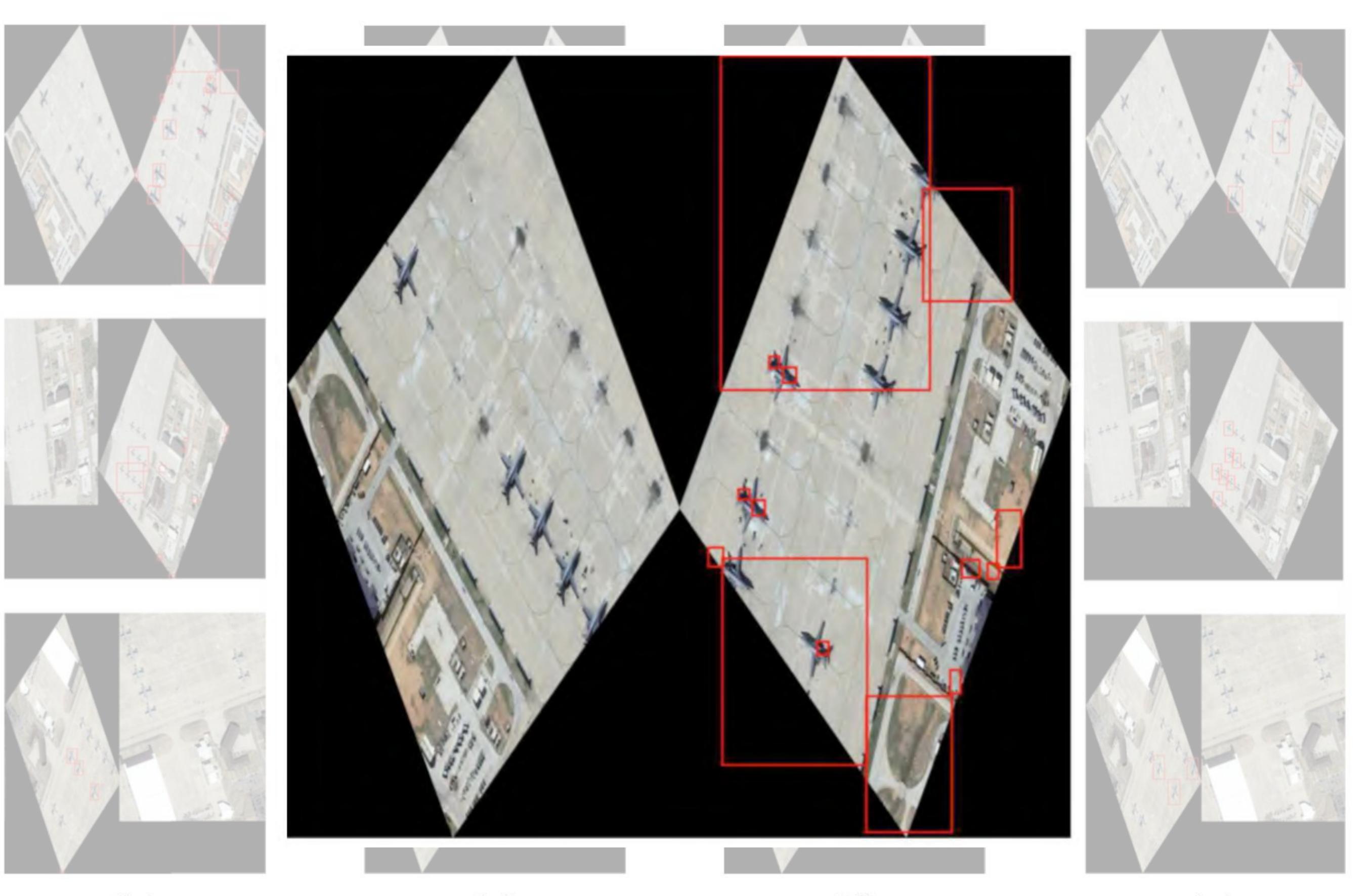






2. Experiments on Change Detection





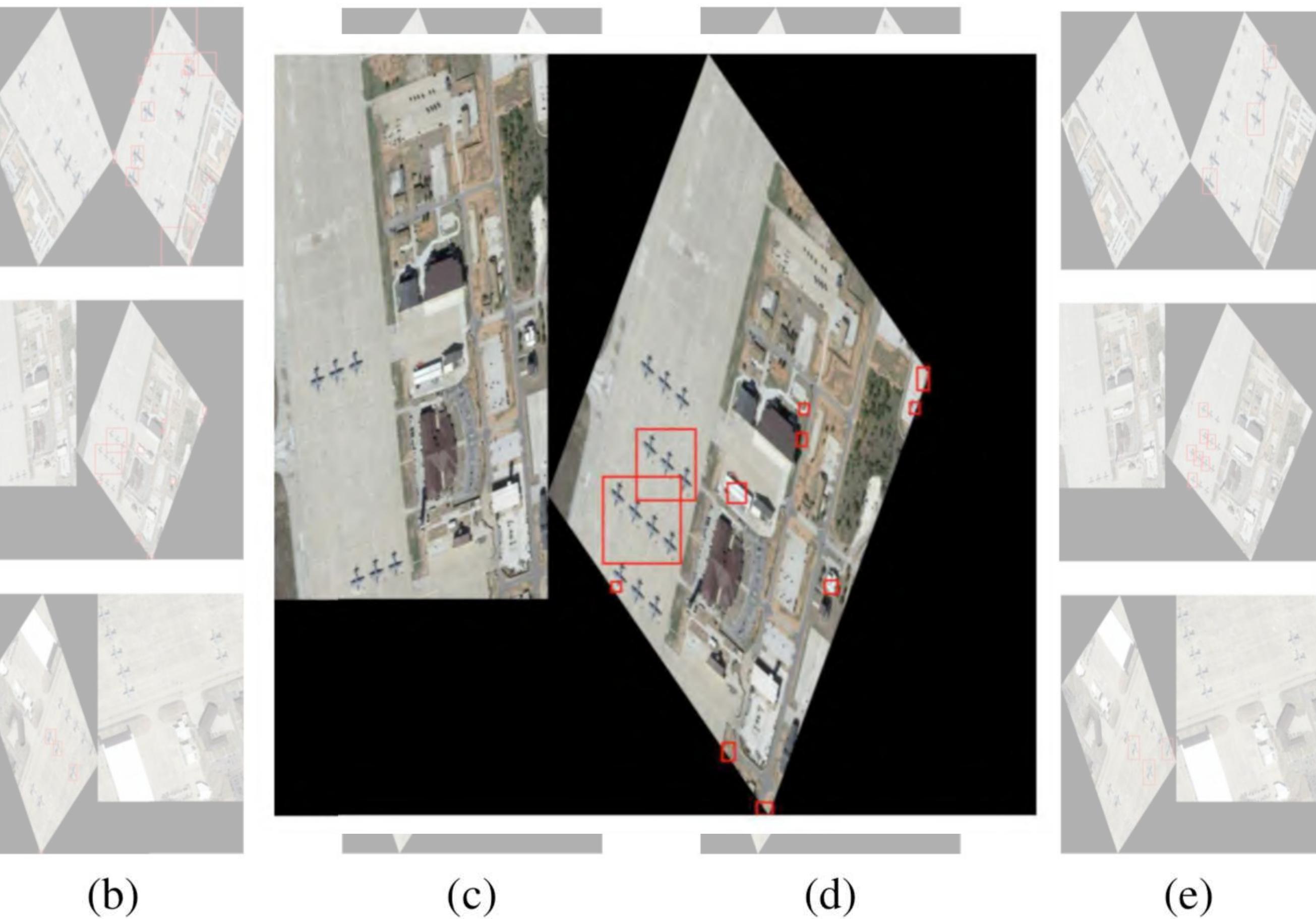






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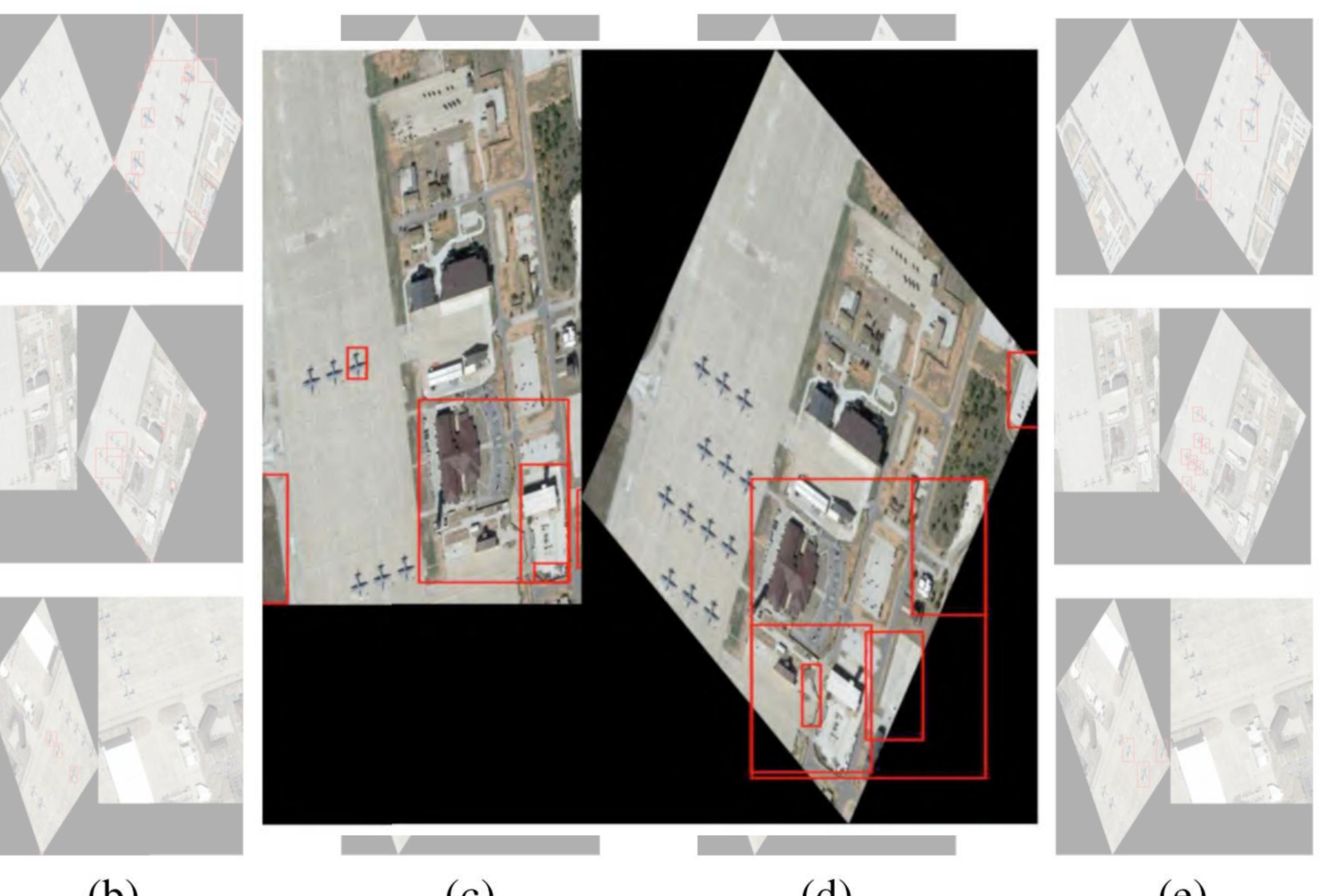






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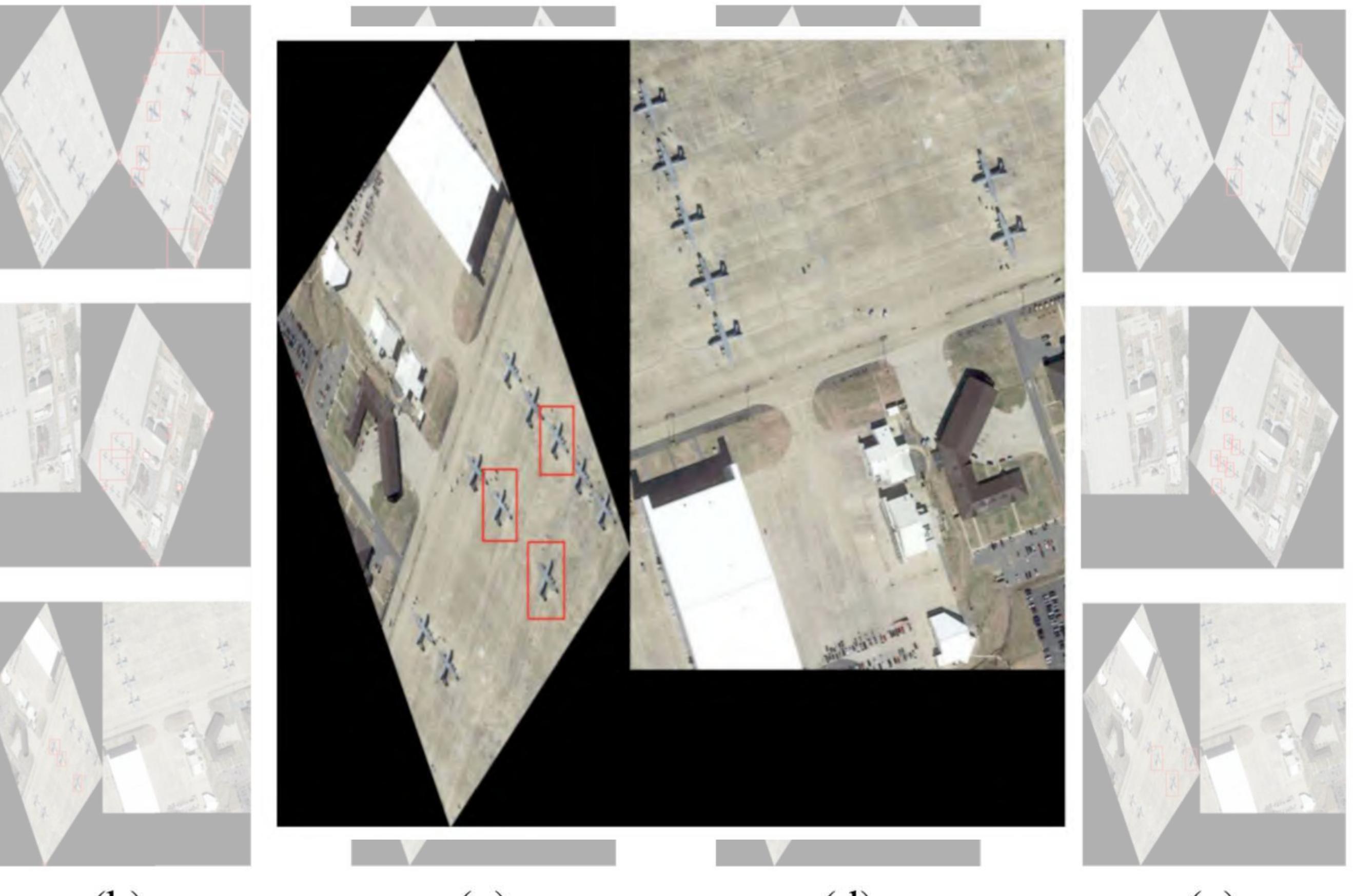


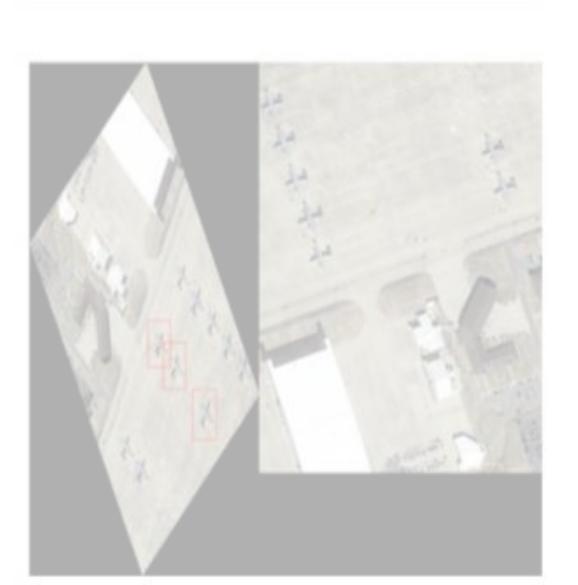




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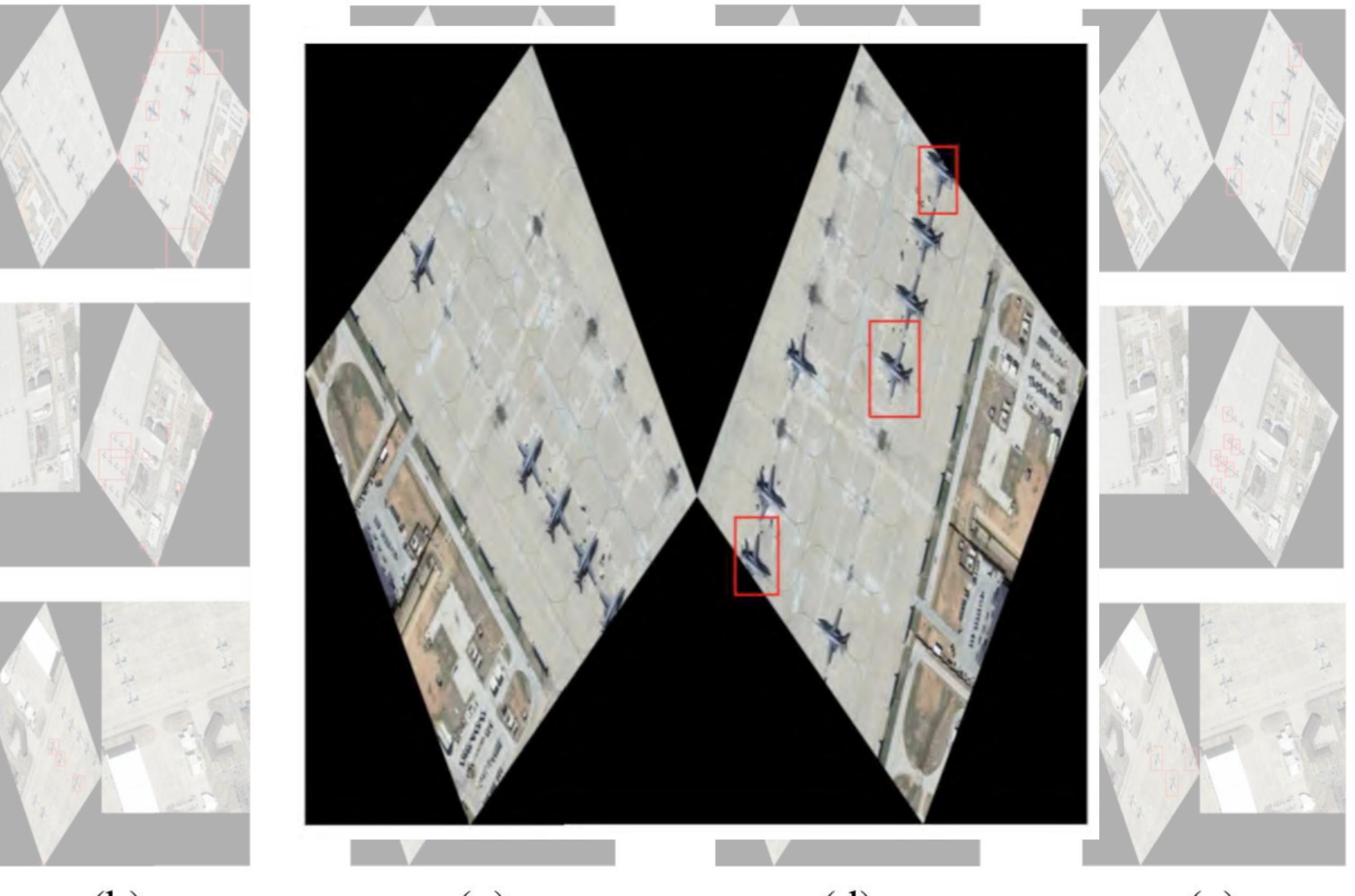




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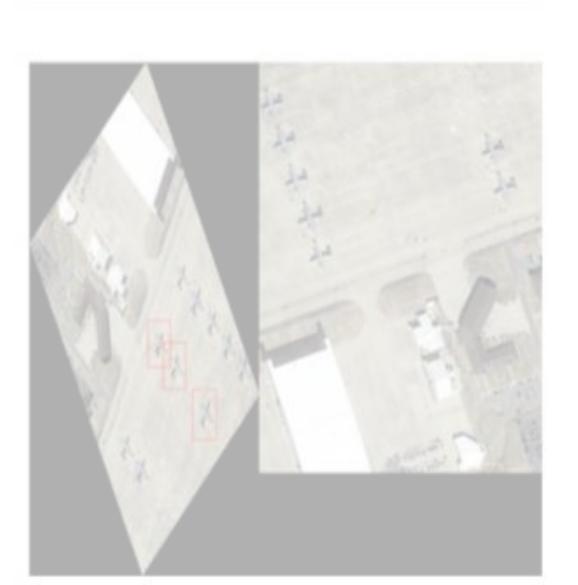


(b) (c)(a) (a) Registration-based approach, (b) DNN-based approach, (c) MSER+ASIFT, (d) AiFRCNN+CPD, (e) AiFRCNN+MR-RPM, (f) AiFRCNN+MR-RPM-SPS.



(d) (e)

(f)

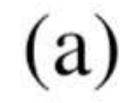




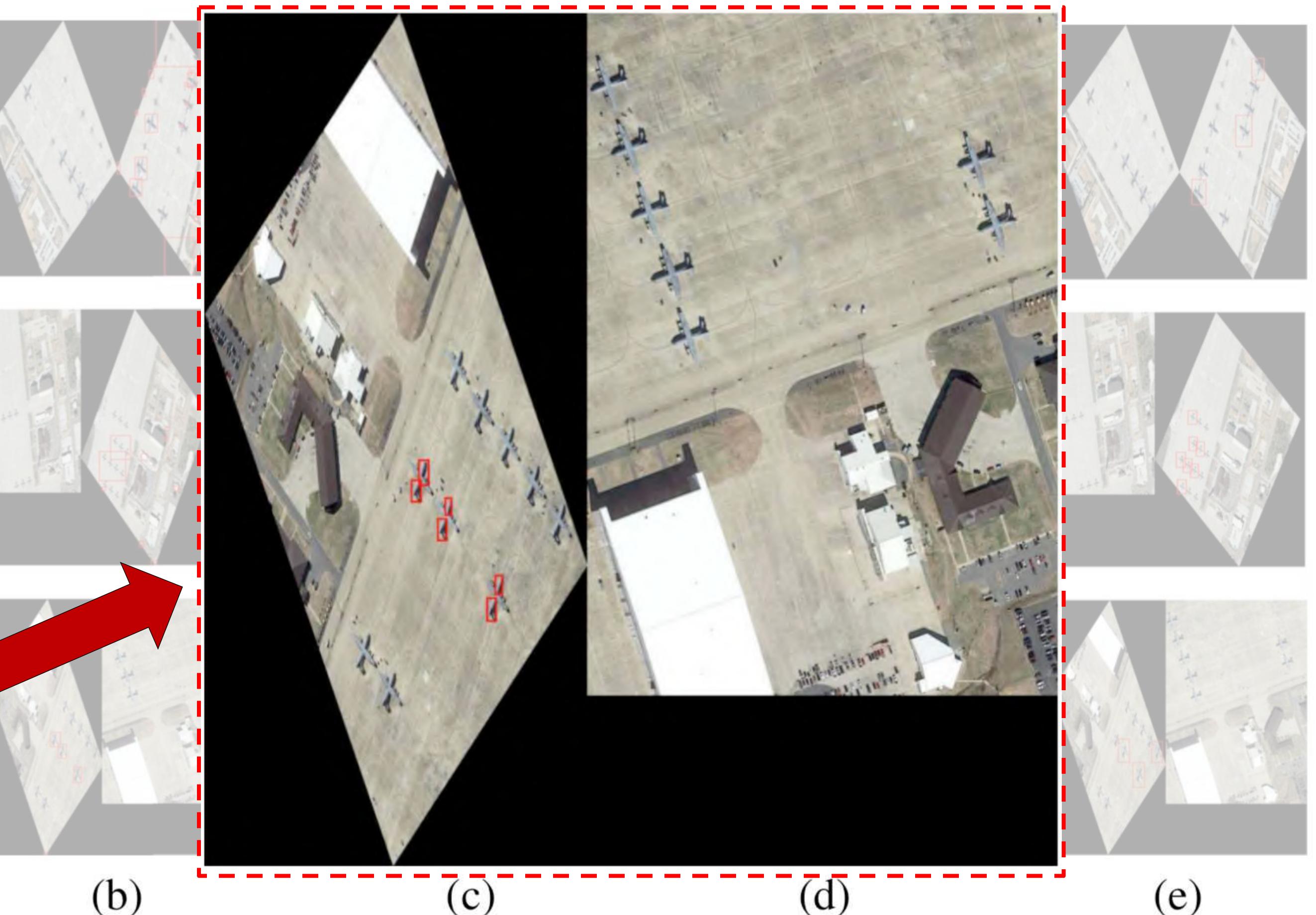


2. Experiments on Change Detection





(f)(a) Registration-based approach, (b) DNN-based approach, (c) MSER+ASIFT, (d) AiFRCNN+CPD, (e) AiFRCNN+MR-RPM, (f) AiFRCNN+MR-RPM-SPS.



(b)

(c)







Conclusion

and point sets matching.

 It is robust to view angle variation without registration. • The result is rich in semantic information.

An novel object-specific change detection approach is proposed for objects monitoring task, which decomposes the task into object detection









Future Work

The proposed approach will be evaluated on heterogeneous multitemporal images.







