Expert Systems with Applications 42 (2015) 5047–5055

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A novel texture feature based multiple classifier technique for roadside vegetation classification

Sujan Chowdhury [a,*], Brijesh Verma [a], David Stockwell [b]

[a] Central Queensland University, Australia
[b] Queensland Transport and Main Roads, Australia

ARTICLE INFO

Article history:
Available online 3 March 2015

Keywords:
Feature extraction
Support vector machine
k-Nearest Neighbor
Neural network
Hybrid technique

ABSTRACT

This paper presents a novel texture feature based multiple classifier technique and applies it to roadside vegetation classification. It is well-known that automation of roadside vegetation classification is one of the important issues emerging strongly in improving the fire risk and road safety. Hence, the application presented in this paper is significantly important for identifying fire risks and road safety. The images collected from outdoor environments such as roadside, are affected for a high variability of illumination conditions because of different weather conditions. This paper proposes a novel texture feature based robust expert system for vegetation identification. It consists of five steps, namely image pre-processing, feature extraction, training with multiple classifiers, classification, validation and statistical analysis. In the initial stage, Co-occurrence of Binary Pattern (CBP) technique is applied in order to obtain the texture feature relevant to vegetation in the roadside images. In the training and classification stages, three classifiers have been fused to combine the multiple decisions. The first classifier is based on Support Vector Machine, the second classifier is based on feed forward back-propagation neural network (FF-BPNN) and the third classifier is based on -Nearest Neighbor (*k*-NN). The proposed technique has been applied and evaluated on two types of vegetation images i.e. dense and sparse grasses. The classification accuracy with a success of 92.72% has been obtained using 5-fold cross validation approach. An (Analysis of Variance) test has also been conducted to show the statistical significance of results.

1. Introduction

Vegetation classification is a significant area of research as it has many applications such as identification of trees, grasses, crops, weeds, and vegetables. This research mainly focuses on roadside vegetation for fire risk area identification. The most important advantage of roadside vegetation classification is that it helps identifying various types of grasses and trees which can prevent roadside fires and save property and lives. In Australia, there is a huge loss of infrastructure and human lives due to frequent fire. The current techniques on fire risk area identification mainly focus on satellite images which are inefficient in identification and prediction of roadside fires. Hence there is a need for new techniques using roadside video images for identification of the fire risk. A pre-requisite for vegetation classification is the knowledge about different vegetation types on the roadside. Roadside contains different types of grasses, trees, shrubs and weeds. We initially focus on dense and sparse grass classification because dense grass is sensitive for high fire risk compare to sparse grasses.

Designing and implementing automatic image classification algorithms have been an important research field for decades. There are many existing approaches for solving classification problem such as *k*-Nearest Neighbour (*k*-NN) (Cho, Conners, & Araman, 1991), Adaptive Boosting (AdaBoost) (Liu, 2010), Artificial Neural Networks (ANNs) (Petrová, Moravec, Slavıková, Mudrová, & Procházka, 2012), Support Vector Machines (SVMs) (Yang, Wang, Wang, & Zhang, 2012) and wavelet based techniques (Rehman, Gao, Wang, & Wang, 2012).

In recent years, the combination of multiple classifiers (Hai & Thuy, 2012) and fusion of classifiers (Kang & Park, 2009) rather than traditional use of a single classifier, have received much more attention due to its effectiveness in classification problems (Wong & Hsu, 2006).

This paper proposes a new feature extraction technique suitable for vegetation classification combined with three different types of classifiers such as neural network, Support Vector Machine and *k*-Nearest Neighbour. Three diverse classifiers are specifically selected to improve the diversity which will improve the accuracy.

* Corresponding author. Tel.: +61 0426937599.
E-mail addresses: s.chowdhury2@cqu.edu.au (S. Chowdhury), b.verma@cqu.edu.au (B. Verma), David.R.Stockwell@tmr.qld.gov.au (D. Stockwell).

http://dx.doi.org/10.1016/j.eswa.2015.02.047
0957-4174/

The strength of the proposed method is new feature extraction and incorporation of the idea of multiple classifiers with a majority voting. The major weakness of the proposed method lies in the fact that, it combines multiple classifiers so it will require a lot of time to train the multiple classifiers with feature vectors.

The paper is organized as follows: a short description of relevant research work is presented in Section 2. Proposed feature extraction and classification technique is presented in Section 3. Section 4 contains experimental results and analysis. Section 5 presents the conclusions and future research directions.

2. Literature review

Image based multiple object classification has given rise to strong interest in computer vision due to its numerous applications. Hence, roadside object classifications have been studied extensively. The prospect of automating the process is thus attractive and has inspired much research on identifying every object on roadside. However, the current empirical research cannot guarantee any form of optimality in terms of proper classification and accuracy. Initially, we start with the grass object which is one of the major reasons for roadside fire in Australia. A comprehensive literature review on feature extraction and classification techniques has been conducted. The advantages and disadvantages are identified and presented. It is clear that the feature extraction, feature selection and implementation of a suitable classification techniques are key issues for a successful vegetation identification (Kamavisdar, Saluja, & Agrawal, 2013). In Cingolani, Renison, Zak, and Cabido (2004), the key problems for vegetation classifications have been identified.

Research in the field of weed classification started with Tang, Tian, Steward, and Reid (1999), who performed texture based weed classification using GW (Gabor wavelet) to classify images into broadleaf and grass categories. Although it can classify effectively, a serious drawback of this method was that sample images were limited to 40 images with 20 samples for each class. Another drawback with the method was the processing time as each weed image needs to perform four frequency levels. An active shape model for weed classification based on the 19 most important weed species in Danish agricultural field has been introduced by Søgaard (2005) and listed accuracy that ranged from 65% to 90%. Another interesting technique for real time weeds control system for oil palm plantation was proposed by Ghazali, Razali, Mustafa, and Hussain (2008) and listed 80% accuracy by using a combination of grey-level co-occurrence matrix (GLCM), Fast Fourier Transform (FFT), and Scale Invariant Feature Transform (SIFT) features. Recently Rumpf et al. (2012) adopted approaches based on SVM decision-making for weed classification showed promising results. Mustapha and Mustafa (2005) developed an algorithm to extract texture based features based on GW to categorize broad and narrow leaf weeds, which achieved an accuracy 88.17%.

Another class of weed classification technique proposed by Ishak, Hussain, and Mustafa (2009) which utilizes the combination of a Gabor wavelet (GW) and Gradient Field of Distribution (GFD) to extract a new set of feature vector. In their work, an Artificial Neural Network (ANN) has been applied for classification purpose. A total of 400 images of 200 grasses and 200 broadleaf weeds with different lighting conditions were used to test the effectiveness and listed accuracy was 93.75%. In Tellaeche, Pajares, Burgos-Artizzu, and Ribeiro (2011), a new approach for detecting a special kind of weeds: *Avena sterilis* has been proposed. The segmentation done in their approach was based on binarization and morphological opening and classification carried out through the SVM framework. In terms of memory and computation power their approach shows promising performance compared to previous works. A similar type of research work based on erosion and dilation segmentation algorithm for weed recognition has been described in Siddiqi, Ahmad, and Sulaiman (2009b). The algorithm was applied on 240 images and results showed over 89% accuracy on broad and narrow images. The problem with the proposed classifier was that the lighting conditions, wind and other natural environment parameters greatly degraded the performance of the proposed classifier. Similar kind of work based on edge link detector has been introduced in Siddiqi, Ahmad, and Sulaiman (2009a). Additional works by Ishak et al. enhanced the study of weed classification by introducing several feature detection and classification technique (Juraiza Ishak, Mokri, Mustafa, & Hussain, 2007; Juraiza Ishak, Mustafa, & Hussain, 2008; Juraiza Ishak, Mustafa, Tahir, & Hussain, 2008).

More recently, an automated machine vision system that can distinguish crops and weeds from digital images is presented in Ahmed, Al-Mamun, Bari, Hossain, and Kwan (2012). In their approach, they analyzed 14 features to find out the optimal combination of features that can characterize weeds and crops. They achieved above 97% accuracy over a set of 224 test images. They used SVM for the classification.

An statistical weed classifier approach has been presented in Ahmad, Muhamin Naeem, Islam, and Bin Abdullah (2007). This approach analyzed 140 sample images to find out the variance of each image and proposed a threshold value. If the value of the target image is above the threshold then it classifies it as broad otherwise narrow and achieved 97% classification accuracy.

A very few research works has been found for detecting weeds in lawn. In Watchareeruetai, Takeuchi, Matsumoto, Kudo, and Ohnishi (2006), an approach is presented for detecting weeds in lawn using Bayes classifier and morphology operations. The accuracies between 77.71% and 91.11% were achieved. Li (Li & Zhu, 2010; Li & Chen, 2010) presented shape features and multi feature fusion using Ant Colony Optimization algorithm and Dempster–Shafer's Theory.

An automated weed classification method using Local Binary Operator (LBP) indicating the potentiality of the proposed method in classifying weed images with high accuracy and computational efficiency is introduced in Ahmed, Bari, Shihavuddin, Al-Mamun, and Kwan (2011). The limitation of the proposed work was that it couldn't separate or categorize mix weed images.

Moreover, Guerrero et al. (2013) have developed a strategy based on images acquired from a vision system for crop row identification. According to their method, crop lines are identified by intrinsic and extrinsic parameters along with their perspective projections. The limitation of their proposed method is that it will not work in complex scenario where great number of weed patches invades the intra row spacing. The reason is that, they explore in the horizontal direction and they consider that beyond the horizontal line all are weed. Another application on crop field proposed by Romeo et al. (2013) for greenness identification has been presented. The main finding of this paper is incorporating the idea of fuzzy clustering strategy for adjusting the threshold which was dynamic. The proposed work performs well in green vegetation. But it will not be applicable on grass region identification as in real scenario grasses are not always green. We see various kind of grass with various shapes and colors. Most recent work for crop row identification (Jiang, Wang, & Liu, 2015) is based on multi-ROI. The method uses estimation of center points of crop rows based on multi-ROIs and it shows superior performance over Hough transform method. However, this approach was based on the assumption that all crops and weed should be green, and this assumption will be invalid in reality.

Methods based on visible spectrum have been used successfully for detection of roadside vegetation. For example, some researchers (Harbas & Subasic, 2014a) used color and texture features on roadside images to detect the vegetation. However, the method