There are point-to-point replies to particular questions. These issues will be incorporated in relevant ways to the final text.

As suggested by the reviewer 2 the paper is of general interest for the geo-science research community and within the scope of GI journal. We believe that the work will be of high significance in implementation of image segmentation algorithms for change detection scenarios in satellite imagery. Change detection is an important part of many remote sensing applications. We have taken two images from EGU satellite image http://ew.eo.esa.int/web/guest/events/-/journal_content/56_INSTANCE_QCx4/10122/19805?showFull=true&area=Earthquakes for ASAR satellite image as on 21st September,2010 and 21st march 2011 after the earthquake tsunami occurrence. Based on the change in the pixel position we carried out a number of steps after using graph cut based algorithm for image registration. Some earlier statements made has been changed and more results substantially included to increase the authenticity of the work done. We have tried to make the paper as comprehensive as possible this time around. We obtained a transformation matrix for the deflection of pixels. As we get optimum transformation ,it is necessary to retrieve the transformation from minimized error matrix. Plotted the image histogram according to the transformation. Hereby we calculated the area for the transformation ranges and then regionally segmented for transformation ranges of different pixel ranges. This method requires separate steps like matching of salient feature regions, followed by both local rigid transformation and higher-order global transformation.

We have also tried to concisely touch the five six points that we have worked this paper except making the image registration scenario for analysis. According to the reviewers question for the methodology to be used in other applications as well, so a user-friendly description of the actual method including validation (error estimates) would benefit a wider audience. This can be done by sharing the matlab code. Yes the entire matlab code can be shared as and when required for disaster scenarios and other matlab experts. The study proposes a new method to pass the deformation field across resolution levels in order to enable multi-level non-rigid registration using graph-cuts where P denote a set of pixels and segmentation can be done by assigning label lp Є L to each pixel p,q Є P,energy minimum function for pixel values resulting to

$$E(L) = \sum_{p \varepsilon P} D_p(l_p) + \sum_{(p,q)\varepsilon N} V_{p,q}(l_p, l_q)$$

The proposed function for this problem is given below:

$$C(I_r, D(I_f)) = [\exp(\sum_{x\varepsilon X} \| I_r - D(I_f) \| - \partial(I_r, D(I_f))) \text{ where } \partial(I_r, D(I_f)) = \min(\sum_{x\varepsilon X} \| I_r - D(I_f) \|).$$

For better implementation of analogies DataCost $D(I_f)$ is a height by width by num_labels matrix where Dc(r,c,l) equals the cost for assigning label l to pixel at (r,c). When using Sparse Smoothness Dc is of (L)x(P) where L is the number of labels and P is the number of nodes/pixels in the graph. Smoothness Cost a labels by b labels matrix where $Sc(l_a, l_b)$ is the cost of assigning neighboring pixels with label a and label b. This cost is spatially invariant optional arrays defining spatially varying smoothness cost. The smoothness cost $V_{p,q}(l_p, l_q) = V(l_1, l_2) * w\_pq$ where V is the Smoothness Cost matrix w_{pq} is spatialy varying parameter. Labels: a width by height array containing a label per pixel whereby we have taken a window of 15* 15 for probability of pixel width.

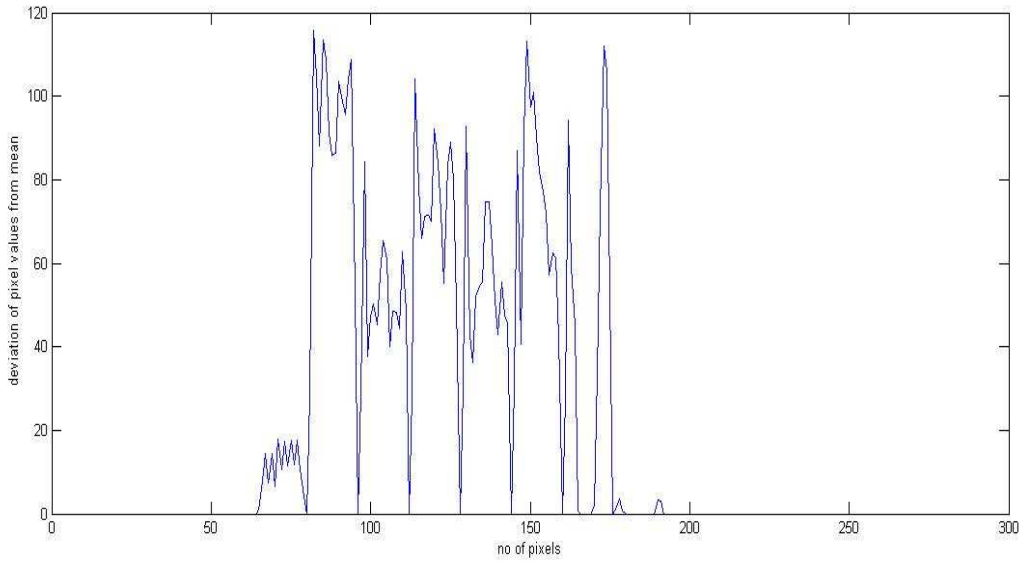
We implemented a one-step improved graph cut method for non-rigid registration based on . Image registration helps us find an optimal transformation, *T**, which spatially matches a floating image, *If* , to the reference image, *Ir,* based on some measure of intensity dissimilarity *C(Ir, T(If)).* Displacement labels to the pixels in the floating image cannot be directly assigned from the above dissimilarity measures. Using an exponential function we can implement displacement labels directly assigned from this data term. Intesity difference between pixels can be established through exponential functions as established by Y. Boykov, O. Veksler, R. Zabih, "Fast approximate energy minimization via graph cuts," IEEE Trans. Pattern. Anal. Mach. Intel. vol. 23(11), 1222–1239, 2001.In: IEEE Transactions on PAMI, vol. 26 (2), for regional segmentation analysis. The way of choosing labels often fails to impose strict penalty in the data term for intensity mismatches. Illumination change associated between two pixels caused by motion of pixels for two concurrent images are not properly taken care of by imposing a smoothing criterion factor. The novel function incorporated by using an exponential term incorporates a strict penalty scenario used for obtaining the data term imposes stricter penalty for intensity mismatch between the floating and reference images caused by motion and any possible change of illumination. The data term was earlier a dissimilarity measure between two images like absolute intensity difference of two images whereas we implemented exponential term eliminating the mean difference that has captured any preregistration intensity difference .Since there are no negative accuracy values the efficiency has subsequently increased as shown in Table 1.Each pixel can be assigned many labels. As just stated, the alpha-expansion algorithm can only be used when the smooth term is metric. If it is otherwise semi-metric, the alpha-beta swap algorithm will be used. Whenever the alpha-expansion algorithm is used, it is guaranteed that the local minimum is within a known factor of the global minimum. We have modified the 1st term for improvement in registration accuracy which was earlier a dissimilarity measure between two images like absolute intensity difference of two images whereas we implemented exponential term eliminating the mean difference that has captured any preregistration intensity difference .Since there are no negative accuracy values the efficiency has subsequently increased. Yes the equations are from the work and apply universally to the field of Discrete Markov Random Fields (MRFs) whereby a label is assigned to each element in a given set of objects.This method is such where max flow or deformation is analogous to the min cut.For 3d deformation _ one can reference C. Rother, V. Kolmogorov, A. Blake. \GrabCut - Interactive Foreground Extraction using Iterated Graph Cuts". ACM Transactions on Graphics (SIGGRAPH), August 2004. And Y. Boykov, V. Kolmogorov. \An Experimental Comparison of Min-Cut/Max-Flow Algorithms for Energy Minimization in Vision". IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 26(9):1124-1137, September 2004.

Table 3 is the analysis of the maximum entropy threshold for the image acquired prior to and after the earthquake occurrence. For an image, entropy is the measure of the uncertainty or lack of structure. When pixels are considered alone, entropy can be calculated for measuring the structural information of the image to segment images— using: (X,Y), the conditional entropy H(Y|X) quantifies the remaining entropy (i.e. uncertainty) of a variable Y given that the value of the change in the window.
We have also performed a discrete labeling of the groups using matlab. According to our observation since local entropy decreases for post earthquake imagery , the surrounding entropy is likely to increase.Using joint entropy sets of features that have maximum joint entropy since these will be the least aligned which provide the most additional information.

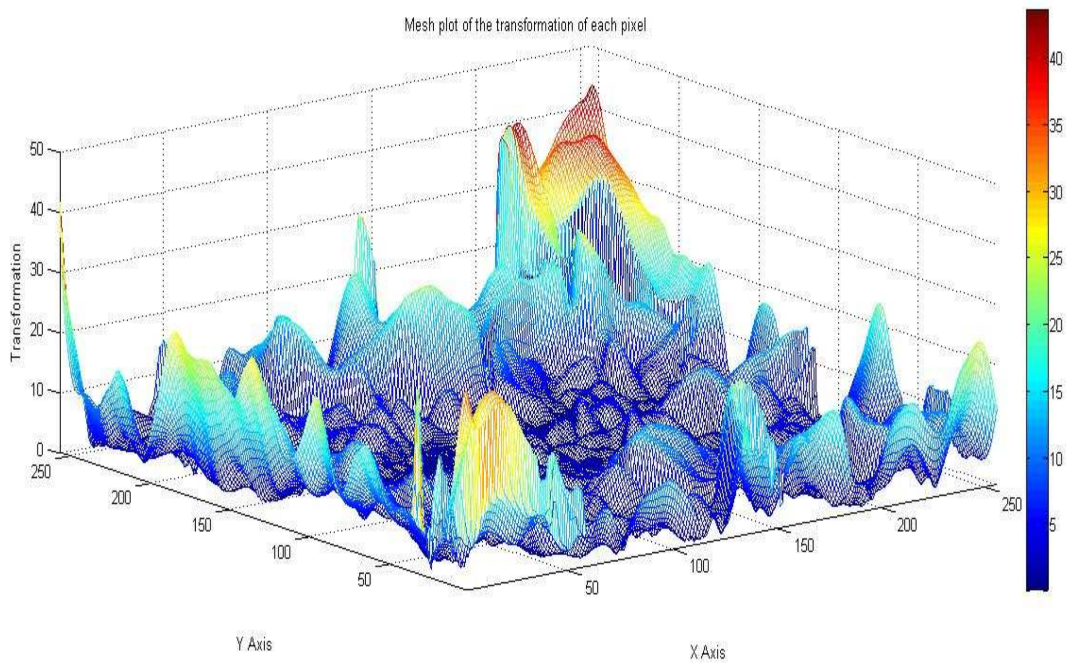
$$H(A,B) = -\sum_{i,j} p(i,j) \cdot \log[p(i,j)]$$

The matlab code for feature selection

```
y=imread('before earthquake.jpg');%source image  or reference image
 y=imresize(rgb2gray(y),[256,256]);
>> x=imread('after earthquake.jpg');% moving image or the image obtained after earthquake occurrence
x=imresize(rgb2gray(x),[256,256]);
>> diff=y-x;
>> y=diff;
>> sortedoutcome = sortrows (y);
outcome = unique (sortedoutcome);
>> numberofgroups = length (outcome);
%Count for earch group the number of cases.
for index = 1:1:numberofgroups
    %voidgroup contains each row contain that group
    voidgroup = find (sortedoutcome == outcome(index));
    outcomegroups(1, index) = outcome(index);
    %The number of cases is the number of rows
    outcomegroups(2, index) = length(voidgroup);
end
%Display results
fprintf ('Outcomes groups and cases:\n');
for index = 1:numberofgroups
    fprintf ('\nGroup number : %d\t\t cases = %d', outcomegroups (1,index), outcomegroups (2,index));
end
fprintf('\n');
```



Task of image registration is to find an optimal transformation, T*, which spatially matches a floating image, If , to the reference image, Ir, based on some measure of intensity dissimilarity C(Ir, T(If)). T(f)=argmin(Ir ,T(I f)) +λS(T).I think our results comparision where we have compared and also given explanation for demons ;graph cut using α expansions and graph cut with lazy snapping as comparable approaches for accuracy of the algorithm in terms of mean and standard deviation for error measures. Outcomes groups and cases: We had a brief notion that images acquired from ASAR satellite image is INSAR images since INSAR stands for Interferometric Advanced Synthetic Aperture Radar images which we felt could be used for Interference. However we do not use the term anymore as we are not using any specific instruments like radar that gives spatial resolution of deformation . ENVISAT ASAR data were provided by the European Space Agency acquired images is what we have used and we have also mentioned in the acknowledgements. Percentage intensity difference between 2 image (image 1 for before earthquake imagery) and image2 (after earthquake imagery) has been calculated and has been found as 25.3587 that intensity difference has infact changed between two images. Segmentation is performed manually by plotting from the mesh plot diagram. According to the study the x and y axis is the coordinate of the pixel and z axis is the transformation or the movement of the pixel to a point in reference to the neighborhood in image 1 to image 2.According to the histogram analysis for Joint intensity histogram for number of pixels vs transformation graph in fig 5; we found that about $5.2*10^4$ pixels have undergone a regional displacement of 10 windows of 15*15 matrix and so and so forth whereby 890 pixels have undergone a displacement of 50 windows of 15*15 matrix.Based on the pixel values we segment the region and restore regions to find the disaster prone regions based on the histogram values accordig to the figure given below.



Fractal term will allow for better region based retrieval for image sensing patches after image segmentation. Variation in smoothness of the resultant image is considered in the energy functional (to enforce natural transitions between pixels). We analyze the the entropy dimension $D1$ gives the regularity of distribution of points on the surface bounded by its window size.We find that the entropy dimensions are correlated to the devastated regions and decrease in size. We calculate the value of D for each window. If a window has high D value, we conclude that the value of C i.e measures the correlation between pairs of points also increases as taken from Multi fractal Dimension and its Geometrical terrain properties for classification of multi band multi-polarised SAR image by H. T. Teng et al *Progress In Electromagnetics Research, PIER 104, 221{237, 2010.* surface information can be deduced indirectly. For rough surface, there are more neighborhood points of different intensity. For homogeneous surface, there are more neighborhood points of similar intensity. This will give a brief analysis of the homogeneity of the region. This proves that the region we had extracted through segmentation were homogenous by nature. We will make more studies by dynamically changing the size of the window and trying to analyze the behavior of the fractal distribution again and again. Following a natural disaster, the local management authorities need rapidly to know the location and the extent of affected areas, along with the assessment of its impact on population whereby they conduct the assessment on the images.So the quote diagnosed in the same visualization framework for change of pixel analysis" actually means analyses rely most often on a pair of images whose dates of acquisition encompass the event of interest. The moving image is registered and compared to the ante-disaster one or the source image which serves as a reference and pixel deviation is measured accordingly.

A whole lot from computer vision research Keith Price Biography :Annotated computer vision bibliography http:/iris.usc.edu/Vision-Notes/bibliography/contents.html.

Technical corrections :We thank Reviewer for the comments. All the suggested technical

corrections will be made in the next revised version.