A Study on Intelligent Algorithms for Change Detection using Remote Sensing Images

J. JENNIFER RANJANI
SASTRA University
School of Computing
Tirumalaisamudram, Thanjavur - 613 401
INDIA
j.jenniferranjani@yahoo.co.in

Abstract: Magnitude of images observed from the remote sensing satellites increases day-by-day and is widely utilized for change detection. Change detection is primitively employed for monitoring the local, global and regional resources, land-cover and land-use monitoring and for environmental studies and disaster management. Remote sensing satellites afford a prospect to obtain the information about the land at varying resolution and time, makes it ideal for change detection studies. A wide variety of algorithms are available for change detection using the remote sensing images and still it is an emerging field. Intelligent algorithms can be employed in supervised, semi-supervised and unsupervised environments. In this paper, we have introduced the drawbacks of the traditional pixel based approaches and the need for intelligent algorithms for change detection. The impact of the latest intelligent change detection algorithms utilizing genetic algorithm, artificial neural network and support vector machine is highlighted. The features of the various intelligent algorithms are summarized and dataset incorporated in the experiments are also indicated. With latest availability of very high resolution images and high computing power, intelligent algorithms are the need of the hour. This paper gives a glimpse on the latest intelligent algorithms available for change detection.

Key–Words: Change Detection, Intelligent Algorithms, Artificial Neural Network, Genetic Algorithm, Support Vector Machine, Remote Sensing.

1 Introduction

Change detection (CD) is the process of identifying alterations on the Earth's surface at varying rates. CD finds its relevance in various practical applications like urban planning and expansion, deforestation, monitoring and assessing disaster and damage, etc. The changes due to a natural or anthropic calamity can be detected using remote sensing images. These calamities are occasionally foreseeable and cannot be sampled on progressively. Hence, the resolution of the remote sensing images is required to be medium to very high for precise analysis of the changes. CD can thus be enumerated on the image acquired after the event and the data in the repository.

Various stages in change detection include identification of geographical locations, extraction of change\no-change or from-to change information [1], recognition of the type of changes, quantification of changes, and accuracy assessment of CD results [2], [3], [4]. Most of the studies on change detection require a detailed "from-to" change; but the basic change\no-change is often found to be sufficient [5]. Remote sensing data used for change detection is affected by factors like spatial, spectral, thematic and temporal constraints, radiometric resolution, atmospheric conditions and soil moisture conditions [6].

The CD algorithms in general can be classified as pixel based and object based method [7]. In pixel based techniques, the spectral features of the pixels are utilized for change detection and measurement without reckoning spatial context. Image differencing [8][9], Image ratioing [10], and Regression analysis [11][12] are the pixel based CD techniques that are dependent on direct comparison between two images. Other pixel based techniques include vegetation index differencing [13] [14], Change vector analysis [15] - [18], principal component analysis [19] [20], Tasselled cap transformation (KT) [21] [22] and Texture analysis [23].

The function to decide the change from no-change is the key aspect in many pixel based CD algorithms. This discrimination decision is often made with the help of an appropriate threshold. However, determining an exact threshold value is an challenge, too low a threshold may ignore areas of change, and a too high threshold will take into account too many areas of change. Traditional pixel based CD methods are used for low to medium resolution images, however, they are inappropriate for Very High Resolution (VHR) remote sensing data [3]. It has been identified that VHR images for CD analysis results in a number of issues like accuracy in geo-referencing, increased reflectance capriciousness in each class, dissimilar acquisition features etc. [24].

Another drawback of the pixel based CD techniques is its inability to model the contextual information. The spatial features and relationships in natural images cannot be modelled with pixel based techniques. The above mentioned reasons demand alternate algorithms for CD in remote sensing images. With the availability of increased computational power in the recent times, traditional techniques based on the statistical analysis and visualization of data, can be effectively replaced with sophisticated algorithms based on machine learning.

In this paper, we have summarized the several artificial intelligence (AI) based techniques like genetic algorithms, artificial neural networks, and support vector machine for change detection using remote sensing images. The outline of the paper is as follows, section 2 covers the various artificial intelligence techniques available in literature for change detection for remote sensing images. This sections covers the need for a particular algorithm, its features and the dataset on which the algorithm was tested. Section 3 concludes the paper.

2 Artificial Intelligence Techniques for Change Detection

2.1 Genetic Algorithm in Change Detection

Latest computational technologies with the help of high-powered parallel processors, enable us to perform computationally complex algorithms algorithms faster. This lead to use of genetic algorithm (GA) to solve change detection problems. The suitability of GA for extracting decision rules for land cover classification using remote sensing data was initially studied in [25]. It has been identified that the performance of classification algorithms is not uniformly influenced by all the variables of the collected data. Hence, a feature selection procedure comprising of hypothetical testing for numerical determination of attribute significance, normalization of the significance score and identification information gain ratio is adapted. These steps aid in determining the number of vital attributes that are to be included in the classification model. The classification rules from the collected datasets are then extracted using the genetic evolution process including genetic representation, rule conversion, population initialization, fitness evaluation, selection, crossover, mutation and replacement. The objective of GA is to search the rule that yields maximum performance among all the rules in the population. Two changes to the traditional GA approach are incorporated: first, the crossover operators at any time are randomly replaced with another, if the system convergences towards the local optima, then an adaptive adjustments of crossover and mutation are made to divert the system towards the global optima. The modified GA system was tested on two popular datasets, Landsat and AVIRIS and it has been verified that the GA ruled based model incorporates fewer rules compared to the decision rule approach.

Unsupervised change detections algorithms, in general, rely on a tuned parameter or *a priori* assumptions in image modelling. In [26], GA is utilized to evolve the initial binary change detection masks over generations to obtain the final change detection mask. For each divergent regions, change/no-change, the mean square error (MSE) between the difference image and its mean is calculated. The cost value for the change detection mask is obtained using the weighted sum of the MSE of the change/no-change region. Thus, the system can yield change detection results without *a priori* information. In [27], the difference image is assumed to follow the Gaussian Mixture Model (GMM) and is a mixture of two distributions comprising the change and the no-change regions. The GMM parameters are estimated using Expectation-Maximization (EM) algorithm. The separation between the change and no-change pixels in GMM is obtained by minimizing a cost functions using GA. The proposed algorithm was tested on two datasets, ASAR images collected on Bangladesh and part of India in 2007 by ESA Envisat Satellite to analyse the changes due to flood and the second dataset consists of of multi-spectral images collected on the part of Alaska in 1985 and 2005 by Landsat 5 TM to determine the changes in the land.

2.2 Artificial Neural Networks in Change Detection

Artificial neural networks (ANNs) has evolved as one of the vital tools for classification of remote sensing images. The ANN is a non-parametric supervised algorithm, data-driven and self adaptive without any specific functional specification of the data model. Also, they are able to approximate any functional representation with a specific level of accuracy. For the afore mentioned reasons, ANNs provide a channel for managing the complex data effectively. Like any other techniques ANN also has its associated issues: A suitable ANN architecture with a specific number of hidden nodes, required learning rate, momentum value, total number of iterations required, and the encoding technique to denote the input and output data should be determined. Often a trail and error based strategy is adopted to find these parameters.

VHR images provide a greater level of insight into the temporal land cover changes, at the same time processing large quantum of data and dealing with the associated errors in registration and classification is a challenge. In [28] a single neural network architecture for VHR images with two distinct stages to perform land cover change analysis is proposed. The proposed neural architecture can simultaneously exploit multi-spectral and multi-temporal information that is related to the pixel spectral reflectance changes and can produce the final output map by merging three NN results. The key advantage of this technique is it ability to detect the changes and recognise the type of the class transition. The experiment in carried on the images obtained from Quickbird and Thematic Mapper (TM) Landsat-5 over two test sites: Rock Creek-Superior, CO and Tor Vergata University, Rome.

Unsupervised pulse-coupled NNs (PCNNs) is a NN algorithm inspired by the visual cortex mechanism of small mammals, where information from the eye is received by the visual cortex in the brain [29]. In [30], a new dimension to change detection is provided using PCNNs. A specific signature of the scence is created from the ripples generated by each iteration and is compared successively for generating the change output map. The striking aspect of PCNNs is that it can utilize the contextual and spectral information at the same instance, which makes it as an ideal choice for change detection using VHR images. Also, PCNNs do not have to pass the information through multiple layers as done in the case of ANNs. PCNNs have only one layer of neurons that process the input received directly from the original image and to generate the resulting pulse output image. Regions around Tor Vergata University campus is considered for the proposed study and the images were obtained from the Quickbird. An object accuracy of 90.7% with no false alarm is obtained and is also fast compared to the algorithms based on multi-layer ANNs.

In [31], multi-layer perceptron NNs (MLP-NN) and PCNNs based automatic CD algorithm is implemented and tested over the regions of Tor Vergata University, Italy. The supervised MLP-NN is used to obtain the land cover map for each acquisition and the unsupervised PCNN is used to measure the correlation between the images and to identify the hot spots. The final CD map is obtained by mapping the results of post-classification analysis and PCNN module. In [32], a CD algorithm for high spatial resolution imagery is proposed combining PCNNs and a correlation based normalized moment of intertia (NMI) feature which is invariant to scale, shift and rotation. The hot spot changed areas are detected using the EM algorithm. First data used in the experiments was obtained by QuickBird over Wuhan University, China in 2002 and 2005. The second dataset was obtained from IKONOS in 2002 and 2004.

The next advancement to the NN based change detection algorithms is the inclusion of Hopfield Neural Network which can perform deterministic optimization faster [33] [34]. When the HNN converges to a stable state, its energy is equivalent to the minimum of the optimization function. HNNs are stochastic in nature and this helps to avoid getting confined in a local minima and can thus improve the solution. In [33], the difference image is modelled using Gaussian Markov Random Field (GMRF), the parameters of the GMRF model are determined using the EM algorithm. Pixels in the difference images are considered as neuron connected to its neighbours and HNN is utilized for estimating the changes using the maximum *a posteriori* (MAP) estimator. Here, the CD problem is equated as a MAP estimation problem and a relationship is established between the MAP of GMRF and the energy function of HNN. The datasets used in the experiments include: (1) two multispectral images taken by TM Landsat-7 in an area of Mexico in 2000 and 2002 and (2) second set consists of two images acquired over the Lake Mulargia by TM Landsat-5 is 1995 and 1996.

A method that compares the results from sub pixel mapping to the original fine spatial resolution land cover map to obtain the land cover change map is proposed in [34]. Synthetic multi-spectral images with distinct class separabilities are generated to actually test the uncertainty in spectral separability of the input image and point spread function of the sensor. And the proposed technique was able to separate more real changes from noise. Set of images over the tropical regions in Brazil collected by the Landsat-MODIS are used for the experiments.

Supervised CD algorithms are dependent on the set of available labelled patterns. Active learning techniques can be adopted to handle the inadequacy in labelled data [35]. Active learning involves query based algorithm and the learner creates repeated informative queries during the learning process. Answers to few queries are given by the human annotator, which in turn helps the learner to refine its knowledge based on these answers. In [35], two variants of the radial basis function NNs and MLP under active learning environment is used for detecting the change/no-change as a binary output. Uncertainty sampling and query-bycommittee are the two techniques used by the active learner for query selection process. Few among the collected random labelled patterns are used in training the network and after convergence, the remaining patterns are used to test the network. The effectiveness of the proposed algorithm is established using the test dataset collected over Mexico, Sardinia Island of Italy and the southern part of Peloponnesian Peninsula, Greece by the Landsat-7 enhanced TM+.

Self organizing map (SOM) are a special category of unsupervised NNs also called as the Kohonen network, here the neurons become tuned to classes of patterns specifically through competitive, unsupervised or self organizing learning. In [36], the two approaches based on the concurrent SOM for supervised and unsupervised land cover CD is proposed. Concatenation of multitemporal image features and classification using concurrent SOM are the steps involved in the supervised stage. And the unsupervised stage comprises of image comparison, unsupervised pseudo training set generation, multi-temporal feature concatenation and classification using concurrent SOM. The datasets incorporated in the experiments include: Landsat-5 TM bitemporal image over Mexico taken before and after two wildfires and the second is a TerraSAR-X image acquired in the Fukushima region, Japan before and after the Tsunami.

2.3 Support Vector Machine in Change Detection

Support vector machine (SVM) is a non-parametric, statistical, supervised learning technique that makes no assumption about the underlying data distribution. It implements structural risk minimization function for classification. In [37], a time-adaptive SVM to one class problems is introduced. The proposed system is suitable for non-stationary problems that require methods that does not assume the data is identically distributed. Adaptive individual models are made to fit short segments of the full time interval and all models are learned simultaneously using a coupling term. This forces the neighbour model to be identical and a regularization effect is introduced on the sequence of models. Dissimilarity between adjacent models indicate the presence of abrupt changes between them.

An interactive segmentation based change detection algorithm is used in [38], where the user input markers to change and no-change classes in the difference image. The pixels labelled by these markers are then trained using SVM classifier. The decision for a pixel also considers its neighbourhood thus it provides increased classification accuracy. Markov random fields and level-set methods are employed to include the spatial context in the decision process. A variety of images are considered for the experiments taken over an agricultural area in basin situated over the Po river, and forest regions in the island of Elba, Italy and VHR images over Riyadh and Mina, Saudi Arabia by the Landsat-5 TM and the IKONOS-2 respectively.

Semi-supervised novelty detection (SSND) have only unchanged samples labelled and no information about changes lie among the unlabelled data. In [39], cost-sensitive SVM that do not require heavily supervised parameter selection is proposed, which uses the entire solution path in single optimization to facilitate and speed up parameter selection for SSND. Another algorithm produces classification boundaries by forcing the solution to be coherent through the path. Optimal classification boundaries can be selected using a low-density criterion and thus, can avoid recourse to cross validation. Multi-temporal images acquired by SPOT and Landsat-5 TM over the Gloucester in the UK and Bastrop in Texas respectively are used for validating the proposed algorithms.

A range of CD algorithms are are also available for Synthetic Aperture Radar (SAR) Images, however, CD in SAR images suffers from lack of samples required for the training process. Recently, SVM is widely used for addressing the CD problem [40] - [42]. In [40], semi-supervised SVM based on cluster-neighbourhood(CN) kernel is proposed for CD using SAR. The collected samples are divided into two neighbourhoods using k-means clustering. The composite-ratio kernal is modified using the statistical features based on neighbourhood to obtain the CN kernel. The proposed CN kernel can determine the information of unlabelled samples with few available labelled samples.

In [41], the CD in SAR images is obtained using a hybrid conditional random field (HCRF) model. The model is developed by including the log-ratio image statistics in the conditional random field model. Thus, the proposed technique can integrate texture features, statistics, spatial interaction of the log-ratio into the change detection process. The proposed algorithm is composed of three components namely the unary potential, pairwise potential and log-ratio image model. SVM using texture features is used to model the unary potential, the multi-level logical model is used to capture the pairwise potential and the generalized Gamma distribution is employed to model the statistics of the log-ratio image. In [42], the CN kernel mentioned above is replaced with the label-information composite kernel created based on the spatial contextual information. A anisotropic Gaussian kernel analyses the anisotropic textures of the bitemporal images. The kernel is iteratively updated with the latest output from the SVM until the changes map converges.

3 Conclusion

In this paper, we have summarized the major intelligent techniques deployed in change detection using remote sensing images. With the advent of latest computational technologies, intelligent algorithms that require more computational complexities are made possible for solving real time problems like change detection. In this paper, we have discussed the latest intelligent change detection algorithms that utilizes genetic algorithms, artificial neural networks, and support vector machine. These algorithms are suitable for different scenarios like supervised, semi-supervised and unsupervised change detection.

References:

[1] J. Im, J. Rhee, J.R. Jensen, M.E. Hodgson, An automated binary change detection model using a calibration approach, *Remote Sensing of Environment* 106, 2007, pp. 89–105.

[2] P. Coppin, I. Jonckheere, K. Nackaerts, B. Muys, and E. Lambin, Digital Change Detection Methods in Ecosystem Monitoring: A Review, *International Journal of Remote Sensing* 25, 2004, pp. 1565–1596.

[3] J. Im and J.R. Jensen, A Change Detection Model based on Neighborhood Correlation Image Analysis and Decision Tree Classification *Remote Sensing of Environment* 99, 2005, pp. 326–340.

[4] R.D. Macleod, and R.G. Congalon, A Quantitative Comparison of Changde Detection Algorithms for Monitoring Eelgrass from Remotely Sensed Data, *Photogrammetric Engineering & Remote Sensing* 64, 1998, pp. 207–216.

[5] J. Im, J.R. Jensen, M.E. Hodgson, Optimizing the binary discriminant function in change detection applications, *Remote Sensing of Environment* 112, 2008, pp. 2761–2776.

[6] J.R. Jensen, *Introductory Digital Image Processing: A Remote Sensing Perspective*, Prentice Hall, Toronto, 2005.

[7] D. Lu, E. Moran, S. Hetrick, and G. Li, Land–use and Land–Cover Change Detection, In: Q. Weng (Ed.), *Advances in Environmental Remote Sensing Sensors, Algorithms and Applications*, CRC Press Taylor & Francis Group, New York, 2011, pp. 273–290.

[8] N.A. Quarmby, and J.L. Cushnie, Monitoring Urban Land Cover Changes at the Urban Fringe from SPOT HRV Imagery in South–East England, *International Journal of Remote Sensing* 10, 1989, pp. 953–963.

[9] P.R. Coppin, and M.E. Bauer, Digital Change Detection in Forest Ecosystems with Remote Sensing Imagery, *Remote Sensing Reviews* 13, 1996, pp. 207-234.

[10] P.J. Howarth, G.M. Wickware, Procedures for Change Detection using Landsat Digital Data, *International Journal of Remote Sensing* 2, 1981, pp. 277–291.

[11] A.K. Ludeke, R.C. Maggio, and L.M. Reid, An Analysis of Anthropogenic Deforestation using Logistic Regression and GIS, *Journal of Environmental Management* 31, 1990, pp. 247–259.

[12] A. Singh, Change Detection in the Tropical Forest Environment of North eastern India using Landsat, *Remote Sensing and Tropical Land Management*, John Wiley, 1986, pp. 237–254.

[13] T.L. Sohl, Change analysis in the United Arab Emirates: an investigation of techniques, *Photogrammetric Engineering & Remote Sensing* 65, 1999, pp. 475–484.

[14] E.H. Wilson, and S.A. Sader, Detection of forest harvest type using multiple dates of Landsat TM imagery, *Remote Sensing of Environment* 80, 2002, pp. 385–396.

[15] R.D. Johnson, and E.S. Kasischke, Change vector analysis: a technique for the multispectral monitoring of land cover and condition, *International Journal of Remote Sensing* 19, 1998, pp. 411–426.

[16] J. Chen, P. Gong, C. He, R. Pu, and P. Shi, Land-use/land-cover change detection using improved change-vector analysis, *Photogrammetric Engineering & Remote Sensing* 69, 2003, pp. 369–379.

[17] K. Nackaerts, K. Vaesen, B. Muys, and P. Coppin, Comparative performance of a modified change vector analysis in forest change detection, *International Journal of Remote Sensing* 26, 2005, pp. 839–852.

[18] Y. Bayarjargal, A. Karnieli, M. Bayasgalan, S. Khudulmur, C. Gandush, and C.J. Tucker, A Comparative Study of NOAA–AVHRR Derived Drought Indices using Change Vector Analysis, *Remote Sensing of Environment* 105, 2006, pp. 9–22.

[19] J.A. Richards, Thematic mapping from multitemporal image data using the principal components transformation, *Remote Sensing of Environment* 16, 1984, pp. 35–46.

[20] J.S. Deng, K. Wang, Y.H. Deng, and G.J. Qi, PCA-based land-use change detection and analysis using multi-temporal and multi-sensor satellite data, *International Journal of Remote Sensing* 29, 2008, pp. 4823–838.

[21] S. Jin, and S.A. Sader, Comparison of time series tasseled cap wetness and the normalized difference moisture index in detecting forest disturbances, *Remote Sensing of Environment* 94, 2005, pp. 364–372.

[22] J. Rogan, J. Franklin, and D.A. Roberts, A comparison of methods for monitoring multitemporal vegetation change using Thematic Mapper imagery, *Remote Sensing of Environment* 80, 2002, pp. 143–156.

[23] D. Tomowski, M. Ehlers, and S. Klonus, Colour and Texture Based Change Detection for Urban Disaster Analysis, *Urban Remote Sensing Event(JURSE)*, 2011 Joint, pp. 329–332.

[24] M.A. Wulder, S.M. Ortlepp, J.C. White, N.C. Coops, and S.B. Coggins, Monitoring tree–level insect population dynamics with multi–scale and multi–source remote sensing, *Journal of Spatial Science* 53, 2008, pp. 49–61.

[25] M.-H. Tseng, S.-J. Chen, G.-H. Hwang, and M.-Y. Shen, A Genetic Algorithm rule based approach for Land–Cover Classification, *ISPRS Journal of Photogrammetry and Remote Sensing* 63, 2008, pp. 202–212.

[26] T. Celik, Change Detection in Satellite Images using a Genetic Algorithm Approach, *IEEE Geoscience and Remote Sensing Letters* 7, 2010, pp. 386–390.

[27] T. Celik, Image Change Detection using Gaussian Mixture Model and Genetic Algorithm, *Journal of Visual Communication and Image Representation* 21, 2010, pp. 965–974.

[28] F. Pacifici, F. D. Frate, C. Solimini, and W. J. Emery, An Innovative Neural-Net Method to Detect Temporal Changes in High-Resolution Optical Satellite Imagery, *IEEE Transactions on Geoscience and Remote Sensing* 45,2007, pp. 2940–2951.

[29] R. Eckhorn, H. J. Reitboeck, M. Arndt, and P. Dicke, Feature Linking via Synchronization among Distributed Assemblies: Simulations of Results from Cat Visual Cortex, *Neural Comput.*2, 1990, pp. 293–307.

[30] F. Pacifici, and F. D. Frate, Automatic Change Detection in Very-High Resolution Images with Pulse-Coupled Neural Networks, *IEEE Geoscience and Remote Sensing Letters* 7, 2010, pp. 58–62.

[31] C. Pratola, F. D. Frate, and G. Schiavon, Toward Fully Automatic Detection of Changes in Suburban Areas from VHR SAR Images by Combining Multiple Neural-Network Models, *IEEE Transactions on Geoscience and Remote Sensing* 51, 2013, pp. 2055–2066.

[32] Y. Zhong, W. Liu, J. Zhao, and L.Zhang, Change Detection based on Pulse-Coupled Neural Networks and the NMI Feature for High Spatial Resolution Remote Sensing Imagery, *IEEE Geoscience and Remote Sensing Letters* 12, 2015, pp. 537–541.

[33] A. Ghosh, B. N. Subudhi, and L. Bruzzone, Integration of Gibbs Markov Random Field and Hopfield-Type Neural Networks for Unsupervised Change Detection in Remotely Sensed Multi-temporal Images, *IEEE Transactions on Image Processing* 22, 2013, pp. 3087–3096

[34] Q. Wang, W. Shi, P. M. Atkinson, and Z. Li, Land Cover Change Detection at Subpixel Resolution with a Hopfield Neural Network, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 8, 2015, pp. 1339–1352.

[35] M. Roy, S. Ghosh, and A. Ghosh, A Neural Approach under Active Learning Mode for Change Detection in Remotely Sensed Images, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 7, 2014, pp. 1200–1206.

[36] V.-E. Neagoe, R.-M. Stoica, A.-I. Ciurea, L. Bruzzone, and F. Bovolo, Concurrent Self-Organizing Maps for Supervised/Unsupervised Change Detection in Remote Sensing Images, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 7, 2014, pp. 3525-3533.

[37] G. L. Grinblat, L. C. Uzal, and P. M. Granitto, Abrupt Change Detection with One-class Time-adaptive Support Vector Machines, *Expert Systems with Applications* 40, 2013, pp. 7242–7249.

[38] H. Hichri, Y. Bazi, N. Alajlan, and S. Malek, Interactive Segmentation for Change Detection in Multispectral Remote -Sensing Images, *IEEE Geoscience and Remote Sensing Letters* 10, 2013, pp. 298–302.

[39] F. D. Morsier, D. Tuia, M. Boregeaud, V. Gass, J.-P. Thiran, Semi-supervised Novelty Detection using SVM Entire Solution, *IEEE Geoscience and Remote Sensing* 51, 2013, pp. 1939–1950.

[40] L. Jia, M. Li, Y. Wu, P. Zhang, H. Chen, and L. An, Semisupervised SAR Image Change Detection using a Cluster-Neighborhood Kernel, *IEEE Geoscience and Remote Sensing Letters* 11, 2014, pp. 1443–1447.

[41] H. Li, M. Li, P. Zhang, W. Song, L. An, and Y. Wu, SAR Image Change Detection based on Hybrid Conditional Random Field, *IEEE Geoscience and Remote Sensing Letters* 12, 2015, pp. 910-914.

[42] L. Jia, M. Li, Y. Wu, P. Zhang, G. Liu, H. Chen, and L. An, Change Detection based on Iterative Label-Information Composite Kernel Supervised by Anisotrophic Texture, *IEEE Transaction on Geoscience and Remote Sensing* 53, 2015, pp. 3960–3973.