CLASSIFICATION OF GROUND PENETRATING RADAR IMAGES USING HISTOGRAM OF ORIENTED GRADIENTS AND SUPPORT VECTOR MACHINE

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Master of Engineering (Electrical)

Faculty of Electrical Engineering
Universiti Teknologi Malaysia

JANUARY 2016

To my supervisor, family and friends for taking care of me during my studies

ACKNOWLEDGEMENT

Firstly, I would like to express my sincere gratitude to my advisor Dr. Musa Mohd Mokji for his continuous support of my research work, for his patience in correcting my writing and his sharing of immense knowledge especially in his field of expertise. This thesis would not have been possible without his guidance and persistent help. I would like to thank Dr. Syed Abd. Rahman, Dr. Usman and Dr. Zaid from CVViP research group, for their insightful comments and suggestions on my work.

My sincere thanks also goes to my friends and fellow members of the research lab, particularly Jeevan, Siew Ching and Say Voon, who had been great companions throughout the course of my research.

Last but not the least, I would like to thank my family members, especially my father and mother, for their unwavering moral, spiritual and financial support in my life.

Kher Li

ABSTRACT

Ground Penetrating Radar or generally known as GPR is an important and popular method in subsurface imaging due to its non-destructive nature. GPR data interpretation requires expertise from human operator which is a time consuming and costly task as the data amount can be enormously large. In this study, a framework that pairs up Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM) is proposed to detect subsurface targets in GPR data automatically. HOG feature descriptors are extracted by characterizing the target appearance and shape from hyperbolic signatures that appear in GPR images. Extracted feature descriptors are then sent to SVM for classification. Contribution of this research includes designing the best SVM classifier model by considering the best kernel and its optimized parameter settings. The proposed algorithm is compared to the most commonly used approach (Hough Transform) to evaluate its performance. In this research, the data sets consist of images that are collected using different GPR system models. Despite having limited sample images for training, the proposed method managed to detect hyperbolic signatures in GPR images. SVM classifier with probabilistic estimation model shows better performance for its flexibility in decision making using confidence level while SVM without probabilistic estimation model shows high false positive rate of more than 50%. Moreover, results from the experiments have also shown that the proposed method is able to produce higher detection rate with a much lower false positive rate than that of Hough Transform. The accuracy of target detection using the proposed method records an average detection rate of 89.40% and 7.38% of false positive rate for all the data sets used in this research. Apart from the improved performance, the proposed method also offers flexibility to control detection tasks through an adjustment on the probabilistic estimation model.

ABSTRAK

Radar Pengimbas Tanah atau lebih umum dikenali sebagai GPR ialah suatu peranti yang penting dan popular dalam aplikasi pengimejan di atas permukaan tanah kerana ia tidak merosakkan tanah. Interpretasi data GPR memerlukan kepakaran daripada pengendali yang berpengalaman dan ini merupakan suatu tugas yang memerlukan masa and kos yang tinggi, kerana jumlah data GPR yang dikumpul boleh menjadi amat besar. Dalam kajian ini, satu rangka kerja yang berasaskan Histogram Berorientasikan Kecerunan (HOG) dan Mesin Vektor Sokongan (SVM) dibina bagi tujuan pengesanan dalam data GPR secara automatik. Diskriptor HOG diekstrak dengan mencirikan hiperbola dalam imej GPR dari segi rupa dan bentuk. Ciri diskriptor kemudian dihantar kepada SVM untuk pengelasan. Sumbangan kajian ini termasuk mereka model pengelas SVM dengan menentukan kernel yang terbaik dan tetapan parameter-parameter yang paling optimum. Bagi tujuan penilaian prestasi, algoritma yang dicadangkan telah dibandingkan dengan kaedah popular yang biasa digunakan dalam aplikasi ini, iaitu Jelmaan Hough. Dalam kajian ini, data set yang diguna merangkumi imej-imej yang dikumpul dari model sistem GPR yang berbeza. Meskipun imej sampel yang digunakan untuk pelatihan adalah terhad, kaedah yang dicadangkan berupaya mengesan hiperbola dalam imej-imej GPR. Pengelas SVM dengan model anggaran kebarangkalian memaparkan prestasi yang lebih baik kerana kebolehlenturan dalam pengelasan yang berasaskan aras keyakinan, manakala SVM tanpa model anggaran kebarangkalian menunjukkan kadar positif palsu yang melebihi 50%. Di samping itu, keputusan eksperimen juga menunjukkan kaedah yang dicadangkan mencapai ketepatan pengesanan yang lebih tinggi dan kadar positif palsu yang lebih rendah daripada Jelmaan Hough. Purata ketepatan pengesanan yang dicatatkan oleh kaedah yang dicadangkan adalah sebanyak 89.40% dengan kadar positif palsu serendah 7.38% bagi semua set data yang digunakan dalam eksperimen ini. Selain daripada peningkatan dalam prestasi, kaedah yang dicadangkan juga menawarkan kebolehlenturan dalam mengawal tugas pengesanan melalui penyelarasan dalam model anggaran kebarangkalian.

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LIST OF ABBREVIATIONS

BoW	–	Bag of Visual Words
DMM	–	Depth Motion Map
EHD	–	Edge Histogram Descriptors
EM	–	Electromagnetic
GPR	–	Ground Penetrating Radar
HADA	–	Hyperbolas Automatic Detection Algorithm
HMM	–	Hidden Markov Model
HOG	–	Histogram of Oriented Gradients
HT	–	Hough Transform
KKT	–	Karush-Kuhn-Tucker
MSE	–	Mean Square Error
PD	–	Probability of Detection
PLS-DA	–	Partial Least Squares Discriminant Analysis
PSNR	–	Peak signal-to-noise ratio
RBF	–	Radial Basis Function
RDP	–	Relative Dielectric Permittivity
ROI	–	Region of Interest
SNR	–	Signal-to-Noise Ratio
SVM	–	Support Vector Machine

LIST OF SYMBOLS

d	–	position of radar
t	–	two-way travelling time of signal
v	–	propagation velocity of signal
t_0	–	shortest two-way travelling time of signal
a	–	distance between center and the vertices
b	–	measure of hyperbola width
D	–	burial depth
(h, z)	–	peak position of hyperbola / parabola
c_v	–	velocity of light in vacuum
ε_r	–	dielectric constant of the medium
$\hat{I}(i, j)$	–	GPR image before background removal
$I(i, j)$	–	GPR image after background removal
M	–	height of image
N	–	width of image
$G(x, y)$	–	ROI image
M_X	–	gradient mask in x-direction
M_Y	–	gradient mask in y-direction
$\|G(x, y)\|$	–	magnitude of ROI
$\theta(x, y)$	–	orientation of ROI
c	–	column number
r	–	row number
m	–	size of cell in pixel
$\mathbf{v}$	–	block descriptor after block normalization
F	–	number of features
$\mathbf{d}$	–	HOG descriptor vector
s	–	image scale
P_s	–	image scale start point
P_i	–	image scale interval

P_e	–	image scale end point
p	–	distance of vertex from focus
$E(x, y)$	–	binary image with extracted edges
HT	–	accumulator array of Hough Transform
T	–	threshold for accumulator array of Hough
A	–	constant that defines size of parabola
$\mathbf{w}$	–	decision hyperplane normal vector
$\boldsymbol{x_i}$	–	i^{th} data point
$\boldsymbol{\lambda}$	–	support vectors
$f(x_i)$	–	decision function of SVM
$\boldsymbol{y}$	–	class of data inputs
X	–	matrix of data inputs
C	–	parameter C in kernel function
γ	–	parameter γ in kernel function
$K(\boldsymbol{x_i}, \boldsymbol{x_j})$	–	kernel function
$\hat{f}$	–	decision value
k_c	–	number of classes
p_i	–	class probabilities
$\boldsymbol{r}$	–	estimate pairwise class probabilities
n	–	degree of polynomial kernel function
A_r	–	Tolerance rate across probability estimation in SVM

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

This chapter covers a brief introduction to Ground Penetrating Radar (GPR) system in section 1.1 and the rest of the sections are clarifying the framework of doing this research.

1.1 Background

At the ancient times, a shovel could be the best tool we may find in subsurface investigation. As the technology evolves, the world has gone so much digitized and easier with the utilities like electricity, water and gas, telephone and internet services. Most of these utilities pipes are buried under the ground for safety purposes, space saving and also better vision of city landscaping.

For that reason, blind excavation is no longer a good option when it comes to maintain the buried utilities. The work of digging might destruct the structures of utilities and it makes an extremely exhausting work just for the inspection. Thus, we need a geophysical method that can gather a great deal of information about the subsurface and preserving them at the same time. For pipes and cables that are made from metal, metal detector is commonly used in the early stage of site investigation. Somehow, the equipment could not perform when it comes to detect non-metallic utilities. Materials like fiber, plastic or concrete need a better radiolocation equipment as they are rather fragile and hence the need to be handled with care.

Ground Penetrating Radar (GPR) is one of the most popular geophysical approach to locate and detect subsurface anomalies. It is also a non-invasive equipment with the purposes of investigating the location and depth of buried targets. GPR can be used on different types of medium, including soil, concrete, pavements, fresh water and wood. Using high frequency range (typically from 1 to 1000MHz) [2] of radio waves, GPR transmits electromagnetic pulses into the ground. When the pulse hits an interface between materials of different dielectric constants, it will be reflected and then picked up by the receiver antenna. The larger the difference in the dielectric properties, the more wave energy will be reflected back to the antenna.

The data collected are in fact pseudo images of the surveyed ground by recording the two-way travel time of the pulses. Target reflections are in hyperbolic patterns where the features and properties of the curves can be of use in computing significant information like depth or dimension of the corresponding target.

The application of GPR covers a number of fields, including earth sciences, civil engineering, quarrying, archaeology, military and more. However, the focus of this research work converges on utilities detection only. This is obliging as it allows proper design, planning and costing at the planning stage of a project and also prevents delays at the later stage. Other than that, it also reduces the risk of utility damage while increases the construction productivity at the same time.

Though GPR makes a great tool in site surveying, it still comes with its own drawbacks. The effectiveness of GPR profiling could be limited by several external factors like coupling effect of the antennas, depth of buried targets or composition of the ground. Hence, the image processing techniques that applied on the GPR system plays an important key to improve the performance of the GPR profiling.

1.2 Problem Statement

There is no doubt that Ground Penetrating Radar (GPR) system has emerged to be so accommodating in ground surveillance, but it comes with inadequacies as well. There are so many available GPR devices sold in the market, yet most of them require experienced operators to handle with the system itself. As GPR data interpretation requires expertise and experience from human operator, a practical application of the device would actually cost more in terms of time and money. It can also be a tedious work when there is an enormous amount of data for interpretation. It is prone to human error considering there are ambiguous factors that could cause unwanted noise in the radargrams.

To determine the burial depth of the interested target, one has to excavate the investigation site. This might ruin the structure of the buried targets during the process of excavation. GPR system has indeed provided a very good solution by profiling the subsurface information into radargrams. However, a resolution is still needed to automatically estimate the burial depth based on the information given in the radargrams.

There are quite a few of available software developed individually or tagged along with the GPR system itself to assist operators to examine the data captured. Most of them are still lacking since they require users to perform manual mapping or hyperbola fitting [3] at the final stage to acquire the profiling of buried targets. Hough Transform is the conventional method used to detect hyperbolas in GPR images [4]. This method requires a fine adjustment on the parameters in order to obtain a desirable output. Therefore this can be challenging as the size of hyperbolic signatures varies with the size of the target.

These mentioned issues can be made into one conclusion which infers the demand for the development of automated target detection in the GPR system. With the aid of an automated system in subsurface mapping, the site surveying work would be less troublesome and human operators could be substituted by then. Flexibility in detecting hyperbolic reflections of various sizes should be offered so that it would be less hassle in data interpretation. Finally, an estimation on the burial depth is preferred to help in site investigation.

1.3 Objectives

Geophysical investigation using GPR system covers a wide range of research work as it is extensively used for numerous purposes in different industries. Since there is a lot to be studied, the aim of this research is categorized into four main objectives:

1. To detect the target reflections in GPR data automatically using Histogram of Oriented Gradient (HOG). The main focus of the study is to develop an algorithm that detects target reflections in GPR images automatically, regardless of which GPR system that is used to capture the data.
2. To estimate the depth of the buried targets. The designated algorithm should be able to estimate the burial depth of the interested targets. This is important as

an accurate information on the targets allows proper design and planning at the later stage.

3. To compare the performance of HOG with Hough Transform in the application of detecting target signatures in GPR images automatically. Comparison will be made among these two techniques with respect to their implementation and performance.
4. To optimize a Support Vector Machine (SVM) classifier model for hyperbolic signatures detection in GPR system. Analysis is done towards different parameters and kernel function of the SVM to obtain the best detection results in regards to the HOG features.

1.4 Scope / Limitations

The designated algorithm will be implemented using MATLAB throughout this whole research. The data set to be tested comprises both real and synthetic GPR data, where the synthetic data is simulated by MATGPR [3] that is written in MATLAB source code. The idea to have the algorithm tested in both real and simulated data is to verify its ability to cope with practical application.

In this study, the target detection phase to parameterization of target will be carried out offline. GPR images to be used are from various GPR system so that the algorithm can prove its flexibility and dynamicity in dealing with different GPR data formats.

There are a few limitations of this research and one of them is that the proposed algorithm could not recognize the material type of the detected target. Considering that different materials could share the same relative dielectric permittivity (RDP), therefore it is hard to identify the material type precisely. However, materials of the utilities could be classified accordingly to their burial depth if a standard worksheet for utilities installation is provided.

Sources of GPR images that are used in this research could be categorized into two, namely known source and unknown source. The term of source here indicates the model of GPR system and its configuration. Since there is an issue of limited source of GPR images, the images to be trained at the classifier are from Google Image where its source is unknown.

1.5 Contributions

The proposed algorithm aims to improve the concept of manual mapping in site surveying using GPR, which is generally applied in the available present software. The notion of this research is to have the popular feature descriptor, Histogram of Oriented Gradient (HOG) integrated into the methodology to perform automated target detection in GPR Images. A framework that pairs up HOG and Support Vector Machine (SVM) classifier is designated to solve the fine-tuning difficulties in the most conventional method in the application. Other than being more flexible in implementation, the proposed method also has shown better performance at target detection in the experiment results. Part of the contribution in this research also covers the work done in designating the best SVM model that would give the optimal performance of the proposed algorithm. The contribution of the task includes finding the SVM model with the best kernel function and its best corresponding parameter settings.

1.6 Thesis Organisation

This thesis consists of six chapters and they are organized such that Chapter 2 discusses previous works that are done on target detection using GPR and how localization of the interested anomalies was completed. In Chapter 3, the details on the methodology will be discussed as well as its implementation. The algorithm will then be tested on the available data sets. Results will be recorded and further discussed in Chapter 4. Finally, Chapter 5 wraps up the conclusion of the study and its future work.

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