



This is the Author's version of the paper published as:

Title: Swimming Pool Identification from Digital Sensor Imagery using SVM

Author: D. Tien, T. Rudra and A. B. Hope

Author Address: dtien@csu.edu.au

trudra@ics.mq.edu.au

Conference Name: Digital Image Computing Techniques and Applications

Year of Conference: 2007

Editor: M. Bottema

Publisher: IEEE

Pages: pp523-527

URL: Abstract: Australia is a country often marred by serious bushfires. In January 2003 it witnessed a significant natural disaster when Canberra was struck by firestorms. The Ash Wednesday fires in Victoria resulted in 75 deaths twenty years earlier. Events like these have made environmental and emergency management research a focus in Australia. In this paper, we introduce a Support Vector Machine (SVM) technique to classify small area water bodies, swimming pools in particular. These features provide a valuable source of water for Emergency Services and play a crucial role in fighting bushfires in urban areas of Australia.

CSU Research Output

<http://researchoutput.csu.edu.au>

Swimming Pool Identification from Digital Sensor Imagery using SVM

David Tien
School of Accg & Comp Sc.
Charles Sturt University
Bathurst - 2795

Tarashankar Rudra
Dept. of Computing
Macquarie University
Sydney – 2109

Anthony B. Hope
Dept of Lands
Govt. of NSW
Bathurst - 2795

Abstract - Australia is a country often marred by serious bushfires. In January 2003 it witnessed a significant natural disaster when Canberra was struck by firestorms. The Ash Wednesday fires in Victoria resulted in 75 deaths twenty years earlier. Events like these have made environmental and emergency management research a focus in Australia. In this paper, we introduce a Support Vector Machine (SVM) technique to classify small area water bodies, swimming pools in particular. These features provide a valuable source of water for Emergency Services and play a crucial role in fighting bushfires in urban areas of Australia.

I INTRODUCTION

Remote sensing is a subset of the broader field of *geomatics*, which is a group of technology dedicated to collect, store and analyse geo-spatial information and also complements the disciplines of Geographic Information Systems (GIS), surveying and cartography. Remote sensing is the science, technology and art of obtaining information about objects from a distance and it provides a means to differentiate patterns and relationships that are not apparent from conventional imagery. Conventional imagery captured by airborne cameras as also now productive sources of digital sensor data and are being used to produce maps of the earth's land surface, natural resources and urban infrastructure. The images captured by remote sensing satellites and airborne digital sensor devices are extensively used in assessing disaster events, planning and monitoring emergency response activities.

Climate fluctuation in Australia over the last century have shown it to be a country susceptible to extreme drought and flood conditions. Natural disasters have been well recorded over this time, with more recent events of the Canberra firestorms in 2003 that resulted in 390 homes destroyed [1] just one example. Black Friday bushfires in 1939 saw 2 million hectares burnt and 71 lives lost [2]. Ash Wednesday fires of 1983 saw a repeat of these statistics [2]. Image processing methods to increase the usability of digital sensor imagery are an important research area for Australia to pursue.

Archived image data can be used to study the change in land cover, bio-physical processes and human activities. Although there are various challenges [4] in the processing of digital sensor imagery for object detection, this paper introduces a disaster management technique by showing how real-time images of swimming pools with water in a region can be identified from aerial photographs to assist in dousing bushfires in fringe urban areas of Australia.

The paper is organized as follows. In section one; we briefly introduce the importance of remote sensing and digital sensor imagery for environmental and emergency services analysis. In the second section we review remote sensing and digital image analysis processes followed by an overview of image segmentation techniques in section three. In section four, we present our digital airborne sensor derived imagery identification technique using SVM. In the fifth section we explain our experimental procedure followed by our conclusion in section six.

II REMOTE SENSING AND DIGITAL IMAGE ANALYSIS PROCESSES

Remote sensing process consists of the following steps:

1. Illumination of features of the earth by radar system by emitting microwave pulses.
2. The energy reflected by the object is detected by the sensors in the satellite or aircraft using films, scanners and digital cameras or antennae if it has radar.
3. The recorded data is transmitted to earth station receivers where it is processed for display and further analysis.
4. The data is analyzed by using the techniques of visual interpretation, digital image enhancement and automated classification to derive information.

Interpretation of digital remote sensing data is one of the key aspects of remote sensing. It can be done by one of two ways [5] –

1. Quantitative analysis – It involves the use of computer to examine each pixel in the image individually to make a judgment about pixels specifically based upon their attributes.
2. Photo or image interpretation – It involves visual interpretation by inspection of data by human analyst or interpreter from image data.

The above two methods may complement each other and have their own advantages and disadvantages [5].

There are two main image enhancement techniques –

1. Radiometric – The methods involved in this technique are the following –

- a) Histogram modification rule – Histogram of an image is a graph constructed from number of pixels with given brightness versus brightness value. The mapping of brightness values associated with contrast modification can be given by –

$$y = f(x) \text{ ----- (I)}$$

Where ‘x’ is the old brightness value of a particular bar in the histogram and ‘y’ is the corresponding new value of brightness.

- b) Linear contrast modification – It is the most common modification operation. In this method equation (I) can be expressed as –

$$y = f(x) = ax + b \text{ ----- (II)}$$

- c) Saturating Linear contrast enhancement – When a particular region of interest in an image occupies a restricted brightness value range, this technique is applied to expand that range to the maximum possible dynamic range of the display device with all other regions being mapped to either black or white.

- d) Automatic contrast enhancement – Satellites and aircraft sensors are adjusted such that a variety of land cover types over many images can be detected without leading to saturation or loss of useful signal as noise. This technique is applied on the raw data to produce a product with good contrast.

- e) Logarithmic and exponential contrast enhancement – It is useful in for enhancing dark and light features between original and modified images.

- f) Piecewise linear contrast modification – It is a more general version of Saturating Linear contrast enhancement method; here the user specifies breakpoints as (new, old) pairs. It is important to have the function starting at (0, 0) and culminating at (L-1, L-1).

- g) Cumulative Histogram – This technique falls under the category of histogram equalization where a uniform histogram is produced from an average quasi-uniform histogram.

2. Geometric – This technique is applied to enhance the geometric details of an image. It is related to smoothing, edge detection and enhancement and line detection of an image.

Template operators – In this technique, a template, box or window is defined and moved over the image row by row and column by column and the template response is given by summation of the products of pixel brightness values covered by the template in a particular position and the template entries. For an M by N pixel sized template, the response for image pixel i, j is given by –

$$r(i, j) = \sum_{m=1}^M \sum_{n=1}^N \Phi(m, n) * t(m, n)$$

Where $\Phi(m, n)$ is the pixel brightness value, addressed according to the template position and $t(m, n)$ is the template entry at that location. This technique is also referred as convolution.

III IMAGE SEGMENTATION TECHNIQUES

One of the key aspects of analysis is to distinguish the objects of interest in images from the rest or background. The techniques that are used to uncover the objects of interest are referred to as segmentation techniques i.e. segmenting the foreground from background. The most common segmentation techniques are thresholding and edge finding which are described below [6] –

1. Thresholding – This technique is based upon a simple concept. A parameter θ called the *brightness threshold* is chosen and applied to the image $a[m, n]$ as follows -

```
If a [m, n] ≥ θ Then
    a [m, n] = object = 1
Else
    a [m, n] = background = 0
End If
```

The above version of the algorithm assumes that we are interested in extracting light objects on a dark background. For extracting dark objects on a light background we would use –

```
If a [m, n] < θ Then
    a [m, n] = object = 1
Else
    a [m, n] = background = 0
End If
```

The output is the label “object” or “background” which, due to its binary nature, can be represented as a Boolean variable “1” or “0”. However, the test condition can be based upon some other properties rather than simple brightness (for example, if for water, Blueness $\{a [m, n]\} \geq \Theta_{\text{blue}}$), but the concept is clear. There are different methods and algorithms to get around with this problem, some of which are – fixed threshold, histogram derived threshold, Isodata algorithm, background-symmetry algorithm, triangle algorithm, etc. The most complicated part of thresholding is the choice of Θ as there are no general rules of finding it. All the pixels of the objects of interest in an image are produced by segmentation by thresholding.

2. Edge Finding - This technique unlike thresholding techniques employs the process of finding the borders of the objects of interest in an image. The main edge finding techniques are Gradient-based procedure and Zero-crossing based procedure. “To achieve good localization and good detection of edges, a multi-scale approach is needed” [7]. The most common tendency is to combine single scale edge detector outputs at multiple scales and generating a synthesis of these edges. Modern multi-scale edge detection techniques are based on estimating optimum scales for local neighborhoods within the image [8-10].

IV IMAGE IDENTIFICATION USING SVM

A support vector machine or SVM is an algorithm based on statistical learning theory that constructs a hyper-plane that separates two classes with maximal margin. When the input is not linearly separable, the data is transformed with a non-linear map, producing a higher dimensional feature space in which the data can be separated. The separating hyper-plane in this higher dimensional space forms a non-linear decision surface in the original input space. In our study, we assume that every word in game pidgin language can elicit an emotion during game play. “A classification task usually involves with training and testing data, which consist of some data instances. Each instance in the training set contains one “target value” (class labels) and several “attributes” (features). The goal of SVM is to produce a model, which predicts target value of data instances in the testing set which are given only the attributes” [11].

Given a training set of instance-label pairs (x_i, y_i) , $i = 1, \dots, l$ where $x_i \in \mathbb{R}^n$ and $y \in \{1, -1\}^l$, the SVM requires the solution of the following optimization problem:

$$\text{Min}_{w, b, \xi} \frac{1}{2} w^T w + C \sum_{i=1}^l \xi_i$$

$$\text{Subject to } y_i (w^T \Phi(x_i) + b) \geq 1 - \xi_i$$

$$\xi_i \geq 0$$

Here training vectors x_i are mapped into a higher (maybe infinite) dimensional space by the function Φ . Then SVM finds a linear separating hyper-plane with the maximal margin in this higher dimensional space. $C > 0$ is the penalty

parameter of the error term. $K(x_i, x_j) = \Phi(x_i)^T \Phi(x_j)$ is called the kernel function. The four basic kernels are as follows -

$$\text{Linear: } K(x_i, x_j) = x_i^T x_j$$

$$\text{Polynomial: } K(x_i, x_j) = (x_i^T x_j + r)^d, \gamma > 0.$$

$$\text{Radial basis function (RBF): } K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0.$$

$$\text{Sigmoid: } K(x_i, x_j) = \tanh(\gamma x_i^T x_j + r)$$

Here, γ , r , and d are kernel parameters.

The images sensed remotely by aircrafts or satellites contain both spectral and spatial information where the spectral information provides a range of properties and characteristics regarding the surface cover i.e. vegetation and/or soil type at a given location or pixel and the spatial information provides the distribution, variation, and topographic relief of the cover types from pixel to pixel. The main characteristics that determine a pixel’s brightness or reflectance and the digital number (DN) assigned to the pixel are the physical properties of the surface, the cover type, and the topographic slope [12]. In this study we have trained and classified the data for distinguishing a swimming pool from rest of the image from individual pixel values or DN’s of a remotely sensed data. In the figures for the datasets, round plots are for non-essential portions of the image and square are for the swimming pool. The crosses are the support vectors.

V EXPERIMENTAL PROCEDURE

The procedure to classify swimming pool from a satellite image data by using SVM developed by Cawley [13], is as follows:

1. A satellite image was chosen for training.
2. The red, green and blue (RGB) values of individual pixels of the figure were extracted.
3. The RGB values were preprocessed with threshold values of the difference between blue-red and blue-green combinations of individual pixels and a text file generated with appropriate classification.
4. The text file in step 3 was used for training.
5. A test image was chosen and the operation of step 2 performed.
6. The RGB values were preprocessed with difference between the values of blue-red and blue-green combinations of individual pixels and a text file generated.

7. The text file in step 6 was used as a test to classify the data between pool and non-pool portion.
8. The SVM was executed with the files generated in step 4 and step 7.
9. The output of the SVM was an automatically classified text file into pool and non-pool portions of the test image.
10. The text file in step 9 was used to create an image that isolated the pool from the rest of the image.

The original aerial image with dimension 226*365 pixels shown in figure 1 was reduced to figure 2 with dimension 45*65 pixels by cropping it from the left hand corner to facilitate figure 2 to be processed by Pentium 4 processor with 256 MB RAM.



Figure 1: Original training image

The training image cropped from figure 1 with two swimming pools for training the SVM with RBF kernel is given below:



Figure 2: Training image

Figure 3 shows the class one (non-pool portions), class two (pool portions) along with decision boundary generated by the SVM [13].

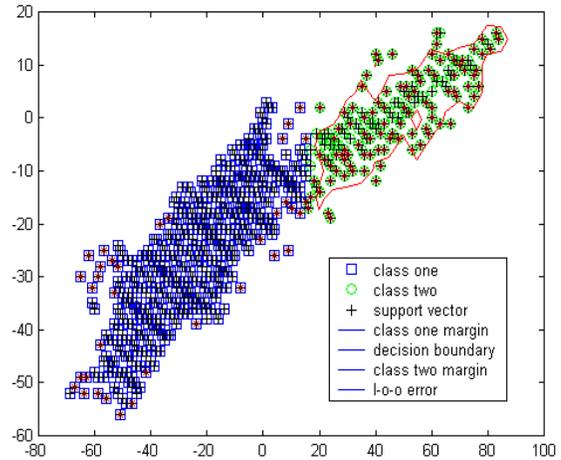


Figure 3: The SVM from figure 1.

The figure below shows the two isolated pools of figure 2 after running the SVM on the training data itself.

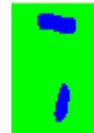


Figure 4: Isolated pools from the training image

The original test image is reduced from figure 5 with dimensions 378*127 pixels to figure 6 with dimension 78*54 pixels by cropping from right hand bottom of the original image.



Figure 5: Original test image

The test image cropped from figure 5 with a single pool is shown in figure 6.



Figure 6: Test image

The pool portion of figure 6 isolated from the rest of the image using SVM is shown in figure 7.

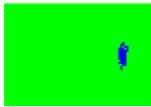


Figure 7: Isolated pool

VI CONCLUSION AND FUTURE WORK

We have been successful in identifying a water body from the rest of the image. We can see from the figure 3 and 4 that we could not determine the actual dimension of the pool, but we could definitely identify it from rest of the image. We will conduct further experiments with parameters on textures to get improved results. We will also conduct more research to identify water bodies under different climatic conditions especially under fog or smog.

More research needs to be carried out on methods for acquiring digital sensor data. The department of Lands in NSW has recently purchased an Airborne Digital Sensor which will enable us to get very high quality images.

Our immediate future work is to process and isolate pools from 4-band images. We have conducted a two step pilot study and have got very encouraging results. The study is based on the following steps:

1. Obtain a binary matrix from the near-infra-red (NIR) band image isolated from the 4-band satellite or aerial image. Mark the dark portions as 1's and the rest as 0's. The dark (black) portions of the image are either water bodies or black objects like roads, etc.
2. Obtain a binary matrix from the image in true-color (RGB) image isolated from the 4-band satellite or aerial image. Mark the blue portions as 1's and the rest as 0's. The blue portions are either water bodies or blue-painted rooftops etc.
3. Perform an intersection of the matrices obtained from steps 1 and 2.
4. Superimpose the matrix obtained in step 3, on the 3-band true-color image with appropriate color coding to uniquely identify the swimming pools and water bodies.

We will conduct further experiments with parameters on textures to get improved results. We will also conduct more research to identify water bodies under different climatic conditions especially under fog or smog. Our research will enable urban fire brigade service of Australia to locate swimming pools with water in real time in a specified area at any given point of time from satellite or aerial images to douse fire threatening urban settlements.

ACKNOWLEDGEMENT

The work has been supported by the Cooperative Research Centre for Spatial Information, whose activities are funded by the Australian Commonwealth's Cooperative Research Centre Program.

REFERENCES

- [1] <http://www.ga.gov.au/urban/projects/archive/canberra.jsp> [Accessed 6th September 2007]
- [2] <http://www.dse.vic.gov.au/DSE/nrenfoe.nsf/LinkView/FAAF080E6756F7904A25679300155B2B7157D5E68CDC2002CA256DAB0027ECA3> [Accessed 6th September 2007]
- [3] Aronoff, S., 2005, Remote Sensing for GIS Managers, ESRI press, California, USA.
- [4] McCoy, R. M., 2005, Field Methods in Remote Sensing, Guilford Press, USA.
- [5] Richards, J. A., Jia, X., 2006, Remote Sensing Digital Image Analysis, Springer, Germany.
- [6] Segmentation, 2007, (online), URL: <http://www.ph.tn.tudelft.nl/Courses/FIP/frames/fip-Segmenta.html>, [Accessed 10th May 2007].
- [7] Sumengen, B., Manjunath, B. S., 2005, Multi-Scale Edge Detection and Image Segmentation, 13th European Signal processing Conference, September 4-8, 2005, Antalya, Turkey.
- [8] Lindeberg, T., 1998, Edge detection and ridge detection with automatic scale selection. *IJCV*, pages 117-156, Nov 1998.
- [9] Elder, J.H. and Zucker, S.W., Local scale control for edge detection and blur estimation. *IEEE PAMI*, pages 699-716, Jul 1998.
- [10] Tabb, M., Ahuja, N., Multiscale image segmentation by integrated edge and region detection. *IEEE Transactions on Image processing*, pages 642-55, May 1997.
- [11] Hsu, C., Chang, C., Lin, C., A practical Guide to Support Vector Classification, (online), URL: <http://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf>, [Accessed, 17th December 2005].
- [12] USGS, 2007, Ground Water Resource Evaluation, USGS Open File Report OF-96-739, (online), URL: <http://terraweb.wr.usgs.gov/TRS/projects/Flagstaff/>, [Accessed 10th May 2007].N.
- [13] Cawley, C., Matlab Support Vector Machine toolbox, (Online), URL: <http://theoval.sys.uea.ac.uk/~gcc/svm/toolbox/>, [Accessed, 20th June 2005].