

AUTOMATIC FEATURE-LEVEL CHANGE DETECTION (FLCD) FOR ROAD NETWORKS

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ABSTRACT:

Automatic change detection and data updating is a very important issue for keeping the temporal accuracy and currency of spatial data sets. Road networks are one of the most important parts of geographic database. Firstly two kinds of new algorithms for detecting feature changes that is buffer detection (BD) algorithm and double-buffer detection (DBD) algorithm are illustrated in detail. The corresponding buffer detection distance formulas are deduced theoretically. Then the change detection techniques between new map and old map are proposed. For change detection between new/old maps with same map scale the so-called buffer detection algorithm is employed and for new/old maps with different map scale a change detection expert system integrated with GIS environment is presented. Corresponding experiments results for detection algorithms are given in the paper. The main difficulty of automatic change detection for road network between new image and old map lies in two aspects: one is the tracing of unchanged road and another is the extraction of new road. For detection and tracing of unchanged old road, automatic detecting algorithms based on GIS information are proposed. For the extraction of new road, some new ideas and strategies including hybrid feature grouping techniques, automatic road recognition based on knowledge base, knowledge inference for road recognition, road re-grouping etc. are discussed. At last conclusions and future work are given.

1. INTRODUCTION

With the fast development of city and expansion of urban, road networks are prone to change and therefore they become main parts to be detected and updated. Road networks are one of the most important geo-spatial objects. Updating road network is a key work for updating geo-spatial information especially in developing countries. Automatic change detection of road networks is the first and crucial step. However, for a long time, manual operation based on visual interpretation is the primary method for updating road and other geographic data. Although extraction of road networks and pixel-level change detection (PLCD) are not fresh topics, systematic research for automatic feature-level change detection (FLCD) and object-level change detection (OLCD) for road networks is little reported in the past literatures (Peled,1998; Macleod,et.al, 1999; Sui,2002).

For PLCD, pre-classification and post-classification are most important and widely applied methods. Aiming at the shortcomings of these methods, some researchers present the integration of many change detection methods. They includes Markov Random Field (Bruzzone,2000), neural network (Dai,1997), mathematic morphology(Maupin,1997), fuzzy logic (Dreshler,1993), based on knowledge (Wang,1993), based on GIS (Peled,1998) and so on. To solve a series of problems including accuracy, speed and automatic processing caused by traditional method that is first registration then change detection, Li (2002) presented a new idea and algorithm for registration simultaneous with change detection. As to application of change detection, some software companies including ERDAS have integrated some PLCD algorithms into basic function modules. However, manual processing is still the major method in these commercial software. Compare to PLCD, although relative research for FLCD and OLCDC has been reported in the literatures, their contents mainly focus on extracting objects from image and a little care is given for change detection algorithms (Chalifoux,1998; Fan,1999; Darvishzadeh,2000). On the other hand, the research for change detection between old

map and new map is very limited although it is more useful in real application.

Indeed, although the research history for change detection is longer than 40 years mature and practical automatic change detection theory framework and technical system are not realized yet. For current change detection theory, stable theory basis and suitable evaluation standard and algorithms are lack. For current change detection algorithms, relative information between new/old images is not fully utilized for PLCD and the discussion and research for FLCD is not enough. Aiming at these this paper focuses on the research for automatic FLCD. The contents are emphasized on two aspects: one is change detection for road networks between new map and old maps; another is change detection for road networks between new image and old map.

The rest of the paper is organized as the follows. In the next section, the algorithms for detecting feature changes including buffer detection algorithm and double buffer detection algorithm are presented and corresponding buffer detection distances are deduced theoretically. In section 3 some new ideas and algorithms for automatic change detection between new and old map are given. And in section 4 corresponding strategies and ideas for automatic change detection for road networks between new image and old map are proposed. The last section summarizes and concludes with a discussion of future work.

2. THE ALGORITHMS FOR DETECTING FEATURE CHANGES

2.1 Buffer detection algorithm

2.1.1 The principle of buffer detection algorithm

For feature level change detection (FLCD), how to compare the difference of two features is a key problem. Feature comparison problem is often considered as shape matching. And in shape

matching research the similarity measurement is often a difficult and puzzled problem. How to define the measurement parameters and procedures is the most important step. At present there are all kinds of measurement parameters for feature comparison, but they are not universal and very sensitive to the shape of features. Aiming at this, the authors propose a new algorithm. The basic principle of new algorithm is making a buffer for a feature and computing the similarity through the length of another feature inside the buffer (Sui, 2002). This is shown as Fig.1. Suppose we make a buffer for old feature F1 with a given buffer distance BufferDis, and we use the new feature F2 to compare the difference of two features. Obviously when the ratio of the feature F2 fall into the buffer created by the feature F1 is smaller, the feature F1 is apt to change. Vice versa. So the detection formula for line feature can be defined as the following:

$$P_{Line} = \frac{L_{outer}}{L_{Total}} \quad (1)$$

In the above formula, P_{Line} represents change ratio for line feature, L_{outer} represents the length outside the buffer, L_{Total} represents the whole length of feature F2.

Similarly, for polygon features the formula is defined as the following:

$$P_{Surface} = \frac{A_{outer}}{A_{Total}} \quad (2)$$

In the above formula, $P_{Surface}$ represents change ratio for surface feature, A_{outer} represents the area outside the buffer, A_{Total} represents the whole area of feature F2.

It can be seen that the changed degree can be controlled by adjusting parameter P_{Line} or $P_{Surface}$. Generally they can be taken as 0.85. Obviously, this algorithm is not sensitive to shape of features and it is universal for all the features comparison.

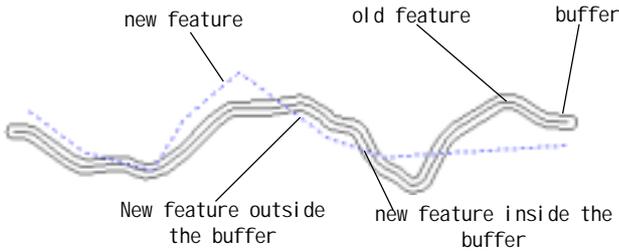


Fig 2 The principle of buffer detection algorithm. (The black middle line is old line feature and the blue dotted line is new line feature.)

2.1.2 The formula for buffer detection distance

One key problem for buffer detection is to how to compute the buffer distance. If ignoring the tiny errors (like data conversion, computing etc.), for change detection between new image and old map, the buffer distance is mainly dependent on the accuracy of origin old map and the registration between new image and old map. Suppose the RMSE of the detecting feature in old map is σ_{map} , the RMSE of registration between old map and new image is $\sigma_{registration}$, then the formula for buffer distance can be deduced as the following:

$$BufferDis_{image-map} = \sqrt{\sigma_{registration}^2 + \sigma_{map}^2} \quad (3)$$

Similarly, for the buffer distance between new map and old map with same map scale, the distance is mainly dependent on the accuracy of origin old map and new map. Suppose the RMSE of the detecting feature in old map is $\sigma_{old-map}$, the RMSE of the detecting feature in new map is $\sigma_{new-map}$, then the formula for buffer distance can be deduced as the following:

$$BufferDis_{map-map} = \sqrt{\sigma_{old-map}^2 + \sigma_{new-map}^2} \quad (4)$$

2.2 Double-buffer detection algorithm

2.2.1 The principle of double-buffer detection algorithm

For feature level change detection (FLCD) based on old map with small scale and new map with large scale, it is necessary to consider the effects of cartographic generalization. As everyone knows, the shape simplification and generalization are implemented by many generalization factors like merging, splitting, exaggerate and so on. The basic principles for shape generalization are as the following (Wang, 1992):

- Keeping the shape similarity of main features
- Keeping the accuracy of key feature points
- Keeping the contrast between different curve segments

This means that there exists quantitative relationship between two features before and after generalization. However, the condition satisfied with this kind of quantitative relationship should be that the difference between two map scales is small. Because of generalization the buffer detection algorithm cannot be suitable for detecting changes between new and old maps. However based on this kind of quantitative relationship, we can define two buffers: one buffer is created by old feature and employed for detecting the change of the new feature comparing to the old feature; and another buffer is created by new feature and employed for detecting the change of the old feature comparing to the new feature. The first buffer can be called front-buffer, shown as Fig.2(b). The second buffer can be called back-buffer, shown as Fig.2(c). The function of back-buffer is to detect the changes caused by generalization and the function of front-buffer is to detect the real objects changes. It can be seen that the whole changes can be detected completely through these two buffers. And based on two buffers this algorithm can be called the double-buffer algorithm. The detecting algorithm for the back-buffer and the front-buffer is same with the buffer detection algorithm. So the detection formula for line features can be defined as the following:

$$P_{Line-after} = \frac{L_{outer-after}}{L_{Total-after}} \quad (5)$$

$$P_{Line-before} = \frac{L_{outer-before}}{L_{Total-before}} \quad (6)$$

$$P_{Line} = P_{Line-after} * W_{after} + P_{Line-before} * W_{before} \quad (7)$$

In formula (5),(6),(7), P_{Line} is change ratio of whole line feature, $P_{Line-after}$ is the change ratio of line feature in back-buffer, $P_{Line-before}$ is the change ratio of line feature in front-

buffer, W_{after} is right factor of back-buffer, W_{before} is the right factor of front-buffer, $L_{outer-after}$ is the length of old line feature outside the back-buffer, $L_{Total-after}$ is the whole length of old line feature, $L_{outer-before}$ is the length of new line feature outside the front-back, $L_{Total-after}$ is the whole length of new line feature. Generally the right factor of front-buffer and back-buffer can be defined as 0.4 and 0.6 separately.

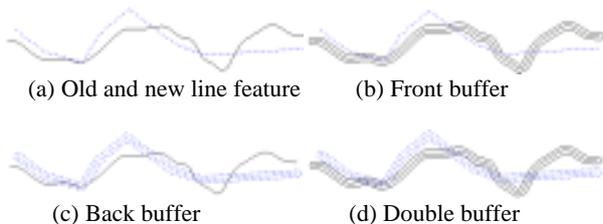


Fig.2 The principle of double-buffer detection algorithm (The black middle line is an old line feature in 1:5000 map and the blue dotted line is a new line feature in 1:10000 map)

2.2.2 The formula for double-buffer detection distance

Different from buffer detection algorithm, the double-buffer detection distance is composed of two buffer detection distances: one is back-buffer detection distance and another is front-buffer detection distance. Two factors including the accuracy of new map and the accuracy of old map are important for the definition of these buffer distances. Another important factor for the back-buffer is the generalization effect values and for the front-buffer distance is the limited distance. So suppose the RMSE of the detecting feature in old map is $\sigma_{old-map}$, the

RMSE of the detecting feature in new map is $\sigma_{new-map}$, the generalization effect value is σ_{gen} , the limited distance is $\sigma_{limited}$, the formula for back-buffer and front-buffer detection distance can be deduced as the following:

$$BufferDis_{Back} = \sqrt{\sigma_{old-map}^2 + \sigma_{new-map}^2} + \sigma_{gen} \quad (8)$$

$$BufferDis_{Front} = \sqrt{\sigma_{old-map}^2 + \sigma_{new-map}^2} + \sigma_{limited} \quad (9)$$

3. CHANGE DETECTION BETWEEN NEW/OLD MAPS

The presentation and practice for change detection between new and old map are mainly based on two reasons: one is that it is necessary to compare and detect the changes between different maps for checking compilation errors and controlling quality in map production procedure; another is that it is a good idea to reduce work burden using change detection algorithm for quickly detecting changes before map generalization. Obviously the former is the change detection between new/old maps with same scale and the latter is for old and new maps with different scale.

3.1 Change detection between new/old maps with same map scale

Suppose new/old maps own same data model and format, then the above proposed buffer detection algorithm is employed for solving this problem. So the key problem for change detection between new/old maps with same scale is depended on the accuracy of detection features in new and old map. An example for change detection between new and old charts with same scale is shown as Fig.3. It can be seen that the positions of the navigation marks in chart change in different time. In order to emphasize the changes the old and new navigation marks are all shown in the chart, shown as Fig.3(c).



Fig.3 An example for change detection example between new/old maps with same scale using buffer detection algorithm

3.2 Change detection between new/old maps with different map scale

Change detection between maps with different map scale cannot ignore the effects of cartographic generalization. The main effects caused by generalization lies on that it is difficult to quantitatively describe and represent the relationship of the features before and after generalization. In order to solve this problem, the change detection expert system is employed (Sui,2002). Considering the virtues of GIS, it is a good idea to introduce change detection into GIS environment. On one hand all kinds of GIS tools can be used for change detection and on the other hand the change detection knowledge base can be built based on GIS knowledge base so as to flexibly process the generalization problems.

Many different change detection algorithms including knowledge rules algorithm, spatial analysis and detection algorithm, double-buffer detection algorithm and so on are employed in detecting changes between new and old maps with different scale (Sui,2002). One difficult problem for detecting changes between new and old maps with different scale is the displacement problem in generalization. When defining the buffer detection distance, the distance and direction of displacement must be considered. In general the displacement objects can be selected according to the attributes or other conditions before generalization. Sometimes when this selection is very difficult the manual operation can be used for this purpose in GIS environment. An example for detecting

changes of road networks in new/old maps with different scale is shown as Fig.4.

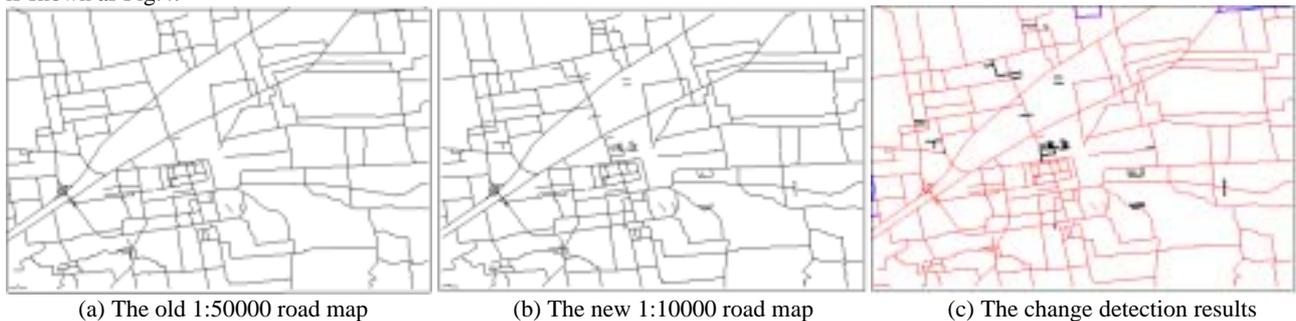


Fig.4 An example for change detection results using the double-buffer detection algorithm (In (c), blue thick lines represent appear road lines, black thick lines represent appear new lines, the back-buffer and front-buffer detection distance is 0.67mm, the change belief value is 0.9)

4. CHANGE DETECTION BETWEEN NEW IMAGE AND OLD MAP

The main difficulty of automatic change detection for road network between new image and old map lies in two aspects: one is the tracing of unchanged road and another is the extraction of new road. For detection and tracing of unchanged old road, automatic detecting algorithms based on GIS information are a good idea. For the extraction of new road, some new ideas and strategies including hybrid feature grouping techniques, automatic road recognition based on knowledge base, knowledge inference for road recognition, road re-grouping etc. are discussed in the following.

4.1 Automatic change detection based on GIS

Extracting road networks from imagery with the help of existing old maps can reduce the difficulty significantly. On one hand, we can suppose roads change very slowly and this means we can extract the road from images based on existent road information. On the other hand, road network own perfect topological properties and this means we can find another road through connected road networks easily. Obviously existing road in the old map can be employed as the start point of finding and extracting road in new image. However, how to detect the new road from images using old GIS information is worth to discuss.

In images with low resolution, i.e., more than 2m per pixel, roads mainly appear as lines establishing a more or less dense network, road tracing is not very difficult. Here we developed a buffer detecting and tracing algorithm. The main idea of this algorithm is to make a buffer for road in old map with a given buffer distance. And in this buffer, query all extracted parallel lines and link them according to the similarity of direction, length of two lines. In this procedure, using buffer detection algorithm for detecting road, four possible results can be detected: road is not changed, road is changed and widen, road is changed partly, road is disappear. The road can be detected and extracted in this procedure under the guidance of GIS information.

In high-resolution images, the appearance of roads is the mixed appearance of all sub-structures including cars, zebra crossing, lane lines and so on. Generally these structures can be taken as the existence proof of road network and they can be used for road extraction. But this is not enough. Because of too much noise and influence in high-resolution images especially this kind of proof is not exclusive, it is necessary to give some prior

information using old GIS data. A good example is the extraction of bridges. The main strategy is to firstly detect rivers using GIS information because river change very slowly and then search those candidate road segments vertical with river central lines. At last these road segments are linked according to some rules and the bridge will be extracted. Another effective proof is cars in roads. Because of good properties of cars, cars structures can be extracted easily and they can be used for assistant in road extraction. It is difficult to directly extract cars from images, but according to prior car models from extracted roads, the difficulty will be reduced significantly. An road extraction model based on cars was developed (Sui,2002,2003).

4.2 Hybrid feature grouping methods for road networks extraction

In middle-level vision, feature grouping is one of the key techniques. Road grouping is the most important technique for organizing short and incomplete road segments into long and more reliable road segments. Hybrid feature grouping methods includes two aspects: the grouping technique based on whole relationship for low-resolution images and the grouping technique based on profile tracing for high-resolution images are employed.

The grouping technique based on whole relationship is that many kinds of grouping contents including geometric properties, image attributes and other direct or indirect information can be quantitatively described [Sui,2003]. Road grouping based on this grouping strategy can be decomposed of two parts: one is grouping similar road segments and another is the extended grouping for non-similar road segments. Grouping similar road segments means to group road segments in given range (generally it is smaller value) according to similarity measurement parameters. The latter mainly groups those non-similar road segments that miss relative road information. After these grouping procedures, the whole framework of road network comes into being.

Opposed to the low-resolution images, in images with high resolution, i.e., less than 0.50m, roads are depicted as elongated homogeneous areas with more or less parallel borders. Because the complex relation between roads and other objects, like cars, buildings or trees, a reliable detection and extraction is often difficult. Sub-structures of roads like zebra crossing, lane line, white line, block line and other road markings have a strong influence on the characteristics of roads. The appearance of these sub-structures in images with high resolution are the multi

fragmented, broken parallel lines. Aiming at this, a new algorithm called profile-tracing algorithm is presented. The principle of the new algorithm consists of two steps:

- Firstly group these lines for creating possible candidate road segments according to profiles;
- Detect changes of road and extract road sides according to the candidate road segments.

For the first step, the main strategy is to select reliable parallel lines as searching start lines, and make profiles at their two vertexes so as to find possible conjoint parallel lines. Then link these parallel lines into one long line and repeat this procedure until all the given conditions can't be satisfied. For the second step, the key problem is whether roadsides can be extracted and how to trace roadsides according to the existence information. For every road segment, maybe it doesn't overlay the whole length of actual road. However, for many road segments, they can supplement each other and form a new line whose length is close to the whole road length. Base on these lines, roadsides can be created with the help of other grouping lines. The road length and width can be defined with the help of GIS information.

4.3 A strategy for extracting road networks from images

Structure features are main representation information of images. Almost all road extraction algorithms employ structure information. However, when there exist strong noise, low contrast and other factors in images, the extraction results using the algorithms based on structure features are often not well. Under this situation using statistical information is a good supplement. But how to define a statistical model and utilize the statistical parameters are key problems. Obviously from the viewpoint of extraction strategy, the hybrid extraction strategy based on structure information and statistical information is the best choice.

Generally, a lot of statistical models are very complex and there are many unknown parameters to be defined. So the algorithms based on these statistical models are not practical. A simple and practical statistical model is necessary. In general, local road segments in images have better statistical properties. Suppose we overlay a window with a given window size on the road in images, the local statistical properties of roads can be reflected from the properties of the gray histogram, gray gradient histogram, gray gradient intensity histogram in the window. So these three parameters can be used as statistical parameters. Candidate road segments can be found if the statistical properties in this window satisfy the following three conditions:

- The grey histogram in the window has only one peak
- The gradient direction histogram in the window has two symmetric peaks
- The gradient intensity histogram in the window has one no-zero peak

According to the above statistical properties of road segments, the authors design a new road-tracing algorithm based on the adaptive template (Sui,2002).

Considering the limitation of traditional Snake [Kass et al.,1988] model for processing the road with larger road width, the authors employ the Ribbon-Snake model for extracting the road features. To avoid slow convergence properties and high sensitivity to initial position of traditional Snake Model, five kinds of condition including continuity, curvature, image features, shape, range are involved in this model. The continuity and curvature conditions are the same definition with the Snake

model. The image features consider not only the gradient parameter but also the texture information. The least squares algorithm is employed for the shape constraint model. The range condition mainly control the selection of initial position in images. Here we use the buffer created by traced road central lines and road width as the searching and restriction range.

4.4 Automatic road recognition based on knowledge base

Automatic road recognition is a necessary task for extracting road networks. After many years of research, people realized that it is impossible to design a common algorithm for recognizing road networks from all kinds of images and it is also not enough to only depend on image information for automatic recognition and extraction. After great efforts of many years, many researchers have waked up to successful extracting of road networks should recur to the knowledge. In this paper, the authors built a road recognition expert system. All the knowledge is put into the knowledge base.

Generally three obstacles hold back automatic recognition: One is how to acquire recognition knowledge, another is that how to represent knowledge quantitatively and the third is how to use knowledge for reasoning and recognizing road. In this framework we first define a basic model for road. Main parameters including grey value, grey variance, the length, width, curvature are involved in the road model. The fuzzy theory is employed for representing road models. According to different parameters we define a series of different fuzzy functions for road model. And a road recognition expert system is built. All kinds of road recognition knowledge are all put in the knowledge base. We use fuzzy production rules for representing road knowledge and uncertain reasoning models for road knowledge reasoning. All the recognition results are represented as belief values. The road segments whose belief value is greater than the given threshold are extracted as road.

4.5 Re-grouping road based on global information and creation of new road

After automatic road recognition the whole framework of road network is built and the hidden semantic contradiction is solved. However, the work of road extraction is not finished. The road network is still incomplete because of the following reasons: the big road gaps caused by rows of trees and buildings, the wrong link among road segments, the missing road caused by wrong recognition and other factors. So it is necessary to further extract and link road network. The principle and the strategy are to use the extracted road segments and the global information of road network for guiding road extraction. On one hand, the existent road can be used as the start point for searching and linking road segments; on the other hand, different road segments can be linked according to some rules like distance, grey value etc. Obviously road re-grouping is not blindfold when high-level information feed back to middle-level or/and low level processing.

Under the guidance of global topological information, the road grouping and linking the iterative procedures until the last road networks are created. The authors think four parts should be processed in this procedure: road re-grouping, creation of road crossings, creation of road branches, iterative road extraction. Some extraction results based on the whole framework in this paper are shown as Fig 5.



(a) Origin image (b) Central lines after feature grouping (c) Road segments after recognition (d) Detection results

Fig.5 Automatic detection and extraction results for road network in low resolution images. (The white lines in origin image are the vector lines of old map. The red circles in detection results are the wrong results).

5. CONCLUSIONS

In this paper two kinds of new algorithms for detecting feature changes that is buffer detection (BD) algorithm and double-buffer detection (DBD) algorithm are illustrated. It can be seen that for the change detection between new map and old map the BD algorithm and DBD algorithm are not only effective for road detection but also for other features. For change detection based on new image and old map, some new ideas and strategies including hybrid feature grouping techniques, automatic road recognition based on knowledge base, knowledge inference for road recognition, road re-grouping etc. are discussed. Corresponding experiments proved that the algorithms are effective and practical. The future work is to focus on integration of all kinds of information for assisting in road extraction and improving the intelligence of automatic objects extraction using image pattern recognition, AI and other techniques. Indeed, automatic change detection and updating is really a very difficult problem. But it is especially useful not only for geo-spatial data updating but some special application such as military fields. For geo-spatial data updating, semi-automatic change detection and updating may be the best approach at present.

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REFERENCE

- Bruzzone, L.,Diego, F.P., 2000, Automatic Analysis of the Difference Image for Unsupervised Change Detection. *IEEE Transactions on Geoscience and Remote Sensing*, 38(3), pp. 2271-1182.
- Chalifoux, S., Cavayas, F.,Gray, J.F.,1998, Map-Guided Approach for the Automatic Detection on Landsat TM Images of Forest Stands Damaged by the Spruce Budworm.*Photogrammetric Engineering and Remote Sensing*,64(6),pp. 629-635.
- Dai,X.L., Khorram, S., 1997,Development of a New Automated Land Cover Change Detection System from Remotely Sensed Imagery based on Artificial Neural Networks, *IGARSS '97, Singapore*,pp.1029 -1031.
- Darvishzadeh, R.,2000, Change Detection for urban spatial databases using Remote Sensing and GIS, *The International Archives of the Phtogrammetry, Remote Sensing and Spatial Information Science*, 34(III),pp.245-251.
- Dreshler,F., et.al, 1993, A Knowledge-Based Approach to the Detection and Interpretation of Changes in Aerial Images, *IGARSS '93, Tokyo*, pp. 159 –161.
- Fan,H., Zhang,J.Q., Zhang, Z.X., Liu, Z.F., 1999,House Change Detection based on DSM of Aerial Image in Urban Area,*Geo-spatial information science*, 2(1),pp.68-72.
- Kass,M.,Witkin, A.,Terzopoulos, D.,1988, Snakes: Active Contour Models. *International journal of compute vision*,1(4):321-331.
- Li, D.R., 2003,Towards the development of RS and GIS in 21 century, *Geomatics and Information Science of Wuhan University*, 28(2), pp.127-131.
- Li, D.R., Sui, H.G., 2002, Automatic Change Detection of Geo-spatial Data from Imagery. *The International Archives of the Phtogrammetry, Remote Sensing and Spatial Information Science*, 34(II),pp.245-251.
- Macleod,R.D.,Congalton, R.G.,1999, A Quantitative Comparison of Change Detection Algorithms for Monitoring Eelgrass from Remotely Sensed Data, *Photogrammetric Engineering and Remote Sensing*, ,64(3),pp.207-216.
- Maupin, P., et.al, 1997, Contribution of Mathematical Morphology and Fuzzy Logic to the Detection of Spatial Change in an Urbanized Area: Towards a Greater Integration of Image and Geographical Information Systems, *IGARSS '97, Singapore*, pp.207 –209.
- Peled, A., 1998, Toward Automatic Updating of the Israeli national GIS--Phase II , *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science*, 32(4), pp.467-472.
- Sui, H.G., 2001,A Framework for automated change detection system. *GeoInformatics & DMGIS'2001*, pp.278-283.
- Sui, H.G., 2002, Automatic Change Detection for Road-Networks based on Features, *Wuhan University*.
- Wang, F., 1993,A Knowledge-Based Vision System for Detecting Land Changes at Urban Fringes, *IEEE Transactions on Geoscience and Remote Sensing*, 31(1), pp.136 –145.
- Wang,J.Y.,et.al,1992,*The Principle of Cartographical Generalization*, Survey and Mapping Press, 1992.