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An Innovative Runway Landing Path Detection using UAV Implementation of the K-Means Clustering Algorithm

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Abstract

Objective: To provide a novel approach for automatic Unmanned Aerial Vehicle (UAV) runway detection, leveraging remote sensing data and advanced image processing techniques. **Methods:** The methodology encompasses Gaussian filter-based despeckling and histogram equalization for preprocessing, followed by Independent Component Analysis (ICA) for feature extraction and segmentation using the K-means clustering algorithm. **Findings:** The research demonstrates successful UAV runway detection, even with unlabeled datasets, underscoring the efficacy of the proposed methods. Notably, the study contributes to automatic target recognition, specifically in Synthetic Aperture Radar (SAR) data analysis, where K-means clustering outperforms Korn B and morphological algorithms. **Novelty :** The K-means algorithms works by clustering the datasets obtained by integrating all the data collected from various sensors that are placed at specific positions in the runway. This work holds significance in facilitating immediate runway identification during emergencies and finds applications in military operations, surveillance, and remote sensing domains.

Keywords: Runway detection; Unmanned Aerial Vehicle; Histogram Equalization; Gaussian filtering; Independent Component Analysis; K-means clustering based segmentation

1 Introduction

In environments where manual piloting is challenging, the necessity for autonomous navigation in UAVs underscores the importance of automatic runway detection. This capability is particularly crucial in emergency scenarios, where swift and secure landings[(1)] are essential amidst challenges such as engine failures or adverse weather conditions[(2)]. Autonomous runway detection not only empowers UAVs to navigate independently but also supports various tasks including surveillance, mapping, and search and rescue operations[(3)]. Moreover, it alleviates the cognitive load on human operators and enhances the overall reliability of UAV operations. The proliferation of Unmanned Aerial Systems (UAS) has led to the emergence of numerous unique programs tailored to small businesses. These programs capitalize on advancements in UAV technology, such as fixed-wing[(4)] and multirotor platforms, for tasks like airborne tracking, image processing, and object detection [5]. While object detection models like Faster R-CNN, YOLO [6] and morphological fusion [7] excel at identifying objects in images, they often require extensive labeled training data and may be sensitive to annotation quality, potentially impacting their performance. Real-time processing may also demand powerful hardware. In contrast, the K-Means clustering algorithm offers an unsupervised approach that does not rely on labeled training data, making it advantageous in scenarios where annotated datasets are scarce or unavailable. K-Means also boasts features such as initialization flexibility, scalability, ease of interpretation, and adaptability to various initialization strategies. The research observes a method of automatic processing that enables effective target detection with high sensitivity through a visual navigation algorithm [8]. UAVs vary based on wing and rotor types, with fixed-wing drones resembling airplanes and requiring runways for takeoff and landing. VTOL UAVs combine helicopter and airplane features [9], while multirotor drones offer agility with multiple rotors. Results from three sequences of experiments demonstrate the effectiveness of the proposed approach in efficiently detecting targets with high speed and low false alarm rates [10]. The subsequent sections of the proposed study include a review of related works, an explanation of the specific phases of the proposed methodology, experimental results, and the conclusion.

2 Methodology

This section is the detailed depiction of overall working of the proposed scheme. Unmanned aerial vehicles, or UAVs, are essential for a variety of tasks where human participation is impractical, costly, or dangerous, such as hazardous material retrieval, traffic monitoring, disaster relief assistance, and so forth. Recently, the applications of unmanned aerial vehicles are diverse, ranging from search and rescue, reconnaissance and surveillance. For, manual landing, the pilot obtains visual cue by naked eyes or through the relayed video taken by the onboard camera. Piloting outside the vehicle needs a lot of training due to the limited situation awareness. As a consequence, a large portion of mishaps happen during the landing phase. Many fixed-wing military UAVs are known to suffer a significant portion of accidents due to human factors during landing and as for Pioneer, almost 70% of mishaps occur during landing. Therefore, it has been very much desired to automate the landing of UAVs, preferably without using expensive aiding systems.

The overall flow of the proposed mechanism is represented as follows:

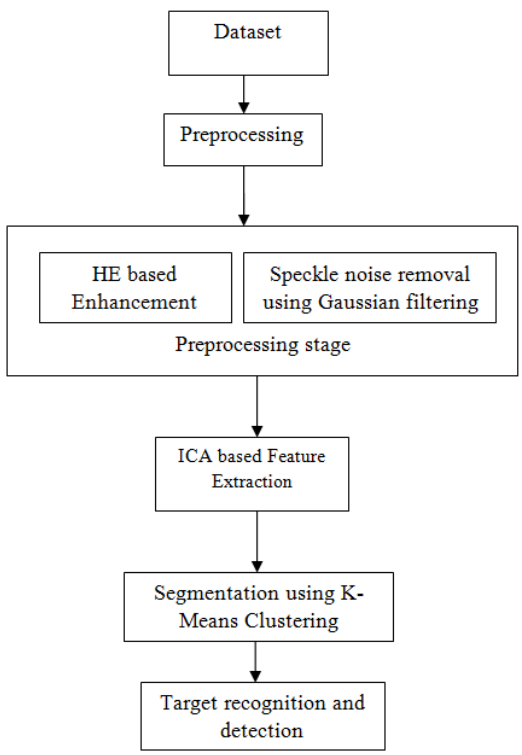

Fig 1. Overall flow of the proposed mechanism

2.1 Input data preprocessing

Initially, the input MSTAR image is preprocessed to remove the noise as the occurrence of noise may cause some defects in the performance of target detection and recognition. In case of preprocessing, enhancement and filtering technique are the most essential steps to be carried out.

The speckle noise present in the SAR images are being removed by means of filtering approach. For this, a Gaussian filtering is employed for despeckling the SAR images.

Images created by consistent energy, like satellite, experience speckle noise. Such noise is more intricate usually to eliminate as the noise intensity vary with the intensity of image. The Gaussian filtering technique is employed for the removal of speckle noise from the SAR images. The Gaussian filter algorithm is represented generally as follows:

Algorithm: Gaussian filter

Input: SAR Dataset image

Output: Despeckled image (Y).

Step 1: Input SAR image from the dataset

Step 2: Gaussian filter is applied, with the use of kernel size 3×3 and σ =0.5 (empirical values), to X which provides the denoised image X.

Step 3: Then, Despeckling is carried out on X with the aid of transformation and step function which in turn provides the despeckled image Y.

Step 4: Estimate the parameters for performance, like MSE, SNR, and PSNR, for the image Y that is despeckled.

Step 5: The output of despeckled image Y is attained

Then, the despeckled image is then enhanced by means of histogram equalization approach. The contrast enhancement system is done with the use of locally AHE adaptive histogram equalization of undesired objects like noise and blocking object.

2.2 ICA based feature Extraction approach

The features are extracted with the use of Independent component analysis (ICA).

The feature extraction process is used for creating a representation, or transformation from the original image. In the satellite image there are some primitive features like texture, shape, edge, darkness, etc. From these features, the most promising features like texture and shape/ edge are extracted for classification accuracy in the proposed methodology. The differences between each pixel and its surrounding pixels in a picture that are classified as textures. As a result, these runway region textural information may be retrieved using ICA and compared to a texture template. The fundamental objective of this step is the characterization. Texture analysis is commonly used to provide unique information on the intensity variation of spatially related pixels in medical images. The choice of an appropriate technique for feature extraction depends on the particular image and application. Texture features are extracted to encode clinically valuable information by using the ICA. The ICA can be mathematically derived as follows, ICA is a relatively new statistical and computational technique used to discover hidden factors (sources or features) from a image such that the sources are maximally independent. Mathematically, given the observed variables,

$$y(t) = y1(t),\ y2(t),\ \ldots,\ yn(t) \tag{1}$$

The above Equation (1) is composed of linear combination of original and mutually independent source,

$$T(t) = T1(t),\ T2(t),\ \ldots,\ Tn(t) \tag{2}$$

At time point t such that the Equation (2) can be expressed as

$$y(t)\ =\ AT(t) \tag{3}$$

where A is a complete rank mixing matrix. Equation (3) is frequently expressed as

$$Y\ =\ W\,Y \tag{4}$$

In this case, the demixing matrix is W = A-1, and z = z1, z2, ..., zn denotes the independent component. The task is to estimate the demixing matrix and independent components only based on the mixed observations, which can be done by various ICA algorithms like fast ICA, JADE, Info max etc. In the principles of ICA estimation, extracted components are non-gaussian and independent. Kurtosis ($\beta 1$) is one of the ways to measure non-gaussianity. The kurtosis values of the gaussian independent variables (ICs) are 0 for sub-gaussian, $\beta 1 \leq 0$, and > 0 for super-gaussian. The definition of the traditional kurtosis measure is

$$\beta 1 = E(y\ -\ \mu)\ 4\ E(y\ -\ \mu)\ 2*2\ -3 = \mu 4\sigma\ 4-3 \tag{5}$$

The traditional kurtosis measurements are likewise susceptible to outliers because they are mostly reliant on sample averages. Furthermore, because the standard measurements of kurtosis boost the values of kurtosis to the third and fourth powers, the effect of outliers is significantly magnified. One advantage of the quantize measures of kurtosis is that it doesn't depend on first moment, and second moment. So it is more robust than classical measure of kurtosis. Hence, by implementing the ICA the features like texture, shape and edges can be that can be extracted.

2.3 Segmentation using K-means clustering

Once after the enhancement of image, clustering based segmentation is employed to segment the image. The clustering process is carried out to achieve effective segmentation. The analysis of clustering was made based on the features in which the subgroups are found depending on the samples. In this, K-means clustering is employed. K-means algorithm is an iterative process that efforts to divide them into K pre-defined dataset distinct subgroups that were non-overlapping (clusters) at which individual point of data becomes one group only. It seeks to maintain the clusters as distant (far) apart as probable while simultaneously attempting to make the data points inter-cluster as comparable as likely. Data points are assigned to clusters in such a way that the arithmetic mean of all the data points that fully belong to a cluster, as well as the sum of the squared distances between the cluster's centroid and the data points, are on the minimum. The more standardized (similar) the data points are in the comparable cluster, the less dissimilarity there is within clusters.

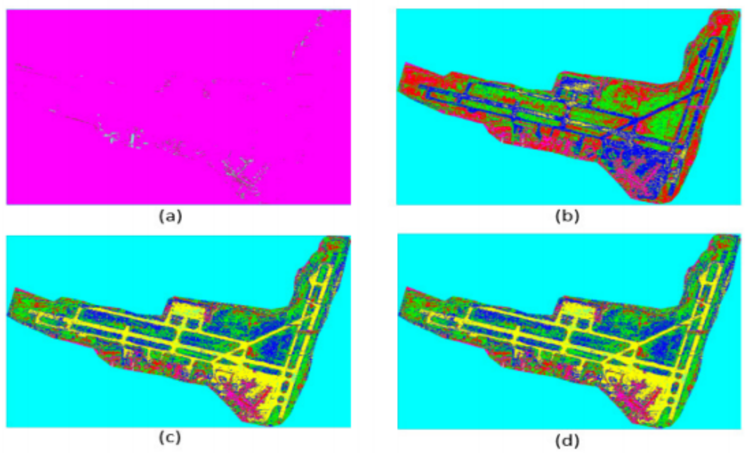

Fig 2. K-means clustering based segmentation analysis

Let us imagine a picture that has to be clustered into k number of clusters, with a resolution of x×y. Let ck represent the cluster centres and p(x, y) represent the input pixels to be clustered. The k-means clustering algorithm is as follows:

1. Set the cluster k and centre numbers to zero.
2. Using the relationship shown below, determine the Euclidean distance, or d, for each pixel in a picture between its centre and each pixel. p(x, y) − ck = d.
3. Based on distance, assign each and every pixel to the closest centre.
4. Using the relation shown below, compute the new centre position after all pixels have been allocated. x∈ck y∈ck p(x, y) = 1 k.
5. Until the tolerance or error value is satisfied, repeat the operation.
6. Reconstruct the picture from the cluster pixels.

Despite its significant benefit of being simple to apply, k-means has a few shortcomings. The arbitrary selection of the starting centroid determines the quality of the final clustering results. Therefore, various beginning centres will provide different results if the first centroid is selected at random. Thus, much care will be used in selecting the starting centre to ensure the desired segmentation. Additionally, we must take computing cost into account while creating the K-means clustering. It is dependent upon the quantity of data items, clusters, and iterations.

Fig 3. (a) The original graphic included dashed lines around an airport, (b) Red-colored runway bricks that were found

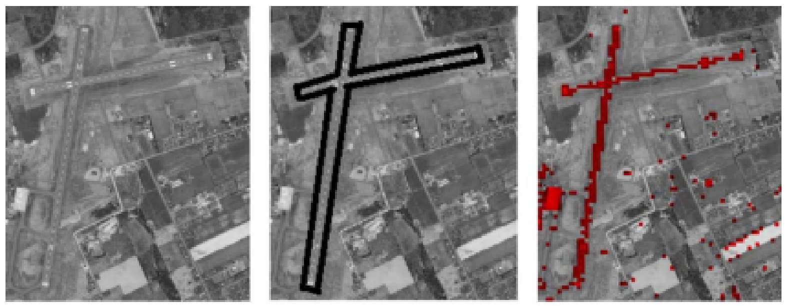

Fig 4. Closer look (a) The Runway, (b) The Border, (c) designated blocks

2.4 Target Detection and recognition

Thus, from the novel soft computing techniques, the target is detected and recognized with high rate of accuracy on comparing other existing approaches.

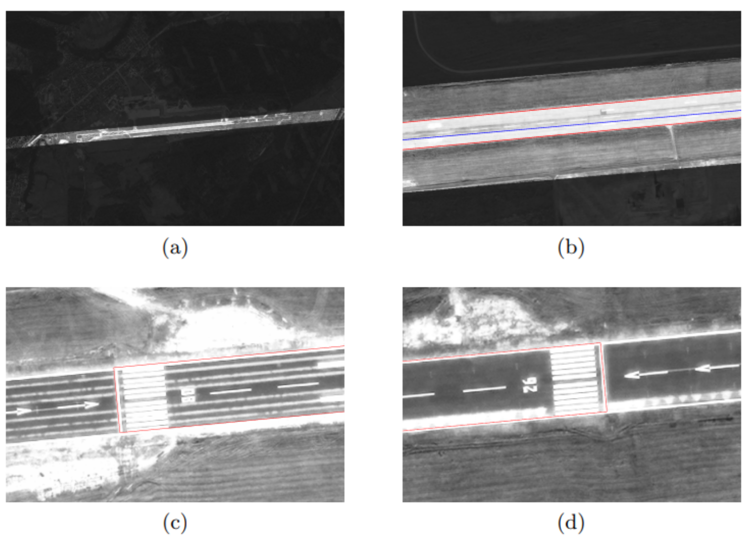

Fig 5. 5: Overview of the runway segmentation process. In (a), the region of interest - found by broadening the runway's axis line - is highlighted. In (b), a standard HT finds the long edges of the runway, displayed in red; the axis line is displayed in blue. In (c) and (d), the threshold markings have been found and the runway region capped

By this method, a less prediction time or setting time is achieved and maximum accuracy is obtained through simulation. Finally, the proposed experimental outcomes are compared with the existing technology. The proposed approach will be used in aircraft sensor based communication between the network (source to destination) to detect the target and to provide a better surveillance for military applications.

3 Results and Discussion

Korn B and morphological algorithms are prone to noise sensitivity, particularly in cluttered environments, where operations like dilation and erosion may worsen inaccuracies. In contrast, K-means clustering, operating on feature vectors rather than pixel values, tends to be more robust against noise. Moreover, morphological algorithms, especially when applied iteratively or on large images, can incur significant computational overhead due to repeated operations, unlike K-means clustering, which is computationally more efficient.

Table 1. Result of Korn B and Morphological algorithm

Image Name	Runway detected	Runtime	Accuracy	False positives	False negatives
Img 1	3	8.32s	79%	2	1
Img 2	2	6.78s	68%	3	0
Img 3	4	10.91s	85%	1	2

This section visualizes the detailed performance analysis of proposed methodology and comparison of this proposed method is made with existing techniques.

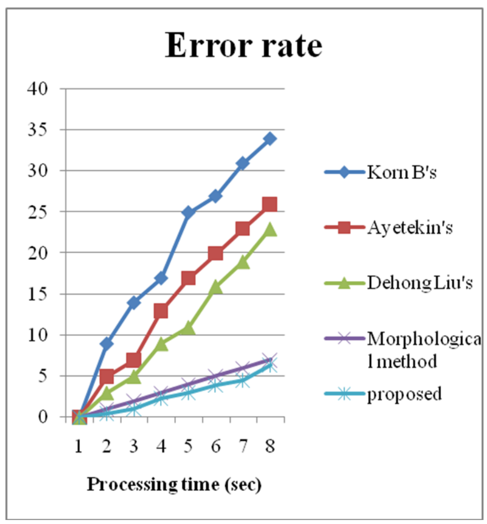

Fig 6. Comparative analysis of error rate

Table 1 and Figure 6 show the comparative analysis of proposed and existing methodologies in terms of error rate. Thus, from the analysis it was evident that the proposed methodology is better in providing reduced error rates.

The comparative analysis of the processing time is represented as follows:

Figure 7 is the depiction of processing time of proposed and existing methods to validate the effectiveness of proposed mechanism.

When compared with the methods proposed in the reference paper, "Unmanned Aerial vehicle's runway landing system with efficient target detection by using morphological fusion for military surveillance system" in "Computer Communication Volume" by Dr. Nagarani (Self citation), the K-means algorithm achieves 94% accuracy with high processing time of 5s and minimum error rate of 6%.

Figure 8 is the comparative analysis of proposed and existing methodologies which represents that the proposed accuracy is better than the existing methodologies. Thus, the target detection accuracy is higher in this proposed technique.

The performance Table 2 illustrates the methodologies used for the runway detection where the Korn B has the highest error rate, processing time and low accuracy. Whereas, the Morphological algorithm possess reduced error rate, processing time and high accuracy than the Korn B. From the table, it is evident that the proposed K-means algorithm has the lowest error rate, processing time and highest accuracy of 94%.

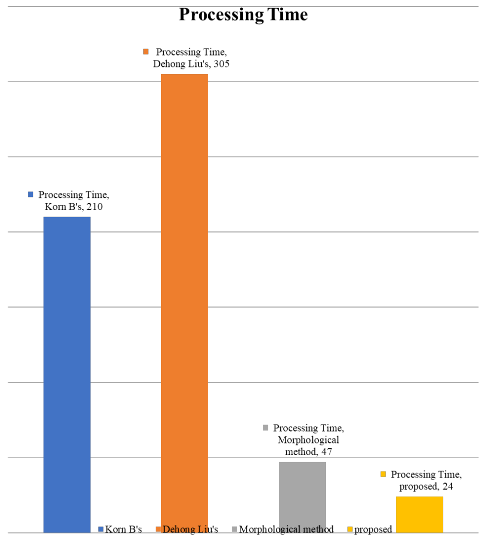

Fig 7. Comparative analysis of processing time

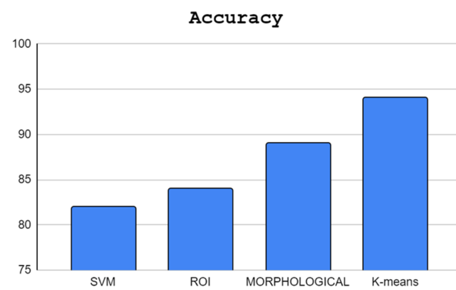

Fig 8. Comparative analysis of accuracy

Table 2. Overall Performance

Methodologies	Error Rate	Processing Time	Accuracy
Korn B	35	200ms	84%
Morphological	7	50ms	89%
K-means Clustering	6	10ms	94%

4 Conclusion

This study explains an approach for automatic runway detection using remote sensing images by implementing a novel K-means clustering segmentation. The exact detection of target or the runway is recognized by the use of some novel techniques. In this, preprocessing of MSTAR image is carried out initially in which histogram equalization-based image enhancement and Gaussian filtering is carried out for speckle noise removal. Then the features are extracted using ICA followed by effective K-means clustering based segmentation approach that uses unlabeled datasets and clustering formulae providing integration of dataset at high end thereby achieving 94% accuracy. The findings underscore the importance of this technology in various applications, ranging from military operations to remote sensing, highlighting its potential to enhance efficiency and effectiveness across a multitude of domains.

References

1) Mohsan SAH, Othman NQH, Li Y, Alsharif MH, Khan MA. Unmanned aerial vehicles (UAVs): practical aspects, applications, open challenges, security issues, and future trends. *Intelligent Service Robotics*. 2023;16:109–137. Available from: https://dx.doi.org/10.1007/s11370-022-00452-4. doi:10.1007/s11370-022-00452-4.
2) Kaljahi MA, Shivakumara P, Idris MYI, Anisi MH, Lu T, Blumenstein M, et al. An automatic zone detection system for safe landing of UAVs. *Expert Systems with Applications*. 2019;122:319–333. Available from: https://dx.doi.org/10.1016/j.eswa.2019.01.024. doi:10.1016/j.eswa.2019.01.024.
3) Bektash O, Naundrup JJ, la Cour-Harbo A. Analyzing visual imagery for emergency drone landing on unknown environments. *International Journal of Micro Air Vehicles*. 2022;14(January-December):1–18. Available from: https://dx.doi.org/10.1177/17568293221106492. doi:10.1177/17568293221106492.
4) Wang Z, Zhao D, Cao Y. Visual Navigation Algorithm for Night Landing of Fixed-Wing Unmanned Aerial Vehicle. *Aerospace*. 2022;9(10):1–27. Available from: https://dx.doi.org/10.3390/aerospace9100615. doi:10.3390/aerospace9100615.
5) Ma N, Weng X, Cao Y, Wu L. Monocular-Vision-Based Precise Runway Detection Applied to State Estimation for Carrier-Based UAV Landing. *Sensors*. 2022;22(21):1–20. Available from: https://dx.doi.org/10.3390/s22218385. doi:10.3390/s22218385.
6) Lalak M, Wierzbicki D. Automated Detection of Atypical Aviation Obstacles from UAV Images Using a YOLO Algorithm. *Sensors*. 2022;22(17):1–22. Available from: https://dx.doi.org/10.3390/s22176611. doi:10.3390/s22176611.
7) Nagarani N, Venkatakrishnan P, Balaji N. Unmanned Aerial vehicle's runway landing system with efficient target detection by using morphological fusion for military surveillance system. *Computer Communications*. 2020;151:463–472. Available from: https://dx.doi.org/10.1016/j.comcom.2019.12.039. doi:10.1016/j.comcom.2019.12.039.
8) Ashraf A, Majd A, Troubitsyna E. Online Path Generation and Navigation for Swarms of UAVs. *Scientific Programming*. 2020;2020:1–14. Available from: https://dx.doi.org/10.1155/2020/8530763. doi:10.1155/2020/8530763.
9) Misra A, Jayachandran S, Kenche S, Katoch A, Suresh A, Gundabattini E, et al. A Review on Vertical Take-Off and Landing (VTOL) Tilt-Rotor and Tilt Wing Unmanned Aerial Vehicles (UAVs). *Journal of Engineering*. 2022;2022:1–27. Available from: https://doi.org/10.1155/2022/1803638. doi:10.1155/2022/1803638.
10) Tang H, Zhu Q, Qin B, Song R, Li Z. UAV path planning based on third-party risk modeling. *Scientific Reports*. 2023;13(1):22259–22259. Available from: https://dx.doi.org/10.1038/s41598-023-49396-4. doi:10.1038/s41598-023-49396-4.