Classification of Changed Pixels in Satellite Images using Gaussian and Hessian Function

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ABSTRACT
Classification of pixels of a satellite image is an important post-processing function in remote sensing applications. Most of the change classification methods focus on classifying the terrain change into different classes of natural objects. The basis of such classifications is statistical distribution and closeness of the spectral signature of the terrain preserved in the pixel. The proposed method makes use of Gaussian and Hessian computations on the intensity profile of the satellite image to classify terrain into 2D or 3D category depending on its curvature. This method is applied to the clusters of pixels which are classified as changes across multi-dated satellite images.

General Terms
Change Detection Algorithm

Keywords: Change detection, Terrain Change Detection, Hessian, Difference of Gaussian.

1. INTRODUCTION
Detection of terrain change through comparison of multi-dated satellite images is an active area of research [4],[5]. The process involves a number of algorithms to condition the images before actual change detection is carried out [1], [2], [3]. These processes such as removal of geometric distortions, radiometric errors and ortho-rectification prior to registration of satellite images are carried out to bring the multi- dated images to a common frame of reference [6],[7],[8],[9]. They are often called preprocessing of a satellite image which demands sub-pixel accuracy. The accuracy of the change detection depends upon the accuracy of the preprocessing steps. Though there are a number of algorithms existing in these processes, it is not fully automatic making the change detection process sensitive to human interaction [9],[10]. In other words, it is still a semi-automatic process involving human software interaction. Post-processing of changed pixels is equally important to interpret and understand the nature of change. Often the post-processing of changed pixels is performed by an expert image interpreter labeling the pixels into different categories of natural objects or by advanced machine classifiers and expert systems. One such category of classifiers uses Artificial Neural Network (ANN) techniques to classify the pixels. Generally an ANN classifier is trained by a known set of training samples of the pixel categories and optimized before applying the classification to real data. All the existing ANN or rule based classifiers can create thematic categorization of the changed pixels leaving the interpretation to the human expert [11], [12].

In this paper we propose a method for classification which will classify the changed pixels of a satellite image into 2D or 3D category. The input to this algorithm is the clusters of changed pixels of an image. Using this algorithm, the changed pixels are classified into three geometrical categories namely edge, blob or a sheet like structures. The process computes the Hessian of each 3x3 matrix around a changed pixel and computes its eigen value and eigen vectors. This method is applied through a shifting window process to the changed regions marked by a Maximum Bounding Rectangle (MBR) encompassing the changed regions. Depending upon the variation of the eigen values of the hessian, each central pixel of the window is classified into edge, blob or a sheet like structure. The semantic relation of the pixels with respect to its surrounding pixels gives the physical interpretation to the pixel so as to classify the change as a 2D or a 3D change of earth objects.

We propose here a Gaussian-Hessian method whose outputs are the changed clusters in the satellite image, classified as 2D terrain change or 3D terrain change. This process is applied to image pairs from different sources such as satellite, still camera and the results are verified against well known changes in the terrain for validation.

Terrain change can be classified as 2D or 3D according to the geometry of the variation and topology of the pixels reflected through its intensity profile. A 2D change is where only the surface of the terrain has undergone change e.g. the cereal field has been changed to paddy giving a different signature of the vegetation or an open area has been submerged with water etc. A 3D change is where the earth surface has undergone vertical change such as construction of a building, digging of a trench or mine etc. Hence looking at the intensity profile of the image it is very difficult to classify the pixels into 2D or 3D type without any supplementary height information. We make use of the curvature generated by hessian function and the orientation of the eigen vectors of the hessian matrix applied to the intensity matrix to classify the pixels into 2D or 3D type. Further this is being reinforced by simulating the scale space through Difference of Gaussian (DOG). In higher scale the 2D changes are submerged whereas the prominent 3D changes are filtered as scale space extremes.

The properties of Gaussian and Hessian functions are discussed in the next section. In section Three the change detection process is explained. Section Four explains the algorithm which uses

Hessian-Gaussian functions to detect the blobness of a pixel. The eigen-values computed from the Hessian-Gaussian algorithm is used to classify the change pixels into pixels of high curvature or flat terrain through a vesselness filter developed by Frangi et al. [16]. The fifth section presents the results obtained using the change classification process.

2.PROPERTY OF GAUSSIAN AND HESSIAN FUNCTIONS

Properties of Gaussian and hessian posses are important mathematically to characterize profiles of geometric objects in general and topology of the intensity profiles of the image in particular. Hence we discuss the characteristic and mathematical properties of these functions manifested as a window operator while processing images. What they yield when applied to spatial data in the form of two dimensional matrix is quite interesting.

2.1 Gaussian function

The 2D Gaussian function is given in Eqn (1)

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} ------------ (1)$$

Where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution. When applied in two dimensions, this formula produces a surface whose contours are concentric circles with a Gaussian distribution from the center point. Values from this distribution are used to build a convolution matrix which is applied to the original image. By computing the 2D Gaussian of a 3x3 window, the central pixel's new value is set to a weighted average of pixels surrounding it. The original pixel's value receives the highest weight and neighboring pixels receive smaller weights as their distance to the original pixel increases.

Gaussian function applied to a 2D-image through a sliding window over the intensity profile of the image blurs the image by reducing the local sharpness of the pixels. The amount of blurring depends upon the spatial arrangements of the pixels, the size of the kernel and the standard deviation of the Gaussian kernel. Hence successive application of the Gaussian to an image captured as a 2D intensity profile of the surface generates the scale space effect whereby it generates successive images as human eye perceives while moving away from the object. Gaussian function being exponential in nature does not alter the prime characteristic of the image as the differential / integral / Fourier transformation of the Gaussian results in a Gaussian function itself. Hence it is a potent method to analyze and compare the image in the scale space without altering its prime characteristics.

2.2 Hessian Function

The Hessian function is given in Eqn (2) in the form of a 2D matrix operator.

Hessian when applied to a function gives the local curvature of the function. 2D-Hessian manifests itself as a matrix of double differential of the intensity profile of the image. Thus the local undulation of the terrain in the form of intensity profile is captured in the 2D Hessian window of the image as given in Equation (2).

For an image, which is a 2D matrix of intensity values, the Hessian of the image is a square matrix of second-order partial derivatives of the image's intensity profile. Given the real-valued function f(x,y) = I the hessian is computed by a 2D matrix as given below.

$$H(x,y) = \begin{bmatrix} \frac{\partial^2 I}{\partial x \partial x} & \frac{\partial^2 I}{\partial x \partial y} \\ \frac{\partial^2 I}{\partial y \partial x} & \frac{\partial^2 I}{\partial y \partial y} \end{bmatrix} \quad \dots\dots\dots\dots\dots.(2)$$

3. CHANGE DETECTION PROCESS.

The entire process of change detection employed is depicted in the block diagram. First we register the satellite images treating the image obtained earlier in date 'D' as the base image and the image obtained later in (D+k) as the recently acquired image. To accurately register the images we employ the Scale Invariant Feature Technique (SIFT) [13],[14] to detect the correspondence between the base and recently acquired image. The process of registration for removal of geometric distortion in the recently acquired image using the SIFT features is discussed in detail in [15]. The Intensity variations in images caused by the intervening atmospheric conditions are different for different times in which the images are captured. Also the changes in the strength or position of light sources in the scene have a profound impact in the pixel strength of the satellite image. In order to remove the radiometric error in the image due to the intervening atmospheric conditions we employ a technique known as intensity normalization [16]. In this method, we pre-compensate this variation in the image due to radiometric effects through intensity normalization. The pixel intensity values in a recently acquired image are normalized to have the same mean and variance as those in the base image viz. Eqn (3).

$$I_2(x) = \sigma_1 / \sigma_2 \{I_2(x) - \mu_2\} + \mu_1, \text{----------------------} (3)$$

where, $I_2(x)$ is the normalized second image and μ_i, σ_i are the mean and standard deviation of the intensity values of I_i, respectively.

The change pixels are computed using the difference of the matrix containing the base image and the registered normalized image $I_2(x)$ as give in Eqn (4).

$$C(x) = I_1(x) - I_2(x) \text{------------------------------------} (4)$$

Alternatively, both images can be normalized to have zero mean and unit variance. This allows the use of decision thresholds that are independent of the original intensity values. Further, the difference of Gaussian of the C(x) is computed, which are subjected to hessian for detection of the eigen-values and eigen-vectors. The eigen-values of the hessian of each 3x3 window are interpreted using the rules given below (Ref Table-1) for its convexity, concavity or flatness in the profile of the image.

The eigen-values of the 2D Hessian are computed for the image window and the relative orientation of the eigenvectors is analyzed depending upon the sign and magnitude of the eigenvectors as given in the table below.

Structure Type	**Eigen Value Conditions**	**Example in Terrain**
Flat Surface Change (Sheet Like Structure)	$\|\lambda_1\| \approx \|\lambda_2\| \approx 0$	Flat 2D change in Terrain surface
Volume Change (Blob Like Structure)	$\|\lambda_1\| < \|\lambda_2\|$ && $\|\lambda_2\| < 0$	3D Volume Change in Terrain Surface (Dark structure in Bright background)
Volume Change (Blob Like Structure)	$\|\lambda_1\| < \|\lambda_2\|$ && $\|\lambda_2\| > 0$	3D Volume Change in Terrain Surface (Bright structure in dark background)
Linear Change	$\|\lambda_1\|/\|\lambda_2\| >> 0$	For Blob like structures in 2D and representing 3D change pixel in the image.

(Table-1, Relative values of Eigen Values and corresponding structures of the pixel)

Based on the relative sign and magnitude of the eigen-values and eigen-vectors as given in the above table the change pixels are classified into 2D change or 3D change. The above process is repeated for Difference of Gaussian (DoG) in the changed clusters to reinforce the classification in the scale space identifying the 3D changed pixels in the satellite image. The entire process is elaborated in section-4 as an algorithm.

4. GAUSSIAN-HESSIAN CHANGE DETECTION AND CLASSIFICATION ALGORITHM

The Hessian is applied to the image in the form of a sliding window and the pixels are classified in to various categories. Further this process is applied to the scale space images created through successive application of the Gaussian. The nature of a pixel is decided depending upon a maximization operation by comparing the succeeding and preceding pixel of the image through a kernel operation as described in the figure below.

Hence successive classification of the changed pixels into 2D and 3D through Hessian and strengthening the categorization through maximization Gaussian kennel is carried out in the changed cluster of the image to understand the nature of the change. The Algorithm for change classification is depicted in the flow diagram (Fig-1)

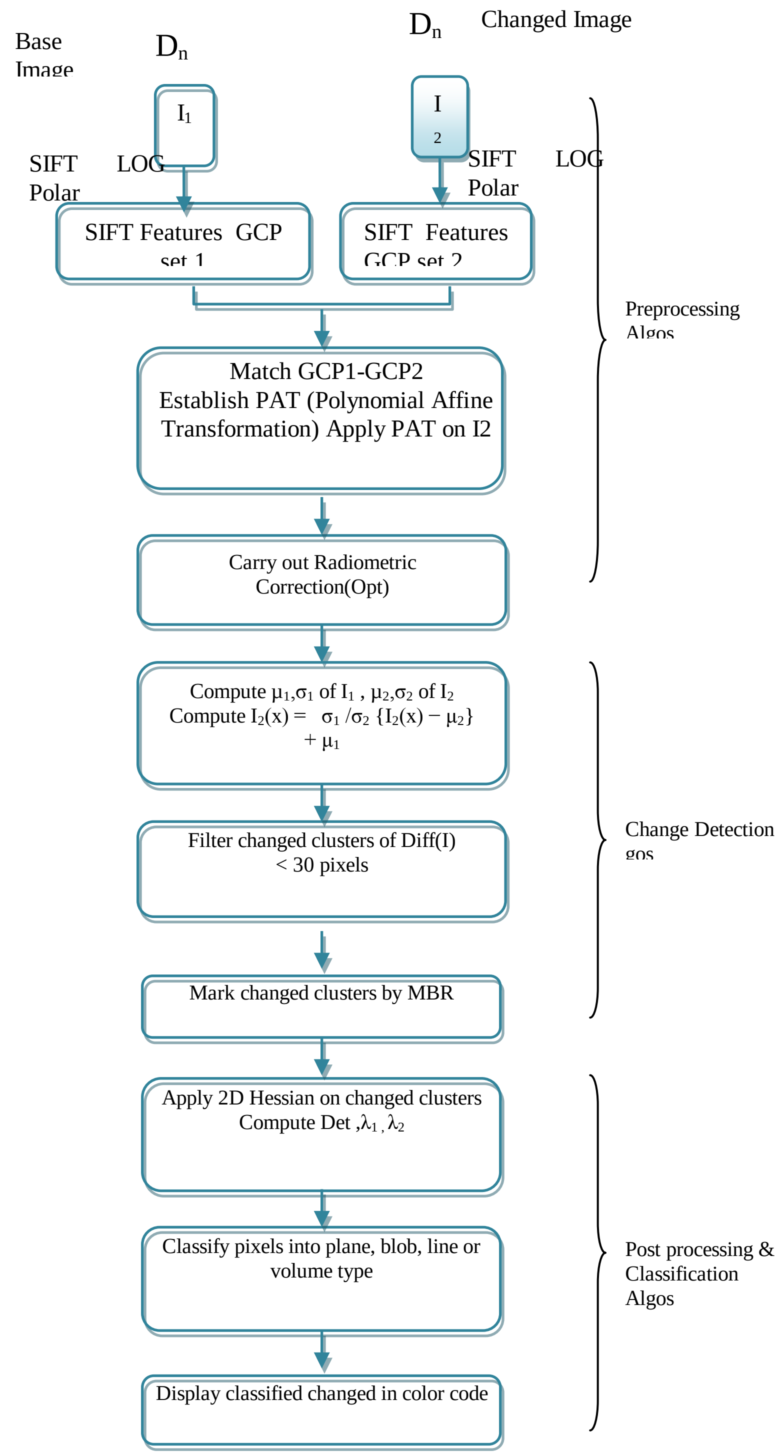


Figure-1. Flow Diagram for Change Detection and Classification

The overall terrain change detection process from multi-dated satellite images is illustrated below.

Input: $I_d(x,y)$, $I_{d+k}(x,y)$ are registered images of the same area obtained at dates D and (D+K) respectively

Let the images be represented by I_1 and I_2 respectively. Let the dimension of each of these images be (wxh) and modeled as a matrix of pixels having intensity values ranging [0..255]

Processing: Compute the pixels in the image I_2 which reflect change in the terrain with respect to the image I_1. Classify the changed pixels into 2D and 3D type depending on the curvature.

Step-1

Compute the mean intensity of the images using eqn (4.1) and the standard deviation using Eqn (4.2) i.e.

$$\mu_i = \frac{1}{M.N}\sum_{n=1}^{N}\sum_{m=1}^{M} I_i(x_m, y_n) \qquad \cdots\cdots \text{Eq} - 4.1$$

$$\sigma_i = \sqrt{\left[\frac{1}{M.N}\sum_{n=1}^{N}\sum_{m=1}^{M}(I_i(x_m, y_n) - \mu_i)^2\right]} \qquad \cdots \text{Eq} - 4.2$$

Where i= 1,2., M and N are width and height of the images.

Step- 2. Normalize intensity of image I_2 using equation (4.3) so that pixel intensity values in I_2 have same mean and standard deviation as that of I_1 i.e.

$$\tilde{I}_2(x,y) = \left(\frac{\sigma_1}{\sigma_2}(I_2(x,y) - \mu_2)\right) + \mu_1 \qquad \ldots \text{Eq} - 4.3$$

Where, μ_1, σ_1 & μ_2, σ_2 are mean and Standard deviation of Image I_1 and I_2respectively. Compute the changed pixels in I_2 using eqn (4.4). This is often known as the change mask.

$$(C(x,y) = I_1(x,y) - \tilde{I}_2(x,y)) \qquad \text{Eq} - 4.4$$

$\bar{I}_2$ is the normalized intensity profile of I_2 with the mean and variance of pixel as that of the image I_1 . Where C(x ,y) represents the image matrix with changed pixels of $\bar{I}_2$

Step-3 Filter insignificant changes reflected as weak intensity difference from the C(x, y) . If (C(x, y) > T_1) then C(x, y) is considered as significant change in the image, else C(x, y) is masked to '0'.

Identify the clusters of such changed pixels in the image and remove the isolated changed pixels so that object level changes can be detected (Objects are clusters of pixels rather an isolated pixel) through a morphological operation which checks the clusters of pixels which has at least 8 connected pixels in the neighborhood (bwareaopen(C(x,y), 8)).

Step-4 Compute the MBR (Maximum Bounding Rectangle) for each of the changed clusters and depict them in the image I_2(x, y). Let these clusters be denoted by C_k(x, y), k= 1…n, number of changed clusters in the image.

Step-5 For each of the changed clusters C_k(x, y), k= 1…n, compute the Difference of Gaussian (DoG) of the intensity pixels in the changed MBR to simulate the scale space manifestation of the clusters viz. Eqn(4.5).

$$L(x, y, \sigma) = G(x,y,\sigma) * C(x,y)$$

$$D_k(x, y, \sigma) = [L(x, y, k\sigma) - L(x, y, (k\text{-}1)\sigma) \text{------------} (4.5)$$

$$D_1(x, y, \sigma) = [L(x, y, 2\sigma) - L(x, y, \sigma)$$

$$D_2(x, y, \sigma) = [L(x, y, 3\sigma) - L(x, y,2\sigma)$$

$$D_3(x, y, \sigma) = [L(x, y, 4\sigma) - L(x, y, 3\sigma) \ldots$$

Step-6 Compute the curvature of the changed objects obtained in the form of changed clusters convolved with the MBR of the clusters. The curvature of the changed pixels is computed using 2D Hessian operation where the 2D hessian operator is convolved with 2x2 changed pixel matrix through a shifting window operation through Eqn (4.6)

$$H(x,y) * D_k(x,y) = \begin{bmatrix} \frac{\partial^2 I}{\partial x \partial x} & \frac{\partial^2 I}{\partial x \partial y} \\ \frac{\partial^2 I}{\partial y \partial x} & \frac{\partial^2 I}{\partial y \partial y} \end{bmatrix} \qquad \ldots\ldots\ldots (4.6)$$

Step-7 Compute the Determinant and Eigen Values and of the above Matrix Viz. compute Δ, λ_1, and λ_2 for each pixel. The magnitude of the eigen values can be interpreted according to the rules given in table-1

Compute the vessel-ness of each pixel and filter those pixels whose vessel-ness is greater than a threshold value identifying them as high curvature pixels through a filter. We use the Frengi Filter for vesselness as given in in Eqn-(4.7).

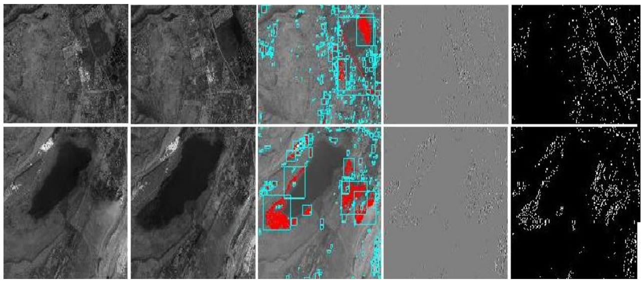
$$V(\lambda) = \begin{cases} 0 & if \quad \lambda_2 < 0 \\ e^{\left(-\frac{R_B{}^2}{2\beta^2}\right)}(1 - e^{\left(-\frac{S\ {}^2}{2\gamma^2}\right)}) & \end{cases} \quad ----(4.7)$$

Where, $V(\lambda)$ is the vesselness filter, $R_B = |\lambda_1|/|\lambda_2|$ is the measurement which accounts for deviation from a blob-like structure, and $S = \sqrt{\lambda_1{}^2 + \lambda_2{}^2}$ which is the norm of the eigen values, differentiate between the foreground (vessel) and back-ground. The β and γ are thresholds which controls the sensitivity of the filter.

Output: The output of the above process is the pixels in the changed clusters marked through MBR. These are all 2D and 3D change pixels in the image. The final filtered pixels through step-7 (Frengi's vesselness filter) differentiate those changed pixels which are marked as 3D change. Pixels filtered and highlighted as vessel like structures or 3D structures are depicted in the final images of the result sets.

5. RESULTS AND DISCUSSION

These classification rules are generally applied in medical imaging for detection of polyps & vessel like structures so that a visual analysis can be carried out before invasive surgery for removal of cancerous cells. The classification rules yield good results in medical imaging where the pixel resolution is in the order of sub-millimeter. In contrast, the pixels in satellite image are of higher resolution of the order of fraction of a meter and hence the change classification proposed in this method yields better results and can capture terrain change of the order of sub-meter.



(a) Image I_1 (b) Image I_2 (c) Changes in MBR (d) Changed Clusters (e) 3D Changes

(Figure-4, Result Set, 2D and 3D Changes classified in Satellite images)

Depicted above are two sets of results obtained from the application of the change detection process described in section-4. In each row the first two images correspond to the registered pair of multidated satellite images at Dn and Dn+k. The third image depicts all the changed clusters which have both 2D and 3D changed pixels. The changed clusters are depicted using MBR (Maximum Bounding Rectangle). The fourth image in each row depicts the hessian of DoG of the changed pixels. The last image only highlights the changed pixels which are classified as 3D changes using the Hessian and Gaussian operations.

The apparent 3D changes can be easily observed in the first row of the results where the aeroplane in the first image has moved away from the apron area resulting in a 3D change in the subsequent satellite image. This has been identified as a changed cluster and has been highlighted as a 3D changed cluster in the final outcome.

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