

# Matching UAV-Based Simulated High-Resolution SAR and Real SAR Images

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## Abstract

Our experiment focuses on generating simulated high-resolution (HR) Synthetic Aperture Radar (SAR) images from the photogrammetric 3D model derived from Unmanned Aerial Vehicle (UAV) imagery. The goal is to match these simulated images with real SAR data of complex scenes containing vegetation, buildings, roads, and the construction of receiving antennas. Simulated SAR reflectivity map was based on ray tracing techniques.

Two feature matching algorithms, namely Scale-Invariant Feature Transform (SIFT) and Oriented FAST and Rotated BRIEF (ORB) were employed for co-registration of the simulated to the real SAR images. The effectiveness of these algorithms is evaluated by their matching rates. The experiment results of the matching process highlight the superior performance of ORB over SIFT, attributed to its robustness against rotation variations and noise. ORB emerges as a versatile choice for high-resolution real and simulated SAR registration tasks.

## 1. Introduction

Synthetic Aperture Radar (SAR) imagery plays a crucial and important role in Remote Sensing applications by offering high-resolution and all-weather imaging capabilities. Its versatility in capturing detailed information from complex scenes makes it invaluable for various fields, including environmental monitoring, disaster management, and defense reconnaissance. However, obtaining SAR images with the desired resolution and accuracy can be challenging, especially in scenarios where ground truth data is limited or inaccessible. While SAR simulation can fill these gaps and be significant in algorithm design, mission planning, change detection, and SAR data analysis.

This study focuses on the generation of simulated high-resolution SAR images based on a photogrammetric 3D model derived from UAV imagery. The aim is to simulate SAR reflectivity maps and subsequently match these simulated images with real SAR data captured from a complex scene.

Our experiment utilized ray tracing-based simulators such as RaySAR (Auer et al., 2016), 3D SAR simulator utilizing the open-source software "Persistence of Vision Ray (POV Ray)" to analyze backscattering contributions. Trace rays through the modeled scene by defining the origin and direction of rays using a virtual orthographic camera aligned with the radar sensor's viewing direction.

In recent years, the integration of photogrammetric techniques with UAV imagery has emerged as a promising approach for generating accurate three-dimensional (3D) models of terrain and objects. These models provide a detailed representation of the scene, offering valuable insights for various applications.

SIFT and ORB matching algorithms are applied to evaluate real and simulated SAR image matching based on their matching rates and performance in handling rotation invariance and noise resistance.

Leveraging such models for simulating SAR images presents an opportunity to bridge the gap between optical and radar remote sensing modalities, enabling enhanced understanding and analysis of complex environments.

By exploring the capabilities of SIFT and ORB algorithms in the context of SAR image registration, this research aims to contribute to the advancement of techniques for integrating photogrammetric 3D models with SAR imaging, facilitating improved analysis and interpretation of the scene which can be related to urban areas. The findings of this study hold potential for enhancing SAR-based applications in diverse fields, including environmental monitoring, urban planning, and infrastructure assessment.

The paper is structured as follows. Background with literature review is provided in section 2, In section 3 Data Collection and the preprocessing steps are presented. Section 4 describes Experiments and Results in SAR simulation (4.1) and Image Matching methods (4.2), Evaluation of matching rates (4.3), followed by Conclusion and Discussion in section 5.

## 2. Background

Different SAR simulation techniques exist, each with its own advantages and limitations (Balz et al., 2015). RaySAR, which is open-source and available for SAR community (Auer et al., 2016), offers high geometric accuracy and support for multi-bounce simulation and focuses on the geometric correctness of simulated signals, particularly in local urban scenes imaged by very high-resolution SAR sensors. The simulator neglects random scattering and instead focuses on deterministic reflection effects at individual man-made objects. RaySAR supports multi-bounce simulation, making it suitable for our research using detailed object geometries and complex scenes.

Integration of optical and radar data through simulated images presented in (Junyi Tao et al., 2011), (J. Tao et al., 2012), (Ilehag et al., 2017). Modified GeoRaySAR utilizes digital surface models (DSMs) generated from WorldView-2 data for SAR simulation techniques by extracting geometric knowledge from these models to identify buildings in high resolution SAR data. It shows significant benefits for urban area analysis, there are limitations related to geometrical differences, shadow effects, and incidence angle constraints that need to be considered for a more comprehensive and accurate interpretation of SAR data in urban environments. Meanwhile processing WorldView-2 DSMs

for SAR simulations may require additional computational resources and expertise, adding complexity to the simulation workflow.

An automatic system for generating and geocoding simulated SAR images approach leverages the SAR simulator RaySAR and LiDAR digital surface models to enhance the accuracy and realism of the simulated urban scenes (Junyi Tao et al., 2013)

Comparing the workflow used in (Auer et al., 2010), the proposed approach includes the generation of different image layers (e.g., double bounce reflection, layover, shadow, ground areas) for the entire scene and individual buildings, considering neighborhood influences. This method enables detailed analysis and object identification. The method involves geocoding the simulated images using SAR orbit parameters and DSM geoinformation, allowing for direct comparison with real SAR data. This geocoding step enhances the accuracy of object identification in urban environments. By integrating advanced simulation techniques, geocoding methods, and LiDAR data, the proposed approach offers a comprehensive solution for object identification in complex urban scenarios using SAR imagery. While inaccuracies or limitations in the input data can impact the reliability of the simulated images and object identification results.

The flexibility and cost-effectiveness of UAVs, combined with advancements in technology and data processing algorithms, have made them a preferred choice for 3D generation and a wide range of other surveying and mapping applications over traditional survey techniques such as terrestrial laser scanning (TLS) or terrestrial photogrammetry (Vacca et al., 2018)

Challenges such as insufficient data, high-resolution images, modal differences, and methodological limitations are identified as key obstacles in multimodal Remote Sensing (MMRS) image registration in (Zhang et al., 2021) and (Jiang et al., 2021). The authors classify three theoretical frameworks for MMRS image registration methods: area-based, feature-based, and deep learning-based methods.

Feature-based matching is a core technique in image registration, involving the identification of distinctive points in images to establish correspondences for alignment. This method is robust to variations in intensity, noise, and occlusions, making it suitable for diverse registration tasks. By detecting key features and finding correspondences between them, feature-based matching ensures accurate alignment between images from different modalities (Nie et al., 2017)

Method for automated control point selection by matching real and simulated Synthetic Aperture Radar (SAR) images was presented in (Ren & Chang, 2011). The paper addresses the challenges of tie-points identification in mountainous areas by utilizing advanced image segmentation, clustering, and outlier screening techniques between real SAR and simulated SAR image from digital elevation model (DEM). Furthermore, the paper introduces a method for outlier screening, making the algorithm robust against backscatter variations in real SAR images. While challenges of tie-point identification in mountainous areas makes this method a valuable contribution to the real and simulated SAR image matching, the algorithm's focus on mountainous areas highlights a gap in its adaptability to diverse terrain types. Future research could explore the algorithm's performance in flat regions, urban areas, or other terrains with distinct features and challenges.

The research on robust registration of multimodal remote sensing images based on structural similarity in (Ye et al., 2017), demonstrates significant advancements in addressing challenges related to nonlinear radiometric differences and structural feature matching. However, there are some limitations in scale and rotation invariance and computational efficiency.

Experimental results in (Fan et al., 2015) highlight that the method based on SIFT with the combination of nonlinear diffusion and congruency achieves subpixel accuracy in image alignment. The outlier removal stage based on phase congruency information effectively eliminates false keypoints, enhancing matching accuracy. The proposed method offers a comprehensive solution to the challenges posed by SAR images, including speckle noise and edge preservation, making it a promising advancement in the field of SAR image registration.

Traditional methods like SIFT and SURF have been widely used but come with computational costs that can be prohibitive for real-time systems or low-power devices. In response to these challenges, ORB (Oriented FAST and Rotated BRIEF) was introduced in (Rublee et al., 2011) as a fast binary descriptor based on BRIEF (Binary Robust Independent Elementary Features).

One of the primary benefits of ORB is its exceptional speed, being nearly two orders of magnitude faster than SIFT while maintaining comparable performance. Additionally, ORB demonstrates robustness to noise, outperforming SIFT in scenarios with varying levels of noise.

Overview of the previous studies motivated us to find their substantial contributions and workflows as a guidance in our experiment, and served to generate meaningful findings and new approaches to address challenges.

### 3. Data collection

For the experiment as real SAR we used TerraSAR-X (TSX) image captured on an ascending orbit in Staring Spotlight mode with an incidence angle of 50° having a pixel size up to 0.25 meter. As a preprocessing step, TSX was orthorectified in SNAP and shown in Figure 1.

To generate simulated SAR high quality 3D model was reconstructed from UAV-captured images with the pixel size 2 cm in software by Agisoft Metashape (Edition, 2024). The Structure-from-Motion (SfM) technique is utilized for generating point clouds from the UAV-captured images.

Figure 2 represents textured 3D from a nadir view just for visualization and interpretation of the area, for the simulation 3D mesh model was used and given in Figure 3.



Figure 1. Orthorectified TSX as a real SAR



Figure 2. 3D textured model

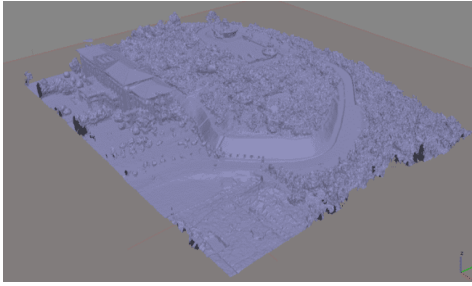


Figure 3. 3D mesh model for SAR simulation

## 4. Experiments and Results

### 4.1. SAR Simulation

Our experimental 3D model was simulated by following workflow given in experiments (Auer et al., 2010). Steps include scene modeling, reflectivity map creation, simulation output, visual evaluation and comparison.

Construction of a 3-D scene model was illuminated, surface properties (reflectivity factors, diffuse/specular reflection strengths), a camera at the observer's position, and one light source done in POV Ray. POV Ray has a typical 3D coordinate system  $\langle x,y,z \rangle$ . The scene was rotated by only y-axis, 0 and 180 degrees, the constructed scenes are shown in figure 4 and 5 respectively.

Geometry poses a significant challenge for image matching and co-registration. In our experiment, we aimed to simulate Synthetic Aperture Radar (SAR) images for various view angle scenarios to augment the dataset and identify the optimal matching algorithm for co-registering the outputs. To prevent overfitting, parameters such as heading from TSX were not applied, only spatial resolution parameters were utilized.

To avoid repetition and convenience the output with the rotation  $\langle 0,0,0 \rangle$  will be mentioned as simulated SAR 0, output with the rotation  $\langle 0,180,0 \rangle$  - simulated SAR 180.

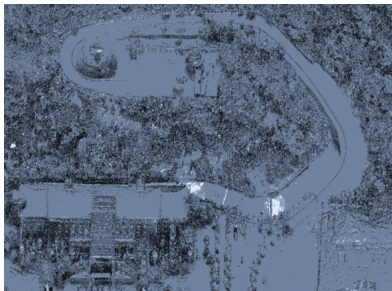


Figure 4. Simulated position of the model in POV Ray with the rotation  $\langle 0,0,0 \rangle$



Figure 5. Simulated position of the model in POV Ray with the rotation  $\langle 0,180,0 \rangle$

The output of the simulation process includes artificial reflectivity maps generated using Ray SAR, which was implemented in MATLAB. The simulated SAR ground range resolution is 0.25 m, allowing for comparison and assessment with real SAR images. Figure 6 and 7 present simulated SAR images showing all reflections in dB.

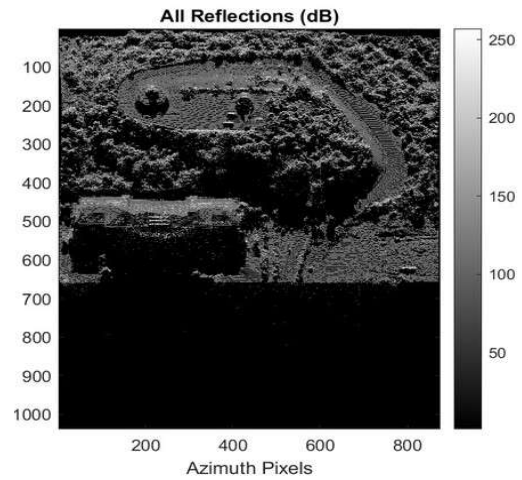


Figure 6. Simulated SAR 0

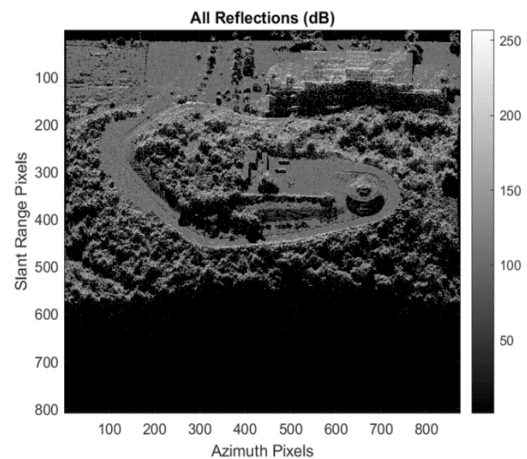


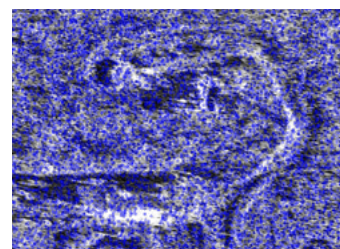
Figure 7. Simulated SAR180

### 4.2. Image Matching

#### 4.2.1. SIFT

The scale-invariant feature transform (SIFT) given in (Lowe, 1999) is one of the traditional methods which is invariant for changes in illumination, scale and distortions.

Finding keypoints and computation descriptors is the first step. Figure 8 (a, b and c) shows all points.



(a)

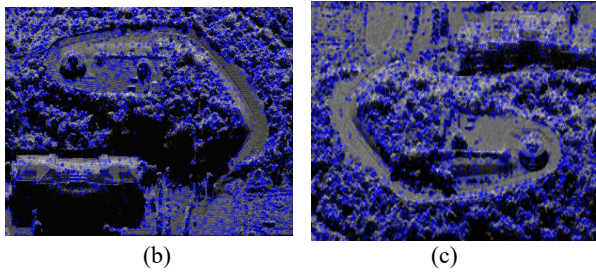


Figure 8. Finding keypoints by SIFT  
 (a) real SAR image, (b) and (c) Simulated SAR images

Algorithm matching keypoints and descriptors between the real and simulated SAR utilizes a brute-force matcher. It applies a ratio test to filter out good matches. If there are enough good matches, it proceeds to find the homography matrix using estimated parameters of a mathematical model from a set of observed data that contains outliers. The matching results are shown in Figure 9-10.

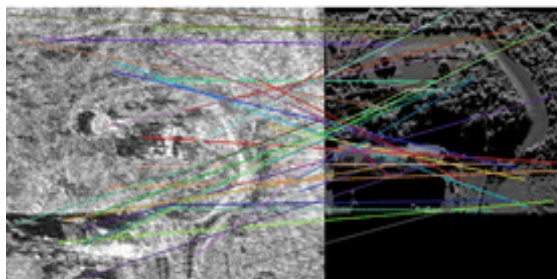


Figure 9. Matching real and simulated SAR 0

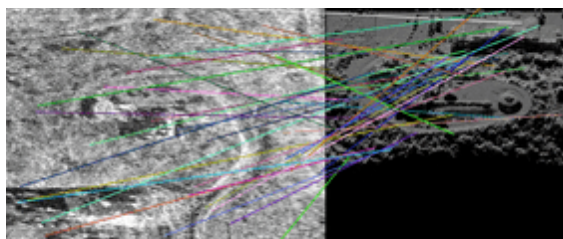
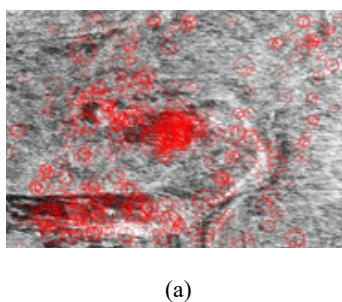


Figure 10. Matching real and simulated SAR 180

#### 4.2.2. ORB

Keypoints and descriptors generated by the algorithm are shown in Figure 11 (a-c).



(a)

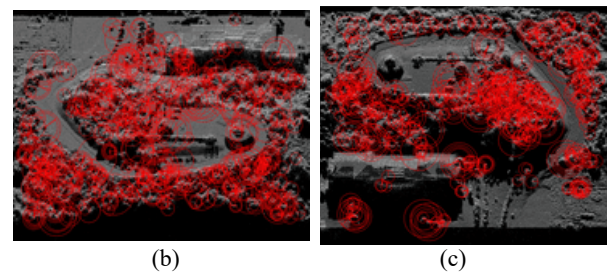


Figure 11. Finding keypoints by ORB  
 (a) real SAR image, (b) and (c) Simulated SAR images

Matching keypoints and descriptors visualized in Figure 12-13.

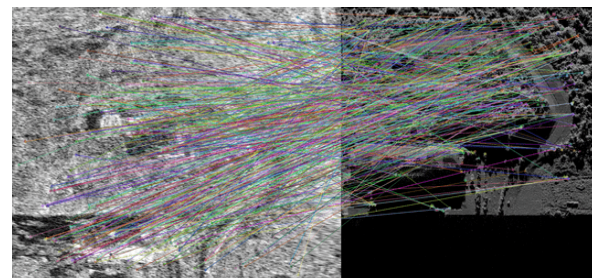


Figure 12. Matching real and simulated SAR 0

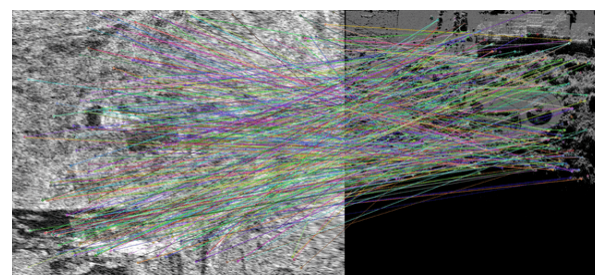


Figure 13. Matching real and simulated SAR 180

Visual inspection of the matched image pairs revealed significant differences in the accuracy and robustness of the registration process.

#### 4.3. Evaluation

In our experiment, we evaluated the performance of two prominent matching algorithms SIFT and ORB for matching simulated and real SAR data captured from complex scenes. First, we conducted a qualitative analysis of the matching results obtained using both algorithms and implemented evaluation methods presented in (Nie et al., 2017). The matching rate is the ratio of correct matches between keypoints detected in two images to the total number of matches found. High rate demonstrates simulated image more similar to the real SAR. Table 1 performs the qualitative analyses of matching using SIFT and ORB based algorithms.

According to the results ORB demonstrated better performance in aligning features across simulated and real SAR images, exhibiting fewer mismatches and better overall consistency compared to SIFT.

Method	Simulated SAR 0	Simulated SAR 180
SIFT	0.04	0.04
ORB	0.31	0.30

Table 1. Evaluation Matching Rate

Moreover, we observed that ORB's rotation invariance and resistance to noise played a crucial role in enhancing its performance in high-resolution SAR registration tasks. These attributes enabled ORB to effectively handle rotation variations and mitigate the effects of image noise, resulting in more reliable and robust co-registration results compared to SIFT.

The results of our experiment demonstrate the effectiveness of ORB as a versatile choice co-registering simulated and real SAR images in complex scenes. ORB offers promising opportunities for enhancing the accuracy and reliability of SAR image registration, thereby facilitating a wide range of remote sensing applications.

In our experiment local coordinate systems were given to simulated and real SAR images to avoid over-complexity, while it is our further task to improve geolocalization.

## 5. Conclusion and Discussion

In this study, we have explored the generation of simulated high-resolution SAR images through the integration of photogrammetric 3D models derived from UAV imagery. By utilizing ray tracing techniques, we simulated SAR reflectivity maps to mimic real SAR data. Furthermore, we employed two distinct matching algorithms, SIFT and ORB, to co-register the simulated SAR images with actual SAR data.

Our investigation revealed promising outcomes regarding the efficacy of ORB in achieving robust co-registration between simulated and real SAR images. ORB's inherent rotation invariance and noise resistance emerged as valuable attributes, making it a versatile choice for high-resolution SAR registration tasks. However, despite these advancements, several limitations were identified throughout the experiment.

One notable limitation lies in the complexity of simulating SAR images accurately, particularly in scenes containing diverse elements such as vegetation, buildings, and different type infrastructures. While ray tracing provides a viable approach, challenges persist in accurately modeling scattering properties and interactions within the scene. Additionally, the performance of matching algorithms may be influenced by factors such as scene complexity, image noise, and geometric distortions, which can impact the accuracy of matching results.

Despite these challenges, our study represents a significant step forward in leveraging UAV-based photogrammetry 3D models and advanced matching algorithms for SAR image simulation and registration.

Future research endeavors should focus on addressing the identified limitations, such as refining simulation techniques and enhancing algorithmic robustness in complex scenarios. Implementing generative adversarial networks can result in higher image quality, increased efficiency, adaptability to different scenarios, ultimately enhancing the overall simulation process.

By overcoming these challenges, we can explore the potential of SAR remote sensing for various applications.

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## References

- Auer, S., Bamler, R., & Reinartz, P. (2016). RaySAR - 3D SAR simulator: Now open source. *International Geoscience and Remote Sensing Symposium (IGARSS), 2016-Novem*, 6730–6733. <https://doi.org/10.1109/IGARSS.2016.7730757>
- Auer, S., Hinz, S., & Bamler, R. (2010). Ray-tracing simulation techniques for understanding high-resolution SAR images. *IEEE Transactions on Geoscience and Remote Sensing*, 48(3 PART2), 1445–1456. <https://doi.org/10.1109/TGRS.2009.2029339>
- Balz, T., Hammer, H., & Auer, S. (2015). Potentials and limitations of SAR image simulators - A comparative study of three simulation approaches. *ISPRS Journal of Photogrammetry and Remote Sensing*, 101, 102–109. <https://doi.org/10.1016/j.isprsjprs.2014.12.008>
- Edition, P. (2024). *Agisoft Metashape User Manual Professional Edition, Version 2.1*.
- Fan, J., Wu, Y., Wang, F., Zhang, Q., Liao, G., & Li, M. (2015). SAR image registration using phase congruency and nonlinear diffusion-based SIFT. *IEEE Geoscience and Remote Sensing Letters*, 12(3), 562–566. <https://doi.org/10.1109/LGRS.2014.2351396>
- Ilehag, R., Auer, S., & D'Angelo, P. (2017). Exploitation of digital surface models generated from worldview-2 data for sar simulation techniques. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 42(1W1), 55–61. <https://doi.org/10.5194/isprs-archives-XLII-1-W1-55-2017>
- Lowe, D. G. (1999). Object recognition from local scale-invariant features. *Proceedings of the IEEE International Conference on Computer Vision*, 2, 1150–1157. <https://doi.org/10.1109/iccv.1999.790410>
- Nie, C., Kong, Y., Leung, H., & Yan, S. (2017). Evaluation methods of similarity between simulated SAR images and real SAR images. *2016 CIE International Conference on Radar, RADAR 2016*, 2, 1–4. <https://doi.org/10.1109/RADAR.2016.8059495>
- Ren, S., & Chang, W. (2011). An automated matching of real and simulated SAR image. *European Microwave Week 2011: "Wave to the Future", EuMW 2011, Conference Proceedings - 8th European Radar Conference, EuRAD 2011*, 301–304.
- Rublee, E., Rabaud, V., Konolige, K., & Bradski, G. (2011). ORB: An efficient alternative to SIFT or SURF. *Proceedings of the IEEE International Conference on Computer Vision*, 2564–2571. <https://doi.org/10.1109/ICCV.2011.6126544>
- Tao, J., Palubinskas, G., & Reinartz, P. (2012). Automatic Interpretation of High Resolution Sar Images: First Results of Sar Image Simulation for Single Buildings. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVIII-4/(June), 313–317. <https://doi.org/10.5194/isprsarchives-xxxviii-4-w19-313-2011>

- Tao, Junyi, Member, S., Auer, S., & Palubinskas, G. (2013). *Automatic SAR Simulation Technique for Object Identification in Complex Urban Scenarios*. November 2014. <https://doi.org/10.1109/JSTARS.2013.2275928>
- Tao, Junyi, Palubinskas, G., Reinartz, P., & Auer, S. (2011). Interpretation of SAR images in urban areas using simulated optical and radar images. *2011 Joint Urban Remote Sensing Event, JURSE 2011 - Proceedings, May*, 41–44. <https://doi.org/10.1109/JURSE.2011.5764714>
- Vacca, G., Furfaro, G., & Dessì, A. (2018). The use of the uav images for the building 3D model generation. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 42(4W8), 217–223. <https://doi.org/10.5194/isprs-archives-XLII-4-W8-217-2018>
- Ye, Y., Shan, J., Bruzzone, L., & Shen, L. (2017). Robust registration of multimodal remote sensing images based on structural similarity. *IEEE Transactions on Geoscience and Remote Sensing*, 55(5), 2941–2958. <https://doi.org/10.1109/TGRS.2017.2656380>
- Zhang, X., Leng, C., Hong, Y., Pei, Z., Cheng, I., & Basu, A. (2021). Multimodal remote sensing image registration methods and advancements: A survey. *Remote Sensing*, 13(24), 1–31. <https://doi.org/10.3390/rs13245128>