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Clouds and Cloud Shadows Removal from Infrared Satellite Images in Remote Sensing System

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Abstract— **Using remote sensing technique to detect tsunamis has aroused a great deal of researchers' interests. It resolves the fatal disadvantage that current DART system has and improves the precise rate of tsunami detection greatly. However, since the system is based on the analysis of infrared satellite images, the detection would fail if the spot is covered with clouds or cloud shadows due to the fact that clouds and cloud shadows would distort the real signal received by satellite sensor. Hence removing clouds and cloud shadows from these infrared satellite images has become critical. Using the technique proposed by Meng et al.[1], this paper designs an algorithm to remove clouds and cloud shadows from satellite images for our remote sensing tsunami detection system. Future work is discussed.**

Keywords—Remote sensing; tsunami early warning system; image de-noise; closest spectral fit (CSF); clouds and cloud shadows(CCS);

I. Introduction

This research is motivated by tsunami early warning system (TEWS). A brief background about our motivation is introduced first.

1.1 Tsunami early warning systems (TEWS)

A tsunami is a series of ocean waves generated by sudden displacements in the sea floor, landslides, or volcanic activity [11]. It kills thousands of thousands lives, destroys buildings and fields. In 2004 Indian Ocean tsunami over 230, 000 people died [10]. In 2011 Tohoku tsunami, over 15,000 people lost their lives [12], and the losses was up to $34.6 billion [13]. Building up an efficient tsunami early warning system is very important.

The present main TEWS is the Deep-Ocean Assessment and Reporting of Tsunamis (DART) developed by NOAA. The system puts pressure sensors at the sea floor. When an earthquake happens under the floor, the sensor detects and records the change of aquatic pressure and sends an acoustic signal to a buoy on the ocean surface. The buoy transmits the received message into radio signal and sends it to a satellite. Finally the satellite sends the information back to a ground station for researchers. DART can pinpoint the earthquakes location, estimate the timing of the tsunami, and predicted tsunami measurement [15]. However, the change in aquatic pressure won't guarantee an occurrence of a tsunami; the high-maintained system does not work properly all the time, and tsunami waves sometimes sneak past the recorders, etc. Consequently, its false warning rate is up about to 75% by [14] and others. In addition, the whole system is very expensive as well as its frequent maintenance.

1.2 Landsat TM Images

Satellite images are ones of the most interesting images in geographic information system (GIS). With Satellites, we can access to remotely sensed images in digital format, analyze them, and rapidly integrate the results into a GIS [19][20].

Using the aerial sensor technology, a satellite can detect and classify objects on the earth with the help of propagated signals, or electromagnetic radiation. In 1980's, Thematic Mapper (TM) became the prime instrument in infrared geostationary Satellites Landsats 4, 5 and 6. It is a scanner (or sensor) with seven spectral bands. The satellites' resolutions 30 meters, and Landsat 7 carries a single sensor, ETM+, whose resolution is up to 15 meters with a panchromatic band.

Among the seven bands, there are a blue band for quasi-natural color images, two bands for mid-IR, and a thermal band.

1.3 Remote Sensing Technique

Lin, et al. proposed a brand new idea in 2010 to detect tsunamis using remote sensing [16]. When a tsunami generates by a sudden displacement in the ocean floor, an infrared geostationary satellite can "see" it at its epicenter. It records what it sees on its infrared image. By analyzing the satellite image using wavelet technique, Lin et al. find the evident signal from the tsunami. They follow their research by investigating tsunamis in Indian Ocean 2004 [16], 2011 Tohoku tsunami [17] and N. Sumatra tsunami of 2012 [18] and in all cases tsunamis are detected successfully from their infrared satellite images.

1.4 Image De-Cloud Approaches

However, what would it be if an infrared satellite image is covered by clouds or cloud shadows (CCS)? Can the proposal in the previous section still work and successfully detect a tsunami?

Over 60% of the our earth is cloud covered [21][22]. Couds and cloud shadows corrupt satellite images such as Landsat images [3]. Hence the study in removing clouds and cloud shadows is critical in our remote sensing system. However, such a research is rare [1]. Mitchell et al. first developed a model in cloud distortion and proposed a filter to remove it in satellite images in 1977 [4], followed by the improvements [5][6]. It is suitable for thin-clouds case which is not general. Another proposal is made by Cihlar and Howawrth [7] and Simpson and Stitt [8], but it is for AVHRR images other than Landsat images. We are interested in the filter developed first by Caselles [9], a multi-date effect brightness correction filter. The filter is improved by [10][1], among which, we are particularly the technique proposed by Meng et al. [1]. The method is called closest spectral fit, or CSF.

II. OUR PROJECT

A. *Closest Spectral Fit*

At the same spot yet different times, the approach needs two images: the base image for application and an auxiliary image. Both images should have no overlapping cloud or cloud-shadow areas. The auxiliary image helps the base image to map its pixels contaminated by clouds or cloud shadows (CCS) to their most spectrally similar pixels, with the location-based one-to-one correspondence. By replacing these pixels in CCS area with their most spectrally similar pixels, clouds and cloud shadows are "removed".

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B. *Our Algorithms*

The technique is suitable for our purpose:

1. The multi-images at the same area in different times are available by Landsat images.
2. The examination of non-overlap of cloud pixels or cloud-shadow pixels in both images is practical.
3. It meets our goal ---- our algorithm would be easy to be implemented and coded.
4. The last but the most important, it applies to all cases in any cloud densities.

We adopt the technique and improve it for our needs to the following steps:

Step 1 Prepare both base and auxiliary images

For the image we need to analyze (as the base image), choose an appropriate image in the history records at the same spot as its auxiliary one. The areas with CCS in the base image should be cloud-free and shadow-free in the auxiliary one. Such an examination can be implemented visually, but in the future, software can fulfill the function and choose a best one during a particular period of time (See our Algorithm 1 below).

Step 2 Identify cloud pixels or cloud shadow pixels in base image

It is known that visible and near-infrared bands are sensitive to CCS. Such a property can be utilized to detect CCS. A Landsat TM image has eight spectral brands. Among them, band 1, 3, and 4 are bands most sensitive to CCS [1]. As long as their digital values of spectral bands are out of certain thresholds, clouds or cloud shadows are present. For example, in a cloud area, a pixel's digital value of TM band 1 is greater than 95, and in cloud-shadow area its value of TM band 4 would be less than 55. Particularly, the ration of band 4 to band 3 can tell if it is in a water area with a cloud shadow. We devise an algorithm detecting CCS as the following.

Algorithm 1: Detect clouds and cloud shadows

(psudocode)

Input: base image

Output: PixelSetWithCCS // set of pixels in CCS area

load a pixel "p" from the base image // Read the base image

// pixel by pixel

$p.1$ = digital number of its TM band 1

$p.3$ = digital number of its TM band 3

$p.4$ = digital number of its TM band 4

If $p.1 > 95$

p is in CCS area

push p in PixelSetWithCCS

Otherwise if $p.4 < 55$ and $\frac{p.4}{p.3} > 1.3$

p is in CCS area

push p in PixelSetWithCCS

end

Step 3 Find the most similar pixels for CCS pixels

In the base image, for each pixel in the CCS area, we will search for its most similar pixel. In another word, we need to look for a pixel with the most similar surface reflectance values in the spectral space. This is called closest spectral fit (CSF) [1]. Since the pixels in CCS area have been spectrally distorted, we are no longer able to use their spectral data for such a mapping. That is why we need an auxiliary image which is cloud-free and shadow-free in the same area where CCS are present in base image, because we can do the mapping in the auxiliary image based on the assumption that a pixel's most spectrally similar pixel would not change with or without CCS.

Meng et al. propose using Euclidian Distance to find the "similarity"[1]. We adopt the measure criterion. Given two pixels i and j, the Euclidian Distance D_{ij} is given by

$$D_{ij} = \sqrt{\sum_{k=1}^{7} (i_k - j_k)^2} \quad (1)$$

where k is the index of a brand in Landsat TM. Since there are total seven brands in a TM imagery, k is hence from 1 to 7.

We give an algorithm of finding the closest spectral fit as the following.

Algorithm 2: Find the closest spectral fit (CSF)

(psudocode)

Input: PixelSetWithCCS // set of pixels in CCS area
auxiliary image

Output: PixelSetOfCSF // set of pixels with closest // spectral fit for pixels in CCS // area

```
n = size(PixelSetWithCCS)
m = size(auxiliary image)

for i = 1 to n
      p = PixelSetWithCCS.i    // retrieve i^th pixel in the
                               // pixel set of PixelSetWithCCS
      ED = 0                   // Square of Euclidian Distance
      for j = 1 to m
            q = AuxiliaryImage.j    // retrieve a pixel in
                                    // auxiliary image
            for k = 1 to 7
                  p.k =digital value of band k of pixel p
                  q.k =digital value of band k of pixel q
                  ED+ = (p.k - q.k)^2
            if ED ≠ 0          // Makes sure p and q
                               // are not identical
                  if j == 1
                        S = ED;      // S is the smallest ED
                        CSF = q ;    // q is the closest
                                     // spectral fit pixel
                  else if ED < S
                        S = ED;
                        CSF = q ;
      PixelSetOfCSF.i = CSF
end
```

Step 4 Remove CCS from base image

In Step 3, in the auxiliary image we attain a set of pixels. They are the most similar to pixels which have the same locations as those in the CCS area of the base image. Mapping such a closest-spectral-fit relationship to the base image with location-based one-to-one method, the corresponding pixels with the closest spectral fit for those in CCS area are therefore retrieved. Replacing the pixels in CCS area with their closest spectral fit ones respectively, clouds and cloud shadows are thus removed by overwriting their spectral data.

Algorithm 3: Replace Pixels in CCS by Their CSF Pixles

Input: PixelSetWithCCS
PixelSetOfCSF,
base image // original base image

Output: base image // base image after clouds and cloud // shadows are removed

```
m = size(PixelSetWithCCS)
for i = 1 to m
      p = PixelSetWithCCS.i    // For each pixel in CCS area
      q = PixelSetWithCSF.i    // Retrieve its corresponding
                               // CSF pixel
      p = q                    // Overwrite spectral data of
                               // pixel p with that of pixel q
end
```

III. FUTURE WORK

We need to search for a tsunami event in the history whose Landsat TM image on the spot is covered by clouds or cloud shadows. Due to the fact that infrared satellite system has a short history of less than three decades, and the most recent notable tsunamis are relatively cloud-free at the occurring spots, such an access is not as easy as we hoped, but internationally the access should be available, yet takes time.

Software of the filter is necessary. The software with GUI will automatically read the most recent Landsat TM images, detect if a CCS area is present, search for an ideal auxiliary image in the image database, remove the clouds and cloud shadows, and then analyze the overwritten base image to detect tsunami signal(s). Proving both excellent programming environment and numerical analysis tools such as image processing and wavelet toolboxes, Matlab is an ideal means for us to make such software.

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