Change Detection using Fast Subpixel Mapping Algorithms

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Abstract

As Earth's surface prone to change over years, there is a need to perform change detection (CD). However, it is difficult to obtain remote sensing images with both fine spatial and temporal resolution. In this paper, with the help of Sub-pixel mapping (SPM) both fine spatial and temporal CD images are obtained. Three fast SPM algorithms including SPSAM, Kriging and RBF interpolation methods are proposed for calculating soft class values. FRM is constructed using the soft class values. The auxiliary information available in FRM is used to increase CD accuracy.

Keywords: *Change detection (CD), subpixel mapping (SPM), fine spatial resolution land cover map (FRM)*

INTRODUCTION

Change Detection is the technique to analyze changes in the earth's surface. Change Detection technique is employed in urban expansion, damage assessment, e cosystem monitoring, disaster monitoring and land management. MODIS and Landsat are the existing sensors which have been used for 10 years. But the problem with MODIS is that it can produce images with coarse spatial resolution from 250 to 1000m.But MODIS can provide images with fine temporal resolution. Landsat can provide fine spatial resolution images with 30 m resolution. But it has long revisit time of upto 16 days. Some satellites like World View and GeoEye are able to capture fine spatial resolution image with relatively short revisit time. But due to its high budget and narrow swath hamper their application in change detection to some extent particularly for large areas.

In spatial temporal fusion techniques, fine spatial but coarse temporal resolution images are blended with coarse spatial and fine temporal images in order to achieve

both fine spatial and temporal resolution [1– 5]. However, because of differences in weather, atmosphere and some other factors like uncertain natural changes and human activities during data acquisition sometimes difficult to obtain reliable relationship between the fine and coarse resolution images and sometimes the relationship may not be constant over a long period. For a coarse resolution image, each pixel covers a larger area and generally contains more than one type of land cover class, that is ,it constitutes a mixed pixel. Spectral unmixing technique is used to extract land cover information within mixed pixel [6–8]. It is a technique to estimate the proportion of land cover classes within each mixed pixel. On applying spectral unmixing for CD, however , one can only obtain quantitative information about the changes with coarse spatial resolution.

Therefore, we need to perform change detection with both fine spatial and temporal resolution. This paper presents five algorithms inorder to achieve change detection with greater accuracy.

METHODS
Applying SPM to change detection without any auxilliary information will result in many errors in form of noise.

Inorder to increase accuracy of SPM for a single date image, the information can be borrowed from images taken before it and after it in time. This could be helpful to separate real changes from noise.

Steps:
1. Soft Class Value Calculation.
2. Class Allocation.
3. Proportion Changes Measurement.
4. Subpixel Adjustment.
5. Change Detection.

Soft Class Value Calculation
In input image every pixel is divided into sub-pixels using zoom factor. We have used five fast STHSPM algorithms to calculate soft class values for every sub-pixel. The STHSPM algorithm is a type of SPM algorithm that first estimates the soft class values and then allocates the hard class to each sub-pixel. The fast STHSPM algorithms are bilinear interpolation, bicubic interpolation, SPSAM, Kriging and RBF interpolation method.

Class Allocation
After calculating the soft class value for every subpixel using the five algorithm, the subpixels must be allocated to every class. Here, we have considered three classes namely, RED, GREEN and BLUE. The subpixels are allocated based on the visiting order and soft class values are
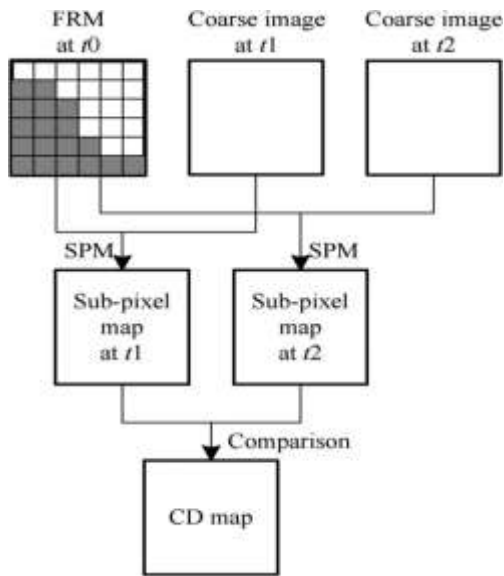
Fig. 1: CD between Multitemporal Corase Images with FRM.

calculated. The subpixels which are not belonging to any of the three classes are put into other class that is colored YELLOW. Atlast FRM is constructed by doing class allocation.

Proportion Changes Measurement

The proportion of an image may be changed over time. For example proportion of a particular class may be increased or decreased after some years. Such changes are measured for every pixel in a class by comparing with the constructed FRM. The difference between the two images is measured for every pixel.

Subpixel Adjustment

After measuring changes subpixel adjustments are done in the copy of FRM. Let the difference between the two images that is between a FRM taken at time t0 and the image taken at time t1 be Δk. The subpixel adjustments are done as follows:

1. If $\Delta k > 0$, then some sub-pixels inside the class k' are changed to class k.

2. If $\Delta k = 0$, then no change for class k.

3. If $\Delta k < 0$, then some sub-pixels within class k are changed to k'.

The changes are done in the copy of the frm and the resultant is SPM1. Original FRM is kept as such in order to compare with the same image taken at another time to generate SPM2.

Change Detection

By comparing the images taken at time t1 and t2 as shown in Figure 1 with FRM at time t0, the changes are found and adjustments are done to get SPM1 and SPM 2. The difference between two images is found and at last change detection (CD) map is generated. These steps are repeated for every algorithm by using different zoom factors.

EXPERIMENTS

Three datasets are used in this paper. The dataset must be the same image taken at three different times. Here, Figures 2–4 are the images of Yellow river taken in 1994, 2009 and 2004.
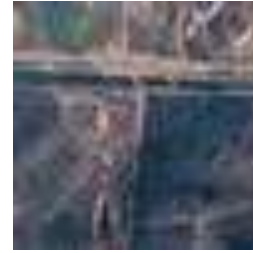

Fig. 2: Input Image taken in 1994.

Fig. 3: Input Image taken in 2004.

Fig. 4: Input Image taken in 2009.

Pre Processing Step

The initial image taken at time t0 is cropped for 50x50 pixels (as shown in Figure 5) and every pixel is subdivided into subpixels as in Figure 6.

Fig. 5: Cropped Image.

Fig. 6: Resized Image.

Soft Class Value Allocation

In order to obtain both fine spatial and temporal resolution, every pixel in an image is zoomed using zoom factor. Figure 7 shows that for every subpixel soft class values are calculated using five fast STHSPM algorithms. The following section explains how the soft class values are calculated using those algorithms.

Bilinear Interpolation

Bilinear interpolation considers the closest 2x2 neighborhood of known pixel values surrounding the unknown pixel. It then takes a weighted average of these 4 pixels to calculate soft class value. This results in much smoother looking images than nearest neighbor. The weight is calculated for every subpixel.

The weight is calculated as in [9, 10].

Weight = 1-

where,

d = D/D0 = relative distance of point to output pixel

D = Euclidean distance of point to output pixel

D0 = Limiting distance

n = weight exponent

Bicubic Interpolation

Bicubic interpolation considers the closest 4x4 neighborhood of known pixel values surrounding the unknown pixel. It then takes a weighted average of these 16 pixels to calculate soft class value. This results in much smoother looking images than nearest neighbor. The weight is calculated for every subpixel.

Kriging

In Kriging based SPM, the soft attribute value is a weighted linear combination of N observed values. The weight of every sub-pixel is calculated. The proportion of every pixel is measured. The soft class value is calculated by multiplying the weight of every subpixel and its proportion.

It is calculated using the formula,

$$F_k(p_{j,i}) = \sum_{n=1}^{N} \beta_n F_k(P_n)$$

Where,

is the coarse proportion of class k at neighboring pixel

is a weight that is estimated by solving the Kriging system.

RBF Interpolation

The basis function that reflects the spatial relation between subpixel and pixel is calculated first. The next step to be calculated is to find the coefficient of class k for coarse pixel. This is calculated by dividing the proportion of the pixel by its distance. The soft class value is calculated by multiplying the coefficient of class k and the distance.

The soft class value predicted by RBF interpolation is

$$F_k(P_{i,j}) \sum_{n=1}^{N} \lambda_k(P_n)\varphi(P_n, P_{j,i})$$

where, is a basis function that reflects the spatial relation between subpixel and pixel

$$\varphi(P_n, P_{j,i}) = e^{-d^z(\frac{P_n, P_{j,i}}{a^z})}$$

= is the coefficient of class k for coarse pixel .

SPSAM (Subpixel/Pixel Spatial attraction Model)

SPSAM assumes that, for the same class, spatial attraction exists between subpixels and their neighboring coarse pixels. The

soft attribute value is calculated in terms of attraction. The proportion of every pixel is measured. The distance between the centroid of a pixel and its every subpixel is also calculated. The proportion value is divided by its corresponding distance.
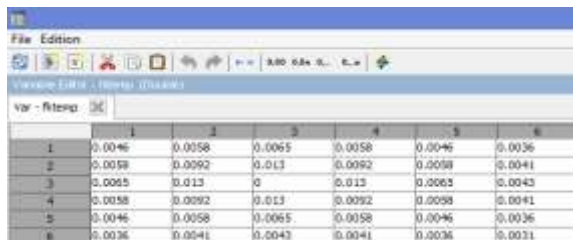
$$F_k(P_{j,i}) = \frac{1}{N} \sum_{n=1}^{N} \frac{F_k(P_n)}{d(P_n, P_{j,i})}$$

where,

N is the number of neighboring coarse pixels

$d(Pn, pj, i)$ is the Euclidean distance between the centroids of pixel Pn and subpixel pj, i,

$Fk(Pn)$ is the coarse proportion of class k at neighboring pixel Pn.

Fig. 7: *Soft Class Value for a Pixel (6x6) using SPSAM Algorithm.*

Class Allocation

Determine the Proprtion

The first step in class allocation is the measurement of proportion of every class. For a particular coarse pixel, the number of subpixels for class k, i.e., is calculated by,

$$E_k(P_j) = round\ F_k(P_j)S^2$$

Find the Visiting Order

The next step is to calculate the visiting of the classes. The class which has highest proportion comes first in visiting order. The next highest proportion class comes next in visiting order. In this way visiting order is calculated.

Allocating Soft Class Values

In this step the soft class values are allocated to every class based on their proportion. The classes are traversed based on their visiting order. The class which comes in the visiting order is traversed first and subpixels are allocated to that particular class. The sub pixels which are not belonging to any of the three classes are marked as other class as shown in Figure 8. At last FRM is constructed as in Figure 9.
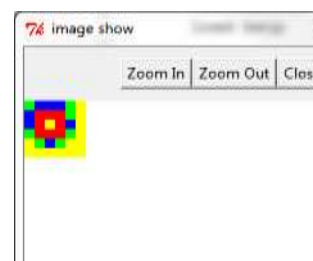
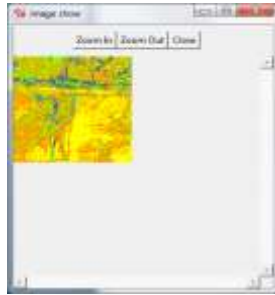**Fig. 8:** *Allocation for a Pixel (6x6) using SPSAM Algorithm.*

Fig. 9: FRM Generated For 50x50 Pixel.

Proportion Changes Measurement

Proportion of an image may be changed over a time. For example if RED class covers 75% initially and after few years its proportion may be decreased or increased. Those changes are calculated using the formula,

$$\Delta k(P_j) = F_k(P_j) - F_{k-H}(P_j)$$

Where,

Proportion of FRM

= Proportion of image taken at time t1

= Changes in proportion.

➢ If $\Delta k > 0$, then some sub-pixels inside the class k' are changed to class k.

➢ If $\Delta k = 0$, then no change for class k.

➢ If $\Delta k < 0$, then some sub-pixels within class k are changed to k'.

Subpixel Adjustment

The changes are measured for every subpixel using the formula mentioned above.

Proportion changes measurement

Fig. 10: (a) SPM1 (b) SPM2.
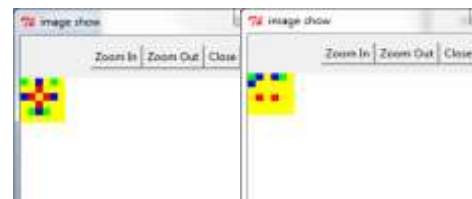
SPM Results for a Single Pixel

Fig. 11: (a) SPM1 (b) SPM2.

Find Proportion Changes

The proportion of an image may be changed over time. Here, we must calculate the proportion changes for ever class in every pixel.

**Proportion Increase and Proportion Decrease Array**

If the proportion of a particular class increases then that class must be placed in proportion increase array. Otherwise, if the proportion decreases then it must be placed within a proportion decrease array.

Adding or Removing Subpixels

Figures 10 and 11 shows that for the classes in proportion decrease array, the subpixels are to be removed from that particular class. Initially, they are shaded

as grey color. For the classes in proportion increase array, the subpixels are to be added from the other classes. The grey colored subpixels can be changed into the needed color or the colors from other class are changed. At last SPM 1 and SPM2 were generated as shown in Figure 12(a) and 12(b).
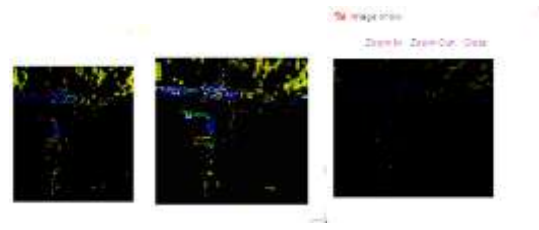
SPM FOR A 50X50 PIXEL
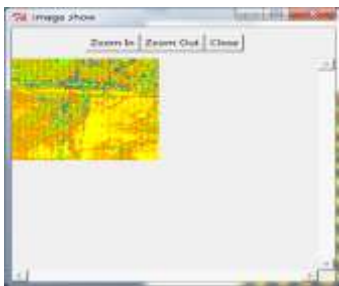
Fig. 12: (a) SPM1.
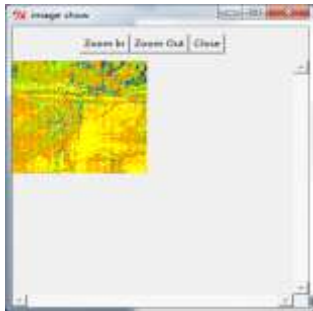
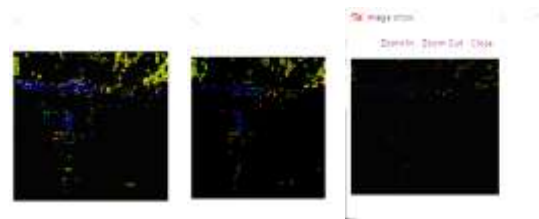*Fig. 12: (b) SPM2.*

Change Detection

The SPM 1 and SPM 2 generated are compared to obtain the change detection map. This change detection(CD) map as shown in Figures 13–17 is generated with greater accuracy which illustrates the changes that has occurred in an image from t1 to t2.
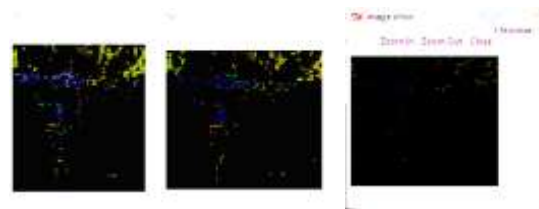
SPSAM Algorithm

Fig. 13: (a) S=6 (b) S=6 (c) S=4.
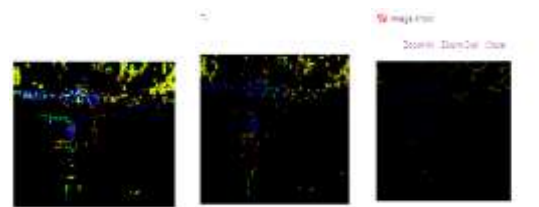
RBF Algorithm

Fig. 14: (a) S=6 (b) S=6 (c) S=4.

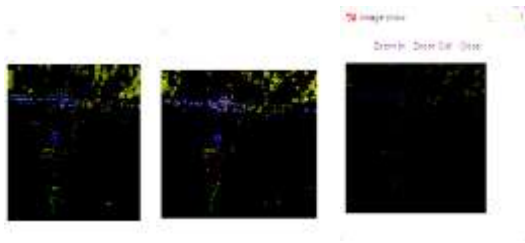## KRIGING Algorithm

Fig. 15: (a) S=6 (b) S=6   (c) S=4.

BILINEAR Algorithm

Fig. 16: (a) S=6 (b) S=6   (c) S=4.

BICUBIC Algorithm

Fig. 17: *(a) S=6   (b) S=6   (c) S=4.*

Accuracy (%)

Table 1 represents accuracy calculation for five STHSPM algorithms at different zoom factors (s=4, s=5, s=6).

**Table 1:** *SPM Accuracy (%) of T1 Image (T0 Reference Map as the Frm) for the Five STHSPM Algorithms.*

|	S=4		S=5		S=6	
	Without FRM	With FRM	Without FRM	With FRM	Without FRM	With FRM
Bilinear	81.99	86.3	80.07	86.2	79.74	85.8
Bicubic	82.6	85.8	80.61	85.8	80.02	85.2
SPSAM	81.90	86.1	79.37	86	78.95	85.4
Kriging	82.41	86	80.09	86.1	79.82	86
RBF	83.06	86	80.76	86.1	79.83	86

Graph

Figure 18(a)-(e) represents the OA of change detection. From this Figure, for all the five algorithms accuracy is increased when FRM is incorporated. From the Table 1, it is observed that as S increases, accuracy value decreases.
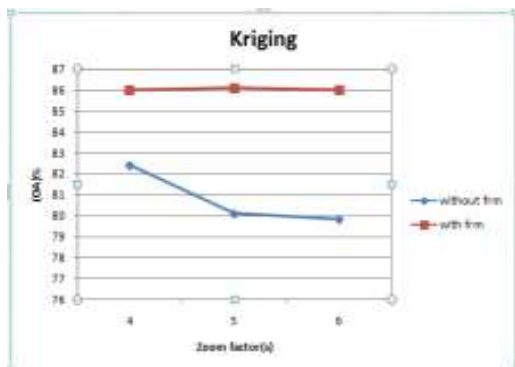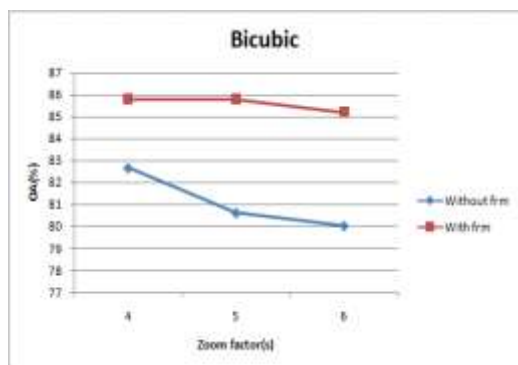

Fig. 18: *(a) SPSAM.*
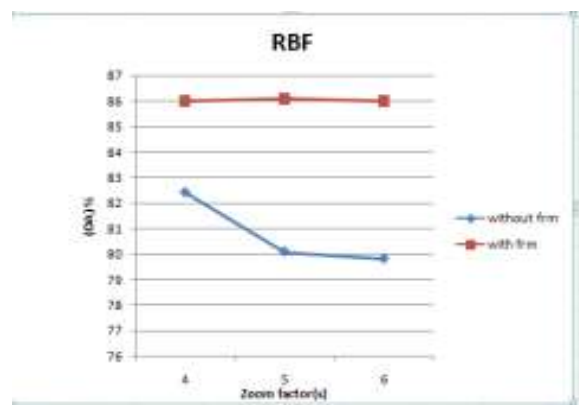
Fig. 18: *(b) RBF.*
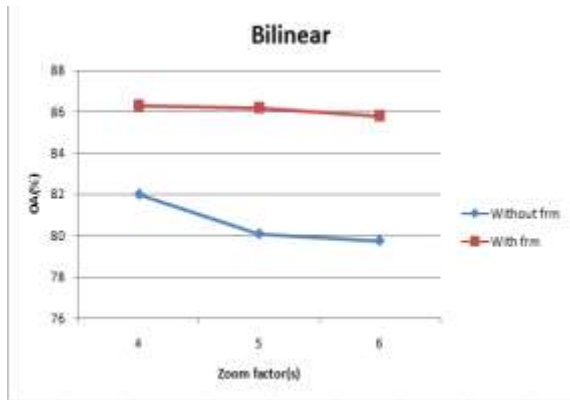
Fig. 18: (c) Bilinear.

Fig. 18: (d) Kriging.

Fig. 18: (e) Bicubic.

From Figure 18, it is shown that using an FRM can increase SPM accuracy and the subpixel CD accuracy for all five STHSPM algorithms.

FUTURE WORK

The future research is based on two aspects: developing new STHSPM-based algorithms for Change Detection with an FRM and seeking new approaches to acquire a reliable FRM. Recently, researchers it have developed another per-field classification-based SPM method, where segmentation map generated from a fine spatial resolution color image.

CONCLUSION

Thus, the five noniterative and fast STHSPM algorithms (bilinear, bicubic, SPSAM, Kriging and RBF based SPM methods) were proposed for subpixel resolution land cover Change Detection. The FRM was taken into account not only in the case of a former FRM and latter coarse image but also in the case of a former coarse image and latter FRM. The STHSPM algorithms determined the subpixels for each class by comparing the soft class values and referring the hard class values in the FRM. The FRM decrease the uncertainty in SPM and increase the supixel resolution Change Detection accuracy. The proposed methods provide fine spatial and temporal resolution Change Detection. The computation time is also very less when compared to other methods and used in various real-time applications.

REFERENCES

1. Qunming Wang, Peter M. Atkinson, Wenzhong Shi. Fast subpixel mapping algorithms for subpixel resolution change detection. *IEEE Trans. Geosci. Remote Sens.* 2015; 53(4): 1692–1706p.

2. F. Gao, J. Masek, M. Schwaller, F. Hall. On the blending of the Landsat and MODIS surface reflectance: Predicting daily Landsat surface reflectance. *IEEE Trans. Geosci. Remote Sens.* 2006; 44(8): 2207–2218p.

3. X. Zhu, J. Chen, F. Gao, X. H. Chen, et al. An enhanced spatial and temporal adaptive reflectance fusion model for complex heterogeneous regions. *Remote Sens. Environ.* 2010; 114(11): 2610– 2623p.

4. T. Hilker *et al.* A new data fusion model for high spatial- and temporal resolution mapping of forest based on Landsat and MODIS. *Remote Sens. Environ.* 2009; 113(8): 1613–1627p.

5. B. Huang, H. Song. Spatiotemporal reflectance fusion via sparse representation. *IEEE Trans. Geosci. Remote Sens.* 2012; 50(10): 3707– 3716p.

6. H. Song, B. Huang. Spatiotemporal satellite image fusion through one-pair image learning. *IEEE Trans. Geosci. Remote Sens.* 2013; 51(4): 1883– 1896p.

7. D. Lu, M. Batistella, E. Moran. Multitemporal spectral mixture analysis for Amazonian land-cover change detection. *Can. J. Remote Sens.* 2004; 30(1): 87–100p.

8. D. Lu *et al.* Fractional forest cover mapping in the Brazilian Amazon with a combination of MODIS and TM images. *Int. J. Remote Sens.* 2011; 32(22): 7131–7149p.

9. V. Haertel, Y. E. Shimabukuro, R. Almeida. Fraction images in multitemporal change detection. *Int. J. Remote Sens.* 2004; 25(23): 5473– 5489p.

10. P. Goovaerts. *Geostatistics for Natural Resources Evaluation*. London, U.K.: Oxford Univ. Press; 1997.