# A REVIEW ON VARIOUS APPROACH FOR PERORMANCE ENHANCEMENT TECHNIQUES OF CLOUD EXTRACTION IN SATELLITE IMAGES

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## ABSTRACT

*The present study is an attempt to identify the characteristics of atmospheric cloud that affects the aerial and satellite images. Images captured by aerial and satellite are projected images where the cloud causes interference in them. The major challenge of satellite imaging is to provide accurate and frequent images to the research world without any discontinuity of data sets. This paper describes the basic technological aspects of image processing with special reference to aerial and satellite image processing.*

**Keywords:-** *Bag of words (BOW),global threshold,local threshold, Smart information reconstruction (SMIR),spatially and temporally weighted regression (STWR)*

## 1. INTRODUCTION

Satellite images known as remotely sensed images, permit accurate mapping of land cover and make landscape features understandable on regional, continental, and even global scales. Transient phenomena, such as seasonal vegetation vigor and contaminant discharges, can be studied by comparing images acquired at different times. Satellite imagery are images of Earth or other planets collected by imaging satellites operated by governments and businesses around the world. Satellite imagery is very cost effective in mapping extended regions.The existence of high quality images enabled mapping changes in land development in the last two decades.

Nevertheless, one of the problems that hindered the use of such imagery is existence of clouds and their associated shadows. Although cloud areas can easily be detected and replaced from other imagery due to their high reflectance, the shadow caused by these clouds represents areas with low illumination conditions that double the image defected areas. This effect of clouds and cloud-associated shadows are widely spread with approximately 66% of the earth surface is covered by clouds throughout the year[1].

A common and complex aspect in aerial and satellite image application is encountered when image is captured from above the clouds. This causes signal attenuation of the image acquisition above the cloud cover and cloud-shadows modifies the ground local luminance. Several methods were used to restore the cloud affected areas. But most of them are used for removing thin clouds[2]. Fusion techniques were also used to account for cloud and shadow defects[3]. These methods require cloud/shadow free images as reference images for processing and so not much reliable. Recent developments in the area include more efficient segmentation results but the performance is greatly influenced by the selection of the thresholds for various spectral tests[4] T.B. Borchartt and R.H.C. de Melo [5] suggested a method which works well but the algorithm fails for the compensation of cloud-shadows and the scaling factors have to be obtained experimentally for each part of the image.

Several methods were used to overcome these problems, techniques such as Bag of words (BOW), global threshold, local threshold, Smart information reconstruction (SMIR), spatially and temporally weighted regression (STWR).

## 2. ANALYSISIS OF DIFFERENT PERFORMANCE ENHANCEMENT TECHNIQUES OF CLOUD EXTRACTION IN SATELLITE IMAGES

### 2.1 Bag of words (BOW)

In this study, a method of automatic cloud detection is proposed based on object classification of image features. An image is first segmented into superpixels so that the descriptor of each superpixel can be computed to form a feature vector for classification. The support vector machine algorithm is then applied to discriminate cloud and noncloud regions.Thereafter, the GrabCut algorithm is used to extract more accurate cloud regions. The key of the method is to deal with the highly varying patterns of clouds. The bag-of-words (BOW) modelis used to construct the compact feature vectors from denselyextracted local features, such as dense scale-invariant featuretransform (SIFT)[6].

To build the BOW model, dense SIFT features [7] are extracted from each object obtained by segmentation. K-means clustering is then used for the generation of the codebook of the features. A training sample of cloud and noncloud objectsis then selected. After learning from the samples by support vector machines (SVMs) [8], segmented image objects can be classified as cloud and noncloud. The final step is to use the GrabCut algorithm [9] to segment the foreground (classified cloud objects) and the background accurately.BOW was initially used for natural language processing and information retrieval with documents that are considered as unordered sets of words, disregarding grammar, and word order [10].Recently, this model has been successfully applied in computer vision, such as image classification, object recognition, and image retrieval [11]–[12]. The BOW model treats each pattern as a collection of features extracted from the image. BOW is suitable for modeling complex objects, such as cloud with varying parts in a compact feature vector.

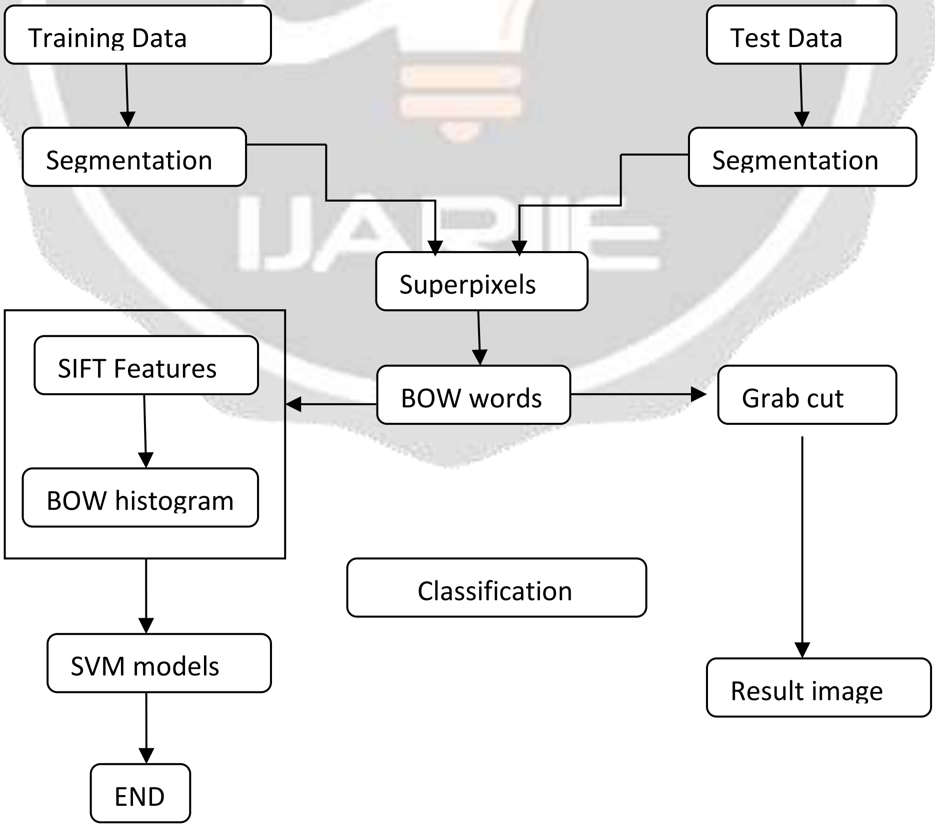

**Fig.1.** Workflow of the proposed approach.

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### 2.2. Global threshold andlocal threshold

In an effective registrationmethod for cloudy satellite images based on global and localthresholds. First, cloud candidates are determined by using optimalthreshold and *k*-means clustering. Then, using the localthreshold, the cloud candidates are further classified into threecategories: thick clouds, thin clouds, and ground. Finally, accurateregistration is performed by eliminating features relating to cloudyareas.
Thick cloudy areas are comparatively easy to segment, and conventional methods based on simple threshold techniques, which are proposed by Otsu [13], Yen *et al.* [14], and Tsai [15], can provide reasonable performance. However, segmentation of thin cloudy areas is a critical task due to the similar intensity values of the cloud and ground features such as roads, houses, and buildings.
Therefore, simple threshold techniques are unable to segment cloudy areas correctly. This problem and propose an effective registration method for remote sensing images that also contain clouds. Fig. 2 shows the main steps involved in two stages of the proposed method. It is notable that, usually, image registration consists of four main steps: feature extraction, feature matching, transformation estimation, and image resampling[16], [17]. Whereas, in the proposed method, two additionalsteps, i.e., cloud detection and segmentation, are carried out before the registration procedure. The main advantage of segmenting the cloudy areas is that the outliers are automatically eliminated.

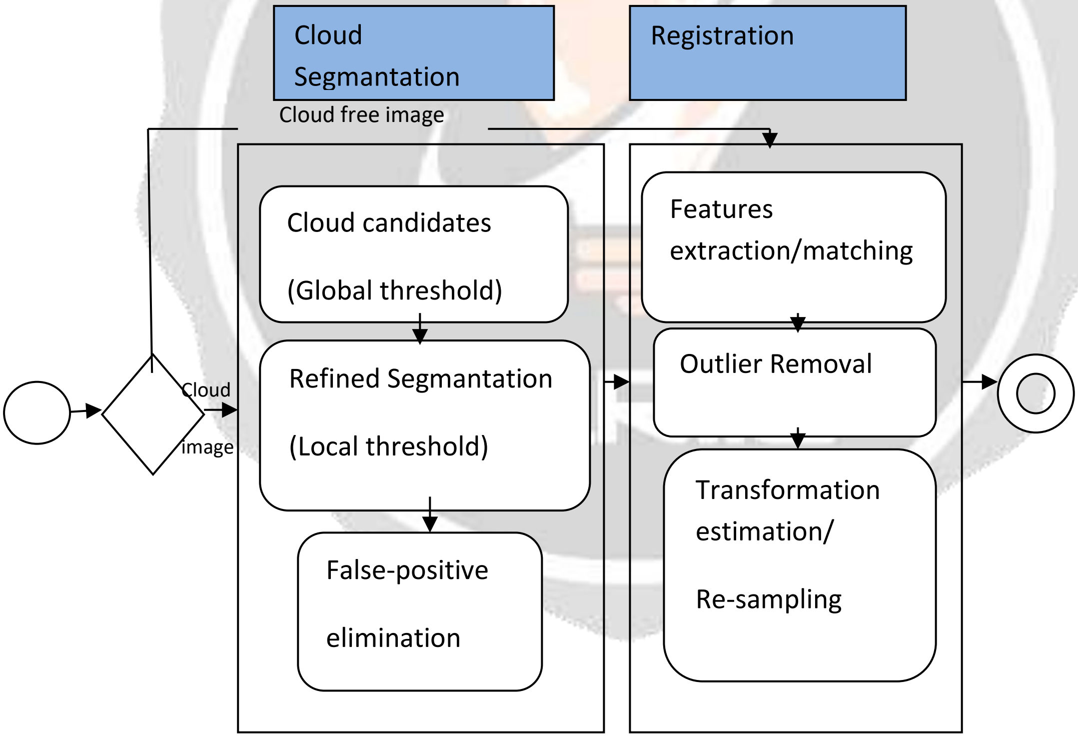

**Fig. 2.** Block diagram of the proposed method**.**

### 2.3 Smart information reconstruction (SMIR)

A novel smart information reconstruction (SMIR) method is proposed, in order to reconstruct cloud contaminated pixel values from the time-space-spectrum continuum with the aid of a machine learning tool, namely extreme learning machine(ELM).A novel information recovery method is proposed here by reconstructing the value of cloudy pixels through the established time-space-spectrum relationships between cloudfree pixels and the cloudy pixels that are cloud-free in the historic time series with the aid of computational intelligenceor machine learning, namely smart information reconstruction (SMIR). The objective of this study is dedicated to developing the SMIR method and advancing its performance in terms of information recovery among data gaps caused by cloud contamination in remotely sensed images.

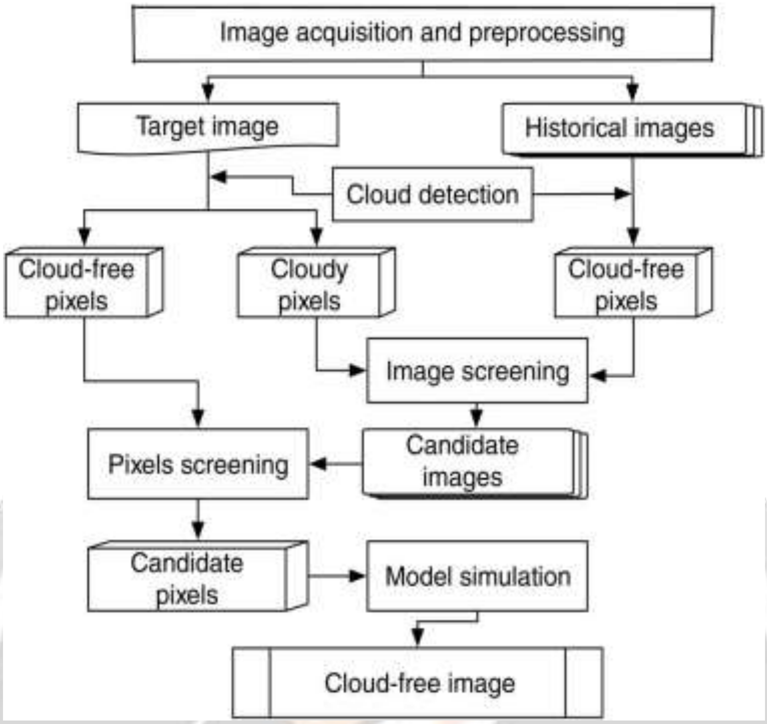

**Fig. 3.** Schematic flowchart of the proposed SMIR method.

### 2.4 Spatially and temporally weighted regression (STWR)

A novel spatially and temporally weighted regression (STWR) model for cloud removal to produce continuous cloud-free Landsat images. The proposed method makes full utilization of cloud-free information from input Landsat scenes and employs a STWR model to optimally integrate complementary information from invariant similar pixels. Moreover, a prior modification termis added tominimize the biases derived from the spatially-weighted-regression-based prediction for each reference image. The results of the experimental tests with both simulated and actual Landsat series data show the proposed STWR can yield visually and quantitatively plausible recovery results.Spatially and temporally weighted regression (STWR) model to produce continuous cloud-free Landsat imagery.

STWR makes full use of cloud-free pixels in the input time series cloud-contaminated scenes and optimally integrates bothspatial and temporal information to restore missing data in each target scene. The major contribution of this focuses on solving a more complex and practical issue: continuous cloud removal. To be specific, our model aims to transfer time-series cloud-contaminated Landsat scenes to corresponding cloud free ones. Moreover, a complete procedure of removing Landsat clouds, including cloud/shadow detection, cloud/shadow labeling, and cloud removal,was provided. The implementation of cloud removal using STWR can be easily extended to the reprocessing of cloud-free remote sensing productions.

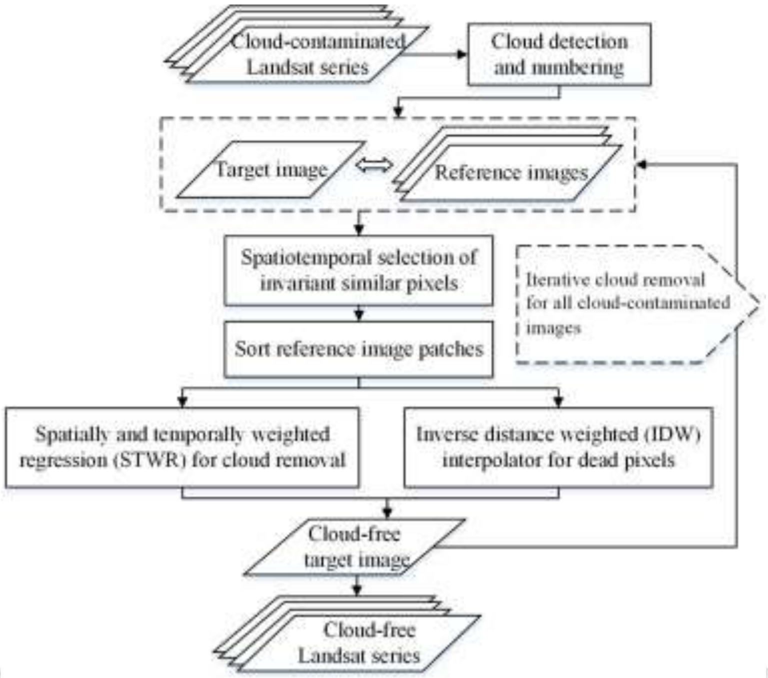

**Fig.4**. Flowchart of the proposed STWR method.

## 3. COMPARARATIVE ANALYSIS OF TECHNIQUES

| Technique Used | Remarks |
|---|---|
| Bag of words (BOW) | The experiments show that the method is insensitive to the number of codewords in the codebook construction of the BOW. |
| Global threshold andlocal threshold | The experiments show that the proposed method provides segmentation accuracy of 93.29%. In addition, registration accuracy is improved by 24.83%, as compared with conventional methods. |
| Smart information reconstruction (SMIR) | The proposed ELM-based SMIR method is capable to recover the missing information with high efficacy for operational use. |
| Spatially and temporally weighted regression (STWR) | With the integration of information on boththe target image and reference image through a STWR model,<br>STWR can efficiently restore cloud-contaminated information. |

**Table 1**: Comparison of techniques

## 4. CONCLUSION

Satellite and aerial images are used for feature extraction among other functions. Images captured by aerial and satellite are projected images where the cloud causes interference in them. The major challenge of satellite imaging is to provide accurate and frequent images to the research world without any discontinuity of data sets. Accurate retrieval of satellite and aerial images based on surface products requires the removal of atmospheric effects like cloud contamination. The BOW method only needs some representative samples to build up a classification model. Combining BOW method with other successful algorithms using multi- temporal images and sensor information could be an interesting future work to improve the accuracy of the extraction. As BOW does not require multi-temporal images; and it does not require additional information about the sensors. The BOW method only needs some representative samples to build up a classification model.

## 5. REFERENCES

[1]“Enhancement of Cloud-Associated Shadow Areas in Satellite Images Using Wavelet Image Fusion” A. Abd-Elrahman, I.F. Shaker, A.K. Abdel-Gawad and A. Abdel-Wahab presented at World Applied Science Journal 2008

[2] Chanda, B., Majumder, D.D.: An iterative algorithm for removing the effects of thin cloud cover form Landsat imagery. Mathematical Geology 23(6), 853–860 (1991) [3] Abd-Elrahman, A., Shaker, I.F., Abdel-Gawad, A.K., Abdel-Wahab, A.: Enhancement of Cloud-Associated Shadow Areas in Satellite Images Using Wavelet Image Fusion. World Applied Sciences Journal 4(3), 363–370 (2008)

[4] Reuter, M., Thomas, W., Albert, P., Lockhoff, M., Weber, R., Karlsson, K.G., Fischer, J.: The CM-SAF and FUB Cloud Detection Schemes for SEVIRI: Validation with Synoptic Data and Initial Comparison with MODIS and CALIPSO. J. Appl. Meteor. Climatol. 48, 301–316 (2009)

[5] Borchartt, T.B., de Melo, R.H.C., Gazolla, J.G.F.M., Resmini, R., Conci, A., Sanchez, A., de A. Vieira, E.: On the reduction of cloud influence in natural and aerial images. In: 18th International Conference on Systems, Signals and Image Processing, pp. 1–4 (June 2011)

[6]“Bag-of-Words and Object-Based Classification for Cloud Extraction From Satellite Imagery”
Yi Yuan and Xiangyun HuIEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 8, NO. 8, AUGUST 2015

[7]D. G. Lowe, “Distinctive image features from scale-invariant keypoints,”*Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, 2004.

[8] V. Vapnik, *The Nature of Statistical Learning Theory*. New York, NY,USA: Springer, 2000.

[9] C. Rother, V. Kolmogorov, and A. Blake, “Grabcut: Interactive foreground extraction using iterated graph cuts, *ACMTrans. Graphics (TOG),*
vol. 23, no. 3, pp. 309–314, 2004.

[10] D. D. Lewis, “Naive (Bayes) at forty: The independence assumption in information retrieval,” in *Machine Learning: ECML-98*. New York, NY, USA: Springer, 1998, pp. 4–15.

[11] L. Fei-Fei and P. Perona, “A bayesian hierarchical model for learning natural scene categories,” *Comput. Vis. Pattern Recog.*, 2005, vol. 2, pp. 524–531.

[12] J. Yang *et al.* “Evaluating bag-of-visual-words representations in scene classification,” in *Proc. Int. Workshop Multimedia Inf. Retrieval*, 2007, pp. 197–206.

[13]Robust Registration of Cloudy Satellite ImagesUsing Two-Step Segmentation Ik-Hyun Lee, *Member, IEEE*, and Muhammad Tariq Mahmood, *Member*, IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, VOL. 12, NO. 5, MAY 2015

[14] N. Ostu, “A threshold selection method from gray-level histogram,” *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-9, no. 1, pp. 62–66, Jan. 1979.

[15] J. Yen, F. Chang, and S. Chang, “A new criterion for automatic multilevel thresholding,” *IEEE Trans. Image Process.*, vol. 4, no. 3, pp. 370–378, Mar. 1995.

[16] W. Tsai, “Moment-preserving thresolding: A new approach,” *Comput.*
*Vis., Graph., Image Process.*, vol. 29, no. 3, pp. 377–393, 1985.

[17] I. Lee and T. Choi, “Accurate registration using adaptive block processing for multi-spectral images,” *IEEE Trans. Circuits Syst. Video Technol.*, vol. 23, no. 9, pp. 1491–1501, Sep. 2013.

[18] D. Lowe, “Distinctive image features from scale-invariant keypoints,” *Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, Nov. 2004

[19]Smart Information Reconstruction via Time-Space-Spectrum Continuum for Cloud Removal in Satellite Images Ni-Bin Chang, *Senior Member, IEEE*, Kaixu Bai, and Chi-Farn Chen.
IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 8, NO. 5, MAY 2015

[20]Spatially and Temporally Weighted Regression:A Novel Method to Produce Continuous Cloud-Free Landsat Imagery Bin Chen, *Student Member, IEEE*, Bo Huang, *Associate Member, IEEE*, Lifan Chen, and Bing Xu IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 55, NO. 1, JANUARY 2017

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