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Performance of SEMI supervised Fuzzy Clustering Algorithm for Change Detection in Remotely Sensed Multitemporal Images

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Abstract: Fuzzy c-means (FCM) clustering algorithm widely used in image segmentation. However, its computational efficiency and wide spread reputation, the FCM algorithm does not take the spatial information of pixels into consideration, and thus may possibly result in low robustness to noise and less accurate segmentation. In this paper, semi supervised fuzzy clustering (SEMI-FCM) algorithm is presented for fuzzy segmentation of magnetic resonance (MR) images. To estimate the intensity in homogeneity, the global intensity is introduced into the logical limited intensity clustering algorithm and takes the local and global intensity information into account. The proposed method has been successfully applied to recorded GMRF + ICM with desirable results. Our results show that the proposed algorithm can effectively reduce the false alarm of image. Comparisons with other HTNN and EM demonstrate the better performance of the proposed SEMI- FCM algorithm.

Keywords: Fuzzy c-means, spatial-contextual, semi- supervised FCM, k- means, GMRF + ICM.

I. INTRODUCTION

Increasing interest and the fundamental role played by change detection techniques in monitoring the Earth's surface. Applications include, among others, damage assessment from natural hazards (floods, forest fires, hurricanes) or large-scale accidents (e.g., oil spills), and also keeping watch on unusual and suspicious activities in or around strategic infrastructural elements (dams, waterways, reservoirs, power stations, nuclear and chemical enterprises, camping in unusual places, improvised landing strips, etc). Most of the well known supervised and unsupervised methods for detecting changes in remotely sensed images perform sequentially an image pre-processing, image comparison to get a "difference" image, and the difference image analysis. In the unsupervised change detection case, the pre-processing steps are necessary to make the two images comparable in both the spatial and spectral domains. The most critical step is to co-register/align the images with a sub-pixel accuracy so that corresponding pixels within the images relate to the same ground area. SIFT algorithm [2] is used to localize and match correspondence interest points, these points will be used to compute an affine transformation to maps one image to the spatial coordinates of the other. SIFT-based Registration for extract a set of correspondence points in a pair, or multiple pairs, of images that are taken at different times and under different circumstances, then Random Sample Consensus (RANSAC) is used to remove the outlier set. Markov-Gibbs Random Field (MGRF) is used to model the spatial-contextual information contained in the resulting change mask. Experiments with generated synthetic multiband images, and LANDSAT5 Images, approved the accuracy of the scale-invariant feature transforms.

A context-sensitive technique for unsupervised change detection in multitemporal remote sensing images is based on fuzzy clustering approach and takes care of spatial correlation between neighbouring pixels of the difference image produced by comparing two images acquired on the same geographical area at different times. Fuzzy clustering techniques have advantages over the context-sensitive process as well as they are less computation intensive. Compared to another context-sensitive technique proposed in the fuzzy techniques proposed here are very simple, less costly and showed improved performance [3]. Gibb's Markov Random Field (GMRF) is a spatio contextual statistical model [4] mainly used for partitioning an image into a number of regions with the constraint of Gibb's distribution as prior probability distribution.

The Spatio-contextual information of pixels is modelled with a GMRF and the iterated conditional mode (ICM) algorithms are used as the MAP estimator. The GMRF model parameters are recursively estimated by the EM algorithm. ICM uses a deterministic strategy to find the local minimum. MAP Estimation Problem with Hopfield Type Neural Network HTNN is a robust and fast optimization technique. Unlike the ICM algorithm which can be seen as a local search algorithm, the stochastic nature of the HTNN helps to avoid getting trapped to a local optimum. Thus it may improve the quality of solution (and therefore of the change detection map) with respect to the ICM algorithm. In HTNN, a proper initialization is necessary to start the iterative process. In GMRF-MAP estimation the algorithm starts with an initial estimate and then converges to a minimum of the cost function.

Many change-detection techniques are used in practice today. Most techniques are semi-automated because analysts still have to manually carry out many image processing tasks such as image registration, threshold tuning, and change delineation. There are also problems associated with semi-automated techniques, including being time-consuming, inconsistent, and difficult to apply to large-scale and global information systems, such as the International Earth Observing System (IEOS) [5].

II. RELATED WORK

Some of the related works are Fuzzy clustering algorithm, Kernel FCM, a modified Kernelized FCM algorithm, spatio-contextual change detection technique.

A. Fuzzy clustering algorithm

The fuzzy c-means algorithm (FCM) [1], have been broadly used in the image segmentation and such a success mostly attributes to the introduction of fuzziness for the belongingness of each image pixel. Fuzzy c-means allows for the ability to make the clustering methods able to retain more information from the original image than the crisp or hard segmentation methods. Clustering is used to panel a set of given observed input data vectors or image pixels into clusters so that components of the same cluster are similar to one another than to members of other clusters where the number of clusters is usually predefined or set by some weight criterion or a priori knowledge. One of the commonly used families of clustering algorithms is the scheme based on function optimization. FCM algorithm belongs to that family. It attempts to find fuzzy partitioning of a given pattern-set by minimizing the objective functional. The FCM algorithm is popular for its simplicity and less computation time, it tends to recover clusters with similar sizes and densities and circular shapes.

B. Kernel FCM

When applying the KFCM [7] framework in image-segmentation problems, the multi resolution segmentation may end up with local optimization procedure. Global mutual fitting is the strongest constraint for the optimization problem and it reduces heterogeneity most over the scene following a pure quantitative criterion. Its main disadvantage is that it does not use the treatment order and builds first segments in regions with a low spectral variance leading to an uneven growth of the image objects over a scene. It also causes an unbalance between regions of high and regions of low spectral variance. Comparison of global mutual fitting to local mutual fitting results show negligible quantitative differences, the former always performs the most homogeneous merge in the local vicinity following the gradient of the degree of fitting. The growth of image objects happens simultaneously as well in regions of low spectral variance as in regions of high spectral variance. KFCM confines that the prototypes in the kernel space are actually mapped from the original data space or the feature space.

C. A modified kernelized Fuzzy C-Means algorithm

Although KFCM can be directly applied to image segmentation like FCM, and to modify the algorithm by taking into account the image topology. For the Modified KFCM (MKFCM) [7] proposed to initialize the cluster centers by using the "Expectation Maximization" (EM) algorithm for an optimal choice of the centers. To take into account the image topology; the statistical parameters of a window around the pixel are considered. For an image *y*, of size *(N × M)*, and a sliding window of size *(p × p)*, the four features extracted from the window centered at pixel *(n, r)* are given by the following equations:

$$\text{Me}=\frac{1}{MN}\sum_{i=-\frac{p-1}{2}}^{\frac{P-1}{2}}\sum_{j=-\frac{p-1}{2}}^{\frac{p-1}{2}} y(n+i,r+j) \quad (1)$$

$$\text{V}=\frac{1}{MN}\sum_{i=-\frac{p-1}{2}}^{\frac{P-1}{2}}\sum_{j=-\frac{p-1}{2}}^{\frac{p-1}{2}} (y(n+i,r+j)-Me)^2 \quad (2)$$

$$\text{Sk}=\frac{1}{MN}\sum_{i=-\frac{p-1}{2}}^{\frac{P-1}{2}}\sum_{j=-\frac{p-1}{2}}^{\frac{p-1}{2}} (y(n+i,r+j)-Me)^3 \quad (3)$$

$$\text{Ku}=\frac{1}{MN}\sum_{i=-\frac{p-1}{2}}^{\frac{P-1}{2}}\sum_{j=-\frac{p-1}{2}}^{\frac{p-1}{2}} (y(n+i,r+j)-Me)^4 \quad (4)$$

D. Spatio-contextual change detection technique

Gibb's Markov Random Field (GMRF) is a Spatio-contextual statistical model mainly used for partitioning an image into a number of regions with the constraint of Gibb's distribution as prior probability distribution [11]. In GMRF, the spatial property of the image can be modelled through different aspects, among which, the contextual constraint is a general and powerful one [12]. Segmentation of an input image is obtained by estimating some spatially varying quantity from noisy measurement. This can be obtained by maximum a posteriori probability (MAP) estimate of the underlying quantity formulated in Bayesian framework. The effectiveness of the Spatio-contextual results are compared with those of MTET, change detection scheme based on the GMRF model and the ICM algorithm, change detection scheme based on HTNN, and change detection scheme using the GMRF model and graph-cut algorithm.

III. PROPOSED WORK

Several techniques have been proposed to enhance the performance of fuzzy clustering with the aid of semi-supervision. Here we have incorporated semi-supervision to the already existing *unsupervised change detection* technique. It has been observed from the results that the present concept can boost up the performance of the existing one. The labelled patterns can be collected in various ways. Here, for experimental purpose labelled patterns from both the classes (*changed* & *unchanged*) are acquired randomly (5% from *changed* & 1% from *unchanged*) from images. The images are generated by manual analysis of two multitemporal images of the various pictures. Memberships (μ_{ik}^{l}) are known & hard for the labeled patterns (X_k^l).

$$V_{i,l}=\frac{\sum_{k=1}^{n_l}(\mu_{ik}^{l})^m X_k^l}{\sum_{k=1}^{n_l}(\mu_{ik}^{l})^m} \quad (5)$$

The memberships(μ_{ik}^{l}) for the unlabeled ones (X_k^l) are initialized using this $V_{i,l}$ by (5). For calculating cluster centers afterwards labelled patterns also participate along with unlabeled ones."Semi" denotes the effect of semi-supervision while evaluating cluster means at each iteration.

$$\frac{\sum_{k=1}^{n_l}(\mu_{ik}^{l})^m X_k^l+\sum_{k=1}^{n_{nl}}(\mu_{ik}^{nl})^m X_k^{nl}}{\sum_{k=1}^{n_l}(\mu_{ik}^{l})^m+\sum_{k=1}^{n_{nl}}(\mu_{ik}^{nl})^m} \quad (6)$$

We have applied the same concept for a clear comparison in GMRF+ ICM also and named the process as SEMI-FCM. As in fuzzy ones the cluster centers are initialized using the labelled patterns only and the labelled & unlabeled patterns both participate while updating them. The assignment (and reassignment) of patterns during optimization is done only for the unlabeled ones.

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IV. EXPERIMENTAL RESULTS

This research work presents the Semi-supervised Change Detection Technique based segmentation and for synthetic images and MR images. We test and compare the proposed method SEMI with some other description algorithms on several synthetic images and synthetic brain MR images from two aspects.

The performance of FCM-type algorithms depends on the initialization, this paper does the initialization and iterations depend upon the input images and choose the one with the best idea function value. This increases the reliability of comparison results acquired in the simulations. The main goals of an image segmentation algorithm are optimization of segmentation accuracy and its efficiency. Considering accuracy, the proposed method is intense on obtaining a robust segmentation for noisy images) and a correct detection of small regions.

Generally, incorporating of spatial information into the segmentation process will dramatically increase the algorithm's computational complexity. Proposed technique, results are compared with those of MTET, change detection scheme based on the GMRF model and the ICM algorithm, change detection scheme based on HTNN, and change detection scheme using the GMRF model and graph-cut algorithm. Each segmentation and the computational complexity of each algorithm were measured in terms of the average iteration number and average running time. The test images china data set and the results are shown Fig. 1.

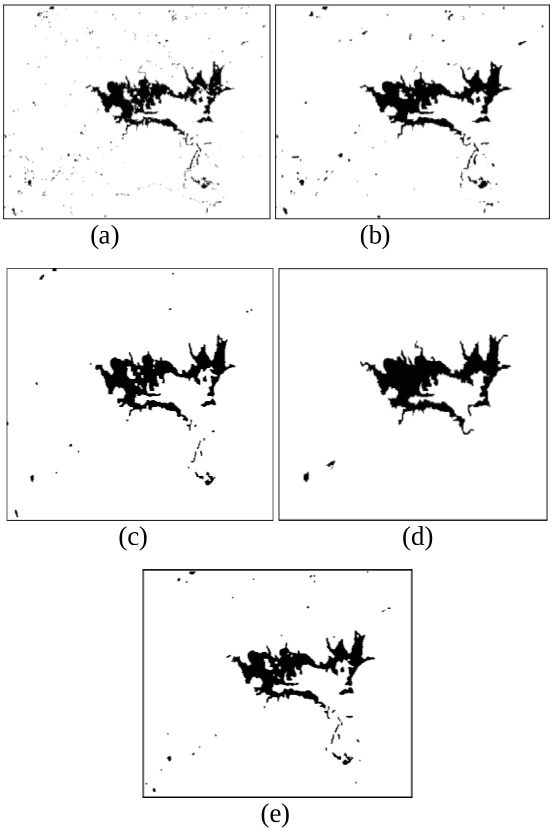

Fig.1 China data set: change detection map provided by (a) GMRF model and ICM algorithm, (b) Context sensitive Hopfield type network, (c) GMRF model and graph-cut algorithm, and (d) HTNN (e)Proposed semi supervised technique.

In this case, the difference image is generated by using only NIR band images, as NIR band is very effective to locate the burned area. Comparison between the proposed algorithm with other HTNN and GMRF graph cut algorithm based on number of iterations as shown in Fig 1. It represent that the accuracy of the algorithm decreases with the increase of the level of false alarm and overall error for all size of image patches.

TABLE I
OVERALL ERROR COMPARISON

Technique	Missed Alarms	False Alarms	Overall Error
MTET (Th = 95)	1015	875	1890
EM+GMRF+ICM	592	1108	1700
HTNN (Th=87)	1193	606	1799
GMRF + Graph-cut (Existing Th = 86)	1093	477	1496
Proposed SEMI-FCM (Th = 84)	838	648	1490

The above table1 shows the comparison of the existing and proposed overall alarms. Compare to existing algorithm the Proposed SEMI-FCM reduces the overall alarm and providing high accuracy of the image.

V. CONCLUSION

A Semi-supervised fuzzy clustering algorithm for detecting changes is presented for fuzzy segmentation of MR images that have been corrupted by intensity in homogeneities and noise. We propose semi supervised method to compute the weights for the neighbourhood of each pixel in the image. The proposed semi supervised fuzzy clustering can not only overcome the effect of the noise effectively, but also prevent the false alarm.

To address intensity in homogeneity, the proposed algorithm introduces the global intensity into the algorithm and combines the local and global intensity information into account to ensure the smoothness of the derived optimal bias field and improve the accuracy of the image. The proposed model can reduce the overall error.

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