FUZZY BASED SOFT COMPUTING APPROACH FOR DISASTER RESPONSE USING CHANGE DETECTION TECHNIQUE

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ABSTRACT:

Optical remote sensing offers excellent opportunity to understand the post earthquake affects both qualitatively and quantitatively. Remote sensing products allow us to explore the land surface parameters at different spatial scales. The testing data for accuracy assessment of classified fraction images can be used from finer spatial resolution multi-spectral images to generate image-to-image accuracy. It has been investigated the pre and post event satellite images (Landsat-7) at sub pixel level to identify liquefaction occurred after M_W7.7 Bhuj earthquake of January 26th, 2001 earthquake. In this paper soft computing based fuzzy algorithm, which is independent of statistical distribution assumption of data, has been used to extract single land cover class from remote sensing multi-spectral images. As a result, using temporal class based modified NDVI data set it is possible to separate water bodies from liquefaction.

KEY WORDS: Earthquakes, Training, Landsat-7, Accuracy, Temporal, soft computing

1. INTRODUCTION

With the advent of operational remote sensing it is now possible to map earthquake induced ground changes by soil moisture conditions. Liquefaction is a soil behavior phenomenon in which a saturated soil looses a substantial amount of strength due to high pore-water pressure generated by and accumulated during strong earthquake ground shaking. During the Bhuj earthquake, strong shaking produced liquefaction in the fine silts and sands below the water table over an area of more than 15,000 sq. km in the Rann of Kachchh. Digital image classification is a fundamental image processing operation to extract land cover information from remote sensing data and it assigns a class membership for each pixel in an image. Often, particularly in coarse spatial resolution images, the pixels may be mixed containing two or more classes. Soft classification methods may help in quantifying uncertainties in areas of transition between various types of land cover. Fuzzy classifications may be beneficial where a mixed pixel may be assigned multiple class memberships.

In general, classification algorithms are statistical in nature and assign a unique value to each pixel. However, a pixel may contain more than one class and such pixels are known as mixed pixels. There are large numbers of soft classifier algorithms in digital image processing for capturing the respective proportions of land cover classes within mixed pixels and characterize land cover more accurately.

Remote sensing technique to map accurately various aspects of earthquake related phenomena such as liquefaction. Gupta *et al.*, (1995, 1998), successfully demonstrated the application of a remote sensing technique to delineate zones of seismically induced liquefaction in the Ganga plains. Ramakrishnan *et al.*, (2006), map the earthquake induced liquefaction around the Bhuj, by calculating the absorption of energy in the NIR and SWIR region of electromagnetic spectrum. Saraf *et al.*, (2002), used picture colour transformation of IRS-1D band 4 data to map liquefaction of Bhuj. Mohanty *et al.*, (2001) and

Singh *et al*., (2001), used image differencing to find liquefaction. Champati Ray *et al*., (2001) and Rao *et al*., (2001) demonstrated applications of principal component analysis and unsupervised image classification techniques, respectively to change detection induced by the Kutch earthquake.

Nianlong *et al*., (2010), applied time series NDVI (Normalized Difference Vegetation index) data to identify land use classification. Wardlow and Egbert, (2008), used a hierarchical crop mapping to classify multi-temporal NDVI data. Lucas *et al*., (2007), studied the use of time-series Landsat sensor data using decision rules based on fuzzy logic to discriminate vegetation type. Kumar and Roy, (2010), has worked with add on bands in multi-spectral dataset of Worldview -2. Based on past research works it indicates that researchers have used multi-spectral, hyper-spectral as well as microwave data for specific land use/land cover (LULC) identification while using temporal data sets with importance of different indices.

These methods help in mapping the liquefaction accurately. However, while going through the literature it has been identified that to find liquefaction using various indices with possibilistic fuzzy classifier has not been explored in the past. In this study it has been tried to identify liquefaction using class based modified NDVI.

2. INDICES AND CLASSIFICATION APPROACHES

A common practice in the remote sensing is the use of band ratio to eliminate the various albedo effects. Based on spectral information of remote sensing data, the user has to decide which spectral bands of data are to be used in different band ratio functions, the most widely used NDVI to improve identifying the vegetated areas and their condition, and given by;

$$NDVI = \frac{\rho_{nir} - \rho_r}{\rho_{nir} + \rho_r}$$

$$\frac{\rho_{nir} - \rho_{red}}{\rho_{nir} - \rho_{red}} \qquad (1)$$

2.1 Possibilistic *c*-Means (PCM) Classifier

In this section,Fuzzy c-Means (FCM) and Possibilistic *c*-Means (PCM) (Krishnapuram and Keller, 1993) approaches have been explained. Let X = $\{x_1,..., x_i ,..., x_N\}$be the set of n objects and V = $\{v_1,..., v_j,..., v_c\}$ be the set of c centroids (means), the FCM provides a fuzzification of the c-means (Bezdek, 1981). It partitions X into c clusters by minimizing the generalized least - square error objective function;

$$J_m(U,V) = \sum_{i=1}^{N} \sum_{j=1}^{c} (\mu_{ij})^m \| x_i - v_j \|_A^2 \qquad (2)$$

where $1 \leq m < \infty$ is the fuzzifier, v_j is the j^{th} centroid corresponding to cluster β_i, μ_{ij} belonging to [0, 1] is the probabilistic membership of the pattern x_i to cluster β_i and $\| x_i - v_j \|_A^2$ is the squared distance (d_{ij}) between x_i and v_j and A is weight matrix, is subject to constraints;

for all i	$\sum_{j=1}^{c}$	$\mu_{ij} = 1$
for all j	$\sum_{i=1}^{N}$	$\mu_{ij} > 0$
for all i, j	$0 \leq \mu_{ij} \leq 1$	

$$d_{ij}^2 = \| x_i - v_j \|_A^2 = (x_i - v_j)^T A (x_i - v_j) \qquad (3)$$

In the FCM, the memberships of an object are inversely related to the relative distance of the object to the cluster centroids. In effect, it is very sensitive to noise and outliers. In addition, from the standpoint of "compatibility with the centroid," the membership of an object x_i in a cluster β_i should be determined solely by how close it is to the mean (centroid) v_j of the class and should not be coupled with its similarity with respect to other classes. Amongst a number of A-norms, three namely Euclidean, Diagonal and Mahalonobis norm, each induced by specific weight matrix, are widely used. The formulations of each norm are given as (Bezdek, 1981);

$A = I$	Euclidean Norm
$A = D_j^{-1}$	Diagonal Norm
$A = C_j^{-1}$	Mahalonobis Norm

where I is the identity matrix, D_j is the diagonal matrix having diagonal elements as the eigen values of the variance covariance matrix and C_j given by;

$$C_j = \sum_{i=1}^{N} \; (x_i - v_j)^T A (x_i - v_j) \qquad (4)$$

In this study value of weighting exponent m has been taken as 2.2 and euclidean Norm of weight matrix A has been taken, as it gives maximum classification accuracy compared to other weighted norms (Aziz, 2004; Kumar *et al.*, 2007). The class membership matrix μ_{ij} is given by;

$$\mu_{ij} = f (d_{ij} , d_{ik}^2, m_{jc}) \qquad (5)$$

where $d_{ik}^2 = \sum_{j=1}^{c} \; d_{ij}^2$

The original FCM formulation minimizes the objective function as given in equation (2) subjected to the condition;

$$\text{for all I} \qquad \sum_{j=1}^{c} \; \mu_{ij} = 1$$

But in PCM one would like the memberships for representative feature points to be as high as possible, while unrepresentative points should have low membership in all clusters (Krishnapuram and Keller, 1993). The objective function which satisfies this requirement may be formulated as;

$$J_m(U,V) = \sum_{i=1}^{N} \; \sum_{j=1}^{c} \; (\mu_{ij})^m \; \lVert x_i - v_j \rVert_A^2 + \sum_{j=1}^{c} \; \eta_j \sum_{i=1}^{N} \; \left(1 - \mu_{ij}\right)^m \qquad (6)$$

Subject to constraints;

$$\text{for all i} \qquad jmax \mu_{ij} > 0$$

$$\text{for all j} \qquad \sum_{i=1}^{N} \; \mu_{ij} > 0$$

$$\text{for all i, j} \qquad 0 \le \mu_{ij} \le 1$$

Here μ_{ij} is calculated from equation (5). In equation (6) where η_j is the suitable positive number, first term demands that the distances from the feature vectors to the prototypes be as low as possible, whereas the second term forces the μ_{ij} to be as large as possible, thus avoiding the trivial solution. Generally, η_j depends on the shape and average size of the cluster j and its value may be computed as;

$$\eta_j = f\,(k, \mu_{ij}, d_{ij}^2, m, N\;) \qquad (7)$$

where k is a constant and is generally kept as unity. After this, class memberships μ_{ij} are obtained as;

$$\mu_{ij} = f\,(d_{ij}^2 \,, \eta_j, m) \qquad (8)$$

2.2 Automatic Land Cover Mapping (ALCM) Approach

For extracting land cover classes, FCM is depended upon number of land cover classes to be extracted from remote sensing multi-spectral image. This can be seen from membership values generated from equation (5), are depended upon summation of distances of unknown feature to mean vectors of land cover classes ($d_{ik}^2 = \sum_{j=1}^{C} d_{ij}^2$). When extracting only one land cover class, in that case $d_{ik}^2 = d_{ij}^2$ and then μ_{ij} for all features becomes one. This concludes that all features in remote sensing multi-spectral image belong to one class, which is not the case. While working with PCM algorithm for extracting single land cover class it behaves as follows: $d_{ik}^2 = d_{ij}^2$ while extracting single land cover class μ_{ij}=1 for class features from equation (5) and

$$\sum_{i=1}^{N} (\mu_{ij})^m = N$$

so, from equation (7) we get

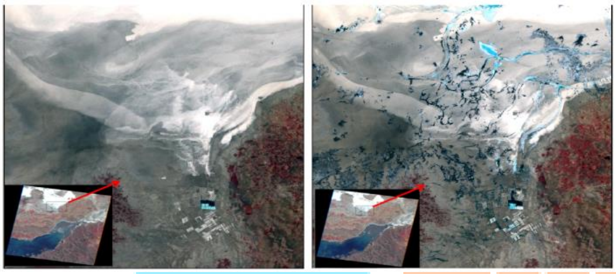
$$\eta_j = f(k, d_{ij}^2, N)$$

now from equation (8), μ_{ij} will be calculated. This indicates that possibilistic view of the membership of a feature vector in a class has nothing to do with its membership in other classes (Krishnapuram *et al*. 1993).

2.3 Test Data and Study Area

The remote sensing data used for this work was Landsat-7 satellite multispectral two date's (Jan'8,

2001 and Fab'9, 2001) temporal data from ETM+ sensor. To create multispectral data 6 spectral bands {blue (0.45-0.515 µm), green (0.525-0.605 µm), red (0.63-0.69 µm), near infrared (0.75- 0.90 µm), mid infrared1 (1.55-1.75 µm) and mid infrared 2 (2.09-2.35 µm)} are used.
The test site (figure 1) for this work has been identified as Rann of Kachchh (Lat 23°22'N-23°38'N and Long 69°52'-70°33'E) in Gujarat state of India for liquefaction identification. To separate liquefied area with pre-earthquake existing water bodies with boundary coordinates Lat 23°13'N-23°16'N and Long 70°05'E-70°09'E was taken.



(a) 8th Jan, 2001 (b) 9th Feb,2001

Figure 1, study area

3. METHODOLOGY

There has been requirement for identifying only one class that is, liquefaction, in Kachchh area. Keeping this in mind, the work was divided into three steps as shown in figure 2. Firstly both pre and post earthquake Landsat-7 multispectral images were identified. To create the model of class based modified NDVI, ERDAS Model Maker was used. In this work NDVI has been modified for enhancing single class liquefaction and water bodies. So IR band was replaced with band-1 and Red with band-7. The output of modified class based NDVI was applied on possibilistic fuzzy classifier (Kumar *et al*., 2010) as supervised classifier to extract single class, liquefaction as well as water bodies separately.

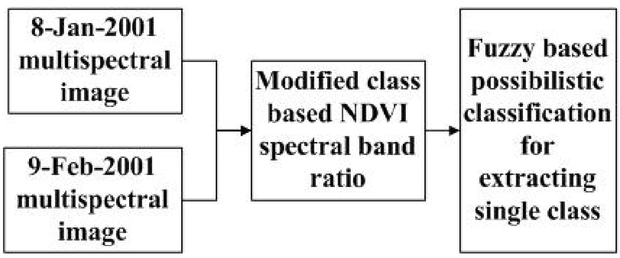
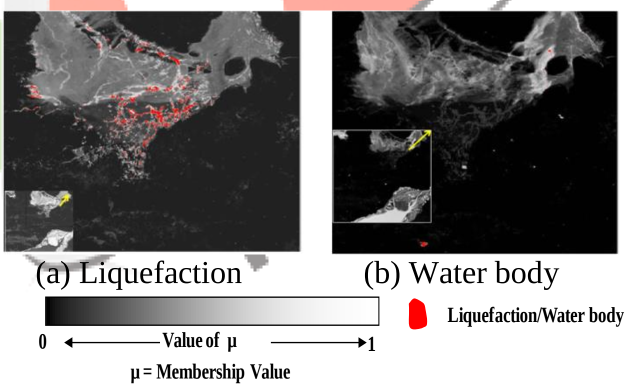


Figure 2, Methodology adopted

4. RESULTS AND DISCUSSION

This study mainly focuses on identifying the areas in and around Kachchh region with abnormal increase in liquefaction after the Bhuj earthquake in 2001. The basic principle behind using the satellite images in mapping the liquefaction changes is that electromagnetic spectrum absorbed by liquefied soil. Class based modified NDVI helps to distinguish reflectance of soils by its moisture content. Total 50 training pixels were used to calculate parameters of possibilistic fuzzy classifier. Fuzzy statistical parameters were calculated using these training reference datasets.

The one class of interest, namely, liquefaction was studied for discrimination with background and especially separates it with water bodies in the study area. While incorporating class based modified NDVI data shadow effect has been minimized in classification output. Due to class based modified NDVI data shadow areas did not merge with class water. While concentrating on membership values from fraction image of liquefaction class it was found in 0.94 to 0.99 ranges. The membership values for water bodies from water fraction image were found in the range of 0.94 to 0.99 (figure 3). This gives clear separation of liquefaction with water bodies present in the area.



(a) Liquefaction (b) Water body

Figure 3, Modified class based NDVI output for single class liquefaction extraction from Landsat-7

5. CONCLUSION

In this study, effect of class based modified NDVI has been studied for extracting liquefaction as well as water bodies in the study area. It was observed that modified NDVI temporal indices gives clear separation of liquefaction with water bodies present in the area (as degree of belongingness to a class). Overall it is concluded, the importance of temporal images in liquefaction identification as well as separation with water bodies present in the area.

This study also helps the importance of class based modified NDVI for water body enhancement.

It was also observed that the methodology proposed in this work requires minimal reference data for training sample and less information requirement about image characteristics for identification liquefaction and water body.

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