**Journal of Innovation and Development**
ISSN: 2958-4752 | Vol. 11, No. 1, 2025

# Application of Obstacle Automatic Recognition Algorithm in Geometry System Design

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**Abstract:** In seismic data acquisition, surface obstacles significantly impact the collection of effective information by affecting the uniformity of source placement or causing missing shots due to the inability to traverse large towns, aquaculture areas, rivers, lakes, and other obstructions. Understanding the distribution ranges of these obstacles allows for adjustments in geometry systems, thereby improving efficiency. This paper discusses several typical satellite image-based automatic obstacle recognition methods, with a focus on detailed explanations of the principles of mean clustering and support vector machines, as well as an analysis of their practical application characteristics. These methods play a crucial role in greatly enhancing productivity.

**Keywords:** Obstacle Recognition, Mean Clustering, Support Vector Machine, Geometry System.

## 1. Introduction

With the deepening of oil and gas exploration and development, domestic and international seismic acquisition regions are increasingly shifting toward areas with complex surface conditions and greater construction difficulties. During three-dimensional surveys, encountering extensive urban areas, aquaculture zones, rivers, and lakes poses challenges for source placement, leading to uneven distributions or even severe shortages. Poor receiver offset conditions degrade reception quality, while the inability to traverse large towns, aquaculture areas, rivers, and lakes results in missing shots, creating local data gaps. Traditional geometry designs employ manual adjustments that consider fold coverage and surface obstacles, often forcibly crossing obstacles and increasing offsets at both ends to meet coverage requirements. However, advancements in technology, precision demands, and expanding production scales have exposed the limitations of manual approaches, which are insufficient to meet modern exploration needs. Manual obstacle recognition and adjustment designs are inefficient and time-consuming.

Image segmentation algorithms are used to identify specific obstacles in images. Since the 1970s, image segmentation has received significant attention, and numerous algorithms have been proposed. Yet, no universal theory exists, nor does a single algorithm suit all scenarios—each has its limitations. Among these, mean clustering and support vector machines are widely applied in various fields and are discussed below in the context of satellite image-based obstacle recognition applications.

## 2. Methodology Principles

### 2.1. Mean Clustering

Clustering divides datasets subsets ensuring high similarity within subsets dissimilarity between based attribute values typically described inter-cluster distances . Basic principle maximizes intra-class similarity minimizes inter-class similarity . As statistical branch clustering analysis researched extensively focusing distance-based approaches many software packages like S-Plus SPSS SAS include tools K-means K-medoids others .

K-means common proximity-based unsupervised learning algorithm pattern recognition dynamic clustering hard partition method simple versatile across data types proposed MacQueen nineteen sixty-seven initializes randomly selecting k centers calculates distances assigns objects nearest center updates centers iteratively until convergence achieved no changes occur indicating completion. Features include examining every sample correctness adjusting re-calculating centers next iteration if correctly classified no adjustments needed convergence reached ending process .

Disadvantages K-means include initialization number clusters selection initial centers sensitivity noise outliers limited discovering spherical clusters despite issues widely used .

### 2.2. Support Vector Machine

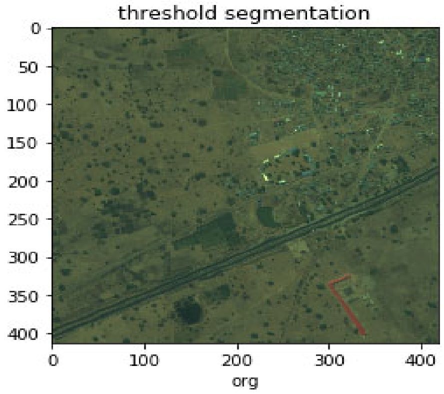
Between nineteen ninety-two ninety-five statistical learning theory developed new machine - Support Vector Machine SVM built VC dimension structural risk minimization principles seeking optimal trade-offs model complexity learning ability best generalization performance solving small sample nonlinear high-dimensional problems exhibiting unique advantages .

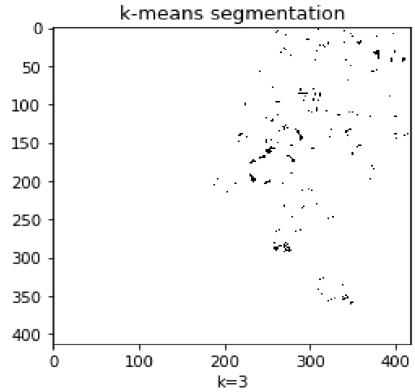
SVM proposed Vapnik statistical learning theory minimizes structural risk selecting appropriate function subsets discriminant functions ensuring minimal actual risks guarantees small error classifiers independent test sets maintaining low errors thus optimal classification generalization capabilities .

Compared K-means SVM offers more stable flexible image segmentation practical applications .

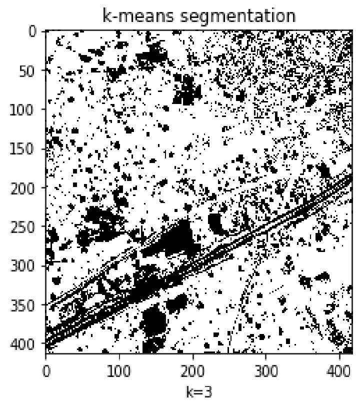
## 3. Application Effects

Seismic data acquisition conducted certain area required understanding building road water body distributions geometry system design satellite images analyzed using K-means SVM recognizing obstacles. Based K-means principle random initialization iterative clustering centers main obstacles segmented analyzed k=3, 4, 5. When k= 3 three centers initialized black objects white background shown Figure 1:



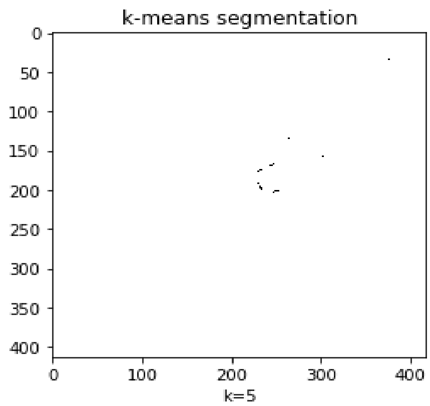

(a) Remote sensing satellite image (b) Building segmentation result

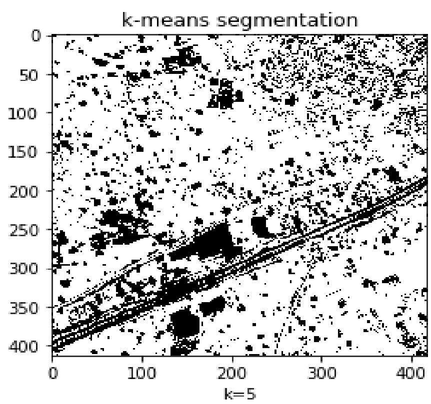



(c) Road lake segmentation result

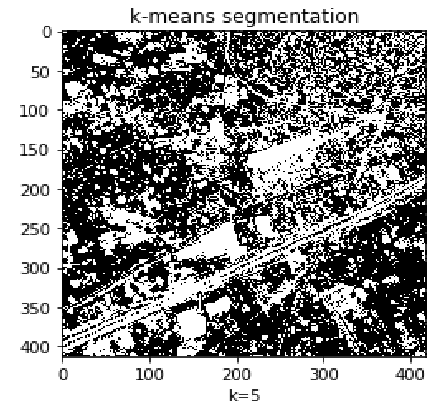
**Figure 1.** k=2 remote sensing image segmentation schematic

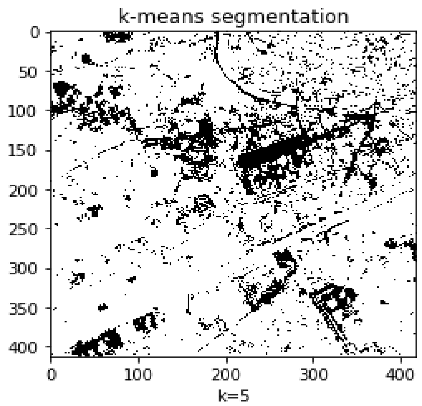
When k=2 two classes Figure one b first class partial buildings Figure one c second class roads lakes trees identified together. When k=4 four centers initialized black objects white background shown Figure 2.




(a) Partial building segmentation result (b) Road lake segmentation result

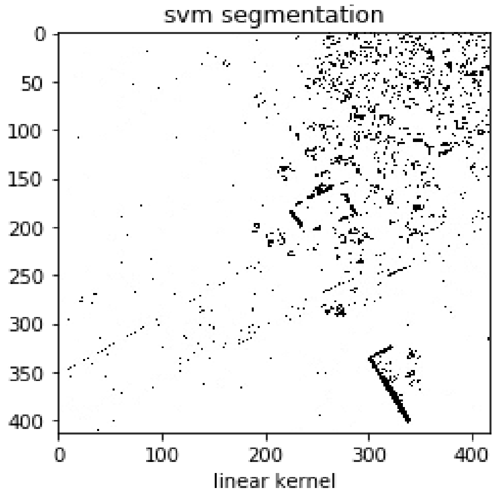


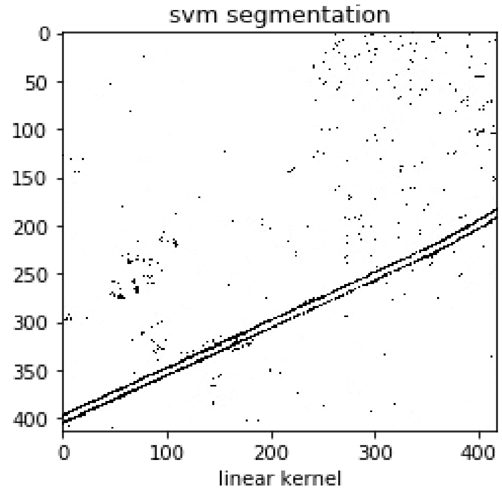

(c) Ground segmentation result (d) Partial road segmentation result

**Figure 2.** k=4 remote sensing image segmentation schematic

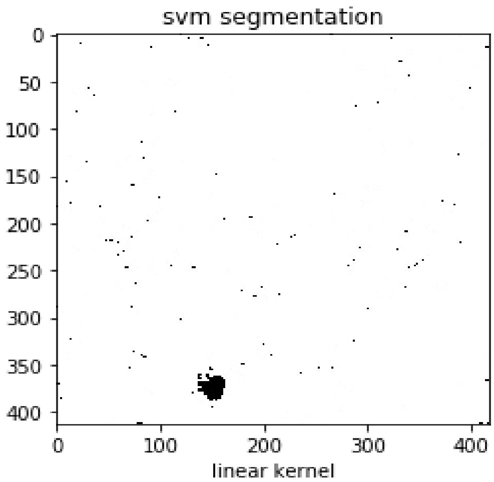
Selecting k values shows K-means performs moderately remote sensing images partially recognizing objects random initialization unable target specific objects results unpredictable uncontrollable.



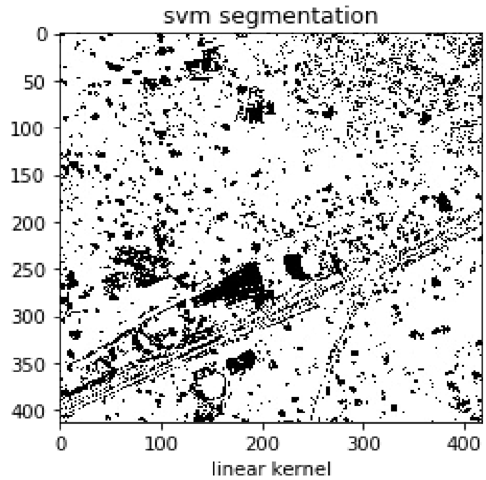

(a) Building recognition segmentation result



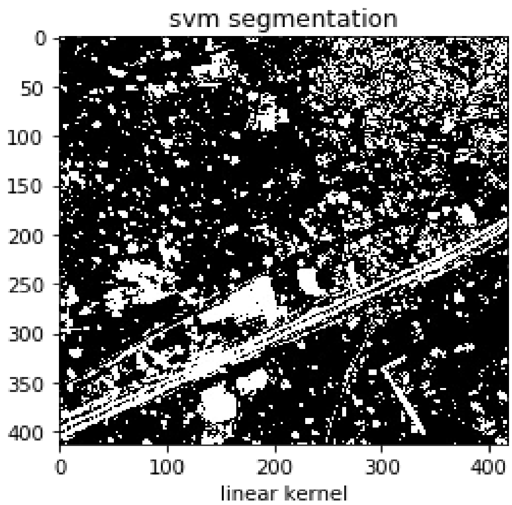

(b) Road recognition segmentation result




(c) Lake recognition segmentation result

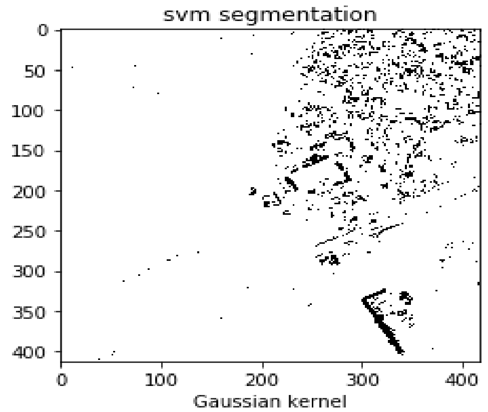



(d) Tree recognition segmentation result

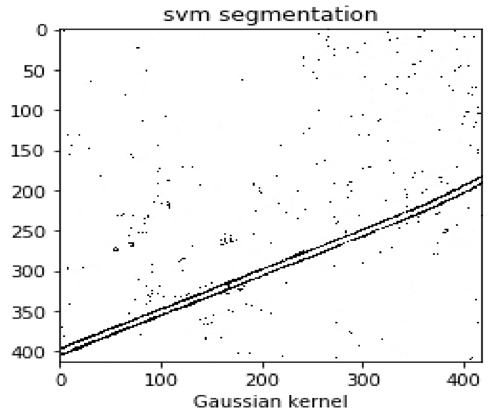



**(e)** Ground recognition segmentation result

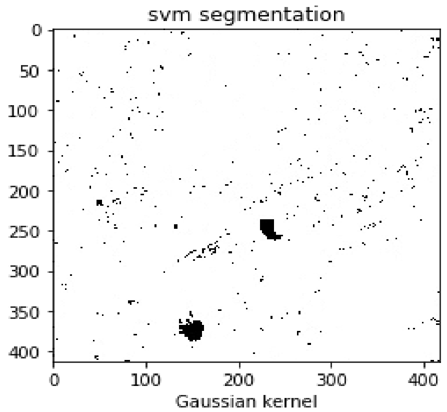
**Figure 3.** Linear kernel function remote sensing image recognition segmentation effect)

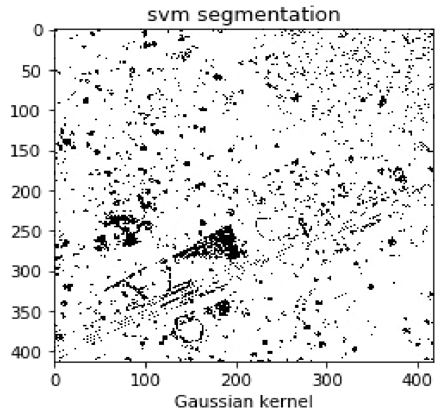



(a) Building recognition segmentation result

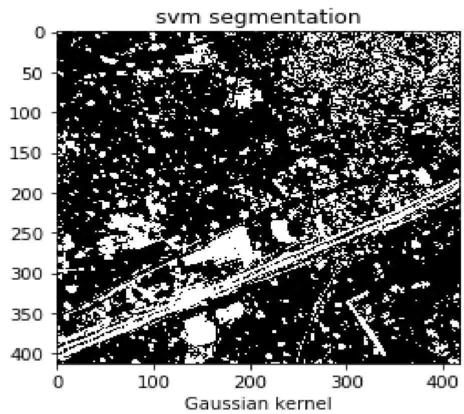



(b) Road recognition segmentation result




(c) Lake recognition segmentation result (d) Tree recognition segmentation result




(e) Ground recognition segmentation result

**Figure 4.** Gaussian kernel function remote sensing image recognition

Using linear kernel SVM overall improves K-means Figure three b buildings recognized well noise present Figure 3(d) only one lake segmented Figure three e poor recognition lakes trees other objects mixed together. Choosing Gaussian kernel improves linear kernel reducing noise Figure four d both lakes fully recognized Figure four e trees still misclassified Generally Gaussian preferred default choice unknown kernel selection .

# 4. Conclusion

The K-means clustering algorithm is widely applied. It calculates similarity among sample classes based on the distance of feature values between data points, enabling obstacle recognition. While its segmentation performance for remote sensing images surpasses threshold-based methods, it still fails to meet required obstacle recognition accuracy. During k-value selection, increasing k does not effectively classify multiple obstacle types but instead subdivides high-pixel-contrast regions. The k-value determines the number of object categories to extract, yet its selection remains subjective and often relies on empirical experience.

In contrast, the Support Vector Machine (SVM), as a supervised machine learning algorithm, requires training on labeled datasets to learn prior information about object classes. This enables SVM to achieve significantly better obstacle segmentation in remote sensing images than K-means, approaching the desired recognition performance. However, SVM's accuracy heavily depends on the quality of training samples—different sample selections may lead to entirely divergent results. Overall, SVM outperforms clustering algorithms in remote sensing image segmentation.

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