GNR602: Course Project

Dynamic Local Binary Pattern Based Feature Extraction for Satellite Image Change Detection

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Introduction

- Multispectral images play a significant role in remote sensing. These images are rich in spatial information, spectral properties and rich in textural details. The The increased complexity of satellite images makes the change detection difficult.
- Textural feature extraction is applied in many areas, as it serves as a major descriptor of the homogeneity in images especially in remote sensing imagery which is rich in textural variations
- Local Binary Pattern based descriptors for color image retrieval are developed for extracting features from individual color spaces and concatenating the histograms form individual color channels to form a single feature vector

Problem Specification

- With the use of remote sensing imagery to model the natural phenomena such as disaster management mitigation, urban development etc., the need to assess the changes due to this phenomena is highly critical.
- The remote sensing data is complex in terms of the color and textural variations.
- Feature extraction is a crucial step in remote sensing image classification which directly affects the classification accuracy.
- The extraction of textural features on such images which are rich in spatial information is extremely important.
- There are many feature extraction techniques already available in the literature. But the main drawback of the existing techniques is the lack of obtaining the minute information embedded in the image. This is a critical stage in enhancing the change detection result.
- This paper presents a Dynamic Local Binary Pattern (DLBP) for textural feature extraction for satellite image change detection

Solution Strategy

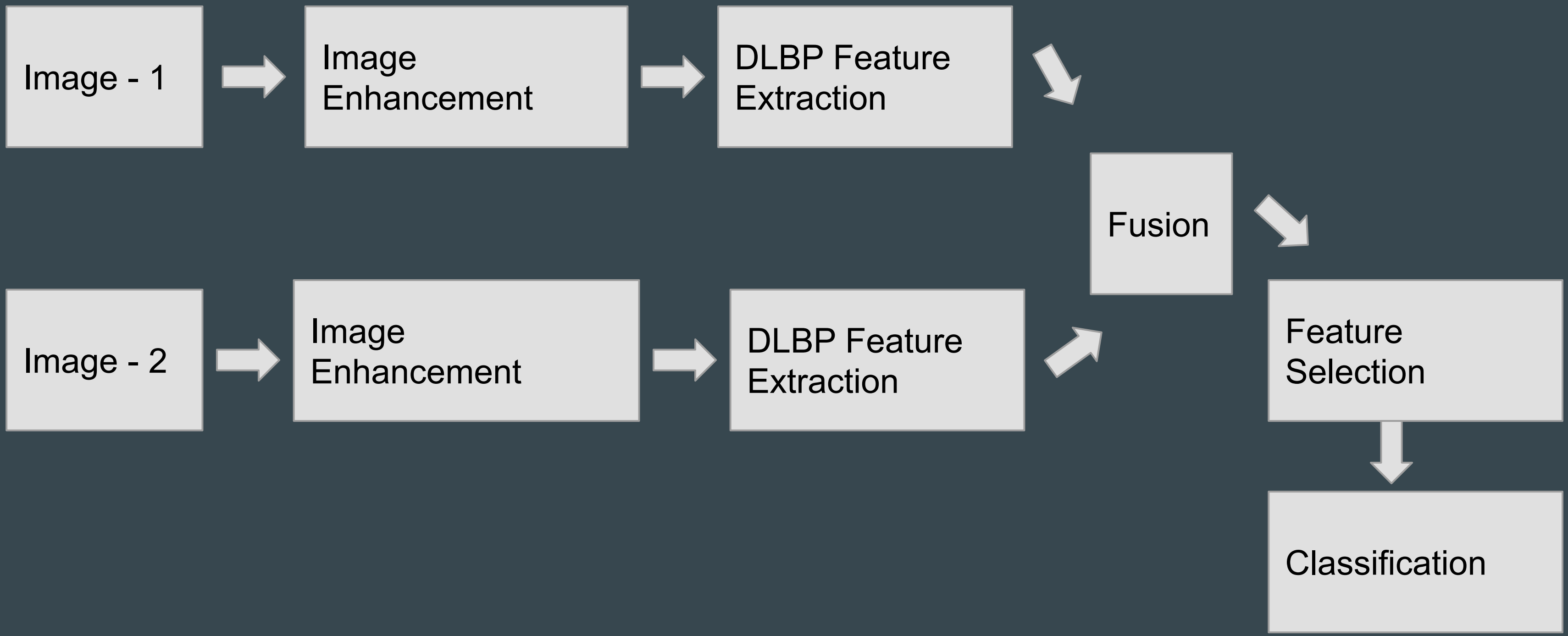


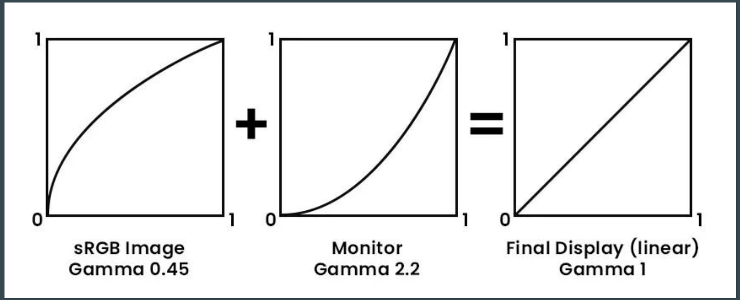
Image Enhancement

It is a smoothing filter which works on the principle of convolution of a mask with the input image. The filter mask is applied as a sliding window over the whole image. The convolution can be represented as:

$$g(x, y) = f(x, y) * w(x, y)$$

$$g(x, y) = \sum_{i=-1}^{1} \sum_{j=-1}^{1} f(x+i, y+j) w(i, j)$$

We apply a gamma correction to the linear RGB values in image A so that B is in the sRGB color space, which is suitable for display.



DLVB Implementation

In DLBP, region based mean is computed and this mean value is compared with the central pixel and further with the neighboring pixels. This is binary coded and represented. The region based mean is computed as:

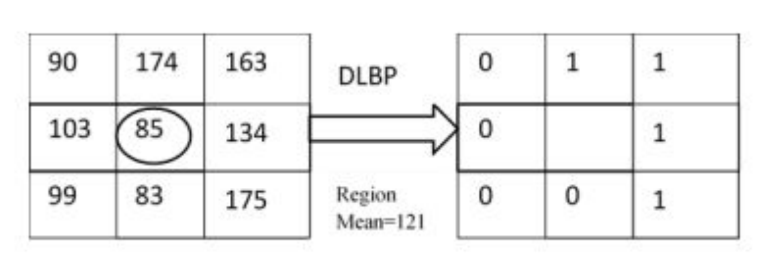
$$Mean_{\mathrm{Re\,gion}} = \frac{\sum_{i=1}^{n} C_i}{n}$$

$$L = \begin{cases} 1, if\ (Mean_{\mathrm{Re\,gion}} \geq C_c) and (Mean_{\mathrm{Re\,gion}} \leq C_i) \\ 0, elseif\ (Mean_{\mathrm{Re\,gion}} \geq C_c) and (Mean_{\mathrm{Re\,gion}} > C_i) \\ 1, elseif\ (Mean_{\mathrm{Re\,gion}} < C_c) and (Mean_{\mathrm{Re\,gion}} \leq C_i) \\ 0, otherwise \end{cases}$$

The DLBP is calculated as:

$$DLBP = \sum_{i=1}^{8} L * 2^{i-1}$$

DLVB illustration



CFS Implementation

- Correlation Feature Subset Selection (CFS) finds feature subsets that have high feature to feature and feature to class correlation. Let n be the number of subsets. The CFS criteria is evaluated for each subset Y where the average feature to class correlation rcf (with f ЄY and c is target class) and average feature to feature correlation rff is low. The CFS criteria is depicted as :

$$CFS = Max_{Y_n}\left[\frac{r_{cf1} + r_{cf2} + \ldots\ldots + r_{cfn}}{\sqrt{k + 2(r_{f1f2} + \ldots\ldots + r_{fifj})}}\right]$$

Fuzzy C- Means Implementation

Fuzzy partitioning is done by modifying the membership grade µij and the cluster centroids v by applying optimization iteratively on the objective function J as:

$$J(U,V)=\sum_{i=1}^{n}\sum_{k=1}^{n}(\mu_{ij})^{m}\|x_i-v_j\|^2$$

where ||xi-vj|| denotes the Euclidean distance between ith data and jth cluster center. After every iteration, membership and cluster centers are modified as

$$\mu_{ij}=1/\sum_{k=1}^{c}(d_{ij}/d_{ik})^{(2/m-1)}$$

$$v_j=(\sum_{i=0}^{n}(\mu_{ij})^{m}x_i)/(\sum_{k=1}^{n}(\mu_{ij})^{m}),\ \text{for all values of } j=1,2,\ldots c$$

Input and Output Data

Ground Truth

Image -1 : Dataset 2009

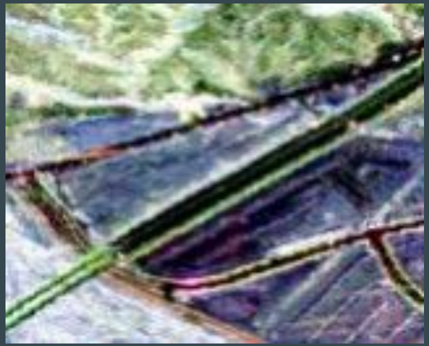
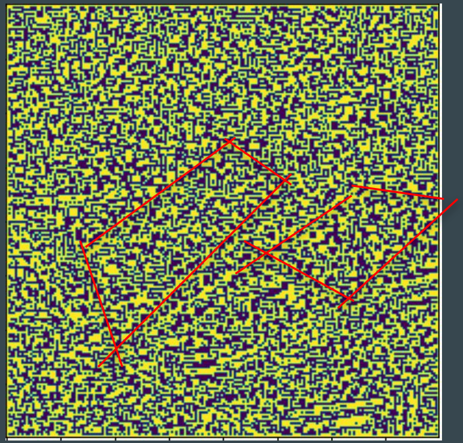


Image -1 : Dataset 2009

Image - 2: Dataset 2015



Output

References

1) https://assets.researchsquare.com/files/rs-1834655/v1_covered.pdf?c=1664225071
2) https://www.researchgate.net/publication/342746139_Creating_RGB_Images_from_Hyperspectral_Images_Using_a_Color_Matching_Function
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