WEED CLASSIFICATION USING GENETIC ALGORITHM OPTIMISED CLASSIFIERS

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ABSTRACT

Automated spot weeding with an efficient weed classification can increase production in crops and reduce herbicide usage. A proposed strategy of applying excessive feature sets followed by feature selection was applied on development of the classifiers to eliminate the non-discriminating features. Artificial Neural Network (ANN) and Support Vector Machines (SVM) were applied in the classification using a combination of image derived features. Optimising the classifier involves a tedious selection of subsets and parameters which can be considered a solution searching problem. Optimising the classifier parameters can be solved using heuristic methods such as Genetic Algorithm since it is a non – convex optimisation problem. In ANN structures, the features subset (input numbers) and hidden neuron layer are configurable while for SVM, the hyper parameter and the feature subset are configurable. In order to optimise the structures, feature subset and parameters, two optimisation approach were considered. These two optimisation approach include using backward Sequential Feature Selection (SFS) and Genetic Algorithm (GA) approach. GA requires a careful design of chromosome and fitness function in representing the structure, parameters and feature sets. In the fitness function for SVM optimisation, the fitness score is weighted between feature reduction term and fitness evaluation term of the candidate solution. For the SVMs optimised with GA, it was observed that all the GA configurations yielded better results (both on validation/test sets) as compared to SFS optimised counterpart. The results suggest that optimisation fitness function for SVM requires a simultaneous selection of feature subset /hyper parameters and a small value of weightage (between 0% to 20%) of the total fitness score should be allocated from the feature reduction term to avoid over fitting to training sets. As for the ANN optimisation using GA, fitness function (which includes the error reduction term, feature reduction term and neuron reduction term) showed lesser generalization with independent test sets in comparison with the SFS optimisation approach. The ANN configuration with SFS feature selection gave best results on validation error therefore showing better subset selection using SFS algorithm as compared to GA selection.

ABSTRAK

PENGUNAAN ALGORITMA GENETIK UNTUK MENGOPTIMUMKAN KLASIFIKASI DATA BAGI TUJUAN KLASIFIKASI RUMPUT-RUMPAI

Penyemburan racun rumput-rumpai secara automatik boleh dilakukan dengan sistem klasifikasi yang cekap bagi membolehkan peningkatan dalam produktiviti dan penjimatan dalam pengunaan racun rumput-rumpai. Suatu strategi yang digunakan untuk membentuk sistem klasifikasi adalah dengan memperkenalkan sekumpulan ciri yang banyak serta menggunakan teknik penyaringan untuk memilih ciri–ciri. Jaringan Neural (ANN) dan Mesin Vektor Sokongan (SVM) digunakan untuk pengelompokan dengan menggunakan ciri-ciri dari teknik pengimejan. Walau bagaimanpun, pengoptimuman pengklasifikasi dari segi struktur dan subset ciri merupakan suatu tugas yang mencabar yang boleh diselesaikan dengan kaedah heuristik seperti Algoritma Genetik (GA) memandangkan ia adalah suatu masalah bukan convex. Dua kaedah digunakan untuk mengoptimumkan pengklasifikasian yang disebutkan iatu i) cara pemilihan ciri secara berurutan (SFS) dan ii) berdasarkan kaedah Algoritma Genetik (GA). Kaedah GA memerlukan konfigurasi fungsi kemantapan yang sesuai untuk berfungsi. Fungsi kemantapan adalah persamaan yang digunakan untuk menilai suatu konfigurasi dan ia terdiri daripada beberapa bahagian. Untuk fungsi kemantapan untuk SVM, ia terdiri daripada 2 bahagian terma (sebahagian untuk mengurangkan ciri dan sebahagian lagi untuk menilai tahap kemantapan). Hasil kajian menunjukkan bahawa bahagian untuk mengurangkan ciri perlu diberi 'nilai kepentingan' yang kurang (diantara 0%-20%) daripada skor kemantapan untuk mengelakkan situasi terlebih padan. Untuk optimisasi ANN menggunakan GA, fungsi kemantapan yang terdiri daripada 3 bahagian (sebahagian untuk mengurangkan maklumat ciri, sebahagian untuk menilai kemantapan konfigurasi dan sebahagian untuk mengurangkan bilangan neuron dalam lapisan tersembunyi), perubahan nilai kepentingan antara tiga bahagian kurang mengubah generalisasi pengklasifikasian berbanding dengan optimisasi SFS. Untuk ANN adalah didapati bahawa konfigurasi SFS memperoleh keputusan yang lebih baik berbanding semua konfigurasi GA. Ini menunjukkan keadah SFS adalah lebih sesuai dari GA untuk ANN dari segi pengoptimuman.

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LIST OF ABBREVIATIONS

ACO	-	Ant Colony Optimization
AGECO	-	EPPO code for Agerantum Conyzoides
ANN	-	Artificial Neural Network
AUC	-	Area Under the Curve
BOIRE	-	EPPO code for Borreris Repens
BRJSU	-	EPPO code for Brassica Juncea
EPPO	-	Plant codes developed by European and Mediteranean Plant Protection Organization (Previously Known as Bayer Code)
ExG	-	Excessive Green Index
ExR	-	Excessive Red
FAR	-	False Acceptance Rate
FFT	-	Fast Fourier Transform
FP	-	False Positive
FPR	-	False Positive Rate
FN	-	False Negative
FRR	-	False Rejection Rate
GA	-	Genetic Algorithm
GLCM	-	Greys Level Co-occurrence Matrix
GPS	-	Global Positioning System
GS	-	Grid Search
Hue	-	Hue colour space
HSV	-	Hue , saturation Value colorspace
Max	-	Maximum value for feature normalization
Min	-	Minimum value for feature normalization
MONO	-	Abbreviation for Monocotyledon group of weeds
NDI	-	Normalized Difference Index
NDVI	-	Normalized Difference Vegetation Index
NIR	-	Reflectance within infrared band
NGRDI	-	Normalized Green-Red Difference Index
PCA	-	Principal Component Analaysis
RED	-	Reflectance within the visible red band

RGB	-	Red, Green, Blue
RMSE	-	Root mean Squared Error
ROC	-	Receiver Operating Characteristic
SE	-	Simbiotic Evolution
SFS	-	Sequential Feature Selection
SVM	-	Support Vector Machine
TN	-	True Negative
TNR	-	True Negative Rate
TP	-	True Positive
TPR	-	True Positive Rate

LIST OF SYMBOLS

A_n	-	First fourier elliptical coefficient for nth harmonic
A_{sig}	-	Parameter for sigmoid curve fitting of SVM output
B	-	Normalized Blue pixel value in RGB colour space
b	-	Blue pixel value in RGB colour space
B_n	-	Second fourier elliptical coefficient for nth harmonic
B_{sig}	-	Parameter for sigmoid curve fitting of SVM output
C	-	Soft Hand Over Constraint for SVM
C_n	-	Third fourier elliptical coefficient for nth harmonic
D_n	-	Fourth fourier elliptical coefficient for nth harmonic
e	-	Error in classifier output
E_{max}	-	Maximum value for each feature in feature scalling
E_{min}	-	Minimum value for each feature in feature scalling
F	-	Distance from each focus to the center in images
G	-	Normalized Green pixel value in RGB colour space
g	-	Green pixel value in RGB colour space
H	-	Hue pixel value in HSV colour space
h	-	Number of hidden neurons
L	-	Hidden layers of processing element for Neural Network
m	-	Central Moment
m	-	Number of training samples
M1	-	First Hu Moment Invariants
M2	-	Second Hu Moment Invariants
M3	-	Third Hu Moment Invariants
M4	-	Fourth Hu Moment Invariants
M5	-	Fifth Hu Moment Invariants
M6	-	Sixth Hu Moment Invariants
M7	-	Seventh Hu Moment Invariants
n	-	Number of samples in validation
N	-	Total number of EF harmonics
p	-	Grayscale Pixel value

R - Normalized Red pixel value in RGB colour space

r - Red pixel value in RGB colour space

s - Skewness

t - Step required to transverse one pixel along the closed contour

T - Basic period of the chain code

w - Distance between the target and outlier support vectors

x_N - Projections of the closed contour in the x axis

y_N - Projections of the closed contour in the y axis

ξ_i - Slack Variable

σ - Sigma, RBF kernel for SVM

η - Normalized central moment

% - Percentage

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CHAPTER 1

INTRODUCTION

1.1 Overview

In recent developments, the advancement of technology in imaging has benefitted various industries such as engineering, internet development, and security. Subsequently, researchers are exploring the concept of imaging technology in agriculture, mainly in discriminating between crops and weeds or between the categories of weeds. This dissertation explores the possibility of applying a species based vegetation classification at a window of approximately 1-4 weeks post emergence. Imaging technology applied in crop/weed recognition can lead to advancement in technology such as automated spot weeding. Spot weeding technology has the potential to increase production in crops while reducing herbicide usage (McCarthy *et al.*, 2010). Researches conducted include various types of crop/weed classification distinguishing the broad category of weeds (Ahmed *et al.*, 2012) and species classification (Weis, 2010). The decision to spray a certain amount of herbicide can be mechanized by applying computer vision system and classification algorithms.

The significant challenges faced in such image based weed classification are the classifier optimization which includes parameter fine tuning and selection of discriminant features to train the classifier. This process is referred to as classifier optimization. In order to optimize such classifiers, various strategies were employed, which involves Grid Search, Sequential Feature Search (SFS) and RELIEF Feature weighting. Although Support Vector Machines (SVM) were often used to develop the classifier for the weed-crop discrimination or the individual weed species, optimizing SVM is known to be a complex task as it requires the selection of hyperparamters and feature subset (Huang and Wang, 2006). Apart from the fine tuning and optimization of the classifier, the selection of specific type of features such as shape and color features is also imperative to ensure optimal classification success.

In order to achieve a sufficient machine autonomy in executing task of automated weed spraying, machine vision is required to identify in the batch of vegetation, if there exist a specified crop, a specified type of weed and more specifically the number of weed counts. This can be achieved by applying image processing technologies with the application of artificial intelligence, such as an Artificial Neural Network (ANN) and Support Vector Machines (SVM). However, the image of vegetation that was investigated needs to be non-occluded from one another. Hence, such methods of analyzing vegetation from shape features are more suitable for early stage of vegetation. Although this limits the application to analysis on certain stages of crops development and types of crops, this is still useful as vegetation are mostly separable in the early stages of development.

Based on the current developments in vegetation recognition , this thesis will attempt to apply Genetic Algorithm (GA) to optimize the selected types of classifiers to recognize individual species of weed and crops using a combination of shape and color features. The advantage of using Genetic Algorithm is that parameters selection and features selection can be done simultaneously.

1.2 Problem Statement

The application of Machine Learning classifiers namely Artificial Neural Network (ANN) and Support Vector Machines (SVM) have been applied in various image classification works but optimization of the classifiers remain an open ended optimization. Various feature selection and parameter selection algorithms were proposed for optimization. However every algorithm has its weakness and the overall best solution (combination of feature subset and parameters) could be harder to discover with more feature subsets in the selection pool and the wide range of parameters. Heuristic approach to optimization such as Genetic Algorithm enables the discovery of such combination of subsets/parameters by a process of 'biological evolutionary' inspired mechanism such as selection/crossover and mutation. However, such heuristic methods are highly dependent on various elements such as fitness function and encoding the classifier parameters into chromosome which can be further refined based on existing literature.

1.3 Research Objectives

Genetic Algorithm provides a heuristic approach to solution search in a vast search space. This feature in GA is a suitable candidate for optimization to select classifier structure and feature subsets. The objectives of the research are:

1) To investigate the feasibility of using Genetic Algorithm to optimize the structure and select features for Back Propagation Artificial Neural Network (ANN).

2) To investigate the feasibility of using Genetic Algorithm to optimize the hyper parameters and select features for Support Vector Machines (SVM).

3) To investigate the feasibility of using Sequential Feature Selection for Support Vector Machines (SVM) and Artificial Neural Network (ANN) for classifying the species of vegetation.

1.4 Research Scope

This thesis will focus on the development of the classification algorithm for non – occluded vegetation images. Most weeds are non-occluded/non overlapping at the stage of 1-4 weeks. The training images are acquired from a fixed distance and setting with controlled lighting, which will be discussed in the following chapter. Only three groups of weeds; Monocotyledon (MONO), Agerantum Conyzoides (AGECO) and Borreris Repens (BOIRE) and one type of crops – Brassica Juncea (BRSJU) were considered as target class and several other classes of weeds considered as outlier class used as image tests for our research work. Weed

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