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Classification of farmland images based on color features ☆

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ABSTRACT

Farmland images recognition and classification are of great significance in farmland environmental perception. Since the open and unstructured farmland environment has complex scenes, and is easily affected by various factors, furthermore, environmental information is uncertain and hard to predict. Based on hue saturation value (HSV), hue saturation lightness (HSL) and hue saturation intensity (HSI) color space models, taking use of image analysis and classification technology, this paper realizes the classification of farmland images in different environments. On the basis of color space, eight color features of the images are extracted. First, we conducted non equal interval quantification and drew the color feature curves, after that, we selected five eigenvectors which can correctly classify the images. Then, principal component analysis (PCA) was used for dimension reduction. Finally, radial basis function (RBF) neural network was joined for the extraction of images in the same scenes and different ones. The performance of the use of multiple color spaces combining with PCA and RBF shows that the average recognition rates of sunny days and cloudy days in the same scenes and different scenes are 100%, 87.36% and 84.58%, 68.11% respectively. Therefore, this method has higher recognition rate than BP neural network.

1. Introduction

During working in farmland, intelligent agricultural robots should perceive the environmental information based on the sensor firstly and then decide the walking strategy and direction [1]. When perceiving environmental information, it can be easily affected by factors such as light, temperature and humidity which are difficult to predict and describe accurately. The above problems bring great uncertainty when the intelligent agricultural robots perceive environmental information in different levels [2]. In order to achieve higher reliability in perception of farmland images, image classification is necessary. The classification in vision, knowledge reasoning and judgment is quite intelligent. Farmland environmental information can be obtained through farmland images classification, without accurate acquisition of which the farmland resource investigation, crop evaluation and disaster prediction cannot be carried out [3]. Thus, the automation and intelligence can be realized, and at the same time, it will greatly promote the development of traditional agriculture to precision agriculture, making the robots better serve for intelligent decision and management of modern agriculture [3].

Comparing with traditional retrieval technology, content-based image retrieval has the incomparable superiority [4]. Therefore, content-based technology is still the main trends of farmland image classification. Content-based image classifications include visual features (such as shape, color, texture and spatial relationships, etc.), statistical features (such as gray-level histogram, mean, etc.), transforming features (such as Fourier descriptor) and algebraic features. Yu Jun [5] proposed an adaptive hypergraph learning method by linking images and their nearest neighbors to generate hyperedges for transductive image classification, and the method simultaneously learns the labels of unlabeled images and the weights of hyperedges, which show the effectiveness of the approach when compared with representative baselines. Yu Jun [6] utilized visual features and click features simultaneously to obtain the ranking model and designed a novel algorithm to optimize the objective function according to the fast alternating linearization method, and then conduct experiments on a large-scale dataset collected from the Microsoft Bing image search engine, which demonstrated that the proposed learning to rank models based on visual features and user clicks outperforms state-of-the-art algorithms. Qiao Yuliang [7] analyzed causes that directly affected the yield of farmland, and adopted statistical features combined with compound method for farmland classification of different yield, which achieved higher classification accuracy. Texture-based image retrieval is very useful in distinguishing areas with similar colors [8], based on HJ satellite remote sensing

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images, Liu Jun [9] used texture features and spectral characteristics of the images to analyze and identify the flood damaged farmland, and the application of maximum likelihood method improved the classification accuracy to some extent. Since farmland crops can be classified by color, Lv Chaohui [10] took normalized color components as the feature vectors of seedlings, and performed segmentation by BP neural network, which achieved the extraction of various seedling images. The use of color feature for image classification is convenient and effective, and different color models with different parameters provided the basis for image classification and recognition.

With the development of computer vision technology, image classification and recognition have been widely used in varieties of industries [11]. Applications of content-based farmland image classification are mainly in farmland estimation, disaster prediction and crop automatic detection, which realized the intellectualized farmland operation. However, the applications in intelligent agricultural robots are lacking, particularly in farmland environmental perception. In multiple feature extraction, Liu Weifeng [12,13] presented multiview Hessian Regularization (mHR) and multiview Hessian discriminative sparse coding (mHDSC) for image annotation, which conducted extensive experiments on PASCAL VOC'07 dataset and demonstrated the effectiveness; Yu Jun [14] learned a unified low-dimensional subspace to fuse the multiple features, and then applied the approach to natural and indoor scenes classification. Aiming to realize the environmental perception of intelligent agricultural robots, this paper studies color information of the images to extract the feature vectors and classifies the morning, noon and evening images. Moreover, existing methods based on color information use single color space for image classification and recognition will not be enough to meet all the images.

In this context, farmland images as the research data, the main goal is to classify the sunny and cloudy morning, noon and evening images of the same scenes and different ones. Multiple color space models based on image analysis technique is proposed for color feature extraction. Our studies make use of non equal interval quantification to reduce the amount of data. Then feature selection is performed by analyzing the color feature curves and typical eigenvectors are acquired by dimension reduction method. Radial basis function neural network (RBFNN) is used to identify the images quantitatively, which has improved the recognition accuracies. By studying farmland image classification, on the basis of this paper, we can create an effective environmental perception mechanism.

The paper is organized as follows. Section 2 describes the materials and methods including image acquisition and preprocessing, and color feature acquisition process. The performance of this approach is described in Section 3. Section 4 presents the conclusions.

2. Materials and methods

2.1. Image acquisition and preprocessing

The images were captured with Kodak camera in Northwest A&F University North Campus agriculture experimental fields. After shooting span of 30 days, we obtained 458 samples in different time, temperature, light and weather conditions with resolutions of 2576×1932 pixels and saved in RGB (Red, Green and Blue) color space in JPEG format. Through observations, farmland images contain multiple objects such as houses, trees, roads, sky, etc., which can be easily affected by the environment. Due to factors of human, equipment and environment, there exist phenomena of bad shooting, fuzzy and unclear, and long exposure time. Then, 380 images were chosen after selection. The obtained images were divided into two categories according to the scenes. One is images of the same scenes (including only green plants and soil) of 197, and another is different scenes (including green plants, soil, road, sky and houses, etc.) of 183.

The images were acquired under varying light, different environments (sunny and cloudy, front lighting and back lighting) and different time of morning, noon and evening. In the experiment, artificial classification was adopted. Four students with quite image processing foundation were chosen to classify the collected 380 images according to hue, saturation and intensity of the images, and the average values were regarded as the final research data. The artificial classification results are shown in Table 1. As shown in Fig. 1 is the types of farmland images.

The following figures are the captured images. Fig. 2 shows the same scenes of sunny and cloudy conditions. Fig. 3 shows the different scenes of sunny and cloudy conditions.

Fig. 4 shows the classification and recognition process of farmland images based on color features. After image acquisition, color features were extracted in the corresponding color spaces, and then non equal interval quantification was conducted. By drawing color feature curves to filter the feature vectors, and using PCA combined with RBF to classify images, finally assessed the classification results.

When images were acquired, stored, processed and transmitted, large noises would exist because of electrical system and outside interference. It would bring difficulties for subsequent image processing, and then filtering pretreatment is necessary for real-time acquisition images. By experimental comparison, we found that the effects of the original images with the processed ones using different filters were not obvious, and it also caused great losses. The farmland images, as the research object, were acquired in different time, which mainly related to the color features. Some works have taken local features of the images for segmentation, but in this paper the classification is related to the global features. Hence, filtering pretreatment and segmentation is unnecessary after analysis.

2.2. Color feature extraction and selection

2.2.1. Color space selection

Color feature is one of the important indicators of farmland images, which can reflect the image information obtained at different times. Color feature has the characteristics of insensitive with the changes of size and rotation of images [15]. This paper aims to classify the morning, noon and evening farmland images, and the images themselves have obvious color features. Based on this understanding, we proposed a method using color features to classify the farmland images [16]. Then how to select the appropriate color feature will determine the accuracy of the recognition algorithm, thus choosing the right color feature vectors is the most important issue. In order to get the right color feature vectors, we need to choose the appropriate color space.

RGB is the most commonly used color space model, because the majority of digital images are described in this model. But the structure of RGB space does not conform to human subjective judgment of color similarity. HSV, HSI, and HSL have better visual

Table 1
The artificial classification results of farmland images.

Image type	Environment	Morning	Noon	Evening	Total
The same scenes	Sunny	47	49	47	197
	Cloudy	18	17	19	
The different scenes	Sunny	46	35	43	183
	Cloudy	18	20	21	