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A GIS study of land cover change detection supported by computer vision

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Abstract In this paper, based on the feature of high accuracy of GIS in the field of construction and land, we adopt GIS to obtain the initial data of land cover change, and find that there is a lot of interference information in the initial data. In this regard, the smooth polygon procedure in Arc Toolbox is used to smooth and thin it. The processed data were input into the support vector machine model, and the detection results were output after iterative training, thus completing the construction of the land cover change detection model based on SVM. Determine the research area and experimental equipment, synthesise the research data and the model in this paper, and carry out example analysis of land cover change. After analysis, it can be concluded that when the smoothing parameter and thinning coefficient are set to 40m and 1.0m, respectively, the processed data can be used for subsequent analysis of land cover change detection. In addition, the overall accuracy of this paper's model in detecting the change points of land cover conversion and land cover gradual change is 0.7368 and 0.7430, respectively, which verifies the superiority of this paper's model in land cover change testing. Compared with 1995, the area of forest land from 2000 to 2020 is increased by 9.81km²~115.6km², which reveals the development direction of land cover change in the future, and explores the application of land cover change detection in the field of construction. This study has practical and realistic significance for urban planning and building construction to make land cover change more rational.

Index Terms support vector machine, geographic information system, urban planning, land cover change

I. Introduction

Land cover and its changes, as an important component of global change, are also one of the main causes of global change [1]. Land cover and its changes at the regional scale reflect the regional socio-economic development. At present, China is in the critical period of building a moderately prosperous society in all aspects, and it is also the period of rapid development of urbanisation, so the study of urban land cover and its change in this context has important theoretical significance and practical value.

Land cover and its change will produce a series of ecological and environmental effects, indirectly affecting the climate, soil, vegetation, water resources and biodiversity, which are closely related to human survival and development, and then affecting the structure and function of the Earth's biochemical circle, as well as the Earth's systematic material cycle and energy flow and other aspects [2]-[6]. Land cover and its changes are closely related to global climate change, biodiversity decline, ecological evolution, and sustainability of human-environment interactions [7], [8].

With the continuous development of science and technology, a new era of using remote sensing satellite means and geographic information systems (GIS) to conduct large-scale land cover surveys has begun. Geographic information system (GIS) is a technical system that collects, stores, manages, calculates, analyses, describes and displays data on objects in the Earth's surface space and their related geographic locations with the support of computer hardware and software systems [9]-[11]. The application of GIS technology is mainly involved in its image analysis and processing, spatial statistical analysis and cartographic functions, of which the spatial analysis function is the main feature of GIS technology, and it is also the main feature of GIS technology. The spatial analysis function is the main feature of GIS technology and the core of GIS technology [12]-[14]. It manages land use data by inputting and editing spatial data, organising and analysing spatial data, querying and managing spatial data, as well as mapping and outputting spatial data, which provides a powerful tool for the analysis and comparison of land cover and its change types [15], [16].

Literature [17] analyses the land cover categories of a place based on a large amount of satellite data for classified change detection, assesses the results of change using two methods of change detection: preclassification and postclassification, and creates a feature class of important land cover categories using maximum likelihood supervised classification techniques. Literature [18] points out that remote sensing and GIS have been proven to be tools for assessing land use and land cover changes, and their detection and prediction of land use and change trends are necessary for urban planning and construction. Literature [19] emphasised that the combination of remote sensing technology and GIS tools is an effective means of monitoring land use and land cover change, and comparing the commonly used change detection methods in remote sensing projects, it was found that the post-classification change detection method of maximum likelihood classifier supervised classification achieves higher accuracy in the classification of regional terrain features. Literature [20] used multi-temporal Landsat imagery with maximum likelihood supervised classification methods to generate land use/land cover maps based on remotely sensed data, so as to carry out a study of spatial and temporal changes in land cover change detection. Literature [21] showed that maximum likelihood supervised classification techniques can train the mean and variance of the data to estimate the probability that a pixel is a member of a class, create signature classes for land cover classes in classified multi-temporal cloudless Landsat thematic mapping images, and achieve spatio-temporal change detection within a region. Literature [22] used ENVI and Arc GIS software to identify land cover changes in remote sensing data and satellite images of a region, and used kappa coefficients to evaluate the accuracy of different land cover classifications respectively, to complete the detection of land use and land cover changes in the region.

Since GIS can only qualitatively analyse land cover changes but not quantitatively, in view of this, land cover change detection research based on GIS-SVM is proposed as the main innovation of this paper, which can not only qualitatively analyse but also quantitatively analyse, which can satisfy the demand of land cover change detection well. The research data of land cover change is collected with the help of GIS, and the smooth polygon program in Arc Toolbox is used to optimise and pre-process the data in view of the existence of many interfering information in the data. Combine the research data with support vector machine to construct the land cover change detection model. The research area and experimental equipment are selected to simulate and analyse the above data preprocessing work, and check whether the data can be used for subsequent detection and analysis work. The user accuracy, producer accuracy and overall accuracy are taken as the evaluation indexes of the detection analysis, and the effectiveness of the model in land cover change detection is verified based on the evaluation indexes. Finally, the model is applied and analysed, and the application of land cover change detection in the direction of construction is outlined to make the research results more convincing.

II. Land cover change detection based on GIS-SVM

II. A. Overview of Geographic Information Systems (GIS)

With the continuous development of science and technology, the combination of geographic information systems (GIS) and mobile devices has become increasingly close, giving rise to a brand-new technology for acquiring, processing and analysing geographic information - mobile GIS [23]. This technology makes full use of the portability of mobile devices (e.g., PDAs, smartphones, etc.), real-time positioning capabilities, and multiple sensor integration capabilities to provide a more convenient and efficient solution for geographic information data acquisition, transmission, processing, and analysis.

II. A. 1) Real-time data updates

Improving the timeliness of geographic information data. One of the core advantages of mobile GIS technology is real-time data update. In the traditional GIS system, data collection, transmission and update usually need to go through a series of complex processes, which takes a long time. Mobile GIS technology breaks this limitation and realises real-time data collection, transmission and update. Staff can use mobile devices to collect geographic information data anytime and anywhere, and transmit these data to the cloud or server in real time, thus ensuring the timeliness of the data. This is of great significance for emergency response, real-time monitoring and other scenarios.

II. A. 2) Location services

Convenient geolocation and related services. The built-in positioning function of mobile devices provides powerful support for mobile GIS technology. With the help of mobile GIS technology, users can conveniently obtain relevant information about their own location, such as nearby attractions, restaurants, petrol stations and so on. In addition, mobile GIS technology can also provide users with real-time navigation, route planning and other services to help users quickly find their destinations in unfamiliar environments.

II. A. 3) Portability

Ideal for field operations. Compared with traditional GIS equipment, mobile GIS equipment is compact and easy to carry, which is especially suitable for field operations. In the outdoor environment, mobile devices can easily fit into pockets or backpacks, making it convenient for staff to use them at any time during field surveys, monitoring and other work. This greatly improves work efficiency and reduces work intensity.

II. A. 4) Integration of multiple functions

One-stop geographic information data collection and processing. Mobile GIS devices can not only carry common sensors, such as cameras and laser rangefinders, but also integrate other specialised sensors, such as temperature and humidity sensors and gas sensors. The integrated design of these sensors enables mobile GIS devices to achieve a wide range of geographic information data acquisition, processing and analysis, providing users with a one-stop solution.

II. B. Methodological design of data acquisition and processing techniques

II. B. 1) Data acquisition process technology flow design

The data collection process is shown in Figure 1. In land cover change detection, for areas where land cover databases have been established, the data collection workload is relatively small, mainly the checking of the original database and the conversion of data, including the conversion of data format, projection and coordinate system. For areas where no vector database has been established, a large amount of work is the digitisation of paper maps.

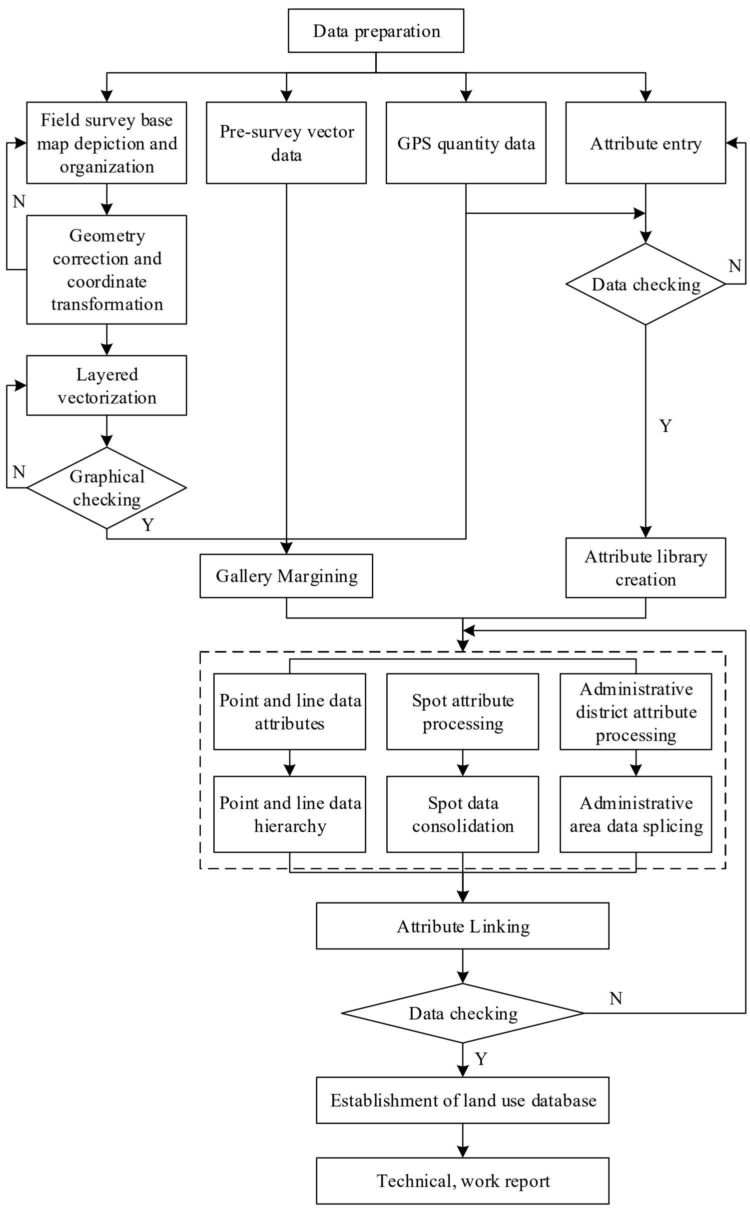


Figure 1: Data acquisition process

II. B. 2) Data processing

The principle of land cover change data processing is that data with low precision is subordinate to data with high precision, and the change data processing methods are as follows:

(1) Data changes that do not involve graphic changes are directly utilised to modify the attribute information of the graphic, and care is taken to maintain the consistency of the data.

(2) Updating of ownership boundaries: Based on the records of the “Land Cover Change Record Handbook” and the base map of the field survey, enter the GIS system to revise the information on the change of ownership boundaries, including the correction of the location of the ownership boundaries, the land class, the code and other series of elements. Special attention should be paid to the fact that when the “Land Cover Change Record Handbook” provides complete parameters of the coordinates of the inflection points, they should be completely and accurately transferred to the currently revised boundary elements.

(3) Updating of line features: Based on the records in the “Land Cover Change Record Handbook” and the base map of the field survey, the GIS system is used to revise the information on changes in line features, including the correction of the location of the line features, their course, land class, code and other series of elements. In particular, when the Land Cover Change Record Handbook provides complete parameters for the coordinates of points of inflection, it should be completely and accurately transitioned to the currently revised line feature elements and the expressions for the different element types of the original plan should be revised, e.g., changing linear elements to polygonal elements, etc., with attention paid to conversion of different layer types and recalculation of line feature codes, numbers, lengths, widths and areas. Recalculation of line feature codes, numbers, lengths, widths and areas.

(4) Updating of maps: According to the records in the “Land Cover Change Record Book” and the base map of the field survey, the smooth polygon program in Arc Toolbox is used to smooth and thin the information of map changes, including the location, boundary, land class, code and other series of elements of all kinds of polygonal features. The correction. It is especially necessary to pay attention to the fact that when the “Land Cover Change Record Book” provides complete parameters of inflection point coordinates, it should be completely and accurately transitioned to the current revised plots, and at the same time, attention should be paid to the re-calculation of the plots' land class code, number and area. Plot change processing consists of two steps:

(a) Plot smoothing processing, the general principle of data smoothing processing is to eliminate the interference components in the data, while maintaining the trend of the original curve.

(b) Spot thinning processing, the process of data thinning is to maintain the smoothness of the line on the basis of shedding some unimportant nodes, reduce the amount of data, until all the annual mapping information is processed.

(5) Change processing of single-layer data. It is mainly the superposition of base year data and change data. The specific processing situation is the same as the detailed area survey.

(6) Comprehensive data processing. Comprehensive data processing is to make spatial superposition of each year's plots, line features, scattered features, administrative jurisdictions, ownership information, etc. to form the annual land resources status quo information, which is the last plots used for statistics. On the basis of the current resource status file, the resource dynamic information can be extracted by making changes. For users who use the detailed investigation area, data comprehensive processing is unnecessary.

(7) Using GPS to directly collect change data information, it can be edited into a map in the corresponding software, and then imported into the GIS system for database updating. GPS data can also be textually imported into the GIS system for graphical editing and attribute editing.

II. C.SVM-based land cover change detection

Support Vector Machines (SVMs) have made significant advances in computer vision tasks such as target recognition, semantic segmentation, and image description, and they have proven to be very effective in capturing global dependencies between different parts of the input. Since GIS can only analyse land cover changes qualitatively but not quantitatively, this section introduces SVM into land cover change detection and proposes an SVM-based land cover change detection method applied to land cover change detection. The basic idea of the method is to take advantage of SVM for two types of data classification problems, and achieve land cover change detection through SVM training and classification, thus reducing the uncertainty caused by threshold selection in conventional change detection methods and improving the efficiency and reliability of the land cover change detection process.

II. C. 1) Support vector machine theory

The principle of the support vector machine is to find the optimal classification hyperplane such that the distance from this hyperplane to the nearest sample in the sample is maximum, while ensuring that the distance on both sides of the classification hyperplane is large enough [24]-[26]. The support vector machine is shown in Fig. 2, where the two classes of data are represented by ○ and □, where β is the classification line, β_1 and β_2 are the straight lines traversing the two classes of samples nearest to β and parallel to β, and the distance between β_1 and β_2 is the classification interval. The equation for the classification line β is denoted as $\omega x+b=0$ and is satisfied:

$$y_i\left[\left(\omega\cdot x_i\right)+b\right]-1\geq 0, i=1,2,\ldots,n \tag{1}$$

where $y_i\in\{-1,+1\}$, denotes the output of x_i, the classification interval is $2/\|\omega\|$, when $\|\omega\|$ takes the smallest value, the classification interval reaches the maximum, at this time, the problem of solving the classification interval is transformed into a problem of solving the minimum value, as shown in Equation (2). At this time, the corresponding classification hyperplane is the optimal hyperplane of the support vector machine, and the samples on the straight line are the support vectors.

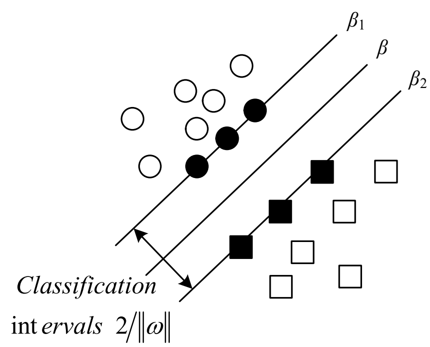


Figure 2: Support vector machine

The process of classification using Support Vector Machines is to find an optimal value of the parameter, where the Lagrange multiplier approach is introduced to solve the problem. To wit:

$$\begin{cases}\min\dfrac{1}{2}\|\omega\|^2\\ y_i\left[\left(\omega\cdot x_i\right)+b\right]-1\geq 0, i=1,2,\ldots,n\end{cases} \tag{2}$$

The new formula constructed after the introduction of Lagrange multipliers is:

$$L(\omega,b,\alpha)=\frac{1}{2}\|\omega\|^2-\sum_{i=1}^{n}\alpha_i\left[y_i\left[\left(\omega\cdot x_i\right)+b\right]-1\right] \tag{3}$$

where α_i is the introduced Lagrange multiplier, which can be obtained by taking the partial derivatives of ω, b, and α, respectively, and letting their values be zero:

$$\begin{cases}\dfrac{\partial L(\omega,b,\alpha)}{\partial\omega}=0\Rightarrow\omega=\displaystyle\sum_{i=1}^{n}\alpha_i y_i x_i\\ \dfrac{\partial L(\omega,b,\alpha)}{\partial b}=0\Rightarrow\displaystyle\sum_{i=1}^{n}\alpha_i y_i=0\\ \dfrac{\partial L(\omega,b,\alpha)}{\partial\alpha_i}=0\Rightarrow\alpha_i\left[y_i\left[\left(\omega\cdot x_i\right)+b\right]-1\right]=0\end{cases} \tag{4}$$

Substituting this into Eq. (3) gives:

$$\max L(\omega,b,\alpha)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j\left(x_i\cdot x_j\right) \tag{5}$$

such that $\sum_{i=1}^{n}\alpha_i y_i = 0$, $\alpha_i \geq 0$, $i = 1,2,\ldots,n$, assuming that the optimal solution in Eq. (5) is α_i^*, then $\omega^* = \sum_{i=1}^{n}\alpha_i^* y_i x_i$ can be derived, and the corresponding coefficient b^* can be calculated from constraint $\alpha_i\left[y_i\left[(\omega\cdot x_i)+b\right]-1\right]=0$, which leads to the optimal classification function:

$$\begin{aligned} y &= \operatorname{sgn}\left(f(x)\right) = \operatorname{sgn}\left(\left(\omega^*\cdot x\right)+b^*\right) \\ &= \operatorname{sgn}\left(\sum_{i=1}^{n}\alpha_i^* y_i\left(x_i\cdot x\right)+b^*\right) \end{aligned} \tag{6}$$

From equation (6), it can be determined to which class of samples the unknown sample belongs. However, a small number of samples may exist between β_1 and β_2, so it is necessary to introduce a fault-tolerant variable δ_i to allow samples to be misclassified at the classification boundary, i.e., Eq. (2) is improved to:

$$\begin{cases} \min\frac{1}{2}\|\omega\|^2 + c\sum_{i=1}^{n}\delta_i, \delta_i > 0, c > 0 \\ y_i\left[\left(\omega\cdot x_i\right)+b\right]-1+\delta_i \geq 0, i = 1,2,\ldots,n \end{cases} \tag{7}$$

However, in real life, many high-dimensional samples belong to linearly indivisible samples, at this time, the difficulty of finding a hyperplane that can classify the data is greatly increased, SVM solves the problem by introducing the kernel function, which is to map the low-dimensional data into a high-dimensional space, and then divide them accordingly in this high-dimensional space. That is:

$$K\left(x_i,x_j\right)=\Phi\left(x_i\right)\cdot\Phi\left(x_j\right),\left(i,j=1,2,\ldots,n\right) \tag{8}$$

In Eq. (8), where, $\Phi\left(x_i\right)$, $\Phi\left(x_j\right)$ denote the nonlinear mapping functions, which are obtained by replacing x_i and x_j in Eq. (5) using this equation:

$$\max L\left(\omega,b,\alpha\right)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j\left(\Phi\left(x_i\right)\cdot\Phi\left(x_j\right)\right) \tag{9}$$

Equation (9) is solved for the original feature space and the best classification function obtained is:

$$y=\operatorname{sgn}\left(\left(\omega^*\cdot\Phi(x)\right)+b^*\right)=\operatorname{sgn}\left(\sum_{i=1}^{n}\alpha_i^* y_i K\left(x_i\cdot x\right)+b^*\right) \tag{10}$$

As can be seen from Eq. (10), the whole calculation process of this function is independent of the data dimension.

Obviously the Gaussian radial basis kernel function has the smallest mean square error and the largest coefficient of determination, so the Gaussian radial basis kernel function is chosen as the kernel function of the support vector machine. Namely:

$$y=\operatorname{sgn}\left(\left(\omega^*\cdot\Phi(x)\right)+b^*\right)=\operatorname{sgn}\left(\sum_{i=1}^{n}\alpha_i^* y_i\exp\left(-g\left\|x_i-x_j\right\|^2\right)+b^*\right) \tag{11}$$

SVM recognition accuracy and penalty factor c and kernel function parameter g (Eq. 11) are closely related, the penalty factor c is mainly used to balance the classification error and generalisation error of SVM, when the value of c is too high, overfitting phenomenon will occur, resulting in a decrease in the ability to generalise; the value of c is too low when the complexity of the model is low, and it is easy to appear underfitting phenomenon. The kernel function parameter g mainly affects the distribution of the input sample points in the kernel space, the larger the value of g, the more detailed the classification, and also prone to overfitting.

II. C. 2) Mathematical modelling

Using the classification advantage of SVM for two and multi-class data, it is applied to the land cover change detection process, and the land cover change detection model based on SVM is shown in Figure 3. The specific implementation steps are as follows:

(1) Match the histograms of the two GIS data and then perform difference processing (single-band images are directly calculated for a single band, and multi-spectral images are calculated for the difference images of the corresponding bands respectively), and derive the difference image.

(2) Select two types of feature samples, change and no change, on the difference image, train the SVM binary detector, and get the binary change detection result map. Calculate the detection accuracy using test samples that are independent of the training samples.

(3) In the unchanged region of the binary detection results, a set of training samples representing different land cover types is selected corresponding to the two time-phase images before and after, and the training samples are used to classify the changed regions of the two time-phase images before and after by SVM at the same time, and the classification results of the time-phase images before and after are obtained.

(4) For the change region part of the binary detection results, corresponding to the land cover category information of the two time-phases before and after, the change transfer matrix is constructed to obtain the change category and direction information.

In order to further explore ways to improve the accuracy of the change detection results, texture feature information is added in step 1, and the SVM method is used to detect changes in the mixed dataset composed of grey-scale difference images and texture difference information.

Change detection is achieved by integrating two SVM classifications by effectively utilising the good properties of SVM for the separation of complex data (linear and non-linear). The first is binary change detection, followed by land cover classification, thus obtaining change category and change direction information while detecting change areas. Compared with the conventional unsupervised binary change detection method, this method can avoid and reduce the detection error caused by the threshold determination algorithm, and also make full use of the SVM classification characteristics to provide richer information for change detection. The classification training samples are selected from the non-changing part of the binary change, which can effectively reduce the complexity and uncertainty brought by the samples coming from the changing region for the category classification, and maintain the consistency of the classification of the before and after time-phase images. The construction of the change transfer matrix is based on the change part of the binary change detection and the feature category information, which can effectively suppress the phenomenon of “exaggerated change” caused by the traditional post-classification change detection method.

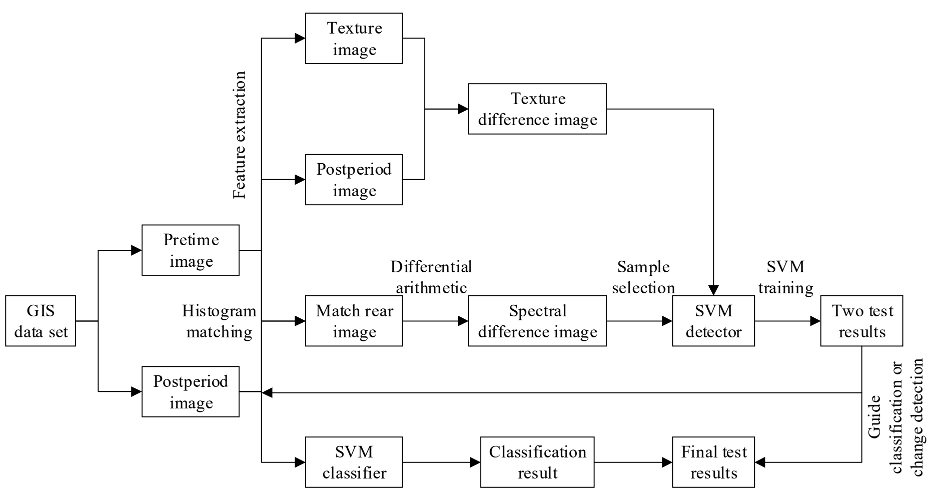


Figure 3: SVM based land coverage change detection model

III. Example analysis of land cover change detection

With the acceleration of urbanisation and the expansion of city scale, urban construction planning has become more and more complex and critical. In order to meet the needs of sustainable urban development, planners need to accurately detect the development trend of land cover change, and the land cover change detection results play an important role in urban planning and construction development. This section explores the effectiveness of the detection model in this paper from four aspects: GIS data processing, land cover change detection results, test validation, and detection application, aiming to promote the sustainable development of urban planning and construction.

III. A. GIS-based data processing analysis

III. A. 1) Overview of the study area

The study area of this paper is City A, located in the northern region of China, which is a typical loess plateau mountainous area with a central longitude of 108°. Its territory is mostly covered by loess, with mountains, plains and hills were once subjected to strong erosion and cutting effect on the formation of beams, walls, mounts and other typical loess plateau geomorphological landscapes. Climate with warm temperate cold semi-arid climate characteristics. Due to low precipitation, rain intensity, strong scouring force, most of the rivers have lower annual flow, larger annual flow variation, river sediment is larger, so the region is also one of the most serious soil erosion, the main performance is the development of gullies and ravines, cutting the beams and mounts, gully extension, gully expansion of the bank, landslides, steep slopes, and open up the land.

III. A. 2) Experimental equipment

The image processing software in this paper adopts ERDAS IMAGINE version 9.2 from ERDAS Corporation. ERDAS IMAGINE is characterised by its advanced image processing technology, friendly user interface, model development tools serving different levels of users, and a high degree of remote sensing image processing and GIS integration functions. The modular operation has great flexibility.

The geographic information software used is ESRI's ArcGIS version 9.3. ArcGIS is one of the most widely used GIS software in the world, is a comprehensive, scalable GIS platform, provides a complete solution for users to build a perfect GIS system.

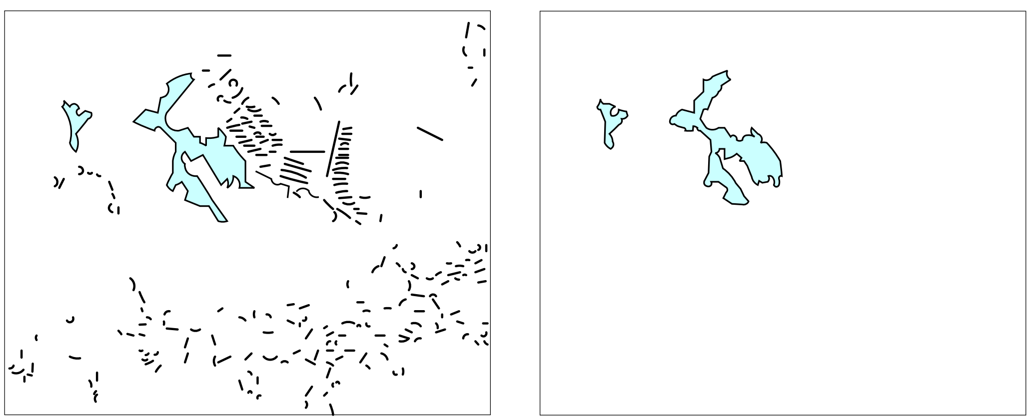
Hardware environment: CPU: InlelPentriurnEZ140l.60GHz.

Hard Disk: 320G.

Memory: 2G.

III. A. 3) Analyses of the processing of small patches of data

In order to reduce noise and facilitate the accuracy of land cover change detection, it is necessary to de-noise the obtained GIS-based data acquisition. First of all, it is necessary to conditionally delete the fragmented small patches to remove as much as possible the interference information, the analysis of the data small patches processing is shown in Figure 4. In the experimental data of this paper, the plots with attribute field shape area less than 400m² are deleted (continuation of the rules of the second land survey). It can be seen that through a certain area screening conditions, basically remove most of the interference information, get better results.



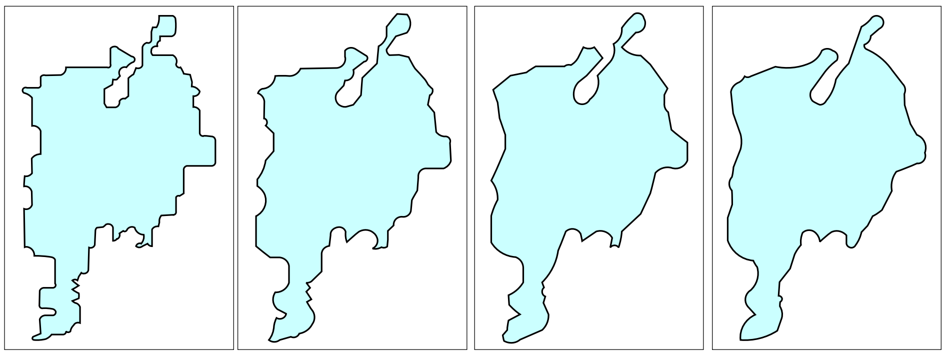
(a) Before (b) After

Figure 4: Data microspecular processing analysis

III. A. 4) Data smoothing

The purpose of extracting the boundary of the change patch is to use the data to do more detection and analysis applications, but the raster to vector polygon shows a jagged shape, so the vector polygon should be smoothed. The general principle of data smoothing is to eliminate the interference components in the data, while maintaining the trend of the original curve.

In this paper, in the process of data smoothing, the smoothing polygon procedure in Arc Toolbox mentioned in subsection 2.2.2 is used. This program has a better effect on the smoothing of the surface data, in the smoothing of the experimental area, the smoothing tolerance selected 10m, 20m, 30m, 40m, from the smoothing effect of the comparison of the best effect of 40m, the effect of the different smoothing parameter processing comparison is shown in Fig. 5, in which (a) ~ (d) were 10m, 20m, 30m, 40m. it can be seen that, the smoothing parameter for the It can be seen that the graphs with smoothing parameters of 10m and 20m still show different degrees of jaggedness, and the graphs with parameters of 40m show better smoothness than the graphs with parameters of 30m, and keep the shape of the original patch better, so the smoothed data with parameters of 40m are used. After smoothing, the boundary line of the surface patch obviously eliminates the jaggedness. Although the smoothing process enhances the aesthetics of the graph, the smoothed data automatically increases many nodes, which leads to an increase in the amount of data. If the data is in a large area, there will be new problems such as the increase of software running time caused by the increase of data volume, which is not conducive to the subsequent analysis operation, so it is necessary to make further thinning treatment for the smoothed data.

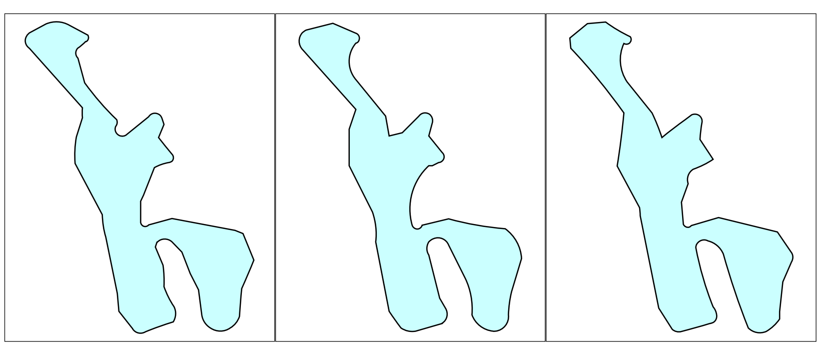


(a)10m (b)20m (c)30m (d)40m

Figure 5: The comparison effect of different smooth parameters is treated

III. A. 5) Data thinning

The process of data thinning is to discard some unimportant nodes and reduce the amount of data on the basis of maintaining the smoothness of the line, using the same method described above to thin the data. When thinning the experimental area, the thinning parameters are 0.6m, 1.0m and 1.2m, and the comparison of different parameters is shown in Fig. 6, in which (a)~(c) are 0.6m, 1.0m and 1.2m, respectively, and the comparison of thinning effect can be seen that, the smaller the thinning parameter is, the better the effect of the processed data will be, but it can't reduce the amount of data effectively, and the parameter 1.2m is 1.2m. After the data processing, the sharp corners have appeared, so after careful analysis, it is decided to use the thinning parameter of 1.0m. The smoothed and thinned data can be used for subsequent analysis of land cover change detection.



(a)0.6m (b)1.0m (c)1.2m

Figure 6: Different parameters were diluted

III. B. Analysis of land cover change detection results

III. B. 1) Sample points

In this paper, the method of support vector machine is used to assess the accuracy of land cover change detection. Firstly, based on the results of continuous change detection, 900 sample points were randomly selected from the above processed data, of which 450 sample points were located in areas where land cover conversion had occurred, and the other 450 sample points were located in areas where land cover gradual change had occurred, and it was ensured that the spacing between the sample points was greater than 500m, and another square roughly equivalent to 30 pixels was created around each sample point buffer around each sample point.

III. B. 2) Evaluation indicators

Confusion matrix is the current method of classification detection accuracy evaluation using binary classification, this paper selects the following three indicators for the evaluation of the detection results, respectively, producer accuracy, user accuracy and overall accuracy for quantitative analysis.

(1) Producer accuracy (PA), is the ratio of the total number of samples correctly identifying a certain class of samples and a certain class of sample points in the change detection results, the formula is as follows:

$$PA_i = \frac{n_{ii}}{n_{i+}} \tag{12}$$

(2) User accuracy (UA), which is the ratio of the total number of samples correctly identified as a particular type of sample point in the change detection results to the total number of samples identified as a particular type of sample point in the change detection, is given by the following formula:

$$UA_j = \frac{n_{jj}}{n_{+j}} \tag{13}$$

(3) Overall accuracy, which is the ratio between the number of correctly identified sample points in the change detection results and the total number of samples, is used to evaluate the effect of change detection with the following formula:

$$OA = \frac{\sum_{i=1}^{k} n_{ii}}{Q} \tag{14}$$

In equations (11) to (13), n_{ii} is the number of samples in which the sample points of category i were correctly classified, Q is the total number of samples, n_{i+} represents the total number of sample points of category i in the correct sample points, and n_{+j} represents the total number of sample points of category j in the detection results.

The accuracy assessment of changed and unchanged sample points is shown in Table 1. A total of 798 sample points were correctly identified in the selected 900 changed sample points, but 102 sample points were detected to have land cover changes in the unchanged sample points, with a user-producer accuracy of 0.8867. In terms of the overall accuracy, land cover change detection based on the Support Vector Machine reaches 0.8561, which is a better land cover change detection.

The producer accuracy of unchanged sample points is calculated as follows:

$$PA_i = \frac{n_{ii}}{n_{i+}} = \frac{743}{743+102} = \frac{743}{845} = 0.8793$$

The producer accuracy for the change sample points is calculated as follows:

$$PA_i = \frac{n_{ii}}{n_{i+}} = \frac{798}{157+798} = \frac{798}{955} = 0.8356$$

The user accuracy for the unchanged sample points is calculated as follows:

$$UA_j = \frac{n_{jj}}{n_{+j}} = \frac{743}{157+743} = \frac{743}{900} = 0.8255$$

The user accuracy of the changed sample points is calculated as follows:

$$UA_j = \frac{n_{jj}}{n_{+j}} = \frac{798}{102+798} = \frac{798}{900} = 0.8867$$

The overall accuracy is calculated as follows:

$$OA = \frac{\sum_{i=1}^{k} n_{ii}}{Q} = \frac{743+798}{1800} = \frac{1541}{1800} = 0.8561$$

Table 1: Accuracy assessment of changes and unchanged sample points

Change detection accuracy	Invariant sample point	Change sample point	User accuracy
Invariant sample point	743	157	0.8255
Change sample point	102	798	0.8867
Producer accuracy	0.8793	0.8356	Overall accuracy:0.8561

After that, this paper extracts the change points on the 798 correctly identified sample points for the accuracy assessment of land cover conversion and land cover gradual change, and the accuracy assessment results are shown in Table 2. The overall accuracies of change point detection for land cover conversion and land cover gradual change are 0.7368 and 0.7430, respectively.Finally, in order to test the differentiation ability of this paper's algorithm in detecting different types of land cover change detection, this paper excludes the unchanged points from all the detected change points, leaving only the change points that are correctly recognised as land cover conversions or land cover gradual changes and the points that are wrongly recognised as the identified category points for confusion matrix evaluation.

The overall accuracy of land cover conversion was calculated as follows:

$$OA = \frac{\sum_{i=1}^{k} n_{ii}}{Q} = \frac{588}{798} = 0.7368$$

The overall accuracy of the land cover gradient is calculated as follows:

$$OA = \frac{\sum_{i=1}^{k} n_{ii}}{Q} = \frac{593}{798} = 0.7430$$

Table 2: Accuracy assessment

Categories	Correct change points	Error identification change point	Overall accuracy
Land coverage conversion	588	210	0.7368
Land cover gradient	593	205	0.7430

The differentiation accuracy of land cover conversion and land cover gradual change in the change sample points is assessed as shown in Table 3, the probability of the change point of land cover conversion being misclassified as land cover gradual change is larger, and the overall accuracy of the two types of change points being differentiated and recognised is up to 0.7375.Overall, land cover change detection based on the Support Vector Machines has a feasible accuracy, and the land cover conversion and the land cover gradual change also have a better differentiation, and can be used for different types of land cover change detection at the level of in-depth analysis.

The producer accuracy of land cover transformation is calculated as follows:

$$PA_i = \frac{n_{ii}}{n_{i+}} = \frac{566}{566+187} = \frac{566}{753} = 0.7517$$

The producer accuracy of the land cover asymptote is calculated as follows:

$$PA_i = \frac{n_{ii}}{n_{i+}} = \frac{611}{232+611} = \frac{798}{955} = 0.7248$$

The user accuracy for land cover conversion is calculated as follows:

$$UA_j = \frac{n_{jj}}{n_{+j}} = \frac{566}{566+232} = \frac{566}{798} = 0.7093$$

The user accuracy of the land cover gradient is calculated as follows:

$$UA_j = \frac{n_{jj}}{n_{+j}} = \frac{611}{187+611} = \frac{611}{798} = 0.7657$$

The overall accuracy is calculated as follows:

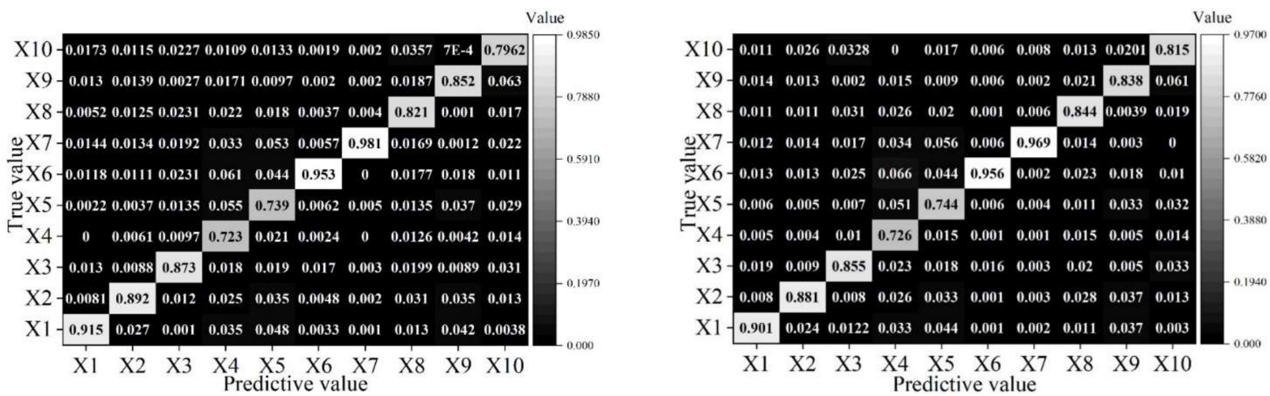
$$OA = \frac{\sum_{i=1}^{k} n_{ii}}{Q} = \frac{566+611}{798+798} = \frac{1177}{1596} = 0.7375$$

Table 3: Differential accuracy assessment

Categories	Correct change points	Error identification change point	User accuracy
Land coverage conversion	566	232	0.7093
Land cover gradient	187	611	0.7657
Producer accuracy	0.7517	0.7248	Overall accuracy:0.7375

III. C. Test validation analysis

The control group is CNN, while the experimental group is SVM, and the two algorithms are applied to test and analyse the river (X1), road (X2), harvested crops (X3), buildings (X4), grass (X5), trees (X6), harvested grass (X7), background (X8), crops (X9) and undefined region (10) respectively, and furthermore, the test and validation analyses are carried out by comparing the results of the two tests to further Verify the effectiveness of the method in this paper, the test validation analysis results are shown in Fig. 7, where (a) ~ (b) are SVM, CNN, respectively. the confusion matrix in the figure shows the correct rate of all kinds of tests and the single misjudgement rate of CNN and SVM on X1~X10, the test accuracy of CNN and SVM on X1, X2, X3, X6, and X7 reach more than 85%, and the accuracy of CNN on X4, X5, X8, X9, and X10 categories, but SVM has better detection in the above categories, verifying the superiority of SVM in land coverage change testing.



(a)SVM (b)CNN

Figure 7: Test verification analysis results

III. D. Analysis of model detection applications

The above verifies the validity of this paper's method by means of algorithm comparison, and then examines the application of this paper's detection model on the change of forest land, grassland, arable land, water body, and building land cover from 1995 to 2020, and the analysis of the model detection application is shown in Fig. 8. As can be seen from Fig. 8, compared with 1995, the area of forest land increased by 9.81km², 24.25km², 18.74km², 21.31km², 115.6km² in 2000, 2005, 2010, 2015, 2020, and the same applies to grassland, arable land, water bodies, and building land, so we will not repeat the details. The model in this paper correctly reflects the land cover change towards the direction of returning farmland to forests, reducing the marine area and increasing the available land, so as to realise the green and sustainable development of the land.

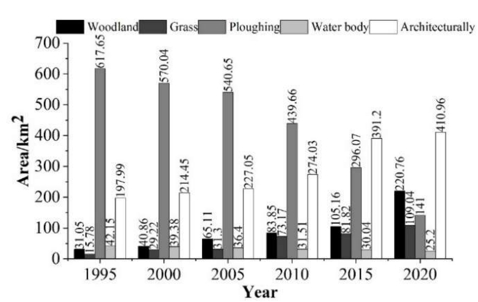


Figure 8: Model test application analysis

IV. Land cover change detection for construction applications

IV. A. Improvement of urban planning

With the help of the detection model in this paper, we can obtain large-scale and high-precision land information, and these data can help urban planners to more accurately assess the traffic demand, optimise the traffic planning, and reasonably plan roads, bus routes, car parks and other transport facilities in order to improve urban planning. Overall, land cover change detection is invaluable to urban planning and building development, providing them with a comprehensive understanding of land resources and helping them to formulate reasonable urban planning and building development strategies.

IV. B. Contributing to the development of urban architecture

The results of the land cover change tests make it possible to identify areas suitable for urban building development. In addition, by analysing the quality of soil and water resources, it is possible to identify areas suitable for school building sites or tourist building sites. This information can help architects and engineers to evaluate the value and potential of land resources, so as to reasonably determine the direction of urban building development and the functional layout of different areas, and to make scientific decisions for the future development of urban buildings.

V. Conclusion

This paper adopts the combination of geographic information system and support vector machine to explore the land cover change detection under the support of computer vision, and after exploring and analysing, the following research results can be obtained:

(1) The data obtained based on GIS is pre-processed and analysed, when the smoothing parameter is 40m and the extraction dilution coefficient is 1.0m, the effect of data pre-processing is more in line with the requirements of detection and analysis.

(2) The overall accuracy of the two kinds of change points being distinguished identification based on the support vector machine reaches 0.7375, which can meet the current demand of land cover change detection, and has a promotional effect on land management and monitoring.

(3) In the land cover change detection confusion matrix, the accuracy of CNN and SVM in X1, X2, X3, X6 and X7 tests reaches more than 85%, but the overall accuracy, SVM is better than CNN, indicating that SVM has a high priority in land cover change detection.

(4) After the model of this paper detected that the area of forest land increased by 9.81km^2, 24.25km^2, 18.74km^2, 21.31km^2 and 115.6km^2 in 2000, 2005, 2010, 2015 and 2020, which accurately reflects the direction of the development of land cover change.

(5) Based on the characteristics of land cover change detection, we explore the application of land cover change detection in the field of construction from the aspects of urban planning and construction development.

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