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A Deep Learning Kernel K-Means Method for Change Detection in Satellite Image

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Abstract: ***Kernel methods are widely used for feature extraction or classification problems because of its advantage due to their good optimization and nonlinear expressive power. Meanwhile, Deep learning technology and related algorithms are the latest trend in vision, speech, audio, and image processing. In this project, a deep-learning based Kernal K-mean method is used to detect changes in bi-temporal satellite images. Nonlinear clustering with the help of deep learning is utilized to partition a pseudo-training set of pixels representing both changed and unchanged areas. Once the optimal clustering is obtained, the learned representatives are used to partition all the pixels of the multitemporal image into the two classes. To optimize the parameters of the kernels, an unsupervised cost function is used. By exploiting the expressiveness of nonlinear kernels with the learning ability of deep networks this project was able to attain an accuracy of around 96% in average.***

Keywords: Change Detection, Kernel K-means, Kernel Parameters, Deep learning, Remote Sensing

1. Introduction

The detection of change over time is a very important aspect of the analysis of digital satellite imagery. The basic logic under change detection is to find the places in the same geographical region and to identify the areas which are not similar in two or more satellite images. There has been a growing interest in the development of change detection methods for the analysis of multitemporal remote sensing imagery during past few decades. This interest stems from the wide range of applications in which change detection methods can be used, like environmental monitoring, agricultural surveys, urban studies and forest monitoring. Changes in land cover and land use in urban areas are dynamic processes, such that transitions occur at varying rates and in different locations within the constraints of, or in response to, social, economic and environmental factors. For many public and private institutions, the knowledge of the dynamics of either natural resources or man-made structures is a valuable source of information in decision making. Regional planners and decision makers engaged in a map updating operation for a changing metropolitan or county area require up-to-date information on the nature and impact of urban expansion or transition to more intensive usage. Map updating is an intensive task requiring timely and accurate information from multiple sources of data especially for detailed mapping of complex urban scenes. The primary method of updating land cover and land use maps has been, and in some case still is, through human interpretation. In this process, the full range of human interpretation capabilities can be employed, including the interpreters own knowledge of the area. However, it is time consuming, subject to errors of omission and the abilities of the interpreter vary greatly. Also, there are limits to the ability of humans to absorb and process large volumes of information.

The satellite images of different spatial resolutions are now being made available very frequently, and the quality of the data is constantly improving both in spectral and spatial dimensions. Based on current collection rates, satellites operated by DigitalGlobe, GeoEye, and Astrium can capture more than 3 million km^2 per day of imagery with a resolution of 1 m or less. At present, IKONOS, QuickBird, WorldView-1, GeoEye-1, WorldView-2, and Pliades 1A capture more than 1.2 billion km^2 per year more than eight times the surface area of all the land on earth. In particular, recent advances in remote sensing technology suggest that satellite based earth observation has great potential for providing and updating spatial information in a timely and cost effective manner. Moreover, the availability of remote sensing data is guaranteed for decades to come, making earth observation a powerful long term change detection instrument. This kind of change analysis, however, has the following problems: a huge volume of data must be processed for detecting only few change areas; many types of satellite sensors are available, but their spectral bands are not always identical in center wavelength and band width; noise due to differences in light conditions, atmospheric conditions, sensor calibration and ground moisture at the two acquisition dates considered causes apparent changes; each image has own geometrical distortion and problems of alignment of multitemporal images;

Concerning this last issue, two images should be registered so that pixels with the same coordinates in the images may be associated with the same area on the ground. This is a very critical step in very high resolution satellite and airborne imagery, especially when the angle of acquisition varies greatly, rendering change detection results unreliable. Recent change detection techniques use either the supervised or the unsupervised paradigms. The first require ground truth samples to train a classifier [1]. The change detection map produced by supervised methods shows every ground cover transitions occurred [2]. The unsupervised approach relies on automatic techniques including thresholding or clustering on a combination of the bi-temporal images. They usually provide binary maps indicating only whether a change has occurred or not [3]. Although the supervised approach exhibits some advantages over the unsupervised one as: the capability to explicitly recognize the kinds of land cover or land use transitions that have occurred; the robustness to the different atmospheric and light conditions at the two acquisition times; the ability to process multisensor and/or multisource images; But in supervised learning techniques the generation of an appropriate training set is usually a difficult and expensive task. This project follows the unsupervised method but has made the best effort to include the advantage of supervised method by the help of deep learning mechanism over a pseudo training set.

Most of the automatic change detection methods uses linear transformation or rely on a linear combination of the multitemporal data which is not an ideal method for images corrupted by either noise or non-normalizable radiometric differences. To reduce these effects, an unsupervised change detection based on nonlinear transformations is used. Recently, kernel methods have proven their effectiveness in many remote sensing applications [4], and in particular for classification tasks. In bi-temporal change detection, methods inferring nonlinear decision boundaries discriminating changes have been capable to improve the accuracy, in particular by reducing the false alarm rate [5]. The main idea of kernel methods is that nonlinear decision rules can be achieved by running a linear algorithm in a higher dimensional feature space, the reproducing kernel Hilbert space (RKHS), where the solution is more likely to be linear. The mapping to that space is implicitly defined by kernel functions replacing dot products in the original formulation, only needing input samples in their original space [6]. The Support Vector Domain Description classifier is an example [7] where applied with an unsupervised initialization to model the change class in a higher dimensional feature space, and benefits of adopting a nonlinear approach are clearly pointed out.

Moving on to the Deep learning method, which is currently the most used method in machine learning. We can see a recent drift to learn high-level features in a completely unsupervised fashion given large enough data sets using deep learning architectures. The success of high-level features in deep learning architectures has been demonstrated in audio and vision, working especially well at scale with sparse auto encoders. While previous computer vision techniques focused on labelled training data sets, deep learning methodology features have shown potential in building classspecifity in an unsupervised setting. The deep learning method is utilized in this project to iteratively determine multiple layers of centroids using clustering, where comparisons are made based on a similarity function. The similarity function being used is the radial basis function (RBF) kernel and the clustering algorithm as is k-means.

The rest of the paper is organized as follows. Section 2 explains the related-works in the field of change detection. Section 3 describes the framework of the method used. Section 4 contains more about the dataset which has been used and other details regarding the execution of this system. And finally, section 5 summarizes the conclusion of this paper.

2. Literature Survey

In the past years a variety of change detection techniques have been developed and efforts have been made to produce comprehensive summary and review on these methods. As one of the pioneer works, [9] classified change detection methods into two types, namely, classification comparison and direct comparison. [10] proposed a classification of three categories, including pixel-based, feature-based and object-based change detection. According to image registration and data sources, [11] classified change detection methods into two types among seven methods. More recent reviews were made by [12] and [13]. [12] generalized the change detection methods into seven types, namely, arithmetic operation, transformation, classification comparison, advanced models, GIS integration, visual analysis and some other methods. They also discussed pre-processing of change detection, choice of the threshold value and accuracy assessment in detail. [13] summarized change detection methods in general terms and propose a classification of direct difference, statistical hypothesis testing, predictive models, shading model, and background modelling and so on. He emphasized the classification of change detection methods but did not solely focus on those in remote sensing.

Obviously, different classification benchmark results in different classification methods. Based on the former classification methods, this article classifies change detection from its essence. Change detection approaches can be characterized into two broad groups, namely, bi-temporal change detection and temporal trajectory analysis. The former measures changes based on a two-epoch timescale, i.e. the comparison between two dates. The latter analyses the changes based on a continuous timescale, i.e. the focus of the analysis is not only on what has changed between dates, but also on the progress of the change over the period. At present, most change detection methods belong to bi-temporal change detection approach. Almost all classifications for change detection algorithms are based on bi-temporal change detection with little attention on temporal trajectory analysis. For bi-temporal change detection, detection algorithms can be attributed to one of the three approaches, namely, directly comparing different data sources (direct comparison method), comparing extracted information (post-analysis comparison method) and integrating all data sources into a uniform model (uniform modelling method). The detection elements of direct comparison method include pixel, basic image features and transformed features. The texture features and edge features are always taken as basic image features. For multispectral remotely-sensed images, transformation is often an important procedure. The detection elements of post-analysis comparison method mainly include objects extracted from images. Based on two most widely-used methods for object extraction, namely, image classification and feature extraction, comparison between objects after classification and feature extraction are typical for the post-analysis comparison method. According to modelling strategies, the uniform modelling method can be categorised as modelling for detection methods and modelling for detection process.

Comparing with the bi-temporal change detection, the temporal trajectory analysis emphasizes more on discovering the trend of change by constructing the curves or profiles of multitemporal data. From the viewpoint of processing methods, temporal trajectory analysis can be decomposed into bi-temporal change detection and then relative post-processing is implemented after the bi-temporal change detection. On the other hand, the so-called long time-series analysis method can be employed for temporal trajectory analysis. Another important application of temporal trajectory analysis is real-time change detection such as video image sequences analysis. Considering above the methods of change detection is classified into seven categories namely, direct comparison, classification, object-oriented method, model method, time-series analysis, visual analysis and hybrid method.

2.1 Object-Oriented Method

Object-oriented method is also called object-based comparison method. The basic strategy is to extract objects from multitemporal images using image segmentation and other feature extraction algorithms and distinguish the changes between corresponding objects. Typically this method is applied to applications such as change detection of man-made objects on high-resolution images, urban data updating, and military reconnaissance. This method compares the extracted objects directly, so it is not sensitive to data noises and geometric distortion. Two critical issues need to be addressed, namely, the methods to compare objects and to identify the changes between objects. [14] proposed the buffer detection algorithm for the object comparison. Ancillary information, e.g. digital maps from GIS, can be used in the object-oriented method. Works with the focus on the integration of GIS for change detection includes. The powerful GIS functions provide efficient tools for multi-source data processing and change detection analysis, so that one can expect more works taking this approach as a generic trend in change detection [12].

The critical challenge of the object-oriented method is the object detection and segmentation. Because feature and object extraction from images is often difficult and prone to error, in practice this method is mostly applied to image-to-map and rarely used for image-to-image change detection. To overcome the difficulty of object extraction, a knowledge-based system is often employed. Another approach is to improve the method of image segmentation techniques, so that more efficient and accurate object extraction can be achieved.

2.2 Model Method

The model method is a more application-oriented change detection method. Different from general change detection methods such as direct comparison and classification, this method can perceive the essential rules of application issues and take change as the core elements to construct mathematical models. The basic strategy is to adopt uniform models that integrate all procedures and methods. Generally this method can be grouped into two kinds, namely, models based on processing approaches (approach-based models) and models based on the course of processing (process-based models). The advantage of the model method is that it considers all factors for change detection and can obtain best results. And it is simple to apply and can be used for H-type change detection problem. However, the greatest challenge in this approach is how to construct suitable models. Even existing suitable models, the application problem is so complex that a lot of parameters is difficult to be obtained. In general, the approach-based models are to model the change contents according to certain postulate conditions, which often closely simulate the actual situations for given applications. The process-based models are to model the process of change detection. All procedures of the change detection are integrated into a uniform framework and are considered as a whole. It should be pointed that it is possible and necessary to combine the approach-based with process-based model methods. However, at present few works has been reported on this approach.

2.3 Time Series Analysis

Time series analysis is mainly used for temporal trajectory analysis. In contrast to bi-temporal change detection, the temporal trajectory analysis is mostly based on low spatial resolution images such as AVHRR and MODIS, which have a high temporal resolution. The trade-off of using these images, however, is the lost of spatial details that makes auto classification very difficult, so that the temporal trajectory analysis is commonly restricted in, for example, vegetation dynamics in large areas, or change trajectories of individual land cover classes. Quantitative parameters such as normalized difference vegetation index (NDVI) or area of given land cover class are often used as the dependent variables for the establishment of change trajectories.

Two approaches are common for time series analysis, namely, long-time serial analysis and real-time image sequences analysis. For non-real-time long-time serial analysis change detection, dynamic Bayesian network seems a good tool. The method uses the time-series dynamic data to produce reliable probabilistic reasoning, which can make both static and dynamic analysis on the change detection of remote sensing images. Although traditional video change detection is based on general video monitoring that is widely applied in bank, traffic control and manufacture, techniques of videography has now been applied to aero-survey and space-borne remote sensing. The real-time image sequences analysis can therefore be used for temporal trajectory analysis. Video monitoring sequence images have high sampling rate in time with large data volume. Moreover, the difference between two sequence images can be quite large, and sometimes the image quality can be quite poor. To efficiently apply video monitoring sequence images to change detection, new challenges are faced to adopt techniques applied in video monitoring fields such as optic flow techniques, Kalman filtering and tracking and background modelling.

2.4 Hybrid Methods

A hybrid method refers to a comprehensive use of two or more methods mentioned above for change detection processing. There exist two typical hybrid kinds: one is to use different detection methods in different detection phases or procedures (procedure-based hybrid analysis) and another is to use different change detection methods respectively and then analyze their results comprehensively (result-based hybrid analysis). The advantage of this method is to make full use of virtues of many algorithms and obtain better change detection results than single method. However, for specific application case how to select hybrid methods is difficult and it is confused to harmonize detection results conflicts caused by different methods. These problems result in complex algorithm and low efficiency.

For the procedure-based hybrid analysis, the combination of classification and algebraic method is popular. The combination of Classification and Object-oriented method is more and more. Previous researches have shown that a combination of two change detection techniques, such as image differencing and PCA, NDVI and PCA, or PCA and CVA, could improve the change detection results. For the result-based hybrid analysis, decision-making fusion strategies such as voting and fuzzy logic etc. are widely applied. This method is very flexible but right of each method is difficult to decide and conflict results are often at risk.

Aiming at different applications, a large number of change detection applications have been implemented and different change detection techniques have been tested. However, last conclusion is no single method is suitable and universal for all application cases even if for specific application choosing best method is unknown influenced by different data sources, image quality, characteristics of the study area, an analysts knowledge of the change detection methods and the skill in handling remote sensing data. Because of the difficulty in identifying a suitable method, in practice different change detection techniques are often tested and compared to provide a best result based on the accuracy assessment or qualitative assessment [12].

3. Proposed Method

The basic diagram of the change detection algorithm used for this project is as shown in figure 1. The success and the stability of the change detection system rely on the specific combination of the central blocks of figure 1. The initialization provides a balanced rough training set on which kernel parameters are generated by the help of kernel k-means algorithm. Once the correct parameters are selected, the partitioning algorithm returns the representatives of the clusters, corresponding to centroids. Finally, these samples are used in a kernel minimum distance classification that generates the change map. Throughout the process, the design of the kernel function determines the representation of the change detection problem, and the two different assumptions of the difference image are detailed in the following.

3.1 Kernel Principals

Generally, the kernel functions are applied to overcome the problems of explicit mapping functions computation. In the feature space, using a kernel means that the value of dot product is directly evaluated by using the value of the samples in input space. Transformed samples are more likely linearly separable in the resulting feature space. The higher dimensional space is induced by a mapping function ϕ, which $\phi(x)$ is mapped sample in higher space H. The kernel values show the similarity between samples. Some popular kernels are: linear, polynomial and radial basis function (RBF).

For change detection purpose, the kernel function can be applied onto the change difference images. Then, in addition to mentioned kernels, Difference Kernel can be obtained by subtracted maps in the higher dimension space. In higher dimension space, the differences of same sample in two subsequent images are defined as:

$$\emptyset(x_i) = \emptyset(x_1^{(t1)}) - \emptyset(x_i^{(t1)}) = \emptyset_1(x_i^{(1)}) - \emptyset_2(x_i^{(2)}), \emptyset_2(x_2^{(2)}) - \emptyset_3(x_i^{(3)}), \dots, \emptyset_{T-1}(x_i^{(T-1)}) - \emptyset_T(x_i^{(T)}) \quad \text{Eqn 1}$$

And by replacing the corresponding dot product with a proper kernel function K, the kernel function equations can be easily computed as equation 2.

$$K(x_i, x_j) = \sum_{t=1}^{T-1} K_t(x_i^t, x_i^t) + K_t(x_i^{t+1}, x_j^{t+1}) - K_t(x_i^t, x_j^{t+1}) - K_t(x_i^{t+1}, x_j^t) \quad \text{Eqn 2}$$

For simplify the computation and separating single- and cross time components we can reach equation 3 as:

$$K\,D(x, x) = k_{t2}(x_i^{t2}, x_j^{t2}) + k_{t1}(x_i^{t1}, x_j^{t1}) - k_{t2t1}(x_i^{t2}, x_j^{t1}) - k_{t1t2}(x_i^{t1}, x_j^{t2}) \quad \text{Eqn 3}$$

where t1 and t2 show first and last time, k_{t2t1} and k_{t1t2} are cross-time kernel functions. Then the resulting difference kernel is composed of four kernels accounting for single time and cross-time similarity information between images.

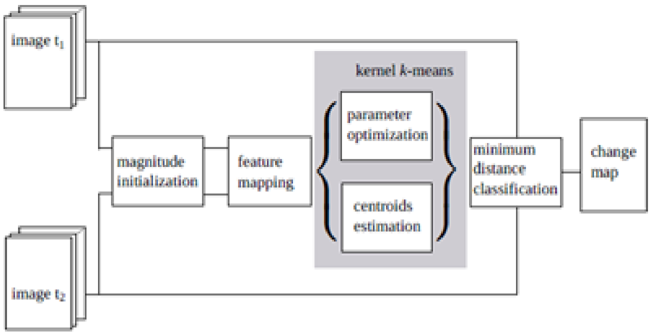

Figure 1: The change detection framework

3.2 Kernel-based K-means for Change Detection

The kernel K-means algorithm is a kernelized version of the well-known K-means clustering technique. In other words, K-means is particularly performed to solve the linear problems where the input space is organized in spherical or radial clusters. The kernel version of c-means instead of working in real physical input space X, works in a higher dimensional feature space H. By this dimensionally transform, the clusters which are non-spherical in input space, are mapped into a spherical one, and consequently can be clustered easily and correctly.

The classical K-means approach is useful to aim a natural partitioning of the input pattern X into K groups. The algorithm works by minimizing distance of elements x_i from clusters gravity center m_c and assigns a cluster membership c to the elements. The algorithm uses an iterative refinement technique. When the pattern assigned to the corresponding clusters, the mean vector m_c is updated by averaging the coordinates of elements of the cluster. Then it provides a new gravity center. The process is iterated until the centers became consistence and algorithm reaches to a minimum of $d^2(x_i;m_c)$. By considering the mapping function ϕ in kernel space, the similarity measure of K-means becomes as equation 4:

$$d^2(\emptyset(x_i, m_c) = \|\emptyset(x_i) - m_c\|^2 , \quad m_c = \frac{1}{N_c}\sum_{j\epsilon\, C_c} \emptyset(x_i)$$

Eqn 4

Then kernel K-means method first groups similar points in higher dimension and then separates them. By expansion of the equation 5 and replacing dot product by a proper kernel function, the kernel K-means formulation is obtained as:

$$\begin{aligned} d^2(\emptyset(x_i, m_c) = {} & \langle \emptyset(x_i), \emptyset(x_i) \rangle \\ & + \frac{1}{|N_c|^2} \sum_{j,m\in C_c} \langle \emptyset(x_j), \emptyset(x_m) \rangle \\ & - \frac{2}{|N_c|} \sum_{j,i\in C_c} \langle \emptyset(x_i), \emptyset(x_j) \rangle \\ & = K(x_i, x_i) + \frac{1}{|N_c|^2} \sum_{j,m\in C_c} K(x_i, x_m) \\ & - \frac{2}{|N_c|} \sum_{j,i\in C_c} K(x_i, x_m) \end{aligned}$$

Eqn 5

The main considerations of proposed kernel K-means Change Detection with deep learning algorithm are initialization and optimization of the cost function. It is obvious that one of the limitations of iterative techniques is the initialization issue. Poor initialization can converge in the local minima, and then the algorithm fails. In order to reach a stable and correct grouping, one possible solution is to initialize the algorithm with a training set which are based on the prior analysis.

3.3 Kernel parameter Estimation

RBF kernel related to Gaussian distribution and for this reason have adaptable results. On the other hand, the changes associated to differences between two images and difference kernel contains admissible information about changes. We used RBF kernels for the kernels generate difference kernel equation 2. Then an optimization problem which is the distance between samples and their cluster center, must be solved.

To obtain the difference kernels parameters, two single- and cross-time parameters should be estimated. The Rayleigh coefficient, in term of cluster-related distance in feature space, is presented in equation 6. This coefficient is calculated from the covariance or normalized scatter matrices of data.

$$\sum_i = \frac{\alpha}{M}\sqrt{\sum x_m x_m^T}$$

Eqn 6

$$\{\sigma^{single}, \sigma^{cross}\} = argmin\left\{ \frac{\frac{i}{m_c}\sum_{i\in C} d^2(\emptyset^{diff}(x_i), m_c}{\sum_{c\notin q} d^2(m_c, m_q)} \right.$$

Eqn 7

It's worth noting that in order to minimize this expression; the kernel c-means technique is wrapped to test different sets of parameters to cluster the same training samples. For this purpose, we used linear search method to obtain the best parameters. After initialization and estimation of optimum kernel parameters, we can apply optimal kernel K-means algorithm on our data sets. Figure 2 presents the flowchart of main step for our approach which is used in this research.

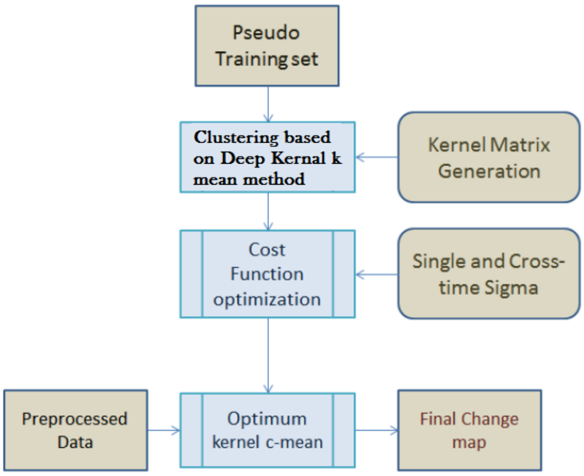

Figure 2: Overview for the main step of the proposed approach

4. Experimental Results

4.1. Datasets

Change happened in Dubai's Islands between 2000 and 2012 figure 4: These images are provided by Earth Resources Observation and Science (EROS) as part of U.S. Geological Survey (USGS). Each image is of size 1600 X 1600 pixels. The images were accured on 12 November 2000 and 27 November 2012. The city of Dubai is situated along the Persian Gulf in the United Arab Emirates. These Landsat 7 images show the area in 2000 and 2012, and give a remarkable view of the changes that have taken place, both on land and in the water. In 2001, work began to create artificial archipelagos along the shoreline of Dubai. The Palm Jebel Ali and smaller Palm Jumeirah are two Palm Islands that can be seen in the 2012 imagery. North from the Palm Islands is a group of smaller islands, created in the rough shape of a world map. Known as The World, this small area has created an additional 144 miles of shoreline.

Figure 3: Dubai-Islands- 2000 and 2012

4.2 Experimental Setup

In order to test the sensitivity to different sizes of the pseudo training set, many situations have been considered. After experimental evaluation, results only on a single set size are reported. A plateau effect in accuracy is observed for growing set sizes. The smallest set reaching this upper limit is considered for analyses. The sample is taken in such a way that the number of pixels is large enough to cover data variability but small enough to allow fast computations, regulated by the size of the kernel matrix. To have robust statistical estimates, 10 different realizations of the pseudo training set are considered followed by as many independent runs of the algorithm. Average and standard deviation of accuracies are reported for evaluation purposes.

The proposed approaches are tested versus the linear counterpart of the considered mappings (both resulting in standard k-means on the difference image) providing a baseline accuracy, and against two automatic change detection methods: the standard CVA [15] and the approach presented in [16]. The former puts a threshold in the magnitude distribution. The latter relies on a patch-based PCA transformation of the difference of intensities images and it clusters changes using binary standard k means. See [16] for details. Note that, for fair comparison, the free parameters of this method are chosen by minimizing the classification error on a labelled validation set. Moreover, since this approach is designed for intensity images (thus unidimensional), an investigation has been carried out in order to select the best input: among single band differences and the magnitude, the latter resulted in higher accuracies and has thus been retained.

For all the nonlinear cases, Gaussian RBF kernels are adopted. This choice is motivated by their interpretability, recast as a local distance (similarity) and by good performances that make this kernel function the most used in many fields. RBF bandwidths are optimized in the interval $\sigma \in [0:1; 10]$.

4.3 Result

Change happened in Dubai's islands: The changes detected in Dubai City after the successful execution of this system is shown in figure 4. The training set are composed by 1000 random pixels out of which 500 pixels each represented the change region and the no change distribution.

Figure 4: Changes detected in Dubai, UAE

By using nonlinear clustering and in particular by adopting the better representation provided by the Ker.Diff.RBF, small deviations to the no change class can be clustered as unchanged pixels, making the detection of large deviations more accurate. In this case, both the CVA and the method of [16] suffered from the non-normalizable differences that appear on the island, that make the standard difference image and the magnitude measure suffer from ambiguity in the representation. Therefore, methods relying solely on the magnitude are supposed to provide worse results than other approaches, as the latter fully exploit the information content of the data. By using deep learning in ker.diff.RBF method the performance was increased considerably. The steps in the execution were simplified by the layered approach.

Table II: Quantitative comparison of the results

Method/Accuracy	False Alarm	Misdetection	kappa	OA
K mean clustering	15.22	5.98	0.7633	88.45
Diff.Lin.	8.34	4.52	0.8741	93.22
Diff.RBF.	7.58	3.80	0.8824	94.52
Ker. Diff.RBF.	5.87	1.64	0.9250	96.13

In the table I and II, the false alarm rate and misdetection rate consequently show the detected changes which are not actual changes and the un-changed pixels which the algorithm considers them as changed pixels. These elements of confusion matrices and also total accuracy and kappa coefficient show improvement of the kernel-based algorithm in accurate detection of changes.

5. Conclusion

A kernel-based deep learning approach to unsupervised change detection has been presented. By exploiting a proper initialization, kernel k-means clustering is used to learn the representatives for the two classes of interest. Issues related to the estimation of the kernel parameters have been tackled by optimizing a geometrical criterion favoring dense groups and distant cluster centers showing a minimum when a convenient representation for clustering is found.

When estimating the similarity of the difference image in feature spaces performances are strongly improved with respect to approaches based on the difference image in the input space. This indicates that a better representation can be obtained by considering single and cross-time relationships among multitemporal pixels. The consequent strong decrease in false alarm rate and slight improvement in detection makes this approach the most accurate. Experimental comparisons showed that relying on the magnitude only the correct discrimination of the changes becomes a difficult task. This is related to the ambiguity of the measure, as well as to its unidimensional representation hiding useful information. On the contrary, by detecting changes in higher dimensional feature spaces, the multitemporal information is unfolded into clusters that are easily detectable. Such approach also reduces the preprocessing corrections, since the single time information is considered separately and regularized by the cross-similarity of the scenes.

Further research is required to investigate the inclusion of contextual and multiscale approaches, as well as multisource information. They can be included in the process by combining specific kernel functions. Type of changes and their direction (e.g. the spectral change vector angles) could also be considered to extend the proposed framework to multiclass change detection.

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