

# **UNIVERSITI PUTRA MALAYSIA**

PLANT IDENTIFICATION USING COMBINATION OF FUZZY C-MEANS SPATIAL PYRAMID MATCHING, GIST, MULTI-TEXTON HISTOGRAM AND MULTIVIEW DICTIONARY LEARNING

SOODABEH SAFA

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Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfillment of the Requirements for the Degree of Doctor of Philosophy

June 2016

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To my family :

My kind and respectful parents who always supported and encouraged me during this study.



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Doctor of Philosophy

## PLANT IDENTIFICATION USING COMBINATION OF FUZZY C-MEANS SPATIAL PYRAMID MATCHING, GIST, MULTI-TEXTON HISTOGRAM AND MULTIVIEW DICTIONARY LEARNING

By

#### SOODABEH SAFA

#### June 2016

# Chairman:Associate Professor Fatimah Khalid, PhDFaculty:Computer Science and Information Technology

Plants identification has become a significant and incentive research area. It is estimated that about half of the world's plant species are still not identified. Making a detailed knowledge of the identity and geographical distribution of plants is required for an effective agricultural biodiversity. Most of the existing plant identification methods are based on both the global shape features and the intact plant leaves. However, for the non-intact leaves such as the deformed, partial and overlapped leaves that largely exist in practice, the global shape features are not efficient and these methods are not applicable. The dried leave parts and noise can degrade identification results and affect the quality of the extracted features which lead to poor classification results. Furthermore, feature extraction methods based on global features such as shape, color and texture do not lead to accurate identification since they cannot adapt to changing environment. In the real world, leaf images can be simply affected by light, position, and size. To overcome this problem, in recent years, researchers obtained some achievements with combination of invariant local features such as Scale Invariant Feature Transform (SIFT) with global feature of leaf images. Beside that, classic bag of visual words algorithm (BoVW) is based on kmeans clustering and every SIFT feature belongs to one cluster and it leads to decreasing classification results. Moreover with simple concatenating features, classification results are not optimal. It is crucial to integrate these heterogeneous features to create more accurate and robust classification results than using each individual type of features.

This study first starts with some preprocessing phases for images with dried and damaged parts in leaves, that applies on images while finding leaf as region of interest (ROI) with Otsu's method. For next, instead of k-means clustring, Fuzzy c-means clustering is combined with Spatial Pyramid Matching image representation to improve the accuracy of classification results. The Fuzzy c-means clustering improved the accuracy of classification task to 40.53%. In the next phase, the local SIFT descriptor is augmented with two global descriptors. One descriptor contains

texture and color called Multi-Textron Histogram (MTH) and improved classification results by second level of discrimination for leaves with similar color and shape. Second one is gist from global features of leaf images. gist descriptor is based on spatial layout of colors, orientation and principal texture. The combination of gist, MTH and SIFT features increased the performance of image identification and showed 49% accuracy. Moreover, instead of concatenating feature vectors together and send to classifier, sparse coding and dictionary learning methods are used and instead of considering all features as one view (visual feature), K-SVD algorithm that is one of the famous algorithms for sparse representation is optimized and developed to multi-view model. The experimental results prove that the proposed methods has improved accuracy by 53.77% compared to concatenating features and classic K-SVD dictionary learning model as well.



Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

# IDENTIFIKASI TUMBUHAN MENGGUNAKAN KOMBINASI FUZZY C-MEANS SPATIAL PYRAMID MATCHING, GIST, MULTI-TEXTON HISTOGRAM DAN PEMBELAJARAN KAMUS BERBILANG PAPARAN

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Pengenalpastian tumbuh-tumbuhan adalah satu bidang kajian yang penting dan menggalakkan. Di anggarkan sekurang-kurangnya separuh daripada tumbuh-tumbuhan masih belum dikenalpasti. Keperluan pengetahuan yang terperinci berkenaan pengenalpastian dan pembahagian geografi saksama bagi tumbuhan adalah diperlukan untuk biodiversiti pertanian yang efektif. Kebanyakan kaedah sedia ada dalam pengenalpastian tumbuh-tumbuhan adalah berasaskan kepada ciri bentuk yang global dan daun tumbuhan yang utuh. Walaubagaimanapun, untuk daun yang rosak, bertindan dan separa yang banyak tumbuh di dunia, kaedah pembahagian geografi saksama adalah tidak cekap dan tidak boleh dilaksanakan Bahagian-bahagian yang rosak dan bunyi latar belakang hingar boleh merendahkan hasil ciri yang diekstrak dan menjejaskan kualiti ciri pengembangan juga mengakibatkan hasil pengkelasan yang salah. Selain itu, kaedah pengesktrakan ciri yang berasaskan ciri global seperti bentuk, warna dan tekstur tidak menunjukkan pengenalpastian yang tepat. Ini disebabkan kaedah tersebut tidak boleh menyesuaikan diri dengan perubahan persekitaran. Dalam dunia sebenar, imej daun ini mudah terjejas dengan kehadiran cahaya, kedudukan dan size daun tersebut. Untuk menyelesaikan masalah ini, para penyelidik baru ini telah mencapai kejayaan dengan menggabungkan ciri asal yang tidak berubah sebagai contoh Scale Invariant Feature Transform(SIFT) dengan imej daun yang bercirikan global. Selain itu, bag of visual words (BoVW) yang adalah berdasarkan pada kelompok k-means dan setiap ciri SIFT tergolong dalam satu pusat pengelompokan membawa kepada pengurangan hasil pengkelasan. Tambahan pula, dengan mudah, ciri hasil pengkelasan tidak optimum. Hal ini penting untuk menggabungkan ciri berbeza untuk menghasilkan pengkelasan yang lebih tepat dan jitu daripada hanya menggunakan ciri setiap individu.

Kajian ini bermula dengan fasa pra pemprosesan untuk imej dedaun yang telah kering dan rosak disamping mencari dedaun *region-of-interestdengan* menggunakan kaedah *Otsu*. pengelompokan *Fuzzy c-means* digunakan berbanding pengelompokan k-means untuk digabungkan bersama perwakilan imej spatial pyramid matching untuk menambah baik ketepatan hasil klasifikasi. Pengelompokan *Fuzzy c-means* 

menambah baik ketepatan tugasan kelasifikasi sebanyak 40.53%. Dalam fasa seterusnya, penghurai setempat SIFT telah diperkukuhkan dengan dua penghurai global. Salah satunya mengandungi tekstur dan warna yang ditakrifkan sebagai Histogram berbilang Textron ataupun Multi-Textron Histogram (MTH). Ia akan menambahbaik hasil klasifikasi oleh aras kedua diskriminasi bagin dedaun yang mempunyai bentuk dan warna yang sama. Penghurai yang kedua pula adalah gist, diperoleh daripada ciri global imej dedaun tersebut. Ciri gist adalah berasaskan kepada ruang susun atur warna dan orientasinya dan tekstur utama. Ruang yang dikenalpasti dilukis secara jujukan ke arah tekstur utama. Gabungan ciri gist, MTH dan SIFT telah meningkatkan prestasi pengecaman imej dan menunjukkan peratusan kejituan sebanyak 49%. Sebalik daripada penggunaan penggabungan ciri vektor bersama dan menghantarkannya kepada pengklasifikasi, kod jarang dan kaedah pembelajaran kamus telah digunakan. Selain daripada mempertimbangkan semua ciri sebagai satu gambaran, kami telah mengoptimumkan algoritma K-SVD. yang mana ia merupakan salah satu algorithma terkenal untuk perwakilan jarang dan digunakan untuk membangunkan model berbilang paparan. Keputusan eksperimen membuktikan kaedah yang dicadangkan ada penambahbaikan dalam kejituan sebanyak 53.77% berbanding dengan penggabungan ciri dan model pembelajaran kamus K-SVD yang klasik.

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# LIST OF ABBREVIATIONS

ACH	Angle Code Histogram
AC	Accuracy
ACO	Ant Colony Optimization
BoVW	Bag of Visual Words
CCD	Center-Contour Distance
C-SIFT	Colored-SIFT
DFH	Directional Fragment Histogram
DCD	Dominant Color Descriptor
DWT	Discrete Wavelet Transformation
GA	Genetic Algorithm
GLCM	Gray-Level Co-occurrence Matrices
GPS	Global Positioning System
G-SIFT	Geometric-SIFT
K-SVD	K-Singular Value Decomposition
LBP	Local Binary Patterns
МАР	Maximum a Posteriori
MOD	Method of Optimal Directions
MFMC	Max Flow Min Cut graph
МТН	Multi-Texton histogram
РСА	Principal Component Analysis
PSO	Particle Swarm Optimization
PHOG	Pyramid of Histograms of Orientation Gradients
ROI	Region of Interest

ROC	Receiver Operating Characteristic
RMSE	Root Mean Square Error
ScSPM	Sparse coding Spatial Pyramidal Matching
SIFT	Scale Invariant Feature Transform
SURF	Speeded Up Robust Features
SVM	Support Vector Machine



# **CHAPTER 1**

# **INTRODUCTION**

## 1.1 Background

Plant identification has become a major research area in the field of botany in recent years. Plant identification refers to the comparison of an unknown plant with a set of known species to decide the specific specie or genus to which it belongs. A detailed knowledge of the identity and geographical distribution of plants is needed for successful agricultural biodiversity. The identification of medicinal plants has also assumed much importance today.

Traditionally, botany experts trained plants taxonomists in identifying species and their relationships in order to assign taxonomic labels (Berg *et al.*, 2007). Taxonomy is the science of naming, describing, and classifying organisms according to their similarities and difference (Swain, 2012). However, the limitations in terms of skilled experts, financial issues, and training time are considerable in conducting the various processes associated with this field, and an expert on a particular specie or family may not be familiar with others. These are the main reasons for the automation of the specie identification process, and this has been aided by the continuous technological improvements in computers and digital cameras.

## 1.2 Motivation

To establish records and maintaining biodiversity in agriculture, a comprehensive knowledge of the identity and geographical distribution of plants is needed. Speed up the collection and integration of botanical raw observation data is a crucial step towards sustainable development of agriculture and biodiversity conservation. Plant species identification is a complex and complicated process which is difficult even for professionals like botanists, farmers, or wood exploiters. Therefore, a taxonomic gap exists in plant species identification, and one promising solution to tackle it is through content-based visual identification of the plants.

Content-based image classification is an important task in the field of image indexing and retrieval and has helped to overcome the limitation of the text-based methods. All content-based image systems require an appropriate representation of the input data image. A feature is defined as an interesting part of an image and represents the image. Features can be represented globally or locally in which the former uses the whole image while the latter focuses on the selection of several regions or blocks of the image to characterize them.

# **1.3 Problem Statement**

The content-based visual identification system utilizes leaf images for tree species identification. The damaged leaves parts and image noise can degrade identification results and diminish the quality of the extracted features and lead to poor classification results. This is even more crucial when the leaves are segmented from the background. Such noises have a major impact on the exploited features in the identification process (Arora *et al.*, 2012).

In addition, Most of the existing plant identification methods are based on both the global shape features and the intact plant leaves. However, for the non-intact leaves such as the deformed, partial and overlapped leaves that largely exist in practice, the global shape features are not efficient and these methods are not applicable. Furthermore, all leaves in one species are not identically shaped, leaves belonging to the same species in different geographical locations or in different seasons have various colors, and leaf colors of different species may have similarities. These issues create significant difficulties in image identification. In fact, the wide variations in leaf sizes, textures, colors, shapes, positions, and light reflections in the same plant species need extracted features to have enough discriminatory power to distinguish the plant species.

Another problem arises when local features are used for plant species identification. In the bag of visual words models that use k-means clustering on local features such as SIFT, the generated visual words are ambiguous, since in hard clustering (k-means algorithm) every SIFT feature in an image is assigned a single code word and belongs to one cluster (philbin *et al.*, 2008). A visual word can be considered as representative of several similar image patches which leads to the loss of information in the classification task. Further, the spatial pyramid matching method is used to match local features.

Different visual features are heterogeneous and carry different characteristics, therefore their individual importance in the classification is ignored by the simple fusion. The simple concatenation of high-dimensional and heterogeneous visual features in a long vector leads to low accuracy of classification results. It is crucial to integrate these heterogeneous features to create more accurate and robust classification results than using each individual type of features. (Sun *et al.*, 2014, Liu *et al.*, 2007).

# 1.4 Research Objective

- 1) To introduce a method that enhance leaf images by using an hybrid morphological operations and dominant color descriptor (DCD).
- 2) To propose a combination of SIFT descriptor as a local feature, Multitexton histogram descriptor, and gist descriptor to achieve greater precision and recall. MTH and gist descriptors provide a second level of discrimination for leaves with similar shapes and colors.
- 3) To improve the accuracy of classification by modifying Spatial Pyramid Matching image representation with Fuzzy c-means clustering.
- 4) To propose a new multi-view dictionary learning for sparse representation of feature vectors by K-SVD algorithm for reduceddimensional and optimum representation of heterogeneous visual features using a through eliminating redundancies and the analysis of high frequency patterns between feature vectors to achieve a higher classification rate.

# 1.5 Scope

Plant identification tasks can be done by flower, stem, leaf, or other organs of plants. This work proposes an automatic supervised classification models that is restricted to leaf visual content from Pl@ntLeaves dataset containing 6630 leaf scans, 2726 leaf pictures with a white uniform background (referred to as scan-like pictures), and 2216 leaf pictures in natural conditions (taken on the tree). The most important reason for choosing this dataset of images is because they have a wide diversity of image rotation, scale, noise, and luminance. These diversities in plant leaf contain leaf, upper side, and lower side, two images from one leaf, leaf with branch and leafage.

# 1.6 Structure of Thesis Organization

This thesis is organized into seven chapters. In this chapter we introduce the background and motivation of plant identification techniques and classification of plant leaf images. The problem statement, objectives, and contributions are explained in this chapter. Also the plant image database used is introduced in this chapter. Chapter two reviews the literature on plant identification while chapter three explains the methodology used in this research. Chapter four presents preprocessing methods for the plant identification task. Chapters five and six provide a description of the features used with a new descriptor and a proposed multi view K-SVD dictionary learning for plant identification, respectively. These two chapters also provide a comparison and discussion with other works. Finally, chapter seven presents an overall summary and the conclusion of the thesis and introduces recommendations for future research ideas.



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## LIST OF PUBLICATIONS

Safa, S, Khalid, F, Abdullah, L, Azman, A. (2014). 'Multi View K-SVD Dictionary Learning for plant Identification'. *International Journal of Applied Engineering Research (IJAER)*, 10(6), 14953-14957.

# Submitted paper

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### **Accepted Chapter Book**

Safa, S, Khalid, F, Abdullah, L., Azman, A. (2016). *Plant species identification* based on spatial pyramid image representation and fuzzy c-means clustering, Research India publication.

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Safa, S, Khalid, F, Abdullah, L., Azman, A. (2014). A new Bag of Visual words model using Fuzzy c-means Clustering for Plant Classification. 3rd International Conference on Interactive Digital Media.



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