AUTOMATIC CLOUD SHADOW DETECTION FROM LANDSAT IMAGES

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ABSTRACT:

Most remote sensing images are affected by cloud shadows in data acquisition processing, which cause serious problems for further analysis of data. Many researchers have offered effective methods to detect these cloud shadows from remote sensing images. Cloud shadows are created when presence of clouds obscure ground features from satellite imagery. The problem caused by cloud shadow is loss of information or occlusion. In this paper a novel automatic shadow detection method from Landsat images is proposed. The experiments are performed on Landsat images and results are obtained. The experimental result demonstrates that our methods can detect shadow regions better compared to traditional approaches.

Keywords: cloud shadow, color conversion, rationing, clustering

[1] INTRODUCTION

The satellite images have lot of applications; they are used for change detection, classification, land use classification etc. Although satellite images have lot of benefits, they are having some serious drawback. Since satellite orbit is fixed and satellite moves through same locations in regular so if some cloud exist in the sky satellite cannot able to obtain the ground information. So cloud covered regions appear brighter in optical satellite images. The cloud also cast shadows which are located near to cloud regions, usually on to left of cloud regions.

The clouds not only hide ground but also cast their shadows on the ground; they impede many applications such as detection of vegetations etc. This means that for many applications it is necessary to remove cloud and their shadows from acquired satellite images.

Shadows have played an important role in remote sensing for almost as long as the science has been in existence. Shadows in remotely sensed images create difficulties in many applications; thus, they should be effectively detected prior to further processing. The principal problem caused by shadows is either a reduction or total loss of information in an image. Reduction of information could potentially lead to the corruption of biophysical parameters derived from pixels values, such as vegetation indices. Total loss of information means that areas of the image cannot be interpreted. However, in general, shadows may cause loss of feature information, false colour tone, and object distortion and they are obstacles in many image interpretation applications. One property that provides a clue to the presence of shadows
is lower luminance, which is the primary property of shadows. However, even though shadows have a lower luminance, the lowest intensity objects in the image are not necessarily shadows. The image intensity is determined by several factors, including luminance, ground reflectivity, and the atmospheric environment. In addition to low intensity, chromatic information can also be used for shadow detection in a colour input image. However, except for lower luminance, none of the other image properties (e.g., higher saturation, higher hue value, or bluish shadow pixels) is inherent to shadow regions in remotely sensed images. In fact, the chromatic properties (hue and saturation) of shadow regions in different remotely sensed images can vary significantly.

Filling these simple search boxes with different relevant terms may return the same set of documents from the database. Posing all of them would not be a good retrieval strategy as it yields the same set over and over again. Intuitively, posing some optimal set of terms that can retrieve a diversified document set covering the entire Hidden database is more desirable than posing the entire set of terms that retrieves and presents the same set of documents repeatedly. Thus, it becomes necessary not only to rank the terms but also select an optimal set from the ranked terms. Our work focuses on how to formulate appropriate query terms for text box based simple search form interfaces that can yield maximum number of documents from the database by posing a minimum number of such terms sequentially on the interface.

[2] LITERATURE REVIEW

The cloud shadows are dark and, of course, they are due the presence of a nearby cloud. The cloud shadows are even more difficult to detect than the clouds themselves. The shadows are not the only dark objects, and cloud shadows can be confused with plots of bare soil, with water bodies or with shadows cast by the terrain. Again, using multi-temporal methods can reduce the risk of confusion: the algorithm must detect a sudden darkening of a pixel. However, the effect of plowing, rainfall or irrigation on a bare soil may be similar to the effect of a cloud shadow. To be sure that the pixels that suddenly darkened are true cloud shadows, it is useful to check that the shadow matches the cloud that casted it. Identifying shadows by a computer is a difficult problem, although it is an easy task for humans. The traditional shadow detection methods are follows.

Thresholding is simply the method of binarizing an image by setting all pixels whose values are greater than some threshold level to “high”, and the remaining pixels to “low”. The classic problem associated with thresholding, is selecting the most suitable threshold level to best separate desired features from undesired features. Since the shadows in high resolution satellite images occupy the lower end of the histogram, with few other features having such low grey levels, thresholding is a potentially ideal method of shadow detection: by choosing the correct threshold level, it should be straightforward to separate shadow from non-shadow, without too many pixels being misclassified.

Image classification is most commonly used with multispectral data, to extract image features. Segmentation is simply the process in which an image is split into a contiguous spatial array of discrete regions.

In region growing segmentation pixels are assigned to regions based on their spatial and spectral distance from those regions to which they could potentially be assigned. The classic
problem with region growing segmentation is that the result is dependent on the starting points
(or, seed points) from which regions are grown. In shadow detection, this problem is much less
of an issue since shadows generally represent the lowest pixel values in the image, and thus the
points with the lowest grey values in the image can be used as seed points from which regions
can be grown. However, before this can be done, the criteria by which pixels are assigned to a
segment must be defined. The common approach is to use the spectral distance between the
pixel in question and the mean grey value of the neighbouring region: pixels which are
radiometrically too distant from the region will not be added. The distance should used to
ensure maximum likelihood of agglomerating all the shadow pixels with fewest non-shadow
pixels comes from an examination of the histogram of the shadowed image.

Wang et al. [2] proposed a scheme to remove clouds and their shadows from remotely sensed
images of Landsat TM. Since shadows smooth the brightness changes of ground, they detected
shadow regions by wavelet transform. Once the cloud pixels are identified, their shadows are
roughly predicted according to the cloud location and the solar illumination direction [3]. The
dark and connected components within the neighborhood of the predicted shadows are
identified as the shadow components. J. D. Tsai [4] based on the invariant color models
transformation of shadow compensation in aerial images, using the characteristics of hue values
and intensity to generate a gray scale image. This image is later applied the thresholding to
obtain the shaded regions.

[3] PROPOSED METHOD

Cloud shadows created by small patches of clouds obscure ground features from satellite
imagery. The cloud also cause cloud shadows so it is required to detect cloud shadow also. The
problem caused by cloud shadow is loss of information or occlusion. Some information is
present but it is occluded. Reduction of information could potentially lead to the corruption of
parameters derived from pixels values. The loss of information means that we cannot able to
interpret those pixel values.

Fig1 shows the location of shadows. Shadow regions located near to cloud region and appear
darker in optical satellite image.

Thus, the shadow regions can be detected by: the calculating the ratio images and the
selection of the shaded regions. In the first step, we have to convert the target RGB image into
YCbcCr color model. Then use the components of hue and intensity is used to generate a ratio
image for shadow detection [5]. The ratio image is generated by:
\[ R = \frac{C_r + C_i}{Y + C_i} \]
where \( C_i \) is a constant which is set to 1. And \( C_i \) is included to avoid the instability when \( Y \) is
very close to zero. The block diagram of the proposed automatic shadow detection is shown in
Fig 2.
In order to distinguish between shadow and non-shadow area, the values of ratio image \( R \) are
scaled to the range of [0,255] to obtain scaled ratio image \( R' \). In the scaled ratio image \( R' \) the
shadow pixels appears brighter than other pixels. After generating the ratio image, the scaled
ratio image \( R' \) is clustered into different classes by standard Fuzzy C-means clustering method.
Number of clusters is set to 3. After clustering, the cluster index for shadow pixels is calculated.
and this index is used for generating the binary shadow mask. Here the ratio image is used for shadow detection and shadow pixels appear brighter in the scaled ratio image.

A binary shadow map of the same size as input image is created to record the detected results of locations of shadow regions.

![Figure 1 Location of cloud shadow](image)

**Figure 2 Block Diagram**

**[4] FUZZY C-MEANS CLUSTERING**

Classify the colors in the scaled ratio image $R'$ using Fuzzy C-means clustering. Clustering is a way to group the objects. The Fuzzy C-means (FCM) [6] is one of the algorithms for clustering based on optimizing an objective function. FCM is one of the popular image clustering method. FCM capable of reducing the uncertainty of pixels belonging to one class and therefore in general provide improved clustering outcome. The Fuzzy C-means algorithm is to minimize the value of objective function:
\[ H(U,V) = \sum_{i=1}^{N} \sum_{j=1}^{k} \lambda_{ij}^m \| x_i - C_j \|^2 \]

where, \( \| x_i - C_j \| \) is the Euclidean distance between \( i^{th} \) pixel and \( j^{th} \) cluster center.
\[ \lambda_{ij} = \frac{1}{\sum_{l=1}^{k} \| x_i - C_l \|^m} \]
\[ C_j = \frac{\sum_{l=1}^{k} (x_i - C_l) \| x_i - C_l \|^m}{\sum_{l=1}^{k} \| x_i - C_l \|^m}, \forall j \in \{1,2,3,\ldots,c\} \]

where,

- \( T \) is the number of pixels in the image.
- \( C_j \) represents the \( j^{th} \) cluster center.
- \( m \) is the fuzziness index \( m \in [1, \infty) \).
- \( N \) represents the number of clusters to be formed obtained from equation 3.
- \( \lambda_{ij} \) represents the membership value of \( i^{th} \) pixel to \( j^{th} \) cluster center.
- \( d_{ij} \) represents the Euclidean distance between \( i^{th} \) pixel and \( j^{th} \) cluster center.

The Landsat data is categorized into different classes by Fuzzy C-means method. The Initial centroids will be chosen randomly. The centroid is the mean of the values of pixels in the cluster. The Fuzzy C-means clustering returns a fuzzy partition matrix, each row of which represents a pixel’s membership value towards a particular cluster. A pixel is assigned to a particular cluster based on the membership value, that is a pixel is assigned to cluster which have highest membership value. Label every pixel in the target image with its cluster index and the cluster contains shadow pixels are taken for further analysis. The cluster index for shadow pixels is found out and that cluster index is used for generating a binary shadow mask that contains shadow pixels represented as black.

![Figure 3 Target Image](image1)  ![Figure 3 Shadow detected image](image2)

[5] MORPHOLOGICAL OPERATIONS

In order to avoid small misclassifications that are to refine the shadow detected results, morphological erosion operation is performed with a structuring element square of size 3. Finally a binary decision map of same size as input image is created to record the detected results of locations of shadow regions.

[6] RESULTS

The evaluation of cloud masks is difficult because ground truth is not available to compare the cloud mask. The performance of the proposed algorithm is evaluated subjectively as no ground truth
truth is available. Fig 3 (a) shows the target image and 3(b) shows the shadow detected image. The detected shadow region is enclosed in red boundary.

[4] CONCLUSION
In this paper, an automatic cloud shadow detection method is proposed. The shadow contaminated pixels of target image is automatically detected. This method involves four steps: color conversion, image rationing, clustering and morphological operations. The image rationing technique used to find out subtle changes in the image. The ratio image is scaled to form scaled ratio image. In the scaled ratio image shadow regions appear darker. They are detected by clustering the scaled ratio image by Fuzzy C-Means clustering. Which result in better detection of shadow pixels.

[4] REFERENCES