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A Comparison between CBR and MLC in Order to Identify an Aquaculture Area from a Coastal Image

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Abstract: Sea reclamation works and fish farming are increasingly common in coastal zones, and how to accurately and rapidly extract the coastal aquaculture area is important for the development of coastal zones. This paper discusses a CBR (case-based reasoning) method. Firstly, using a 10 meter resolution of a multi-spectral remote sensing image of Eastern Guangdong over ten thousands of spatial, spectral, shape and texture features were extracted based on the 1:50000 standard framing of land use thematic data and by using image analysis. Then nine optimized features were selected using the principal component analysis (PCA) and the construction of a case base was accomplished based on these. After that, a multi-scale image segmentation was performed on the 2.5 meter resolution of a fused image of the test area, which is located on the Western Guangdong coast, and CBR classification was applied on all the segmented image objects. In the end, the classification accuracy was evaluated. The CBR classifier classifies an aquaculture area within coastal belts with an accuracy of 84.6 %, in contrast to that the accuracy of the Maximum Likelihood Classifier (MLC) is 82.5 %. The CBR method outperforms the MLC by 2.2 % in prediction accuracy. The advantages of the CBR approach are obvious, particularly in the areas that are far away from the coastlines. In conclusion, the CBR approach could be successfully applied to the extraction of coastal aquaculture areas.

Keywords: Artificial intelligence; case-based reasoning; principal component analysis; multi-scale segmentation; maximum likelihood classification; coastal aquaculture

1 Introduction

Due to the increasing degradation of marine fishery and growing demand for sea food, sea reclamation works and fish farming are increasingly common in coastal zones. While there are economic benefits, environmental problems result also. Therefore, the rapid and accurate extraction of coastal aquaculture areas is important for land use assessment, the aquaculture sites and environmental monitoring.

At present, visual interpretation [1] and spectral-based classification [2] are always used to extract coastal aquaculture areas, and the employment of object-based classification is attempted [3, 4]. High-precision visual interpretation of the coastal aquaculture areas is necessary, but when manually done it has the disadvantage of beeing time-consuming, inefficient and poor repeatability. Spectral-based classification, only uses spectral bands, with which it is easy to generate a “salt-pepper” phenomenon. It has a lower precision and could produce large amounts of data redundancy. Although the object-based classification method is superior to the “salt-pepper” phenomenon, its accuracy depends on the segmentation scale, the accurate acquisition of samples and the construction of the feature space. It is not easy to generate the corresponding rules and the knowledge for image interpretation. Faced with a new remote sensing, the above factors will arise again when construction the object-based representation. This is not efficient. Therefore, we must explore a more efficient method that allows us rapidly and accurately extract coastal aquaculture areas.

Case-based reasoning (CBR) is an artificial intelligence technology which relies on knowledge from old cases to explain a new situation [5]. The method is efficient and consists of knowledge retrieved from old cases, it can improve the solutions and adapt them to the new situation, as well as elicitate knowledge for further reasoning [6]. Currently, there are many image processing applications which use the CBR method. Grimnes & Aamodt [7] presented a system that integrates CBR into a task-oriented model-based system for interpreting abdominal computer tomography (CT) images. Perner [8, 9, 10] used the CBR method for all stages of an image-analysis and interpretation system and established CBR-based image-interpretation systems for different applications. As an example, CBR is used for image segmentation based on the histogram thresholding method [10], and on the watershed segmentation method [8] for medical image segmentation and established image interpretation systems for cell-image diagnosis [11] and other applications.

Li et. al [12] used the CBR method to classify the land use based on radar images. Moreover, they control the spatial distribution of cases through stratified random sampling and by doing so they overcome the “same object with different spectrum” phenomena. Du et al.[6, 13] proposed the concept of the geographical case and the three-component representation model. Based on that they predict a land use change. They obtained good results by using CBR. These approaches construct a case base based on a single spectral image and not on different spectral images. By doing so they failed to take into account the effect of the spectral scale.

Therefore, in this paper, firstly an object-based image-analysis method was used to analyze the aquaculture area on the remote sensing images and nine optimized features were selected, using the principal component analysis to represent the characteristics of the aquaculture area. Then CBR methods combined with multi-scale image segmentation were used to extract the aquaculture area of the test area.

2 A CBR Approach for Extracting Coastal Aquaculture Areas

The specific processes of extracting an aquacuture area from the images in archive SPOT5 are shown in Fig. 1. First, we use the geographic information system assistant (GIS) to extract the data for the cases of the coastal aquaculture area. Because the objects have many characteristics, we used PCA to select the right features of the objects. The selected features and the class label for the aquiculture area made up a case.

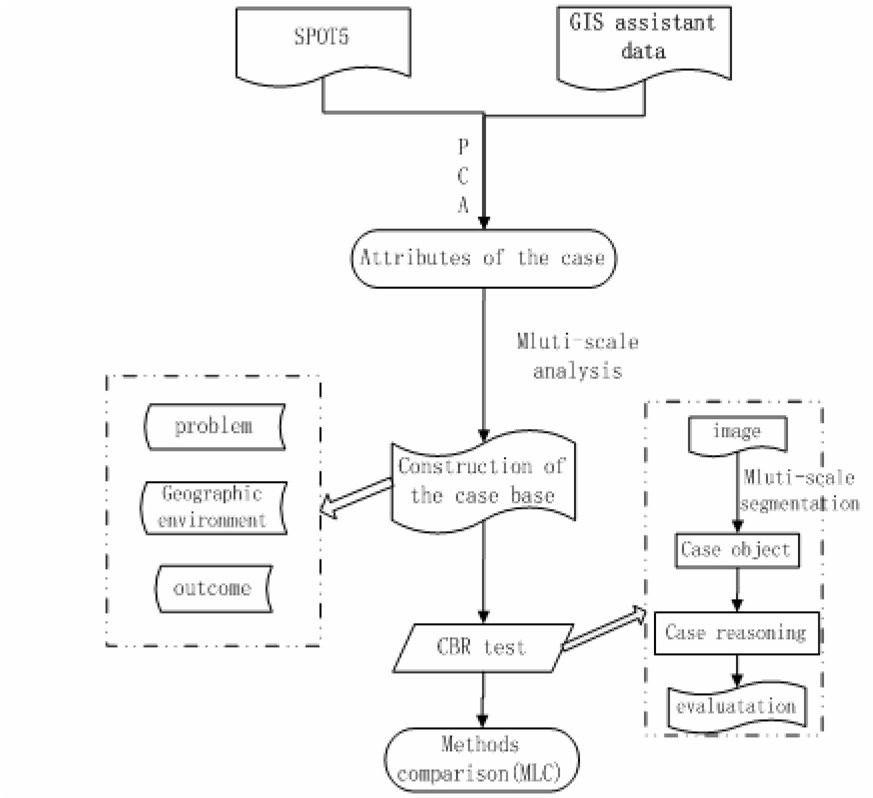


Fig. 1. Overview of method and approach

Then we perfomed CBR image classification on real images that were not included in the case base. We evaluated the results and reported the performance. Multi-scale image segmentation [14] was performed on each new remote sensing image. The segmented image-objects with their extracted features made up the actual case. This case was compared to the cases in the case base. The most similar case was selected from the case base and the class label was compared to the real class label.

In the end, classification accuracy was evaluated over the new remote sensing images. Moreover, we compared the CBR approach with the traditional supervised classification approaches (MLC) [15].

2.1 Case Representation

One of the problems in CBR is how to describe a case. Traditionally, the dual-mode case description with its "problem" and its "solution" part was used to a describe a case. We use the same model but consider not only image features more than this we also consider contextual features. The influence of the environment and the spatial relationship is ignored in most of the CBR applications for costal aquaculture examination. We therefore introduced in the problem description a new component called geographic environment description. By incorporating this new component, the effect of the geographic environment on the problems is considered.

In summary, a case is defined as the coastal aquaculture area features extracted from the remote sensing images and the contextual features describing the geographic environment. Spatial, spectral, shape and texture features were used to describe the costal aquaculture area. The geographic environment includes any geographic factors which may affect the extraction of coastal aquaculture areas, such as distance from coastline, distance from town, temperature and terrain. Besides that we introduce the time t_i in which the images have been taken as another feature since in different month, the object has different appearances in the image. As a result, the case can be defined as follows:

$$\text{Case}_i=\{ S_i ,SA_{1i},SA_{2i},\ldots SA_{ji},SR_{1i},SR_{2i},\ldots SR_{li}, t_i, C_i\} \quad (1)$$
$$\text{with } i=1, 2,\ldots K;\ j=1, 2,\ldots M;\ and\ l=1,2, \ldots N;$$

where i is the case number, S_i is the spatial pattern of the case i, SA_{1i}, $SA_{2i},\ldots SA_{jM}$, are the attributes (totally M) of case i, $SR_{1i},SR_{2i},\ldots SR_{li}$, are quantitative indexes (totally N) of spatial relationships between case i and geographical environment factors, and C_i is the "solution" of the case, i.e. the class label for the costal aquaculture area .

2.2 The Spatial Pattern (S) of the Case and Multi-Scale Image Segmentation

Remote sensing image information is the reflection of the surface spatial pattern and geographic surface characteristics which are dependent on the scale [16]. The extraction of different objects should be carried out at different scales, the scales of the same object in different images also being different. Generally speaking, the larger the segmentation scale more less are the polygons, and, vice versa, the less the segmentation scale more larger are the area of the polygons. In our study, the case in the case base corresponds to a specific scale (1:50000) of the remote sensing image of aquaculture, salt pan and so on. We segmented the new remote sensing image by an image analysis procedure to form the new cases. Due to the different scales we generated different new cases. How to choose an appropriate segmentation scale and make the target case and the cases in case base consistent, plays a vital role in the extraction of information. Therefore, with this method, the primary aim is how to choose a suitable segmentation scale for the objects we want to extract.

Multi-scale segmentation [14] is a region-merging technology which leads to a single pixel object from the bottom of the scale to top of the scale. Small image objects could be merged into a large object. This is done by pair-wise clustering. The objective function is a heterogeneity weight of the image objects that should be minimized. Adjacent image objects are merged if this heterogeneity weight is minimized. If the smallest growth exceeds the threshold defined by the scale parameter value, the process will stop. The standard of heterogeneity consists of two parts: the color criteria hcolor and the shape criteria hshape. And the hshape consists of smoothness hsmooth and compactness hcmpct. With this method, we adjust the weights of the above indexes in order to achieve that the scale segmentation of the image is the best suitable one and that the new image segmentation results are in accordance with the one that were used for the images in the case base.

2.3 The Numerical and Contextual Attributes (SA, SR) of the Case and the Principal Component Analysis for Feature Selection

Chapter 2.1 described how the case base case could be represented. The description of the objects in the remote sensing images can involve number of features about shape, spectral features, and texture. These features can be used to interpret the remote sensing images. It is obvious that there exists feature redundancy, which might lead to the problem of the "curse of dimensionality".

Therefore, feature reduction of a case is an important problem of our work. Dimensionality-reduction methods commonly use linear algebra techniques to project high-dimension space into low-dimension space, especially in the case of continuous data. In this paper, we use the Principal Component Analysis (PCA) to optimize the characteristics of the features. PCA is a linear algebra technology for continuous attributes. It finds new attributes (components), which are in linear combination of the original property of the features [17].

2.4 Case Similarity Computing and Reasoning

CBR solves problems by searching the case base for cases similar to the actual case. Therefore, the development of a proper similarity measure is a main issue of CBR research. The type of the attribute determines the kind of similarity measure that we can chose. In our study, the attributes of the base case are of numeric and string type. Therefore, the overall similarity is a weighted summation of the similarity calculation of the two types of attributes. The similarity of a numeric attribute can be defined as:

$$Sim(f_q^i, f_q^j) = 1 - d({}_q^i, f_q^j) = 1 - d_q^{ij} \tag{2}$$

$$\text{with } d_q^{ij} = \frac{\left| f_q^i - f_q^j \right|}{f_{q,\max} - f_{q,\min}}$$

where f_q^i and f_q^j are two values of the attribute f_q of the case *i* and the case *j*, and $f_{q,\max}$ is the maximum value of the attribute f_q and $f_{q,\min}$ is the minimal value of the attribute f_q.

The time is of string type, such as 2012-04-17. Therefore we would have to calculate a string similarity measure such as the one in [18] or the widely used edit distance [19] or N-gram [20]. That would make the similarity calculation a bit more computationally complex.

The images have been mainly taken on monthly basis and they are compared on monthly basis regardless of the year. Therefore, we can convert the string type similarity into an ordered attribute similarity. We divide 12 months into 12 levels, and the similarity of the level t_i and the level t_j $(1 \le t_i,\ t_j \le 12)$ can be defined as:

$$Sim(t_i, t_j) = 1 - \frac{t_i - t_j}{12} \tag{3}$$

This is the ordered attribute similarity for time according to [21].

Based on the above similarity calculation the case similarity can be defined as:

$$Sim(f^i, f^j) = \left(\sum_{q=1}^{n} w_q Sim(f_q^i, f_q^j) \right) / \sum_{q=1}^{n} w_q \tag{4}$$

where w_q is the weight of the *q-th* attribute, while f_q^i and f_q^j are the values of the target case *i* and case *j* in base case. The function *Sim* is the similarity function of the numerical attributes. Here we define the weight w_q with one. Finally, we get:

$$Sim(f^i, f^j) = \left(\sum_{q=1}^{n} Sim(f_q^i, f_q^j) \right) / n \tag{5}$$

We calculate the final similarity $Sim(i, j)$ by summing up over the similarity $Sim(t_i, t_j)$ of time and the similarity $Sim(f^i, f^j)$ of the features:

$$Sim(i, j) = (Sim(t_i, t_j) + Sim(f^i, f^j)) / 2 \tag{6}$$

Case-based reasoning is first concerned with finding the closest cases in the case base to the actual case and then in the second step to analyze the “outcome” of these cases. The case with the highest similarity value was finally accepted as the “solution”.

3 Case Study

3.1 Data Analysis

We use fifteen scenes with a 10 m resolution, and multi-spectral remote sensing images from the Eastern Guangdong area in our case base. The spatial cover of the images is shown in Fig. 2. Images are taken by quadratic orthorectification. The data are in accordance with the 1:50000 coastal zone classification system standard according to the land use classification in the regulations of coastal islands' satellite remote sensing survey. The image feature extraction can be executed up to level three of the multi-level image scale. Then all images will correspond to the images in the regulations of a comprehensive survey of coastal marine classification code and schematic illustration. The images were manually labeled and interpreted. From the resulting data the eastern Guangdong land use databases has been created. The Accuracy of manually interpretion of the coastal aquaculture area is 93.1%. This accuracy meets the needs of the production of a 1:50000 topographic map.

According to the descriptions in Part 1, firstly, we constructed the history case base based on the land-use database. Because our research focuses on the extraction of the aquaculture area, we chose the aquaculture and other objects which are easily confused with the aquaculture, such as salt pan, reservoir and pool, to complete the construction of the history Case Base. Finally, 6530 objects were selected, including aquaculture 3053, reservoir 194, pool 3177 and salt pan 106.

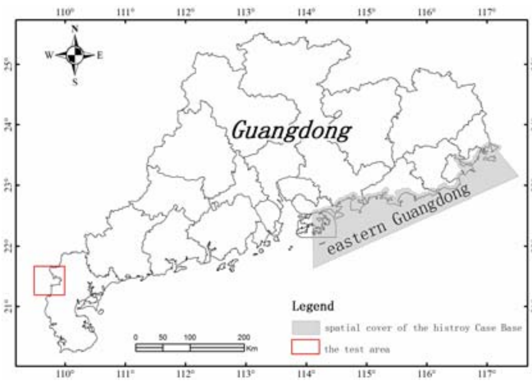


Fig. 2. The spatial cover of the history case base and the test area

3.2 The CBR Approach for Extracting Coastal Aquaculture Areas

3.2.1. The Construction of the Case Base

Over hundreds of spatial, spectral, shape and texture features were extracted based on the above 6530 polygons. The list of features is given in table 1. Then, we employed PCA to reduce the dimensionality and get an accumulation variogram (Fig.3).

Fig. 3 shows that the first ten principal components accounted for 90% of the explained variance, and the first and second principal components accounted for 70% of the explained variance, thus the first and second principal components can be used as a source of measure. Then, analyzing the weight of each attribute of the first and second principal component, we were able to get the changing curve (Fig.4). The attributes having a higher proportion of weight and changing a lot in weight will serve as the ultimate indicators which are listed in table 1.

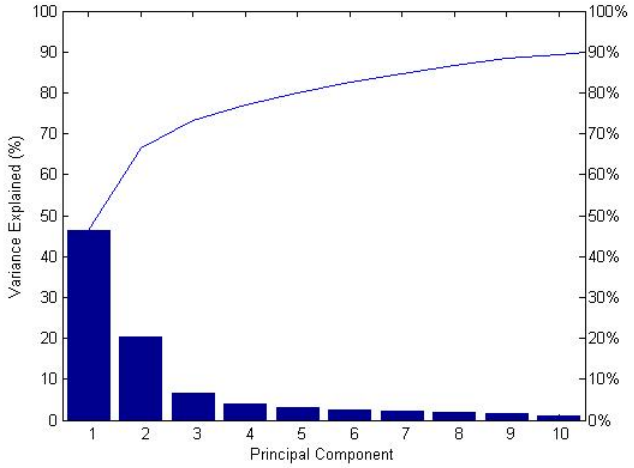


Fig. 3. Accumulation Variogram

Then we completed the construction of the case base of Eastern Guangdong (table 2), according to the nine indicators in table 1. In order to verify the reasonableness of the case library, we made the following test: We randomly selected 1200 cases from the whole library of cases (including 850 aquaculture, 30 reservoirs, 300 pools, 20 salt pans). These cases account for 10% of all cases. We used them as test cases from the case base. Then, after eliminating the 1200 cases from the case base, the case-based reasoning could be done by test-and train evaluation. The resulting confusion matrix is shown in table 3. The resulting accuracy is good enough for automatic classification and confirms that the chosen scale and features are the right case description. The case base is well fill-up.

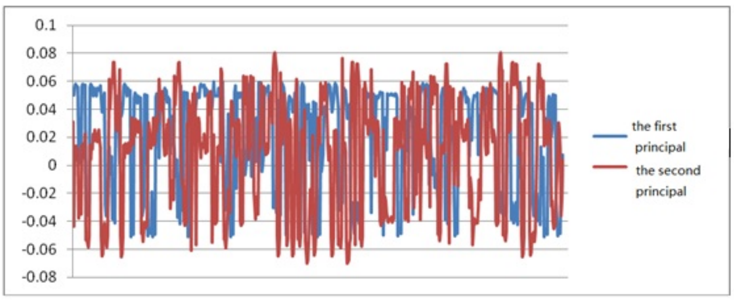


Fig. 4. The curve of Principal component - Weight

Table 1. The best attribute

Num	Indicator	Description	Feature Class
1	GLCM Ang2nd moment	The sum of the squares of all the normalized cells	Texture
2	GLDV Entropy(90°)	If the values of the matrix are relatively close, then the entropy will be greater	Texture
3	GLCM Correlation(0°)	Reflect the local gray image correlation	Texture
4	GLCM Dissimilarity（45°）	The greater the local variance, the greater the dissimilarity	Texture
5	GLCM Mean（45°）	An average expression of GLCM	Texture
6	Rectangular	Rectangular fit	Shape
7	Standard deviation (layer 1)	Standard deviation of pixel value	Spectral
8	Brightness	The mean of spectrum	Spectral
9	Near_Dist	The distance from the coastline	Spatial

Table 2. Case Base of Eastern Guangdong (Where a is reservoir; b is pool; c is salt pan; d is aquaculture; A_1 is GLCM Ang2ndmoment; A_2 is GLDV Entropy; A_3 is GLCM Correlation; A_4 is GLCM Dissimilarity; A_5 is GLCM Mean; A_6 is Rectangula; A_7 is Standard deviation; A_8 is Brightness; A_9 is Date; R is Near_Dist)

FID	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	R	Type
1	0.0072	2.9159	719.5729	11.0729	50.9513	0.9003	12.0044	54.1146	12	4306.9846	d
2	0.0016	3.4187	1262.4851	17.9271	62.9474	0.5035	14.4082	68.9653	12	1808.7676	d
…	…	…	…	…	…	…	…	…	…	…	…
3054	0.0216	3.0051	2084.0302	20.2030	70.9086	0.6485	14.2724	76.8949	12	3173.5235	a
3055	0.0586	2.2976	284.6786	4.5309	50.5084	0.8377	18.3697	51.3262	1	3085.0051	a
…	…	…	…	…	…	…	…	…	…	…	…
3248	0.0042	2.9381	1176.2708	16.0606	61.0551	0.9471	12.0391	64.7733	12	9.8569	c
…	…	…	…	…	…	…	…	…	…	…	…
6530	0.0171	2.2458	2626.8518	30.7241	51.8793	0.8168	8.5062	63.3333	12	4492.9801	b

Table 3. Confusion matrix of the case base

	reservoir	pool	salt pan	aquaculture	total	accuracy
reservoir	12	12	0	6	30	40.00%
pool	2	244	0	54	300	81.33%
salt pan	0	0	14	6	20	70.00%
aquaculture	2	81	2	415	500	83.00%
total	16	337	16	481	850	
accuracy	75.00%	72.40%	87.50%	85.22%		

Overall accuracy: 80.59%

3.2.2 Evaluation of the Multi-Scale Image Segmentation by the Case-Based Reasoning Experiment

In order to verify the effectiveness of the proposed method, we made an experiment based on the image of Shatian town in western Guangdong. This image (see Fig. 2) is not in the case base. The image is fused into 2.5 meter resolution of pan SPOT5 and 10 meter resolution of multi-spectral SPOT5. Then regions of 8000*9000 pixels are cutted out of the whole images as test areas. A false color image of a test area image can be seen in Fig. 5. After pretreatments such as radiometric calibration and geometric correction, multi-scale image segmentation method was used to segment an image. The specific segmentation parameters are shown in table 4. Fig. 6 shows the segmentation results of aquaculture areas at different scales. It can be seen that in the scale of 10, the aquaculture areas are broken. The image is over segmented. In the scale of 80, the aquaculture area is less divided, and in the scale of 40, the segmentation results are more satisfactory. Thus, we calculated the features of all the polygons based on the scale of 40 and constructed the case base from these images. According to the process described in Section 2, a similar reasoning of the aquaculture area will be done (Fig. 7). The specifity in accuracy is given in table 5. The accuracy of extracting the aquaculture area is 84.56 % (table5). However, no similar cases were found for 79 cases with a threshold set to 85% of similarity.

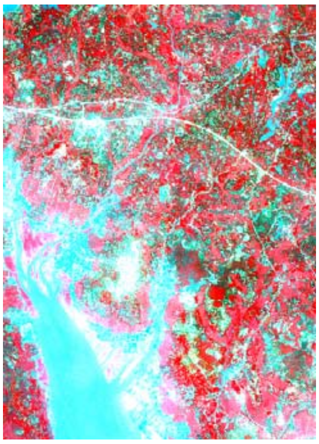


Fig. 5. A false color image of the test area

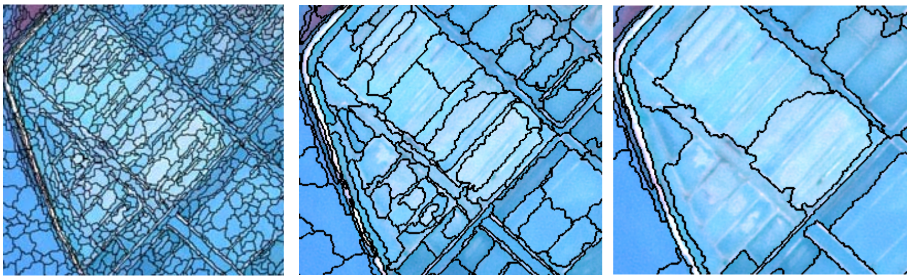
Table 4. Parameters used in multi-resolution segmentation

Scale	Shape weight	Smooth weight	Compactness weight	Color weight	Number of segmented regions
10	0.4	0.5	0.5	0.6	90123
40	0.4	0.5	0.5	0.6	62147
80	0.4	0.5	0.5	0.6	32654

Table 5. Accuracy Assessment Table

Class	aquaculture	pool	reservoir	others	precision
aquaculture	801021.65	86325.62	39254.82	20679.96	84.56%
pool	24365.21	118563.25	8365.85	30907.77	65.07%
reservoir	13256.38	185362.52	213658.93	51127.05	46.11%

units：m^2



(a) scale=10 (b) scale=40 (c) scale=80

Fig. 6. The results of image segmentation with different scales

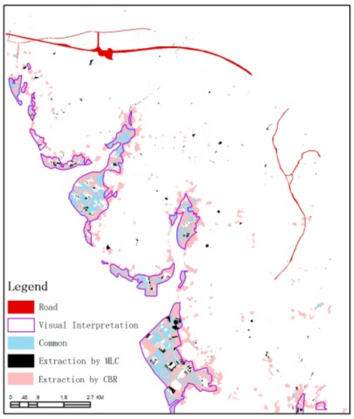


Fig. 7. The results of aquaculture area extraction

3.2.3. Comparison to Results with Minimum Likelihood Classification

In order to evaluate the accuracy derived from the CBR method, we also used the maximum likelihood classification (MLC) to study the extraction of the aquaculture area in the test area. Maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Each pixel is assigned to the class having the highest probability (that is, the maximum likelihood). If the highest probability is smaller than a threshold you specify, the pixel remains unclassified.

Table 6. Confusion matrix of MLC

Class	Aquac-ulture	pool	river	Paddy fields	Reservoir	Sea water	Forested land	User's Accuracy
Aquacu-lture	1856	0	55	0	337	0	0	82.56
Pool	544	849	1	0	0	0	0	60.90
Reservoir	0	0	1	275	1760	0	0	86.44
River	1013	327	944	0	502	0	0	33.87
Paddy fields	0	0	0	2121	1298	0	1	62.04
Seawater	1	0	0	0	0	4287	0	99.98
Forested land	0	0	0	0	194	0	1364	87.55
Producer's accuracy	54.36	72.19	94.31	88.52	43.02	100	99.93	

Overall accuracy is 74.34%

The specific process is as follows: firstly, we choose the samples divided into the following categories: aquaculture, pools, rivers, paddy fields, reservoirs, water, and forested land; then we used the MLC method to get the confusion matrix (table 6) and the extraction results of the aquaculture area (Fig. 7). It is shown that the overall accuracy is 74.34%, the accuracy of the aquaculture area is 54.36% and the manually obtained accuracy of the aquaculture area is 82.56%. MLC's accuracy is lower than the CBR approach. The main reason for this is that the MLC method only uses the spectral features and that it is difficult to choose appropriate samples. As we can see in Fig. 7, most of the regions which are far from the coast are not classified as aquaculture areas in the CBR approach.

4 Conclusion

Based on the analysis of the limitations of current extraction of aquaculture area methods, we propose a CBR approach for extracting coastal aquaculture areas. With this method, the base case can be reused and has the advantage of dynamic, simple, flexible and practical update. In a next step we will analyze different data sources. The time factor and the geography are integrated into the CBR method, giving full consideration to the geographic space, thus making broader application possible. In addition, the CBR method, combined with PCA, can better screen the attributes of the coastal aquaculture area. From the results of the test area based on CBR and MLC, the CBR method has a higher accuracy than MLC, although CBR will take a long time to build the case base the first time, later it will be very convenient. As long as the case base is not properly filled with cases, the accuracy of the CBR method will be influenced. However, while the case base is improved continuously, the accuracy of the CBR method will also be improved. With MLC, the selected samples in one image cannot be reused in another image, also it lacks the possibility of integration of contextual knowledge such as the spatial relationship. With the CBR method one can carry out knowledge accumulation; the reasoning results for an image can be inputted into the case base. Based on this experimental study we can say that the CBR method can sufficiently improve the methods for the extraction of coastal aquaculture areas. CBR allows reasoning based on the cases seen so far as well as knowledge accumulation during the usage of the system. Therefore it helps to improve the understanding of the interpretation process of coastal aquaculture areas based on remote sensing images.

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