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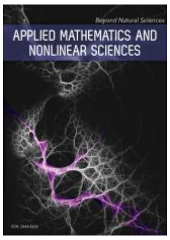

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Computer Image Scene and Object Information Extraction based on Bayesian Network Model

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Abstract

In order to better extract scene and object information from computer image, a construction object extraction algorithm based on Bayesian network is proposed. The algorithm is trained by multi-scene aerial images to build a grain dictionary and map the grain in the actual image to the grain dictionary to obtain the scene information of the image;Then naive Bayesian networks were used to model the constraints of the relationship between architectural targets and the spatial context of scene classes, and the extraction of architectural targets was converted into a posteriori probability problem for solving Bayesian network class nodes. The experimental results show that the proposed algorithm can effectively extract architectural objects from aerial images.The experiment result shows that:In this paper, the proportion of target pixels accurately extracted by the algorithm is taken as the standard to define the standard of target pixels accurately extracted by the algorithm to reach more than 90% of the building target pixels. The average time of training an image is 2 s, which is mainly spent on the convolution operation with the filter. After the training, the average time of processing a single test image is 0.5s. It is proved that Bayesian network model can effectively extract scene and object information from computer image.

Keywords: Bayesian network model; Image scene; Extraction of information
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1 Introduction

One of the main ways for humans to obtain information from the outside world is vision. According to statistics, visual information accounts for about 60% of the information acquired by humans, while auditory information accounts for about 20%. Other information such as taste information, touch information and so on together accounted for about 20%, so we can see the importance of visual information to people. Image is the main behavior of human to obtain visual information [1]. The so-called image is the observation system to observe and record the objective world through various forms, and then directly or indirectly act on the human eye to produce visual perception entity. In the continuous development of computer technology, image processing technology has also received great attention and progress. Image processing is a subject involving many fields. It is the basis of pattern recognition, computer vision, image communication, multimedia technology and many other disciplines. Image processing is to convert the original image signal into a digital format that can be processed by computer programs, and then the computer will use different pretreatment methods such as image enhancement and binarization according to the features of the image [2]. A variety of effective image segmentation techniques are used to process the image elements, so that the information that has an important impact on the conclusion can be enhanced to determine the key characteristics of quantization, and finally the data is transmitted to the control program. In fact, image processing is a process from image to data. The data can be the measured results of target features or the measured results based on symbols. What they describe are the features of the image and the attributes of the target image [3].

In the process of image processing, the line feature is an important clue of human visual perception among the many features of the image, and the line feature also corresponds to the place where the image features have changed. The line feature of the image can outline the linear target in the image contour edge or structure information, including rich position, direction, shape and other information, is one of the most commonly used attributes in image recognition. Feature line extraction is one of the most commonly used image processing methods. In order to enhance the information of the target that people care about in the image, the essence of feature line extraction is to extract valuable contour lines in the image, through which the machine or human eyes can easily observe the local information of the target [4]. The local information of the target is the key factor of target recognition in image analysis and image understanding. For example, in computer vision, the abrupt change of geometric or physical properties of the target object in three-dimensional space will be reflected in the obvious change of its grayscale information when projected into the two-dimensional image, which is often referred to as the image edge. The edge of the object is generally the edge of the object, and the feature line of the object is generally the general name of the feature line and the feature curve, so it can be said that most of the edge is composed of the feature line of the target. The edge image can include the direction and shape of the original image, so edge recognition is to identify the feature line, which is one of the most basic image processing methods[5]. In modern image processing and machine vision, feature line detection is the first required image processing step feature line detection in reducing the amount of image processing data, but also greatly retains the boundary structure of the object information, so through the feature line detection can simplify the need to analyze the image. Therefore, the research of extracting image feature lines has important theoretical significance and practical application value. In addition, in the image information containing multiple targets, how to complete the target separation and classification is also a major work, so the feature line classification method research also has important theoretical significance and practical value[6].

2 Literature Review

As the related sub-tasks of image overall scene understanding such as image salience detection, target recognition, image segmentation, scene classification are widely used in the engineering practice of computer vision, it has become a hot topic in academic research. Remarkable progress has been made in the research of sub-tasks in the overall image scene understanding. If the overall image scene understanding can be organically integrated with tasks and features from the perspective of human scene understanding, it is more in line with human thinking mode, because people always have the awareness of overall understanding unconsciously when observing an image[7]. Meanwhile, it is more helpful to adopt the thinking mode of overall understanding. For example, if the context structure of the realistic three-dimensional scene is known, it will be helpful to understand and speculate the position of a car (common sense tells us that the car will not fly in the air). The ability of computer automation to understand the whole scene is greatly enhanced by means of machine learning. However, since image information involves a large amount of data and many algorithm processing steps, it provides a rare opportunity and condition for academic research. In combination with the research content of this paper, the research motivation mainly includes the following three aspects: machine learning image extraction is shown in Figure 1.

The first is the theoretical challenge. After decades of development, the research of traditional image understanding has formed a huge theoretical system to reveal various laws and phenomena in image understanding. As a new thing derived from its technology, whether the whole scene understanding of image can still be explained by the existing theories and how much to follow the existing law of image understanding are unknown issues, which need to be studied and tested again[8]. For example,1)The Bayesian topic model has been successfully applied in describing scene reasoning, etc., but in fact, the topic model originated from document retrieval, and its application to describe the image itself is a form of technical grafting. To what extent it can reveal the essential features of the image still needs further in-depth analysis and research.2)MRF,CRF is a classical image segmentation method, in order to describe the subtle space or logical relationship in the image, people put forward the form of high-order potential energy to reflect this demand. However, the rationality of this potential energy form still lacks in-depth mathematical explanation. At the same time, if it is necessary to combine image significance detection and segmentation scene classification in the overall scene understanding, it is difficult for a single method or theory to capture the overall understanding performance improvement brought by the interaction of multiple subtasks[9].

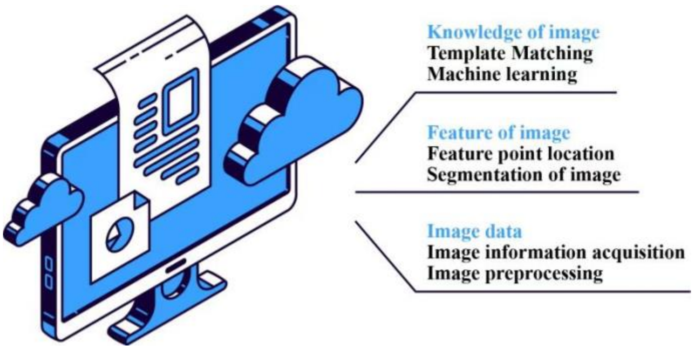

Figure 1. Machine learning image extraction

3 Construction object extraction algorithm of aerial photography image based on Bayesian net

3.1 Construction target extraction method based on Bayesian network

In this paper, the process of aerial image construction target extraction includes three stages: feature extraction classification and Bayesian network target verification[10].For an input image, the grain features are first extracted, then the scene categories in the image are divided based on the weak classifier of grain features, and finally the possible building targets are verified by using Bayesian nets. The whole process of the building targets in the output image is shown in Figure 2.

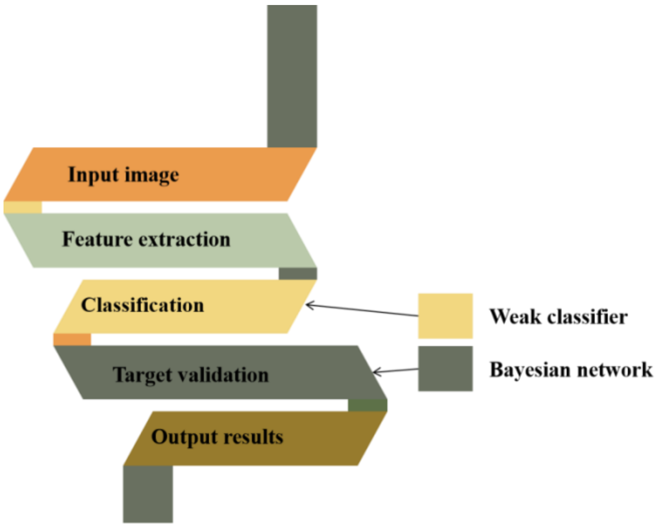

Figure 2. The process of building object extraction in aerial image

3.2 Construction target extraction based on Bayesian network

3.2.1 The construction of naive Bayes net

The scene of aerial image is complex, and the initial classification of scene category is often inaccurate. This is especially true for architectural targets. Therefore, it is necessary to verify the scene class classified by the weak classifier. Bayesian network is an important tool for processing uncertain information[11]. Provides a way to represent causal information. It has been successfully applied to the expert system of medical diagnosis statistics decision making. This paper notes that the correlation constraints between architectural targets and the surrounding environment can be used as the evidence of architectural targets, and the dependence relationship between architectural targets and scenes can be modeled through Bayesian networks. By calculating the probability dependence between them, the effective extraction and verification of architectural objects in aerial images are realized[12].

Common types of relations usually include similar adjacent relations, among which the most common adjacent relations in the Chinese words by the mountain near the sea ~ towering people and clouds are the image description of such relations. In this paper, the adjacent relation type is selected as the causal relation type between architectural target and scene class, and the measurement of the relation constraint between architectural target and environment is expressed as the dependence degree between it and adjacent scene class. Obviously, in terms of category extraction and labeling, the appearance of adjacent scene classes has an enlightening effect on architectural objectives[13]. In the use of Bayesian networks, the first thing to be determined is the network structure of Bayesian networks. In this paper, naive Bayesian wetwork is used as a tool to describe the constraints of the relationship between targets and scenes. The category node is the architectural target class, which is the parent node of all attribute nodes, and it is assumed that attribute nodes are independent of each other. Except for the directed edge between the category node and the attribute node. The property node is no longer connected. The network structure is shown in Figure 3.

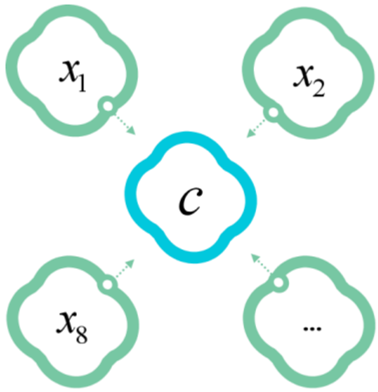

Figure 3. Naive Bayesian network classifier

Common scenes in aerial images of urban scenes include forests, roads, rivers, lakes, buildings, mountains, Bridges, airports, etc. Since the building target in the image is extracted in this paper, the building target is defined as the category node of Bayesian network. Other scene categories are defined as attribute nodes. The value of each node is represented as a binary random variable. A value of true means that the corresponding scene class appears in the image, while a value of false means that the corresponding scene class does not appear in the image. In order to verify the authenticity of the architectural target obtained by the classifier, this paper uses Bayesian network to transform the extraction of architectural target into solving the posterior probability of the class nodes of Bayesian network[14].

In naive Bayes network, the attribute nodes are independent of each other. According to Bayes' theorem, the posterior probability of target class c is:

$$p(c|x_1,x_2,\ldots,x_8) = p(c)\prod_{i=1}^{8}\frac{p(x_i|c)}{p(x_i)}$$
$$p(x_i|c)$$
$$p(x_i = \text{"ture"}|c = \text{" false"}) \tag{1}$$

In the equation: $p(c)$, $p(x_i)$ represents the prior probabilities of the target class or other scenario class, respectively; $p(c|x_1,x_2,\ldots,x_8)$ represents the posterior probability of the target class under the condition of the given scenario class $x_1,x_2,\ldots,x_8$. The probability value depends on $p(c)$, $p(x_i)$ and $p(x_i|c)$.

This paper selects the same number of positive and negative sample images, in which the positive sample image contains the architectural target, while the negative sample image does not contain the architectural target. Same number of positive and negative samples, prior probability $p(c) = 50\%$. $p(x_i)$ is the prior probability of scene class x_i, Suppose that the number of scene class $x_i$in the positive sample image is n, and the total number of positive samples is m,then the probability is

$p(x_i = "ture") = \left(\frac{n}{m}\right)$. The prior probabilities of other scenario classes are calculated accordingly $p(c),\ p(x_i)$. After determining, the conditional probability p $p(x_i|c)$ determines the value of the entire posterior probability.Suppose that the number of scene class x_i adjacent to the building target in the positive sample image is p, the total number of positive samples ism,then the probability is $p(x_i = "ture"|c = "ture") = \left(\frac{p}{m}\right)$; the number of scene class x_i adjacent to the building target in the negative sample image is q, the total number of negative samples is n, then the probability $p(x_i = "ture"|c = "false") = \left(\frac{q}{n}\right)$. Other posterior probabilities are obtained by the complementarity rule[15].

3.2.2 Target verification based on Bayesian networks

The scene of the aerial image is complex, and the scene class divided by the weak classifier may be wrong. There are two possible cases. One is to classify the architectural target into other scene classes. Another is to classify other scene classes as architectural objectives. In order to accurately extract the architectural target in the image, this paper deals with the architectural target category in the category division as follows:It is assumed that this scene class is the construction target class node of naive Bayes network, and other scene classes are attribute nodes[16]. The adjacent scene classes in the category division are selected, and the corresponding attribute node variables are set to true; Attribute node variables corresponding to other scenario classes are false. Finally, judge whether the posterior probability of the target category is greater than that of the non-target category. If so, the target belongs to the architectural target category. Otherwise, it belongs to the non-architectural object class.

4 Experimental results and analysis

Aerial images were obtained by a 15 m long airship with a load of 50 kg purchased by a university video and image processing laboratory. CPS data of aerial image transmission in the experiment was transmitted bidirectional through wireless link, and a large number of aerial images were obtained as training sample set and test sample set. Of these, 2,000 images were used as training samples and 1,000 images were used as test samples[17].

Firstly, define the performance evaluation criteria of the algorithm. For aerial images, the complex background makes it difficult for the existing algorithm to completely and accurately extract the architectural target. Therefore, this paper takes the proportion of target pixels accurately extracted by the algorithm as the standard. The standard of accurate target extraction is defined as that the algorithm can accurately extract more than 90% of the building target pixels. Then, the proposed algorithm and similar algorithms are used to carry out the building target extraction experiment respectively. A construction target extraction algorithm based on local feature sub-and probability statistics method and the target class extraction in the test image by learning the local structure of the target class This paper uses the construction image sample database for training to extract the construction target in the image. Figure 4 shows the performance curve of the architectural target extraction algorithm[18]. The classification threshold of the algorithm in this paper is the distance of the meta-model. Classification threshold is density function; The classification threshold is the threshold for activation map. As can be seen from Figure 4, under the condition of the same false alarm rate, the recognition rate of the proposed algorithm is higher than that of other algorithms, which further indicates the ability of the algorithm based on Bayesian network modeling the relation constraint between targets and environment to extract architectural targets. This method is based on the local feature sub-method and the probability statistic method, and the target category is extracted by learning the local structure of the target category[19].

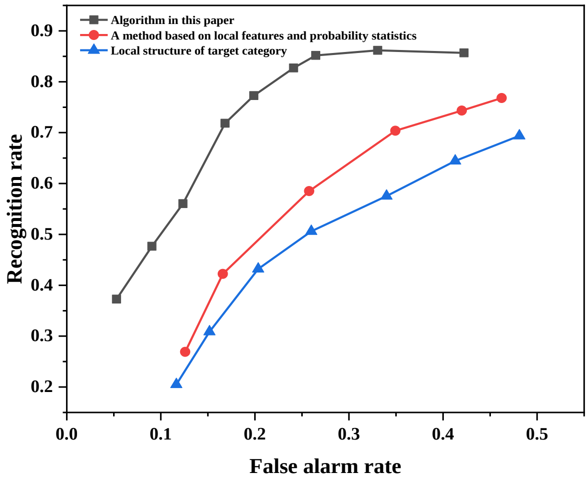

Figure 4. The performance curve of building target extraction algorithm

After analyzing the experimental results, it is also found that a construction object extraction algorithm based on local feature and probability statistics method is difficult to effectively extract the local feature of aerial image, which affects the performance of the algorithm to extract the construction object;There is no modeling environment context for extracting the target category in the test image by learning the local structure of the target category, which leads to the unsatisfactory effect of extracting the building target from the aerial image characterized by complex scenes[20].

In order to better understand the role of classifiers and Bayesian networks in the extraction of architectural targets, the verification steps of the proposed algorithm to delete Bayesian networks were performed, and the experimental results were compared with the original method, as shown in Figure 5. The complete mode is the complete algorithm in this paper, and the deletion verification step is to delete the Bayesian network verification process from the original algorithm. As can be seen from Figure 5, after deleting the steps of Bayesian network verification. The ability of building target extraction of the original algorithm is significantly reduced, which proves that the verification step of Bayes network is indispensable in the whole algorithm[21].

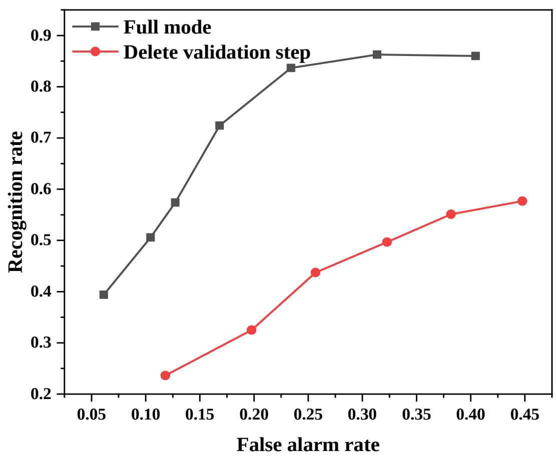

Figure 5. Illustration of the role of Bayesian network verification

In this paper, a computer with a main frequency of 2 GHz CPU and a memory of 1 GB is used to train an image. The average time of training is 2 s, which is mainly spent on the convolution operation with the filter. After the training, the average time of processing a single test image is 0.5s[22-23].

5 Conclusion

The scene of aerial photography image is complex, and the existing methods are difficult to effectively extract the building target. This paper analyzes the dependency between the building target and the adjacent scene class in the aerial photography image. Bayesian net tools are used to model the relationship between environment and architectural targets. Thus, the architectural targets obtained by the weak classifier can be extracted and verified effectively. Experiments on aerial image sets show that compared with similar algorithms. Bayesian networks can effectively remove the architectural target extracted by mistake and improve the recognition rate of the algorithm. In further work, the author will explore the possibility of applying other types of Bayesian nets to the extraction of architectural targets, so as to better represent the constraints of the relationship between targets and environment.

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