INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)

www.ijprems.com
editor@ijprems.com

Vol. 04, Issue 01, January 2024, pp : 261-228

e-ISSN : 2583-1062

Impact Factor : 5.725

A REVIEW ON CHALLENGES AND OPPORTUNITIES IN MOTION ARTEFACTMITIGATION FOR REMOTE SENSING IMAGERY

Sidramappa B[1], Chilagodu Nithyananda[2], Danish Farooq[3], Dr Mohammed Rafi[4]

[1,2,3]Students, Dept of Computer Science and Engineering, India.

[4]Professor, Dept. Of Computer Science And Engineering University B D College Of Engineering, Davangere-577544, Karnataka, India

ABSTRACT

In this paper a review is done on Motion Artifact Mitigation for Remote Sensing Imagery or motion blur in satellite images in Image Processing. In the present world we are facing some problems with the distortions or abnormalities in the captured images or data caused due to some slight movement during the image acquisition. These problems causing factors contribute to motion artifacts in remote sensing. These artifacts can affect the accuracy and quality of the remote sensing data, impacting the interpretation and analysis of the imagery. The Successful mitigation of motion artifacts in remote sensing imagery can be achieved by involving some combination of technological advancements, sophisticated image processing techniques are studied.

Key Words: Motion Artifact, Remote sensing, Satellite, Blur, Distortions.

1. INTRODUCTION

Motion artifacts in various forms of imaging occur due to movement during the image capture process. In remote sensing, these artifacts manifests as distortions, blurring, or inconsistencies in the acquired data, impacting the quality and readability of the imagery. The understanding and mitigating motion artifacts in remote sensing are crucial for obtaining accurate and high-quality data, essential for applications such as disasters and agriculture, urban planning. The motion artifacts arise due to several factors including, platform movement, The unintended motion of the imaging platform such as, satellites, drones, or aircrafts, can lead to blurred or misaligned images. 2nd one is the Object movement, includes rapid motion of the objects within the scene being imaged can cause distortions or smearing and finally, the sensor characteristics includes different sensors have varying sensitivity to motion, affecting their ability to capture clear images. The motion artifacts result in blurring of the images and might appear uncleared due to motion in capturing and may leads to misalignment of the parts of the image i.e., some parts of the image may not align correctly, causing inconsistencies. It also leads to Ghosting, means that multiple or faint images of moving objects might appear, affecting clarity and interpretation. The mitigation can impact on the quality and utility of the remote sensing imagery and can distort actual features, affecting the reliability of collected data. Mitigations can also cause the interpretation issues like blurring or misalignment that may hinder accurate interpretation and analysis of the imagery. These mitigations can be removed by using certain techniques some of them are, Image processing, Improved sensor technology, Motion prediction andcontrol and the Calibration and correction Methods

OBJECTIVES: The objectives of the reviewinclude the following:

- Motion Related position correction using by Doppler's Effect in Synthetic Aperture Radar
- Analysis of Advanced Land Observing Satellite (ALOS-2), Phased Array type L- band Synthetic Aperture Radar (PALSAR) sensor data over the city of mobile
- Highlighting the Problems with the fastprism proposed algorithm
- Analysing of Adaptive Memetic Fuzzy Clustering Algorithm with Spatial Information for Remote Sensing Imagery.
- Understanding the Class-Guided Swin Transformer for Semantic Segmentation ofRemote Sensing Imagery

2. METHEDOLOGY

Motion Related Position Correction usingdoppler's effect:

Here, the method of correction mainly focusses on the Synthetic aperture radar multichannel classification of the maritime scenes commonly called SAR. The displacement effect in the SAR is based on the well-known doppler's effect and isgiven by the formula

$$\delta_a = R * V_r / V_p$$

R is the range of platform to target, Vr is the target range speed and Vp is the SAR platform speed The Synthetic Aperture Radar (SAR) correction method aims to rectify displacement effects caused by Doppler's effect in maritime scenes. Spatial analysis alone cannot accurately capture the time-varying motions of scatterers in the scene, leading to

e-ISSN : 2583-1062
Impact Factor : 5.725
Vol. 04, Issue 01, January 2024, pp : 261-228

target signature distortion within the image. To addres this, the Velocity SAR (VSAR) technique employs MSAR imagery from multiple along-track phase centers for correction.

VSAR involves several key steps

Image Stack Creation: Compile an image stack using M phase center images.

FFT Processing: Apply Fast Fourier Transform (FFT) to each pixel across the time stack.

Velocity Component Adjustment: Shift each velocity component to enforce stationarity by bringing them back to the origin.

Edge Trimming: Remove non-overlapping sections to refine the corrected image.

This VSAR-based realignment of backscatter to precise image pixel locations enables coherent analysis of target motion through eigen analysis of the M × N covariance matrix. It offers a method to rectify spatial spreading and shifting of target signatures caused by motion, facilitating accurate interpretation of dynamic scatterer movements within SAR images.

Analysis of Advanced Land Observing Satellite (ALOS-2), Phased Array type L-band Synthetic Aperture Radar (PALSAR) sensor data over the city of mobile.

The city of Mobile in Alabama, USA, used ALOS/PALSAR images to study ground movement via InSAR techniques. However, the PALSAR images contained errors related to satellite orbits. To rectify this, 19 interferograms from 12 PALSAR images taken between June 2007 and August 2010 were analyzed. Around 1.4 million observations from coherent points were used to assess LOS linear deformation rates.

The results displayed noticeable water level changes in wetland areas but no significant deformations elsewhere. After implementing the proposed model, the map showed a color range of - 5 to 5 mm/year, indicating successful removal of observable orbital errors from estimated deformations. The interferograms post-orbit error removal confirmed the successful elimination of orbital fringes, signifying the model's effectiveness.

However, it's essential to note that employing this model in real scenarios may demand substantial memory. The model simultaneously resolves deformation rate, DEM error, and orbital error, necessitating a large sparse design matrix. In this case, the matrix size reached 27 million rows by 844 thousand columns, occupying around 5 GB of memory—almost double that of the matrix without orbital error parameters. Processing time also doubled, taking about 1188 seconds on a desktopPC compared to 596 seconds without orbital error parameters.

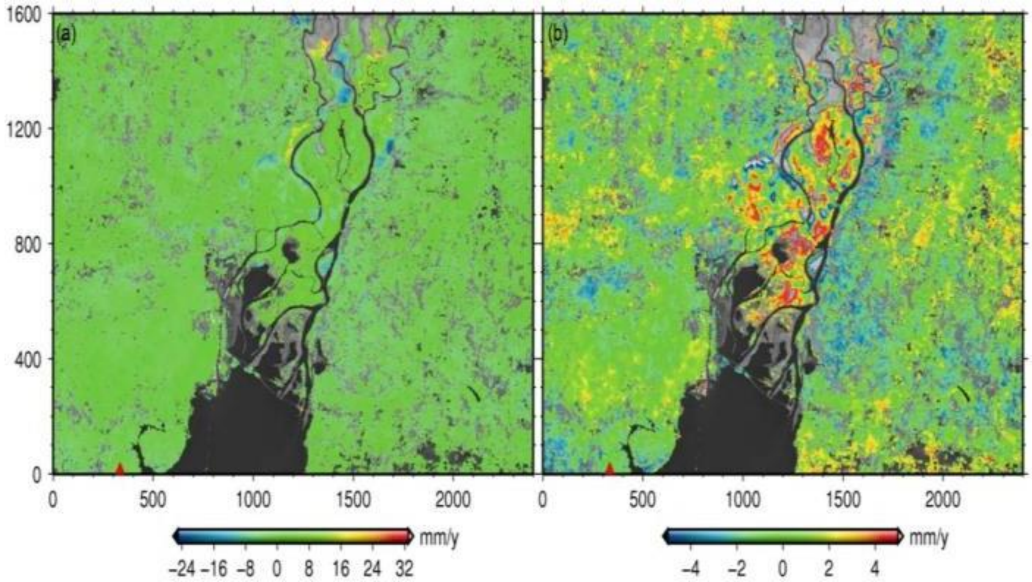


Fig 1(a) Fig 1(b)

Fig.1(a) Estimated linear LOS deformation rate over the City of Mobile. The red triangle is thereference point. 1(b) Estimated linear LOSdeformation rate with a color bar ranging from −5to 5 mm/y

Fast Prism Algorithm problems

The Fast PRISM method is effective when dealing with small interframe displacements in videos, like those where the overlapped areas don't encompass entire objects like buildings. However, in cases where there's significant interframe displacement, commonly seen in airborne videos, a whole building may fall within one overlapped region. The problem arises because the method doesn't consider the spatial characteristics of the image. Consequently, when the vertices of a triangle lie on surfaces with different motion parallax (the apparent displacement of objects when viewed from different positions), the resulting triangle gets distorted upon being mapped onto the mosaic, leading to disfiguration of objects in the scene.

INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)

www.ijprems.com
editor@ijprems.com

Vol. 04, Issue 01, January 2024, pp : 261-228

e-ISSN : 2583-1062

Impact Factor : 5.725

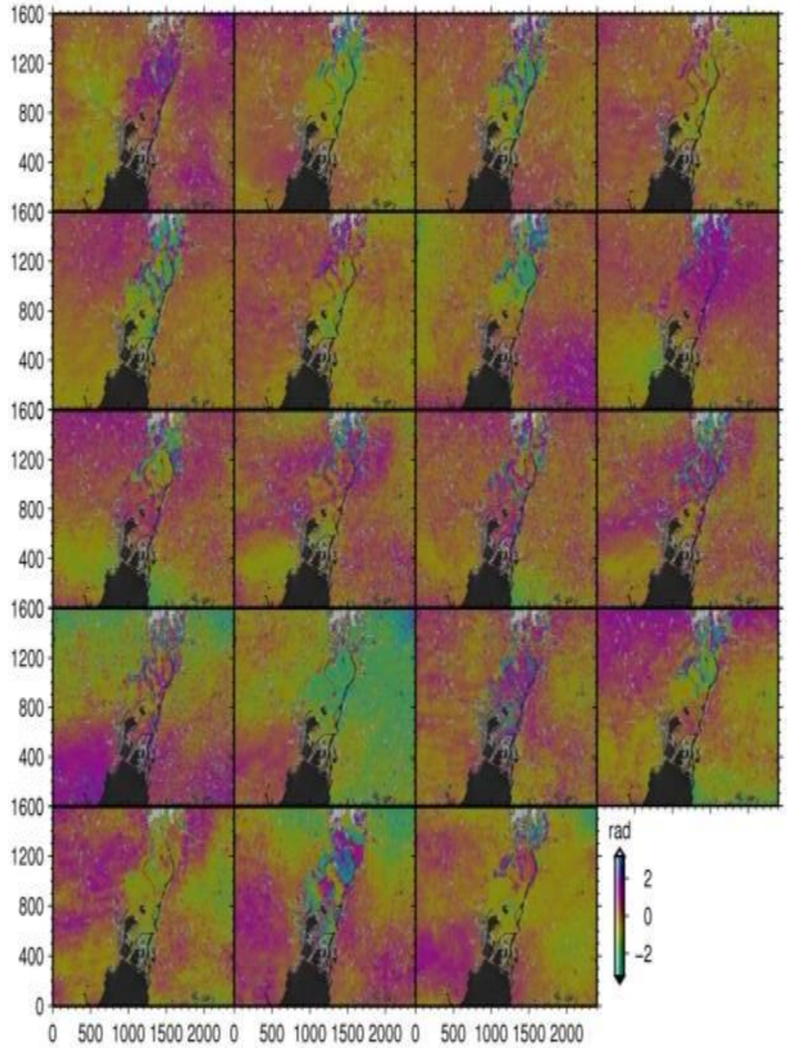


Fig.2 Interferograms after removing the orbital fringes estimated from the proposed model.

This difference in apparent motion causes issues during image processing. As the sensor moves, objects at different heights or distances exhibit varying apparent motions, which can lead to triangles warping in unexpected ways when combined into a mosaic. Consequently, objects in the scene may appear distorted due to this warping effect, impacting the accuracy of the final mosaic.

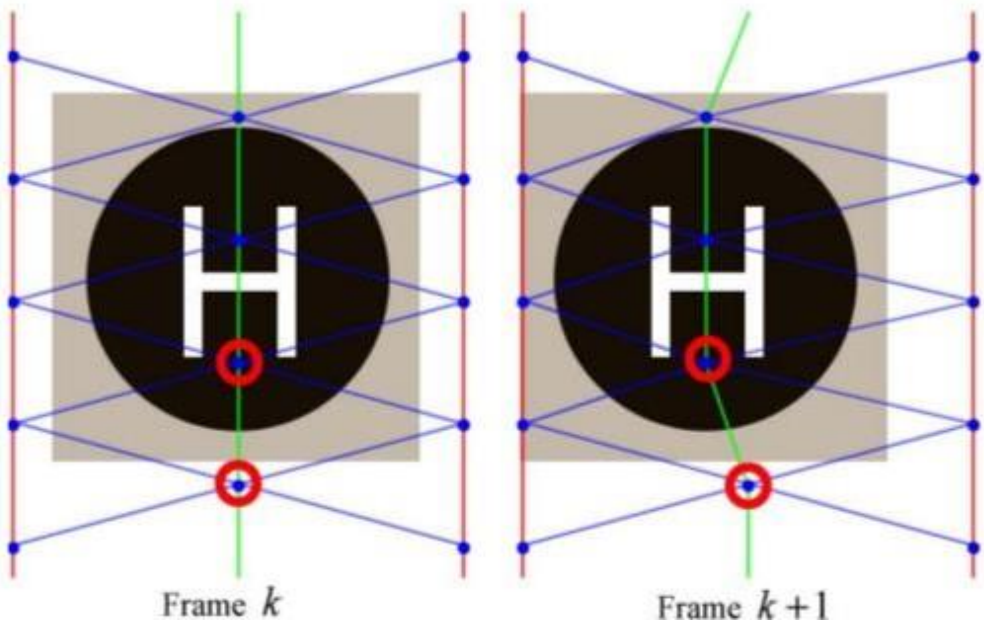


Fig.3 Motion parallax between a helipad whichis at greater height than the ground.

$$v_i = \frac{\sum_{k=1}^{N} u_{ik}^m (1-\alpha_k) x_k + \sum_{k=1}^{N} u_{ik}^m \alpha_k \overline{x_k}}{\sum_{k=1}^{N} u_{ik}^m}$$

$$u_{ik} = \frac{\{(1-\alpha_k)\|x_k - v_i\|^2 + \alpha_k \|\overline{x_k} - v_i\|^2\}^{-1/m-1}}{\sum_{j=1}^{C} \{(1-\alpha_k)\|x_k - v_j\|^2 + \alpha_k \|\overline{x_k} - v_j\|^2\}^{-1/m-1}}$$

$$U_{C\times N} = \left\{ u_{ik} \in [0,1] \middle| \sum_{i=1}^{C} u_{ik} = 1 \; and \; 0 < \sum_{k=1}^{N} u_{ik} < N \right\}$$

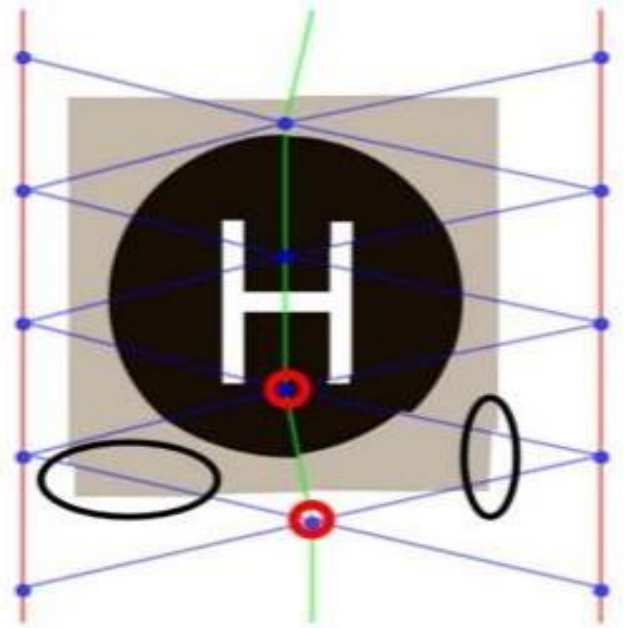


Fig 4 Mosaic formed from the two frames

An Adaptive Memetic Fuzzy Clustering Algorithm with Spatial Information for Remote Sensing Imagery (AMASFC).

AMASFC consists of two main processes: 1) the construction of the objective function and 2) the optimization of the objective function. In the process of the construction of the objective function, a new objective function is proposed with an adaptive spatial information weight by introducing the concept of entropy.

The two processes of AMASFC are described in detail in the following sections.

A. Construction of the Objective Function and Its Traditional Optimization Method The objective function of the proposed algorithm is as follows:

$$Jm = \sum_{i=1}^{C} \sum_{k=1}^{N} u_{ik}^m (1-\alpha_k) \|x_k - v_i\|^2 + \sum_{i=1}^{C} \sum_{k=1}^{N} u_{ik}^m \alpha_k \|\overline{x_k} - v_i\|^2.$$

By minimizing the above equation, we obtain the below simplified equation

Where x_k is a vector representing the pixel for a multispectral remote sensing image, is the total number of pixels.

e-ISSN : 2583-1062

Impact Factor : 5.725

www.ijprems.com
editor@ijprems.com

Vol. 04, Issue 01, January 2024, pp : 261-228

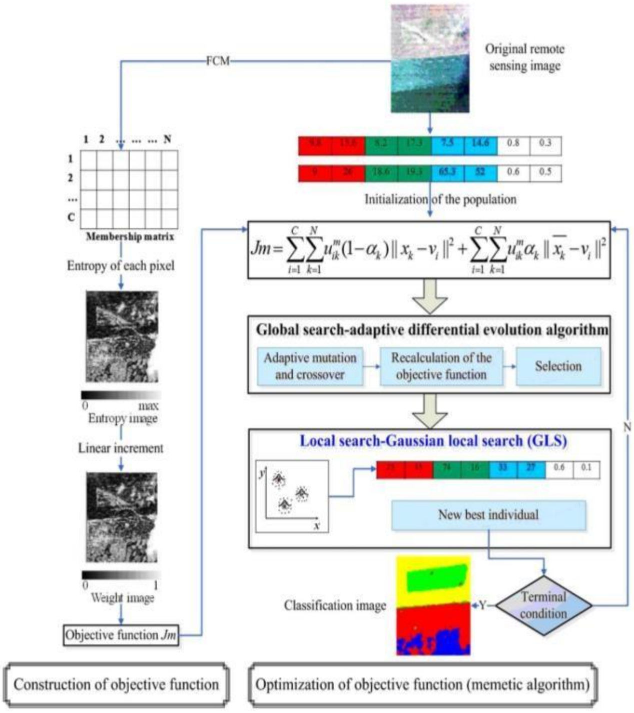
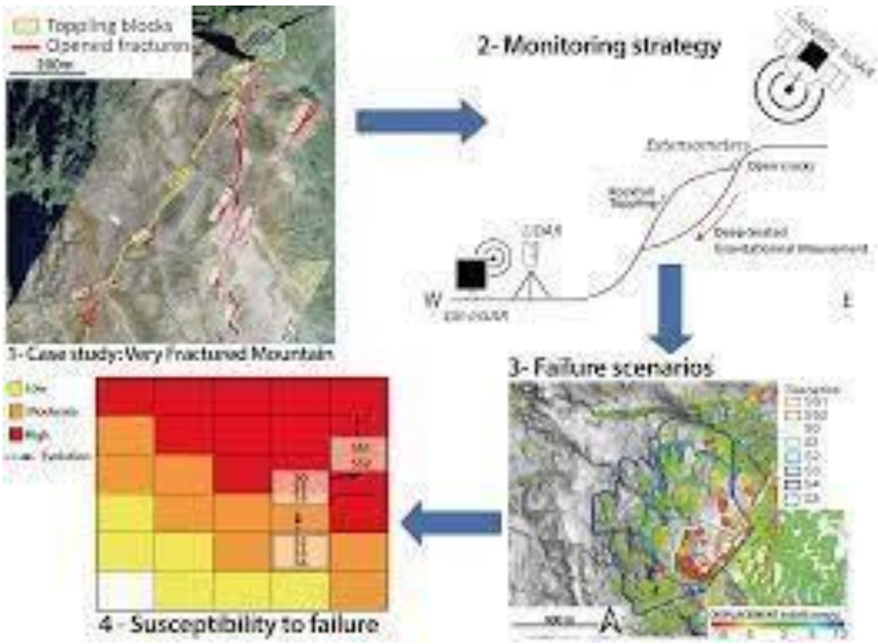


Fig 5. Flowchart of the adaptive memetic fuzzy clustering algorithm with spatial information (AMASFC)

Class-Guided Swin Transformer for SemanticSegmentation of Remote Sensing Imagery Encoder:

The small version of the Swin Transformer (Swin-S) [28] is selected as the encoder due to its excellent trade-off between efficiency and accuracy. Takes an image X ∈ R3×H×W as the input and generates four semantic features at different channel dimensions and resolutions. Thus, we utilize standard 3 × 3 convolution layers
and up-sampled operations to unify the shape of the four feature maps. Finally, we merge the four feature maps and generate an encoding feature Xe
∈Rd×(H/4)×(W/4)
where d is the channel dimension and set as 96. This encoding feature is fed into the decoder for further processing.

Decoder:

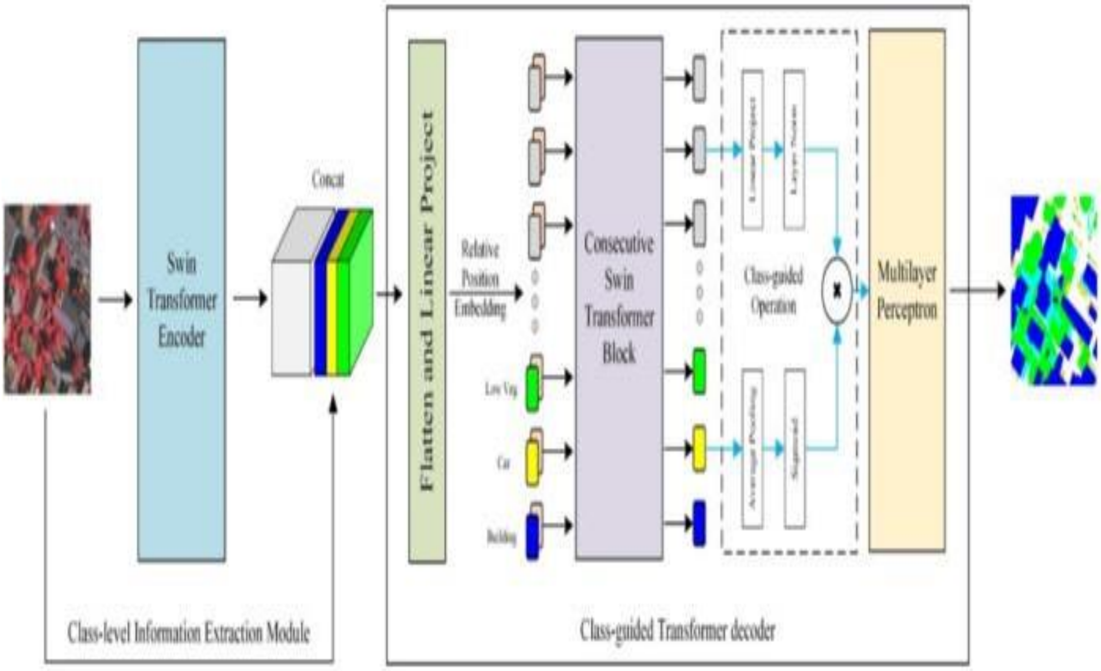


The class-guided Transformer decoder is composed of three stages. In the first stage, the class-level information extraction module (CIEM) captures the class-level context and spatial details automatically. Specifically, the CIEM is composed of three 3 × 3 convolution layers. Each convolution layer is equipped with a Batch Normalization operation and a ReLU activation function. To retain rich spatial details, the extracted class-level feature (denoted by Xc ∈ Rk×(H/4)×(W/4), k is the number of categories) follows the high- resolution feature representation and the down- sampled factor is set as 4

Artifact Mitigation Strategies

Artifact mitigation strategies aim to reduce or eliminate unwanted distortions or anomalies in data or images. These methods involve identifying, correcting, or minimizing aberrations caused by various factors such as sensor limitations, environmental conditions, or processing errors. Common approaches include calibration adjustments, noise reduction algorithms, interpolation techniques, and filtering processes. . By employing these strategies, the goal is to enhance data quality, improve accuracy, and ensure that the final output represents a more faithful and reliable representation of the original information.

Motion prevention	Artifact reduction	Motion correction
Training	Faster imaging	Navigators
Distraction	Insensitive sequences	Self-navigated trajectories
Feed and wrap (for babies)	Gradient moment nulling	Prospective correction
Foam restraints	Saturation bands	Retrospective correction
Sedation	Triggering and gating	
Bitebars/head holders	Phase reordering	
Breathhold		



3. CONCLUSION

The exploration of motion artefacts and their mitigation in remote sensing imagery stands as a pivotal concern in contemporary research. This review paper delved into the multifaceted challenges and promising opportunities that encompass this domain, offering insights into the complexities and advancements within the field.

The review highlighted various challenges associated with motion artefacts in remote sensing imagery. From the impact of platform-induced vibrations to atmospheric disturbances and sensor limitations, understanding these challenges becomes fundamental in devising effective mitigation strategies. The interplay of these factors often complicates image acquisition and processing, leading to distorted or incomplete data, thereby impeding accurate analysis and interpretation.

One of the primary challenges identified involves the inherent trade-offs between sensor capabilities, imaging resolution, and motion artefact reduction techniques. Striking a balance between achieving high-resolution imagery and mitigating motion- induced distortions remains a persistent challenge, necessitating innovative technological interventions.

e-ISSN : 2583-1062

Impact Factor : 5.725

Vol. 04, Issue 01, January 2024, pp : 261-228

4. REFERENCES

[1] K. Ta demir and E. Merényi, "A validity index for prototype-based clustering of data sets with complex cluster structures," IEEE Trans.Syst. Man, Cybern. B, Cybern., vol. 41, no. 4, pp. 1039– 1053, Aug. 2011.

[2] A. K. Jain, "Data clustering: 50 years beyond K- means," Pattern Recognit.Lett., vol. 31, no. 8, pp. 651–666, Aug. 2010.

[3] U. Maulik and I. Saha, "Modified differential evolution based fuzzy clustering fo pixel classification in remote sensing imagery," Pattern Recognit., vol. 42, no. 9, pp. 2135–2149, Sep. 2009.

[4] S. Bandyopadhyay, U. Maulik, and A. Mukhopadhyay, "Multiobjective genetic clustering for pixel classification in remote sensing imagery,"IEEE Trans. Geosci. Remote Sens., vol. 45, no. 5, pp. 1506–1511, May 2007.

[5] A. Ghosh, N. S. Mishra, and S. Ghosh, "Fuzzy clustering algorithms for unsupervised change detection in remote sensing images," Inf. Sci., vol. 181,no. 4, pp.699–715, Feb. 2011.

[6] S. Niazmardi, S. Homayouni, and A. Safari, "An improved FCM algorithm based on the SVDD for unsupervised hyperspectral data classification,"IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 6, no. 2,pp. 1939–1404, Feb. 2013.

[7] S. Lloyd, "Least squares quantization in PCM," IEEE Trans. Inf. Theory,vol. 28, no. 2, pp. 129–137, Mar. 1982.

[8] G. H. Ball and D. J. Hall, "ISODATA, a novel method of data analysis and pattern classification," Stanford Res. Inst., MenloPark, CA, USA, Tech.Rep. AD0699616, 1965.

[9] J. C. Bezdek, Pattern Recognition with Fuzzy Objective Function Algo rithms. New York, NY, USA: Plenum, 1981.

[10] M. N. Ahmed, S. M. Yamany, N. Mohamed, A. A. Farag, and T. Moriarty,"A modified fuzzy c-means algorithm for bias field estimation and segmen tation of MRI data," IEEE Trans. Med. Imag., vol. 21, no. 3, pp. 193–199, Mar. 2002.

[11] S. Chen and D. Zhang, "Robust image segmentation using FCM with spatialconstraints based on new kernel-induced distance measure," IEEE Trans.Syst. Man, Cybern. B, Cybern., vol. 34, no. 4, pp. 1907–1916, Aug. 2004.

[12] S. Krinidis and V. Chatzis, "A robust fuzzy local information c-means clustering algorithm," IEEE Trans. Image Process., vol.19, no. 5,pp. 1328–1337, May 2010.

[13] L. Groll and J. Jakel, "A new convergence proof of fuzzy c-means," IEEE Trans. Fuzzy Syst., vol. 13, no. 5, pp. 717– 720, Oct. 2005.

[14] L. N. De Castro and F. J. Von Zuben, "Learning and optimization using the clonal selection principle," IEEE Trans. Evol. Comput., vol. 6, no. 3,pp. 239–251, Jun. 2002.

[15] S. Bandyopadhyay, "Genetic algorithms for clustering and fuzzy clustering, "Wiley Interdiscip. Rev. Data Min. Knowl. Discov., vol. 1, no. 6, pp. 524– 531,Nov/Dec. 2011.

[16] S. Das, A. Abraham, and A. Konar, "Automatic clustering using an improved differential evolution algorithm," IEEETzans. Syst. Man, Cybern. A, vol. 38,no. 1,pp. 218–237, Jan. 2008.

[17] U. Maulik and I. Saha, "Automatic fuzzy clustering using modified differential evolution for image classification," IEEE Trans. Geosci. Remote Sens., vol. 48, no. 9, pp. 3503–3510, Sep. 2010

[18] C. Brenner, "Building reconstruction from images and laser scanning,"Int. J. Appl. Earth Observ. Geoinf., vol. 6, no. 3/4, pp. 187–198,Mar. 2005.

[19] K. Fujii and T. Arikawa, "Urban object reconstruction using airborne laserelevation image and aerial image," IEEE Trans. Geosci. Remote Sens.,vol. 40, no. 10, pp. 2234–2240, Oct. 2002.

[20] E. Trucco and A. Verri, Introductory Techniques for 3-D Computer Vision.Englewood Cliffs, NJ: Prentice-Hall, 1998.

[21] S. Peleg and J. Herman, "Panoramic mosaics by manifold projection," in Proc. IEEE Conf. CVPR, 1997, pp. 338–343.

[22] S. Peleg and M. Ben-Ezra, "Stereo panorama with a single camera," in Proc. IEEE Conf. CVPR, 1999, pp. 395401.

[23] S. Peleg, M. Ben-Ezra, and Y. Pritch, "Omnistereo: Panoramic stereo imaging," IEEE Trans. Pattern Anal. Mach.Intell., vol. 23, no. 3, pp. 279–290, Mar. 2001.

[24] Y. Li, H. Shum, C. Tang, and R. Szeliski, "Stereo reconstruction from multiperspective panoramas," IEEE Trans. Pattern Anal. Mach. Intell.,vol. 26, no. 1, pp.45–62, Jan. 2004.

[25] J. Y. Zheng and S. Tsuji, "Panoramic representation for route recogni tion by a mobile robot," Int. J. Comput. Vis., vol. 9, no. 1, pp. 55–76,Oct. 1992.

[26] A. Zomet, D. Feldman, S. Peleg, and D. Weinshall, "Mosaicing new views: The crossed-slits projection," IEEE Trans. Pattern Anal. Mach.Intell., vol. 25, no. 6, pp. 741–754, Jun. 2003.

[27] Z. Zhu, A. Hanson, and E. Riseman, "Generalized parallel-perspective stereo mosaics from airborne video," IEEE Trans. Pattern Anal. Mach.Intell., vol. 26, no. 2, pp. 226–237, Feb. 2004

[28] Class-Guided Swin Transformer for Semantic Segmentation of Remote Sensing Imagery Xiaoliang Meng, Yuechi Yang, Libo Wang , Teng Wang, Rui Li , and Ce Zhang

[29] J. R. Fienup, "Detecting moving targets in SAR imagery by focusing," IEEE Trans. Aerosp. Electron. Syst., vol. 37, no. 3, pp. 794–809, Jul. 2001.

[30] R. Lipps, V. Chen, and M. Bottoms, "Advanced SAR GMTI techniques," in Proc. IEEE Radar Conf., Apr. 2004, pp. 105–110.

[31] M. Newey, G. R. Benitz, D. J. Barrett, and S. Mishra, "Detection and imaging of moving targets with LiMIT SAR data," IEEE Trans. Geosci. Remote Sens., vol. 56, no. 6, pp. 3499–3510, Jun. 2018.

[32] M. I. Pettersson, "Detection of moving targets in wideband SAR," IEEE Trans. Aerosp. Electron. Syst., vol. 40, no. 3, pp. 780–796, Jul. 2004.

[33] D. Page, G. Owirka, H. Nichols, S. Scarborough, M. Minardi, and L. Gorham, "Detection and tracking of moving vehicles with Gotcha radar systems," IEEE Aerosp. Electron. Syst. Mag., vol. 29, no. 1, pp. 50– 60, Jan. 2014.

[34] C. C. Chen and H. C. Andrews, "Target motion induced radar imag ing," IEEE Trans. Aerosp. Electron. Syst., vol. AES-16,no. 1, pp. 2–14, Jan. 1980.

[35] D. A. Ausherman, A. Kozma, J. L. Walker, H. M. Jones, and E. C. Poggio, "Developments in radar imaging," IEEE Trans. Aerosp. Electron. Syst., vol. AES-20,no. 4, pp. 363–400, Jul. 1984.