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# Environment change monitoring system with weather alert monitoring

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## ABSTRACT

Natural disasters such as earthquakes and tsunamis often have a devastating effect on human life and cause noticeable damage to infrastructure. Active research has been ongoing to mitigate the impact of these catastrophes and preclude the economic losses. The existing methods that utilize pre-event and post-event images not only require the immediate and guaranteed availability of the appropriate data set but are also encumbered by manual mapping of the images, necessitating the indication of corresponding control points in the two images. This paper highlights the use of only post-event imagery in the absence of reference data to achieve a more timely delivery to produce damage maps as the output. This eliminates the need for manual geo referencing of images. Our method incorporates simple linear iterative clustering (SLIC) for segmenting the images into uniform super pixels and extraction of 62 features for each super pixel. We used various classifiers of which Random Forest classifier was found to give a comparatively high accuracy of 90.4% over others. To enumerate the accuracy of the method proposed, we used 1500 data regions of which 20% were used for testing, and 80% were used for training. The aerial images taken by GeoEye1 after the 2011 Christchurch earthquake and 2011 Japan earthquake and tsunami are utilized in this study to detect building damage. In the case of availability of ground truth, we compare the histograms of the pre- and post- imagery to quantify similarity as the SSD (Sum of Squared Distances) value and thus, our approach produces an assessment as an output map displaying the extent of damage in the area covered by each super pixel. We consider 6 levels of damage ranging from 1 to 6, where 1 signifies no damage, and 6, maximum damage.

## INTRODUCTION

The increasing occurrence of natural disasters has led to a growing public awareness about the impact of catastrophic phenomena. To understand and also mitigate the consequences of such events on humans, infrastructure and the environment, substantial research is being carried out. Despite swift developments in the field of technology, prevention of the damage caused by such natural hazards is rarely achieved. Thus, disaster damage assessment has been a challenging area of study, owing to the need for a faster response and recovery mechanism. Delivering timely and accurate information for assessment of damage in disaster-struck areas is of critical significance in order to provide management and relief. Aerial imagery has been extensively used in the detection of damages owing to their high spatial resolution. Remote sensing using space and airborne sensors can prove efficient in furnishing immediate response and in providing aid in the recovery phases of disaster management. A near real-time diagnosis of the areas affected by the disaster can be cost-effective since it has the potential to limit the search and rescue resources. The objective of this study is to utilize the information provided by

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high resolution satellite imagery by extracting textural features for post-disaster damage assessment. One critical aspect of this study is timely delivery and to ensure this, this paper presents a method for automating damage identification and assessment followed by dissemination of this information to National Response Groups and rescue agents. This process mainly involves:

- Identification of the disaster-struck area via an alert system or government representative.
- Acquiring the post-event imagery promptly.
- Analysis and damage identification solely based on post- imagery.
- Acquiring pre-event imagery subject to availability.
- Analysis and damage assessment based on pre- and post- imagery (if pre- event images are available)
- Dissemination of information, statistics and output maps to rescue agents.

In this paper, we propose a statistical model able to perform flood detection by using information and data fusion [1-5].It is based on Bayesian networks (BNs), one of the most common types of probabilistic graphical models combining probability theory and graph theory, which introduce graph structures into a probabilistic model to represent dependence assumptions among the involved variables. BNs are a statistically well-founded method to combine imagery information with ancillary data, such as distance from the river, digital elevation models (DEMs), hydraulic models, etc. This combination is not restricted to a specific sensor, and it can exploit the informations.

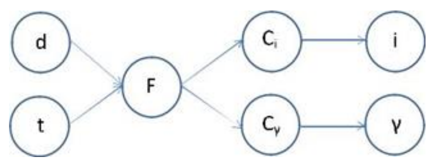



**Fig.1.BN scheme**

From time series of images. In our case, it is also capable of describing the dynamics of the flooding event.

In recent years, BNs and, more generally, probabilistic graph-ical models have been used as a data mining tool in many research fields, but rarely to process remote sensing data. In  a BN has been applied to two Landsat TM scenes ac-quired at different times on the same area, obtaining an overall change detection classification accuracy that overcomes the one obtained by other methods. However, to our knowledge, the capability of BNs to join different kinds of data has been scarcely exploited. In a simple probabilistic graphical model has been applied to estimate the state of roads during flooding, combining a DEM with satellite optical images: the obtained results outperform other methods based only on the exploitation of imagery data or only on DEM information. On the other hand, BNs have been successfully used to construct risk assessment systems for natural disasters, such as rock falls, avalanches , or wildfires: various kinds of data, such as land cover types extracted from the Corine Land Cover database, road and building densities, have been fused by means of BNs to obtain reliable risk maps, although none included remotely sensed imagery. In this paper, a BN is used in a flood detection problem to integrate multitemporal SAR intensity and InSAR coherence data with geomorphic and other ground information.

## PROCESS

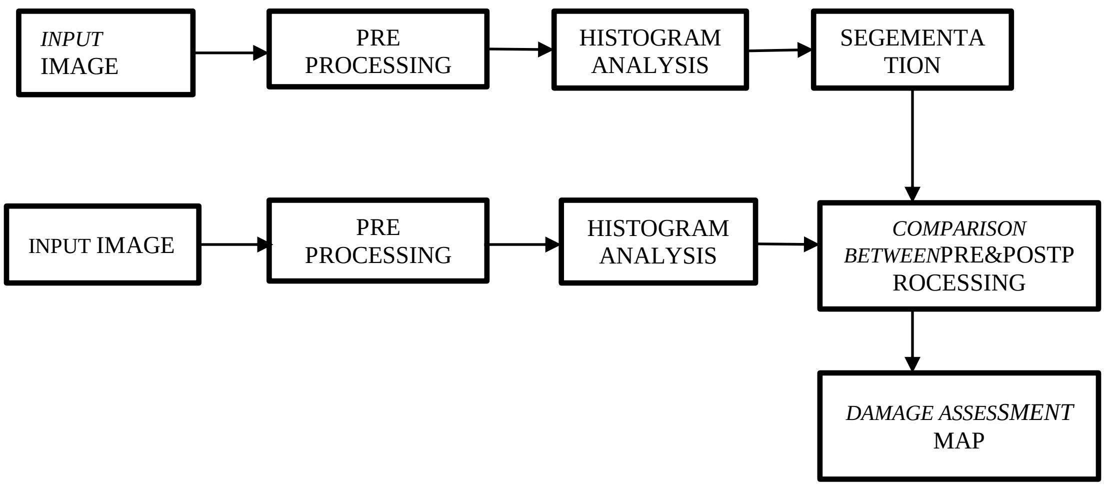
### Input Image

Multispectral remote sensors such as the Landsat Thematic Mapper and SPOT XS produce images with a few relatively broad wavelength bands. Hyperspectral remote sensors, on the other hand, collect image data simultaneously in dozens or hundreds of narrow, adjacent spectral bands.

These measurements make it possible to derive a continuous spectrum for each image cell, as shown in the illustration below. After adjustments for sensor, atmospheric, and terrain effects are applied, these image spectra can be compared with field or laboratory reflectance spectra in order to recognize and map surface materials such as particular types of vegetation or diagnostic minerals associated with ore deposits [6-10].Take hyperspectral image as input.

## PROPOSED SYSTEMS

### Block diagram




## PREPROCESSING

The pre-processed images will have some noise which should be removed for the further processing of the image. Image noise is most apparent in image regions with low signal level such as shadow regions or under exposed images. There are so many types of noise like salt – and – pepper noise, film grains etc., All these noise are removed by using algorithms. Among the several filters, weiner filter is used. In preprocessing module image acquired will be processed for correct output. Pre-processing was done by using some algorithm. For all images the pre-processing should be done so that the result can be obtained in the better way. To find out the transformation between two images precisely they should be pre-processed to improve their quality and accuracy of result. If these images are too noisy or blurred, they should be filtered and sharpened.

Pre-processing is a common name for operations with the images at the lowest level of abstraction both input and output is the input images. The aim of pre-processing is an improvement of image data that suppress unwanted image data distortions or enhance the some image features important for the further processing. Four categories of image pre-processing methods according to the size of pixel neighbourhood that is used for the calculation of new pixel brightness:

- Pixel brightness transformations
- Geometric transformations
- Pre-processing methods that use a local neighbourhood of the processesd pixel,
- Image restoration that requires knowledge about the entire image.

If preprocessing aims to correct some degradation in the image, the nature of a priori information is important: 1.Knowledge about the nature of the degradation; only very general properties of the degradation are assumed, Knowledge about the properties of the image acquisition device, the nature of noise (usually its spectral characteristics) is sometimes known,

Knowledge about objects that are searched for in the image, which may simplify the pre-processing very considerably .If knowledge about objects is not available in advance it can be estimated during the processing.

## Histogram Analysis

An image histogram is a type of histogram that acts as a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each tonal value. By looking at the histogram for a specific image a viewer will be able to judge the entire tonal distribution at a glance.

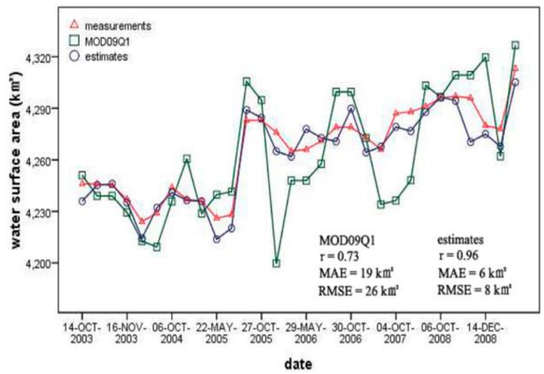



**Fig1.1 Histogram analysis**

Image histograms are present on many modern digital cameras. Photographers can use them as an aid to show the distribution of tones captured, and whether image detail has been lost to blown-out highlights or blacked-out shadows. This is less useful when using a raw image format, as the dynamic range of the displayed image may only be an approximation to that in the raw file.

The horizontal axis of the graph represents the tonal variations, while the vertical axis represents the number of pixels in that particular tone.[1] The left side of the horizontal axis represents the black and dark areas, the middle represents medium grey and the right hand side represents light and pure white areas. The vertical axis represents the size of the area that is captured in each one of these zones. Thus, the histogram for a very dark image will have the majority of its data points on the left side and center of the graph. Conversely, the histogram for a very bright image with few dark areas and/or shadows will have most of its data points on the right side and center of the graph.

Image editors typically have provisions to create a histogram of the image being edited. The histogram plots the number of pixels in the image (vertical axis) with a particular brightness value (horizontal axis). Algorithms in the digital editor allow the user to visually adjust the brightness value of each pixel and to dynamically display the results as adjustments are made [3] Improvements in picture brightness and contrast can thus be obtained.

In the field of computer vision, image histograms can be useful tools for thresholding. Because the information contained in the graph is a representation of pixel distribution as a function of tonal variation, image histograms can be analyzed for peaks and/or valleys. This threshold value can then be used for edge detection, image segmentation, and co-occurrence matrices.

## SEGMENTATION

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyse. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics [11-15].

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

Several general purpose algorithms and techniques have been developed for image segmentation. To be useful, these techniques must typically be combined with a domain's specific knowledge in order to effectively solve the domain's segmentation problems.

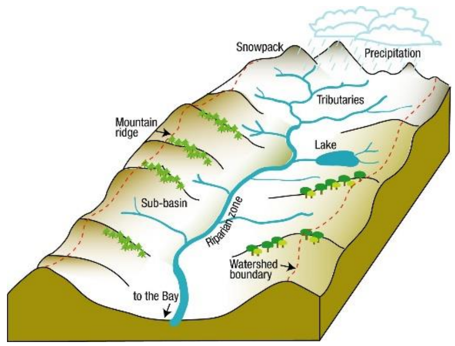



**Fig.1.2 segmentation**

## FUZZY C MEANS SEGMENTATION

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method is frequently used in pattern recognition. Fuzzy c-Means Clustering performs clustering by iteratively searching for a set of fuzzy clusters and the associated cluster centres that represent the structure of the data as best as possible. The algorithm relies on the user to specify the number of clusters present in the set of data to be clustered. Given a number of clusters c, FCMC partitions the data $X = \{x1, x2,\ldots,xn\}$ into c fuzzy clusters by minimising the within group sum of squared error objective function.

## SYSTEM IMPLEMENTATION

Implementation is a stage in the project where the theoretical design is turned into a working system and is giving confidence on the new system for the users, which it will work efficiently and effectively. It involves careful planning, investigation of the current System and its constraints on implementation, design of methods to achieve the changeover, an evaluation, of change over methods. Apart from planning major task of preparing the implementation are education and training of users. The implementation process begins with preparing a plan for the implementation of the system. According to this plan, the activities are to be carried out, discussions made regarding the equipment and resources and the additional equipment has to be acquired to implement the new system. Implementation is the final and important phase, the most critical stage in achieving a successful new system and giving the users confidence. That the new system will work.The system can be implemented only after through testing is done and if it found to working according to the specification.

After the system has been tested, the implementation type or the changeover technique from the existing system to the new system is a step-by-step process. In the system at first only a module of the system is implemented and checked for suitability and efficiency. When the end user related to the particular module is satisfied with the performance, the next step of implementation is preceded. Implementation to some extent is also parallel. For instance, modules which are not linked, with other modules are implemented parallel and the training is the step-by -step process.

## CONCLUSION

This paper presents a methodology for detection of damage post disasters by examining the textural features from high resolution aerial imagery. The proposed technique makes use of the post event images and uses SLIC as a segmentation method to obtain superpixels for labelling. The training data is labeled manually and classified using six classifiers with the highest accuracy obtained from Random Forest. In presence of prevent imagery, the approach in this paper compares the histograms of the pre- and post-imagery and obtains a similarity index for each super pixel. Essentially, lower the SSD measure, more similar are the histograms and lesser is the damage. We classify each super pixel into one of the five categories representing five different levels of damage, 1 representing the least and 6 the most amount of damage in the area and obtain output maps for the same.

Experimental results show good capabilities of identification of a large area interested by the flood phenomenon, partially over-coming the obstacle constituted by the presence of scattering/ coherence classes corresponding to different land cover types, which respond differently to the presence of water and to inundation evolution. In particular, our BN-based data fusion approach allows to both mitigate the false alarms and to correctly identify flooded areas in events characterized by complex land cover ground conditions and time evolution. In conclusion, BNs appear to be a powerful tool to perform data fusion in the analysis of complex real-world systems, such as natural hazard detection. Further studies will be conducted by considering the introduction of other variables, such as imagery by optical sensors or other ancillary information. In this respect,another advantage of the BN representation could be exploited, i.e., its modularity. In fact, depending on the independence relations between new and old variables, some local probability models could be reused, and only some conditional probability terms would need to be inserted in the computation, without rewriting the whole joint probability. Furthermore, the proposed methodology exhibits the great advantage that the analysis of conditionally independent variables (which is, at present, the most time-consuming step) can be performed in parallel, thus improving its potential applicability to near-real-time post event mapping purposes.

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