EXTRACTION OF MAN-MADE FEATURES FROM HIGH RESOLUTION SATELLITE IMAGERY

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

DN	Digital Number
DWT	Discrete Wavelet Transform
EMR	Electro Magnetic Radiation
FFT	Fast Fourier Transform
GIS	Geographic Information Systems
MRA	Multi Resolution Analysis

CHAPTER 1. INTRODUCTION

1.1 Background

Earth scientists actively collect resource data to test hypotheses and simulate or model the environment. The data is collected using either in situ or remote sensing methods. Measurements from the sensors using either method provide much of the data for physical geography and other earth science research.

Remote Sensing is defined as the technique of obtaining information about objects through the analysis of data collected by special instruments that are not in physical contact with the objects of investigation. This relatively new science is gaining popularity in a number of applications, starting from geology and soil mapping to archaeology, from weather forecasting to mineral extraction. Other application areas include, land use/land cover analysis, agriculture, forestry, rangeland, water resource, urban and regional planning, wetland, wildlife ecology and environmental assessment, to name a few.

Another area of research, and one that is relevant to this thesis is urban monitoring and assessment. Urban and regional planners require continuous acquisition of data to formulate governmental policies and programs. These policies and programs might arise from domains which range from social, economic, and cultural to environmental and natural resource planning. The role of urban and government planning agencies is becoming increasingly more complex and, as such, they are increasingly acting to a wider range of timely, accurate, and cost effective sources of data of various forms in order to plan/design the urban and semi-urban fringe to curb/expand the related activities. The challenge today in order to detect the change in an urban environment by detecting man-made features from imagery

Modern remote sensing satellites are equipped with high-resolution sensors and electronic cameras that enable ground stations to receive highly detailed images in digital format and instantaneously relay them to designated locations continuously. Moreover, being in digital format, the information can be easily stored, retrieved and made available for post processing analysis. The automation of photographic analysis is one of the research topics in remote sensing today.

In the past, civilian satellite sensors had not been able to provide data of sufficiently high spatial resolution (i.e., large mapping scale) to identify the features of interest in urban areas, such as individual buildings, roads and areas of open space. The situation has changed with the advent of a number of commercial satellite sensors that provide image data with a spatial resolution as fine as 1m (i.e., roughly speaking, they are able to detect objects approximately 1m by 1m in size).

In the field of remote sensing, the rapid development of technology and the opening of the image market have made high spatial resolution data available. The new high spatial resolution satellite imagery from IKONOS with a pixel size of 1 meter (PAN band) offers a new quality of detailed information about the earth's surface, and objects such as house plots, streets, and trees. Therefore, the extraction of these objects is of great interest. Man-made feature extraction is typically based on high-resolution aerial imagery and has been widely studied in photogrammetric, as well as the computer vision community, for many years. Different techniques and methods combine geometric and chromatic attributes as well as stereo information about contours and their flanking regions from multi-view imagery.

The problem is that while the sensor technology available for civilian use has effectively `advanced' overnight, this has not been mirrored by an equivalent improvement in the techniques used to process the resultant data. A multitude of research effort is now concentrated on improving segmentation, more specific aspects of it, like edge detection. It is well known that much information regarding image structure, even in gray-scale images, is provided by means of extracting edge information. Recent developments in multi-resolution analysis such as wavelet transform help to overcome this difficulty of scaling by analyzing data at various levels/resolutions. Shape classification helps to group/cluster the extracted objects.

1.2 Scope

Singapore is a highly urbanized city with high-rise public housing estates, commercial buildings and low-rise estates. Less attention has been on low-rise units in the semi- urban fringe. The study is to investigate the feasibility of auto-detection of man-made features like buildings in the local context using recently available high resolution

IKONOS imagery.

Satellite imagery and aerial photographs have been used for a long time for the extraction of urban features. The classical classification using spectral information at present is supplemented by more recent spatial analysis techniques. This helps to take into account the geometric and contrast information as opposed to the purely spectral classification of urban features. The main consideration is the resolution with which the urban features are classified. As the resolution increases, the spectral homogeneity of the pixels decreases and so normal spectral classification less accurate. The alternative is to use the edge classification scheme. Edges of an image mostly reflect the information of the image and contain the basic character of the image. Traditional edge detection methods are divided into two categories: time field and frequency field. In time field methods are detectors like the Sobel edge detector, Prewitt edge detector, Canny edge detector, etc. In the frequency field are various kinds of bandwidth-based filters. Methods that only enhance edges like the Sobel edge detector cannot be applied in the cases somewhere parts of the image are homogenous and some parts are sharp variations. In the frequency field, the normal Fourier transform has no resolution in the time field. Any modification of any frequency will influence the whole time zone leading to poor results.

The wavelet transform has made much impact as a new method of information processing. Wavelet transformation is sometimes known popularly as the mathematical microscope as it has resolution both in the time and frequency domains, and is localized. It is therefore able to focus onto any detail of the analyzed object by taking finer steps in the time field or space field. This technique can give good results with respect to edge detection.

Edges obtained by any of the edge detection methods above are grouped to reconstruct meaningful object shapes by matching to pre-defined object models. Shape classification plays a major part in the image segmentation approach. Like pixel-based supervised classification techniques, this classification method consists of two parts – the training stage with representative data (the object models and their shape features) and the classification stage with classifier model.

The above-explained techniques were grouped together to achieve optimum output, rather than the application of any one particular technique. The proposed technique described contributes to the eventual goal of using image-processing techniques to generate maps of urban land use directly from digital remotely sensed images with the minimum of manual intervention. The grouping and its advantages are clearly explained in Chapter 2.

1.3 Objective

The underlying goal of the research is to develop a feasible, accurate and rapid method of determining building outlines that combines remote sensing interpretation with image processing techniques. An important technical objective is the application of digital image processing technology such as Canny edge detection technique as the best type for information extraction due to the double threshold and good localization properties; multi-resolution wavelet analysis for decomposition of the image to greater levels of details; and template matching for shape classification The method developed will be a step towards the goal of semi-automating the procedure to maintain the data derived from remote sensing methods.

1.4 Organization of the thesis

The organization of the thesis is as follows. The literature review chapter surveys previous similar attempts to develop applications similar and the techniques used in this study.

Urban remote sensing techniques are discussed in detail in the third chapter. This chapter provides the reader with essential background knowledge in satellite remote sensing and digital image processing. The chapter also provides details of the wavelet theory, edge detection and shape classification and describes the proposed technique.

Details of the implementation of the proposed algorithm are discussed in the fourth chapter, which also provides details of the parametric study to determine good operating values for some of the parameters in the algorithm.

The fifth chapter presents the results of the feature extraction and assess the accuracy of the study, together with the advantages and shortcomings of the method proposed in the study.

The final chapter presents the conclusions and suggests areas for future improvement.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

Utilization of remote sensing data for urban studies is crucial in certain aspects like urban monitoring, land use feature extraction, etc. to name a few. Due to the recent surge in the acquisition of satellite data, there have been many attempts in the study of these in the urban arena. IKONOS, which is the first commercial 1m-resolution satellite, has been successfully launched in 1999 and, many 1m-resolution satellites are being launched within few years. The availability of such high-resolution satellite images may change the mapping, photogrammetry and remote sensing world. Because the shortcomings of airborne photogrammetry, such as small coverage, difficulties in periodical acquisition may be overcome and many objects that were not identifiable in low-resolution (10-30m) may be detected in high-resolution images. One of the major objects that can be extracted from the images are buildings. Extracting buildings is so far done using high-resolution airborne images or low-resolution satellites images. Hence, algorithms for man made feature extractions from 1m resolution images can hardly be found in literatures. As mentioned in the previous chapter, image processing techniques have been used in this study to extract building features. There are many algorithms and techniques available in the market of digital image processing; choosing the ones required for this study is the challenging task. It is very important to review the previous studies and the nature of various algorithms before starting the actual study.

2.2 Related Research

2.2.1 Application related studies – satellite remote sensing of urban areas

Remote sensing of urban areas reflects the power of using multiple sources of satellite imagery with geographic information and the expertise of urban areas. With the rapid growth in population throughout the world, it is crucial to have a well-concerted plan for urban expansion.

Satellite images give urban planners synoptic views of large areas, which allow them to lay plans for urban expansion effectively [6]. Li Yingcheng et al [37] in their paper described satellite remote sensing as a means of monitoring with high speed, accurate and efficient. It not only gives the amount and location of the change information of land use, but can also be used to check the data supplied by local government. It gives the administrators with scientific assistance in the macro managing, planning and utilizing the land resource. It is also an important means in constructing the system of national land use dynamic monitoring. Jothimani [23] describes this subject of urban sprawl mapping and monitoring as one of the operational applications of satellite remote sensing data, irrespective of its spatial and spectral resolution of the satellite-borne sensors. From the earliest data (Landsat-MSS) with comparatively coarse resolution to the present high spatial resolution data (IKONOS - panchromatic), detecting the changes in land cover and its use, especially the delineation of built up environment has been proved efficient. The visual interpretation technique which has an edge over the digital analysis and interpretation of the built-environment has been advocated in conjunction with the topographical maps to operationalize the techniques. Multi-temporal and repetitive satellite data offer unique opportunities for mapping and monitoring some of the elements of urban core, its dynamics and the resultant urban structure. The complexities and elements of urban dynamics as well as the required satellite data characteristics are controlling factors in urban inventory and analysis.

2.2.2 Wavelet Approaches to Image Processing

A fundamental property of wavelets is their ability to describe detail both in time and in frequency [26] proposed a wavelet approach due to its scale aspect. They discussed about texture and its properties and such that texture analysis methods extract the characteristics that are believed to be most important in particular texture characterization problems. The normal analysis methods highlight different aspects of texture, which is a too general and vague concept to encompass in a single description. But the shortcoming is that, the wavelet approach has not been utilized to the highest extent in this paper and only applied for frequency splitting.

Fatemi-Ghomi et al [10] discussed at length about the wavelet based texture segmentation. They reported that a good textured image segmentation scheme should consist of a method for estimating texture features taking the non-stationary nature of the feature image planes into account. Essentially, they have described textures in the image by a series of features derived from the wavelet transform at different levels of transform. This leads to a classical problem in pattern recognition – that of choosing appropriate features to use when performing a clustering analysis. Therefore, there is a need to be able to not only quantify the performance of the final segmentation of the images by the various methods, but also examine the choice of features that have been used. Friha et al [28] experimented with the same and have concluded that multi-resolution decomposition can be exploited to detect edges within images and make a clear distinction between useful information data and noise. Kun Wardana Abyoto [16] added to the above reports of wavelets as a tool for scale characterization and included that the general weakness of all the texture analysis procedures is that they primarily focus on the coupling between image pixels on a single scale [5] [30] [31] [2].

Several important problems in the areas of image processing can be seen as learning problems [24], where a set of data is to be split into a set if classes as in edge detection. Since image regions of different frequency content have different perceptual relevance, it is often the case that the task of learning can be handled best in a multi-resolution framework. For some of these problems, a scale-dependent learning algorithm is combined with a multi-resolution image decomposition to achieve scale independence. This study shows the application of wavelet based neural network on edge detection.

Designing neural network architecture is a very complicated task especially for problems like edge detection where the number of layers and units are to be specified. This study is feasible in applications, which require less number of edges to be detected, but in an environment like a remote sensing, this study is difficult.

Laure et al [3] reported the approach of wavelet transform in image fusion. When images are merged in wavelet space, the data can be processed at different frequency ranges. A number of applications have been listed in this paper but not much in detail has been discussed. The paper shows that wavelets can be used for image fusion applications for applications such as image misregistration and processing artifacts.

Karras et al [15] reported a method for improving the recognition for abrupt image changes without increasing the noise levels too much. This was achieved by a combination of local and global methods. These considerations made them employ the wavelet transform, aiming at extracting informative features for quite different and much more demanding task of detecting the critical edges for image structure identification. The Sobel edge detector has been used in this study. Through this approach the main objective was to reduce the noise level but at the cost of image structure information.

2.2.3 Current Edge Detection Methods

Marr and Hildreth [4] introduced the theory of edge detection and described a method for determining the edges using the zero crossings of the Laplacian of Guassian of an image. Haralick [25] determined edges by fitting polynomial functions to local image intensities and finding the zero-crossings of the second directional derivative of the functions. Canny [12] determined edges by an optimization process and proposed an approximation to the optimal detector as the maxima of gradient magnitude of a Gaussian smoothed image. Clark [14] and Ulupinar and Medioni [9] independently found a method to filter out false edges obtained by the Laplacian of Gaussian operator. Bergholm [8] introduced the concept of edge focusing and tracked edges from coarse to fine, to mask weak and noisy edges. A curve-fitting approach to edge detection was proposed by Goshtasby and Shyu [1] in which edge contours were represented by parameters curves that fitted to high-gradient image pixels with weights proportional to the gradient magnitudes of the pixels. Recent advances in edge detection include a method by Elder and Zucker [13] to determine edges at multitudes of scales, and an adaptive smoothing method by Li [29] to remove noisy details in an image without blurring the edges. Many other edge detection techniques have been developed in the recent past. Among the edge detection methods proposed and developed so far, the Canny edge detector is the most rigorously defined operator and widely used [18]. The popularity of the Canny edge detector can be attributed to its optimality according to the three criteria of good detection, good localisation and single response to an edge.

Luiz Alberto Lisoba da Silva Cardoso [19] experimented with the Canny algorithm for edge detection in his study of computer aided recognition of man-made structures in aerial photographs. This was chosen after excelling in tests he did against multi-level thresholding edge detectors. According to him, it meets the optimality criteria concerning non-spurious edge detection, accuracy on the edge location and avoidance of double edge detection. Neil Rowe et al [22] used the Canny edge detector for the automatic change detection of linear features in aerial photographs. The reason for choosing the particular detector is that it produced longer connected segments than the other algorithms which help in matching features. The edge cells were found using two thresholds.

The next step in the field of image vision was the wavelet based edge detection. As single resolution edge detection did not result in much valuable information, in late 1990s, the research in this field became popular. Several images of the same area from multi-sensor are fused together to maintain most of details, restrain noise of the images and enhance the rate of detection. Edges are extracted from the fused result image. This method of image fusion and edge detection based on wavelet transform is discussed in detail by Wu Xiuqing [35]. The result of the experiment showed that, it not only can suppress the noise effectively but also was adapted to detecting distinct edges and weak edges.

Most edge detection methods operate on an image at a single resolution and output a binary edge map. Edges within an image, however, generally occur ay various resolutions, or scales, and represent transitions of different degrees, or gradient levels. Therefore, single resolution edge detection methods do not always yield satisfactory results. The study by Junaid I. Siddique et al [33] developed a multi-resolution method that utilized a multi-rate wavelet decomposition to generate a series of images with progressively lower edge resolution. The series of edge maps is restricted to form a stacking edge map pyramid. This approach is shown to have advantages over the normal edge detection methods.

An image pyramid with multi-resolution is needed for coarse-to-fine image matching such as pattern recognition and template matching. A modern GIS shows a multi-scaling function and an image analysis system should effectively analyze the multi-resolution information of images. According to Li Deren et al [17], the wavelet theory is that which concentrates on the processing of multi-resolution of images.

2.2.4 Review of approaches in template matching

Before the advent of panchromatic imageries and photographs, only the multi-spectral information was used. The early object matching methods include the simple classification algorithms. The process of multi-spectral classification may be performed using either of two methods: supervised or unsupervised. Sameer Singh et al [34] have used the supervised classification techniques such as linear discriminant analysis, mean classifier and K-nearest neighbor methods to identify natural scenes in a FLIR (Forward Looking Infra-Red) images. Regarding the latter technique of classification, Deba Prasad Mandal et al [20] proposed a method on the theory of fuzzy sets which provides suitable tools in analyzing complex systems and decision processes where pattern indeterminacy is due to inherent vagueness (fuzziness) rather than randomness. This is attributed due to the image properties of ambiguity within the pixels due to the possible multi-valued levels of brightness. In a remotely sensed image, the regions (objects) are usually ill-defined (because of both grayness and spatial ambiguities. The image was classified using the spectral information and the thus obtained fuzzy partitioned mages were processed further to detect the man made features.

Invariant moments have been used as features in object recognition, image classification and scene matching. These features extracted from two dimensional images are invariant under image translation, scaling and rotation. Computing invariant moments are computationally intensive. In the matching process, relative size difference and maximum displacement between the reference and template segment are used to dictate the scope of the matching search. HongJiang [11] used the above method to automatically track ice motion. Xiuwen et al [36] used a two layer neural network for extracting hydro-graphic features such as rivers from satellite imageries. Bruce A Draper [7] discusses a similar neural network technique for detecting rooftops from aerial photographs.

According to Bogdan Rusyn [27] the patterns which are obtained during remote sensing with the aim to recognise the small dimensioned objects, it is worth researching the object skeleton reflecting the object structure, rather than the object geometrical properties. This was the study undertaken during the period when they were not many high spatial resolution imageries.

All the papers above discuss the object matching techniques for features those cannot be generalised or predefined. Marina Muller et al [21] experimented a simple matching algorithm, as the house plots normally consist only of a small number of pixels and also of regular shapes. They developed a model database with rotated shape variations. These were matched with clustered segments of the image data by an overlay process of centre to centre. Hence, detection of small objects with the help of multi-step segmentation and template matching was successfully demonstrated on house classification. They have thus proved that shape oriented methods are capable of detecting objects of different sizes in high resolution panchromatic satellite image data.

2.3 Summary

The field of computer vision has made significant advances over the past years. There are now, for example, good and improving algorithms for camera calibration, edge extraction, stereo analysis, tracking, etc. Unfortunately, there are not many developed theoretical or practical understanding of how these components are combined into functioning vision systems. As a result, there are few applications of advanced computer vision technology in the real world, even though the library of available algorithms keeps growing. What is missing is the ability select, parameterize and sequence algorithms in order to perform specific task.

Among the studies done in the field of edge based wavelet analysis [31] [32], not many studies have been done in template matching on high resolution satellite imageries. One such noted study is by Marina Muller et al [21]. They have utilized the multi-step segmentation of the images. The edges obtained at various scales where combined by considering that lines with highest resolution as they are best localized in the image. The classification process was a simple template matching process with pre-defined shape models. Another feature extraction study was done by Luiz Alberto [19] for finding building clusters in orthorectified aerial photographs. The technique was based on the connectivity analysis of a graph derived from the geometric relationships among endpoints of line segments that model edges. This study in detail utilizes the Canny edge detector. In both the above studies, exciting results were obtained. If wavelet analysis was introduced in the first study, the segmentation process would be speeded and automated. In the next study, if multi-resolution analysis and object matching were adopted much better results would be obtained and this would pave the way to reduce human intervention.

From the above discussion, it is clear that there are not many studies which has incorporated the advantages of the best techniques such as the Canny edge detection, multi-resolution wavelet analysis and template matching. The goal of the present project is to investigate the feasibility of extracting building features from high spatial resolution satellite imagery using the Canny edge detection, multi-resolution wavelet analysis and shape classification techniques. Results that will be obtained using such an algorithm will indicate promising techniques that may be applied in future automated analysis systems. The detailed information of such an algorithm is discussed in the next chapter.

CHAPTER 3. URBAN REMOTE SENSING TECHNIQUES

3.1 Urban remote sensing

3.1.1 Fundamentals of remote sensing

From a general perspective, remote sensing is the science of acquiring and analyzing information about objects or phenomena from a distance. Beginning with the early use of aerial photography, remote sensing has been recognized as a valuable tool for viewing, analyzing, characterizing, and making decisions about our environment. In the past few decades, remote sensing technology has advanced on three fronts:

1) From predominantly military uses to a variety of environmental analysis applications that relate to land, ocean, and atmosphere issues;
2) From photographic systems to sensors that convert energy from many parts of the electromagnetic spectrum to electronic signals, and
3) From aircraft to satellite platforms.

Today, we define satellite remote sensing as the use of satellite-borne sensors to observe, measure, and record the electromagnetic radiation reflected or emitted by the Earth and its environment for subsequent analysis and extraction of information.

Remote sensing data are routinely used by planners, resource managers, geographers, and engineers for a number of diverse urban applications. Typical interpretation applications include land use and cover mapping, parking and transportation studies, environmental monitoring, real estate assessment, evaluation of housing quality, choosing possible building sites and planning for urban development. Minus-blue panchromatic (this band includes red and green spectrum. Blue band is usually removed due to its haziness) and color infrared data are preferred for most types of urban studies. Both have the ability to penetrate atmospheric haze, which effectively sharpens the images of all depicted objects.

3.1.2 Extraction of information through digital image processing

Digital image processing involves the manipulation and interpretation of digital images with the aid of a computer. This form of remote sensing actually began in the 1960s with a limited number of researchers analysing airborne multi-spectral scanner data and digitised aerial photographs. Digital image processing is an extremely broad subject, and it often involves procedures that can be mathematically complex. The central idea behind digital image processing is quite simple. The digital image is fed into a computer one pixel at a time. The computer is programmed to insert these data into an equation, or series of equations, and then store the results of the computation for each pixel. These results form a new digital image that may be displayed or recorded in pictorial format or may itself be further manipulated by additional programs. The possible forms of digital image manipulation are literally infinite.

Most satellite sensors detect electro magnetic radiation (EMR) electronically as a continuous stream of digital data. The data are transmitted to ground reception stations, processed to create defined data products, and made available for sale to users on a variety of digital data media. Once purchased, the digital image data are readily amenable to quantitative analysis using computer-implemented digital image processing techniques. Sabins (1987) provides a good description of such techniques which include data error compensations, atmospheric corrections, calibration, and map registration. These steps discuss essentially involve pre-processing the data for subsequent interpretation and analysis. Another group of techniques is designed to selectively enhance the digital data and produce hard-copy image formats for interpreters to study. For these images, some of the principles and techniques of airphoto interpretation can be applied to the manual analysis of the image information content (Lillesand and Kiefer (1987)). A third major group of digital processing techniques involves information extraction through the implementation of a wide range of simple to complex mathematical and statistical operations on the numerical data values in the image. The results of these operations provide output such as derived information variables (that might relate to terrain brightness or vegetation condition), categorized land and water features, or images showing changes over time.

However, virtually all the digital imaging procedures may be categorized into one (or more) of the following seven broad types of computer-assisted operations:

1. Image rectification and restoration.
2. Image enhancement.
3. Image classification.
4. Data merging and GIS integration.
5. Hyper-spectral image analysis.

6. Biophysical modelling.

Image Enhancement: The goal of image enhancement is to improve the detect ability of objects or patterns in a digital image for visual interpretation. However, because certain enhanced images do not resemble their original form, the user must understand changes caused by the processing if interpretation is to be correct. Enhancement can be divided into the following categories:

1. Contrast stretching
2. Spatial filtering
3. Edge enhancement
4. Directional first differencing
5. Multi-spectral band ratioing
6. Simulated natural color
7. Linear data transformation

These operations are applied to the digital image data after the appropriate preprocessing like geometric correction, steps have been completed.

3.2 Wavelet theory

3.2.1 Introduction to wavelets

The wavelet transform is perhaps one of the most exciting developments in the last decade that brings together researchers in several different fields such as signal processing, image processing, communications. This chapter provides an introduction to the wavelet transform theory. The fundamental idea behind wavelets is to analyse according to scale. Indeed, some researchers in the wavelet field feel that, by using wavelets, one is adopting a whole new mindset or perspective in processing data. This is with reference to the localized functionality of wavelets unlike Fourier analysis.

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. This idea is not new. Approximation using superposition of functions has existed since the early 1800's, when Joseph Fourier discovered that he could superpose sines and cosines to represent other functions. However, in wavelet analysis, the *scale* that we use to look at data plays a special role. Wavelet algorithms process data at different *scales* or *resolutions.* At this juncture, a window can be defined. Window is simply a square wave. Because a single window is used for all frequencies in the wavelet frequency transform, the resolution of the analysis is the same at all locations in the time-frequency plane. The effect of the window is to localize the signal in time. If we look at a signal with a large "window," we would notice gross features. Similarly, if we look at a signal with a small "window," we would notice small features. The result in wavelet analysis is to see both the forest *and* the trees, so to speak. This makes wavelets interesting and useful. For many decades, scientists have wanted more appropriate functions than the sines and cosines which comprise the bases of Fourier analysis, to approximate choppy signals. By their definition, these Fourier functions are non-local (and stretch out to infinity). They therefore do a very poor job in approximating sharp spikes. With wavelet analysis, we can use approximating functions that are contained neatly in finite domains. Wavelets are well suited for approximating data with sharp discontinuities. The wavelet analysis procedure is to adopt a wavelet prototype function, called an *analysing wavelet* or *mother wavelet.* For instance, temporal analysis is performed with a high frequency version of the prototype wavelet, while frequency analysis is performed with a low frequency version of the same wavelet. Because the original signal or function can be represented in terms of a wavelet expansion (using coefficients in a linear combination of the wavelet functions), data operations can be performed using just the corresponding wavelet coefficients.

3.2.2 Comparison of Fourier and wavelet transforms

3.2.2.1 Similarities between Fourier and wavelet transforms

The fast Fourier transform (FFT) and the discrete wavelet transform (DWT) are both linear operations that generate a data structure that contains $\log_2 n$ segments of various lengths, usually filling and transforming it into a different data vector of length 2^n.

The mathematical properties of the matrices involved in the transforms are similar as well. The inverse transform matrix for both the FFT and the DWT is the transpose of the original. As a result, both transforms can be viewed as a rotation in function space to a different domain. For the FFT, this new domain contains basis functions that are sines and cosines. For the wavelet transform, this new domain contains more complicated basis functions called wavelets, mother wavelets, or analyzing wavelets.

Both transforms have another similarity. The basis functions are localized in frequency, making mathematical tools such as power spectra (how much power is contained in a frequency interval) and scale grams (to be defined later) useful at picking out frequencies and calculating power distributions.

3.2.2.2 Dissimilarities between Fourier and wavelet transforms

The most interesting dissimilarity between these two kinds of transforms is that individual wavelet functions are *localized in space.* Fourier sine and cosine functions are not. This localization feature, along with wavelets' localization of frequency, makes many functions and operators using wavelets "sparse" when transformed into the wavelet domain. This sparseness, in turn, results in a number of useful applications such as data compression, detecting features in images, and removing noise from time series.

One way to see the time-frequency resolution differences between the Fourier transform and the wavelet transform is to look at the basis function coverage of the time-frequency plane. Figure 1 shows a windowed Fourier transform, where the window is simply a square wave. The square wave window truncates the sine or cosine function to fit a window of a particular width. Because a single window is used for all frequencies in the WFT, the resolution of the analysis is the same at all locations in the time-frequency plane.

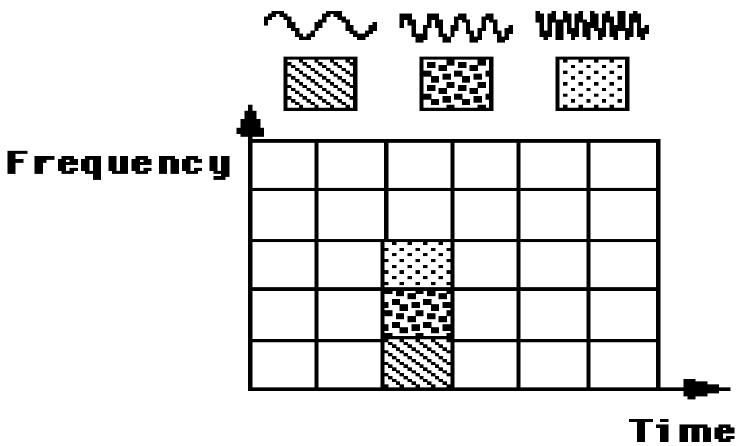

Fig. 3.1. Fourier basis functions, time-frequency tiles, and coverage of the time-frequency plane.

<u>Note:</u> The time-frequency graphs are given to explain the features of the wavelets as the author was not able to obtain literature in relation to the study.

An advantage of wavelet transforms is that the windows *vary*. In order to isolate signal discontinuities, one would like to have some very short basis functions. At the same time, in order to obtain detailed frequency analysis, one would like to have some very long basis functions. A way to achieve this is to have short high-frequency basis functions and long low-frequency ones. This happy combination is exactly what you get with wavelet transforms. Figure 2 shows the coverage in the time-frequency plane with one wavelet function, the Daubechies wavelet.

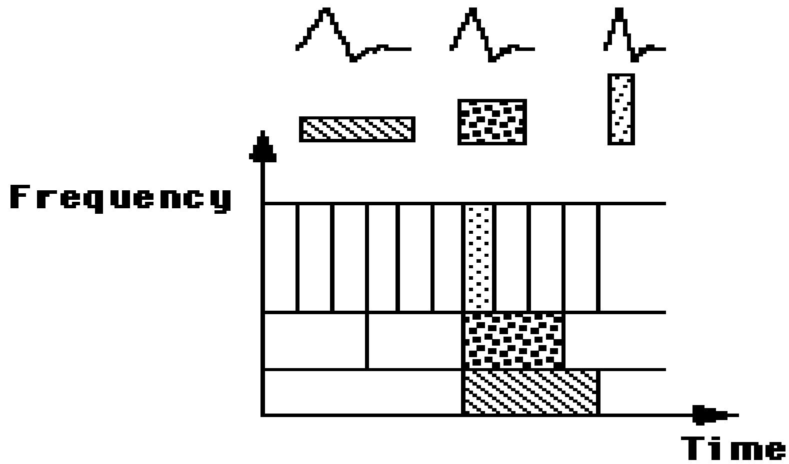

Fig. 3.2. Daubechies wavelet basis functions, time-frequency tiles, and coverage of the time-frequency plane.

Note: The time-frequency graphs are given to explain the features of the wavelets as the author was not able to obtain literature in relation to the study.

One thing to remember is that wavelet transforms do not have a single set of basis functions like the Fourier transform, which utilizes just the sine and cosine functions. Instead, wavelet transforms have an infinite set of possible basis functions. Thus wavelet analysis provides immediate access to information that can be obscured by other time-frequency methods such as Fourier analysis.

3.2.3 Discrete wavelet transform

Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates lot of data. It is rather remarkable to note that, if the chosen scales and positions are based on powers of two -- so-called *dyadic* scales and positions -- then the analysis will be much more efficient and just as accurate. Such an analysis is obtained from the *discrete wavelet transform* (DWT). An efficient way to implement this scheme using filters was developed by Mallat (1988). A discrete wavelet transform can be used to compute the multi-resolution representation of signals (rows and columns of images in this study). The following sub section discusses this in detail.

3.2.4 Multi-resolution wavelet analysis

Although the time and frequency resolution analysis are results of a physical phenomenon (the Heisenberg uncertainty principle) and exist regardless of the transform used, it is possible to analyse any signal by using an alternative approach called the **multi-resolution analysis (MRA).** MRA, as implied by its name, analyses the signal at different frequencies with different resolutions. MRA is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. This approach makes sense especially when the signal at hand has high frequency components for short durations and low frequency components for long durations. Fortunately, the signals that are encountered in practical applications are often of this type.

A digital image is a two-dimensional light intensity function which has been discretised both in spatial coordinates and in brightness. It can also be considered as a matrix whose row and column identify a point in the image and the corresponding matrix element (or pixel) value gives the grey level at that point. In computer vision, algorithms have been developed for understanding the content of these images. Following the pioneering work of Rosenfeld and Thurston (1971) in computer vision, the following have come to be widely accepted;

1. It is difficult to analyse the information content of an image directly from grey level intensity of the image pixels.
2. The local changes or singularities of the intensity of an image are much more important than the grey level intensity of that image.
3. An image contains important information in a wide range of sizes, and this information is often independent from one size to another.

The advantage of a multi-resolution technique is that it can provide a coarse-to-fine and scale-invariant decomposition for interpreting the image information. At different scales, the details of an image generally characterise the different sizes of the scene: the lower resolution provides a “global” view of an image, while the higher resolution provides the “details” of the image. Some of the multi-resolution techniques such as these introduced by Mallat enable to decompose a function on some orthonormal wavelet basis where the information at separate levels are not corrected. Noise is one of the biggest obstacles in image interpretation. Algorithms have been proposed to remove or reduce noise in images. But, since there is less noise at lower resolution and the image discontinuities at low resolution clearly stand out from the noise, one can often perform image processing operations, such as edge detection, with less interference from the noise at lower resolution and then transfer the results to a higher resolution. This is one of the very important advantages of the wavelet analysis.

3.3 Edge detection approach

3.3.1 Purpose of edge detection

Edge detection is a problem of fundamental importance in image analysis. In typical images, edges characterize object boundaries and are therefore useful for segmentation, registration, and identification of objects in a scene. The edge detection algorithm is designed to enhance rapid changes in DN levels from one pixel to the next. These very abrupt changes represent high spatial frequencies called edges. An edge can be a boundary separating two different features or a line that differs from the features on both its sides. The purpose of edge detection is to facilitate the extraction of lines from a wide variety of geographical map images. Its property is to reduce the image down to the prominent edges. Edges carry useful information about the object boundaries which can be used for image analysis, object identification and image filtering.

3.3.2 Types of edge operators

One class of operators accentuates edges by introducing undershooting and overshooting, respectively, at the lower and higher sides of edges. Such operators include un-sharp masking, statistical differencing and linear high-frequency emphasis filters such as operators based on the Laplacian. The other class of edge enhancing operators increases the slope or gradient of edges producing step like edges. Although the operators accentuating edges can produce more subjectively pleasing images than can others, they are extremely sensitive to noise. Therefore, their application to image processing is rather limited. On the other hand, operators increasing the slope of edges can suppress noise components, while producing step like edges. So they have been used for smoothing images and for pre-processing images before contour and edge detection.

Local maxima of the gradient magnitude identify edges. When the first derivative achieves a maximum, the second derivative is zero. For this reason, an alternative edge detection strategy is to locate zeros of the second derivatives of the continuous image. To recover the edges, the gradient image must be segmented using a global or local (i.e., adaptive) threshold operator. The choice of a threshold value determines the resulting segmentation and, therefore, the perceived quality of the edge detector.

3.3.3 The Canny edge algorithm

The Canny edge detector belongs to the class of the gradient operators. Among the edge detection methods proposed earlier in the previous section, the Canny edge detector is the most rigorously defined operator and is widely used. This is the work John Canny did for his Masters degree at MIT in 1983.

The objective function of the Canny edge detector was designed to achieve the following optimisation constraints:

1) Maximize the signal to noise ratio to give good detection. This favours the marking of true positives.

2) Achieve good localization to accurately mark edges.
3) Minimize the number of responses to a single edge. This favors the identification of true negatives, that is, non-edges are not marked.

The Canny algorithm and Thresholding

The Canny operator works in a multi-stage process. The Canny edge detection algorithm has the following steps:

1. Smoothening of the image with a Guassian filter. The Gaussian smoothing in the Canny edge detector fulfils two purposes: first it can be used to control the amount of detail that appears in the edge image and second, it can be used to suppress noise.
2. Computation of the gradient magnitude and orientation using finite difference approximations for the partial derivatives.
3. Perform non-maximal suppression. Any gradient value that is not a local peak is set to zero. The edge direction is used in this process.
4. Find connected sets of edge points and form into lists.
5. Threshold these edges to eliminate *insignificant* edges. Canny introduced the idea of *thresholding hysteresis*. This involves having two different threshold values, usually the higher threshold being 3 times the lower. Any pixel in an edge list that has a gradient greater than the higher threshold value is classed as a valid edge point. Any pixels *connected* to these valid edge points that have a gradient value above the lower threshold value are also classed as edge points. That is,

once you have started an edge you don't stop it until the gradient on the edge has dropped considerably.

The upper tracking threshold can be set to quite high and lower threshold quite low for good results. Setting the lower threshold too high will cause noisy edges to break up. Setting the upper threshold too low increases the number of spurious and undesirable edge fragments appearing in the output. Threshold plays an important role in the performance of the edge detector as the probability of missing an edge and probability of marking false edge depends on the threshold. The thresholds are based on the amount of noise in the image. This thresholding technique has been of much importance in this research.

3.4 Template matching

Template matching is the process of finding a correspondence between certain features in the image and similar features of the object model to;

1. Identify the type of features to use
2. Determine the procedure to obtain the correspondence between image and model features.

Template matching is a simple case, in which instances of prestored patterns are sought in an image. Template matching has been performed at the pixel level and also on higher level.

3.5 The proposed wavelet-edge template matching technique

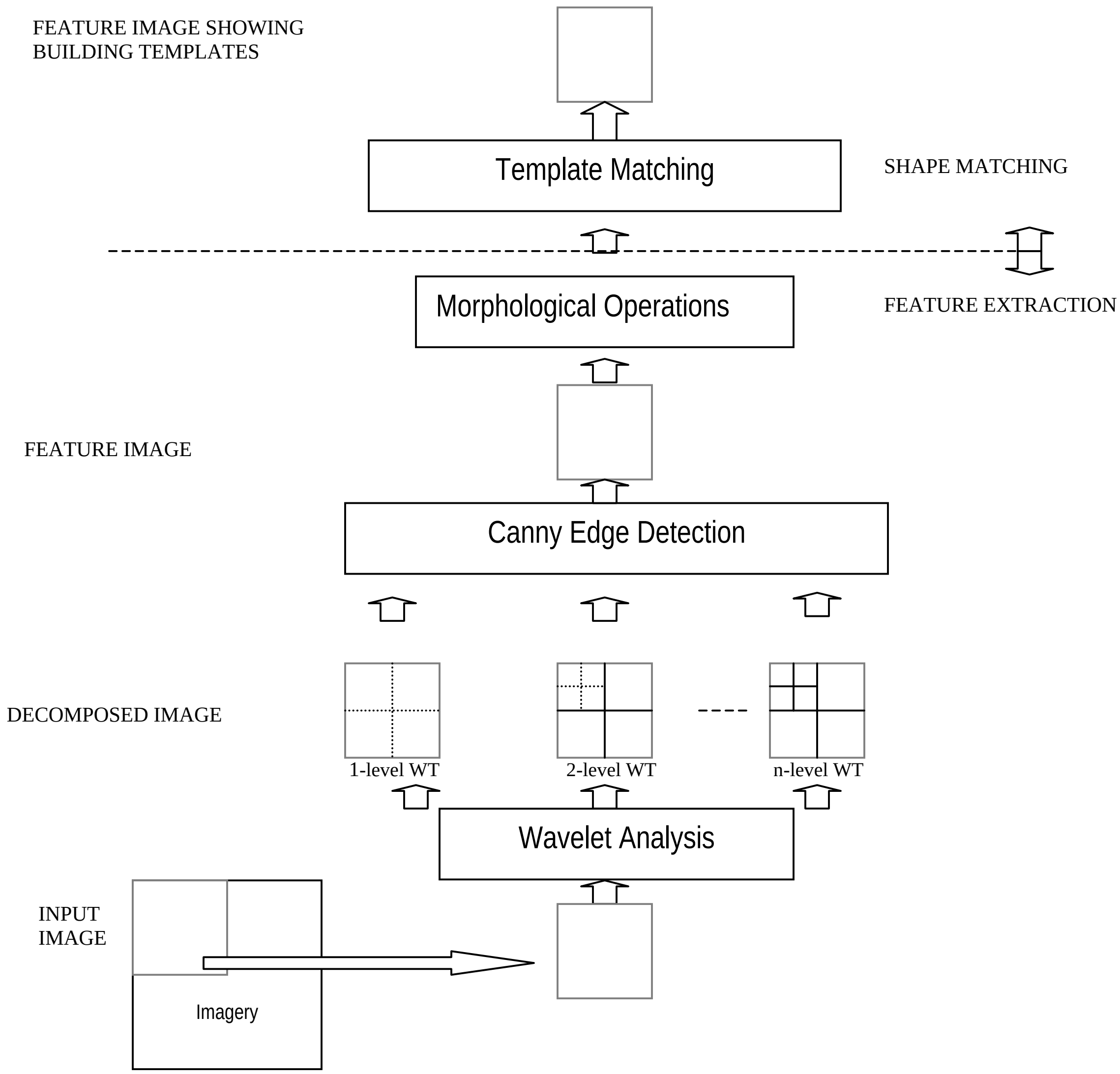

Fig. 3.3 Flowchart depicting the proposed algorithm

The above (Fig. 3.3) flowchart describes the proposed technique for this study. The test site is extracted from the input imagery of the study area. The extracted imagery is passed through the wavelet analysis in the first part. The advantage of a multi-resolution technique is that it can provide a coarse-to-fine and scale-invariant decomposition for interpreting the image information. At different scales, the details of an image generally characterise the different sizes of the scene: the lower resolution provides a “global” view of an image, while the higher resolution provides the “details” of the image.

The wavelet scaled image is then passed through the Canny Edge detector. The choice of a threshold in the technique, determines the resulting segmentation and, therefore, the perceived quality of the edge detector. The advantage of the double threshold Canny edge detector would be maximum signal to noise ratio, marking of true positives and identification of true negatives to rule out non-edges.

Finally template matching is carried out and building outlines are identified. It is one of the basic techniques of shape matching procedures. The first part is constitutes the feature extraction and latter being the shape matching. The superiority of the above proposed study and the grouping of techniques is discussed in Chapter 2.

3.5.1 Detection of local intensity variation

This is the first step of the actual study. The wavelet analysis was applied on the extracted image data. Discrete wavelet transforms (DWT) are fast (linear complexity) algorithms implemented via digital filter banks. The Discrete Wavelet Transform can be extended to two dimensions as a combination of two one dimensional transforms, applied independently in the horizontal and vertical directions. This independent application is possible because the DWT is a separable transform. A different filter can be used in each direction and the filter tree generalises to a quad-tree structure where only the tree branches which use the filter in both directions are used for further calculation. The

DWT make use of the fact that a signal may be decomposed into two parts -- a smoothed signal and a detail signal. The smoothed signal is decomposed over a set of basis functions (the scaling function) while the detail signal is over the wavelet basis. During the decomposition, the resolution decreases exponentially at the base of 2. In the case of 2D images, the DWT can be applied to each dimension separately. This results in an image **X** being decomposed into a first level approximation $\mathbf{X_a^1}$, and detail components $\mathbf{X_h^1}$, $\mathbf{X_v^1}$ and $\mathbf{X_d^1}$, correspoding to the horizontal, vertical and diagonal details. Thus,

$$\mathbf{X = X_a^1 + \{ X_h^1 + X_v^1 + X_d^1 \}} \qquad (1)$$

and iterating the process to N levels,

$$\mathbf{X = X_a^N + \sum_{i=1}^{N} \{ X_h^i + X_v^i + X_d^i \}} \qquad (2)$$

Accordingly, wavelets provide a framework for decomposing signals into a hierarchy of frequency components, each represented with spatial resolution proportional to frequency. The sub band decomposition obtained by wavelet transformation allows for the more precise modification of edge details at various scales. As a result, the edge resolution can be more accurately controlled than through simple linear filtering. The multi-resolution wavelet analysis was done. With the wavelet analysis having the scaling advantage, many resolutions were experimented. As the resolution decreases, the contrast between the features also decreases. It is found from the study that for the extraction of man-made features, the high resolution is suitable, because the wavelet approach effectively reduces the contrast of the image at lower scales.

3.5.2 Edge based segmentation approach

Image segmentation is a partitioning of an image into related sections or regions. These regions may be later associated with informational labels, but the segmentation process simply gives each region a generic label (region 1, region 2, etc.). In the context of Earth remote sensing, informational labels would generally be a ground cover type or land use category. Most image segmentation approaches can be placed in one of three classes:

1. Threshold techniques
2. Edge-based methods
3. Region-based techniques, and
4. Connectivity-preserving relaxation methods.

Edge Based Method

Basically, the idea underlying most edge-detection techniques is the computation of a local derivative operator. The first derivative of the grey-level profile is positive at the leading edge of a transition, negative at the trailing edge, and zero in areas of constant grey level. Hence the magnitude of the first derivative can be used to detect the presence of an edge in an image. Written edge based algorithms were gradient operators. Gradient operators are to find changes of pixel grey levels by local derivative operation. In terms of detecting edges, they detect edges as well as noises. Gradient operators are vulnerable to noises. To overcome this noise effect with gradient operators, an algorithm combined with thresholding and gradient operators is suggested. In this study the Canny edge detection is so applied due to its thresholding hystersis.

3.5.3 Shape matching

Shape classification of objects is an important problem in computer vision. Here we try an approach based on template matching. We represent objects as templates or models. Template matching is a natural approach to shape classification. In this study two types of template matching are adopted: block template matching and edge template matching.

The experiments and implementations are discussed at length in the next chapter.

CHAPTER 4. DETAILS OF IMPLEMENTATION

4.1 Focus of the study

The main feature for the detection of objects in panchromatic images is their individual shape characteristic. Therefore, the process of semi-automatic detection consists of two steps: first, elements or boundaries of the objects are extracted using the edge-based segmentation technique. Second, these results are grouped to reconstruct typical object shapes, which can be matched by predefined object models.

Smaller objects are preferably extracted by edge based segmentation based techniques, due to lower spectral variations of their pixels. Hence, the reconstruction problem can be reduced to the search of optimal segmentation thresholds for each object. In this study, the thresholds are varied to determine the optimal value. Consequently, the edge detected features are extracted based on the template matching method. This two-step approach, multi-step segmentation and shape matching, is explained in detail in the following sections.

4.2 Imagery and Study Area

The imagery used in this study is from Space Imaging’s IKONOS satellite. Space Imaging launched IKONOS on September 24, 1999. The ground resolution of each band is 1-meter panchromatic (nominal at <26deg off nadir) with a spectral resolution between 0.45 - 0.90 microns; it was the first commercial satellite to give 1meter resolution imagery. New high resolution satellite imagery like IKONOS, with a pixel size of 1 meter, offers a new quality of detailed information about the earth's surface as even small objects such as house plots, streets and trees can now be detected.

The first step of the study was to extract an area in the city of Singapore as the test site. A few problems encountered during this stage:

(1). Many of the buildings were irregular shape

(2). The ortho-rectified imagery was not available; this resulted in images with high relief displacements and high shadows were evident. Due to the above shortcomings, the study site was carefully chosen to include only buildings with two or three storeys. The study plot selected was a residential area near the East Coast Park (ECP) of Singapore.

Fig. 4.1 shows an isolated area from the image of Singapore. The training sites and the experiment sites are blocked. The area selected has a mixture of tall and low rise buildings that makes it a perfect site to test the proposed algorithm. Fig. 4.2 shows the training site zoomed in. It shows the arrangement of the house plots as a clearer picture.

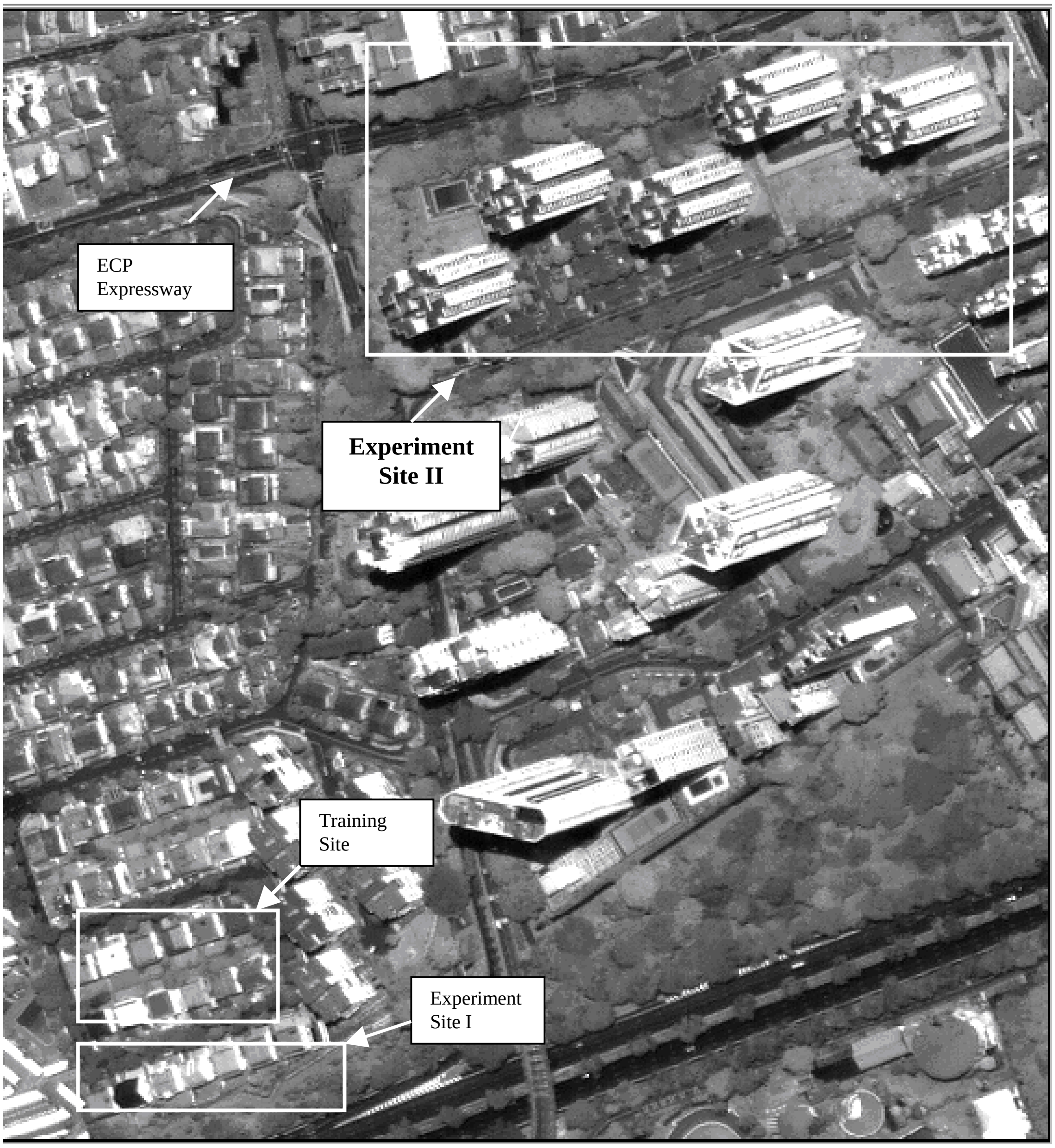

Fig.4.1 IKONOS 1m PAN imagery

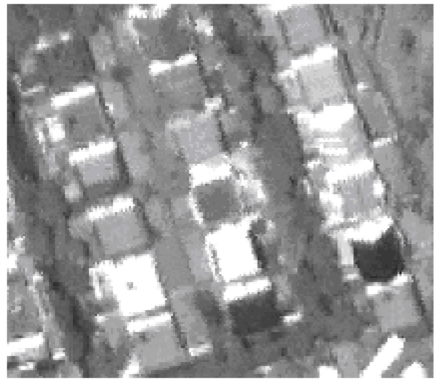

Fig. 4.2 Training site

4.3 Parameters of the wavelet analysis

4.3.1 Choice of wavelet type

The wavelet type used for this study is the Daubechies wavelet. Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal and bi-orthogonal wavelets, thus making discrete wavelet analysis practicable. Only with the introduction of the orthonormal compact support wavelets by Daubechies, did it become clear that there exist basis sets that are simultaneously localized, multiscale, multicenter, and orthonormal. Associated scaling filters are minimum-phase filters. The original Daubechies bases are generated by two related functions, the scaling function and the wavelet. What is new and exciting about the wavelet decomposition methodology is that the wavelet basis functions have what is called compact support. This means that the basis functions are non zero only on a finite interval. In contrast, the sinusoidal basis functions of the Fourier expansion are infinite in extent. The advantage of this wavelet is that, due to its compact support it can be applied to any localized function or signal. In this study the second level Daubechies ('db2') wavelet type is used. "db2" basis is chosen after a visual inspection of the application of wavelets on the image.

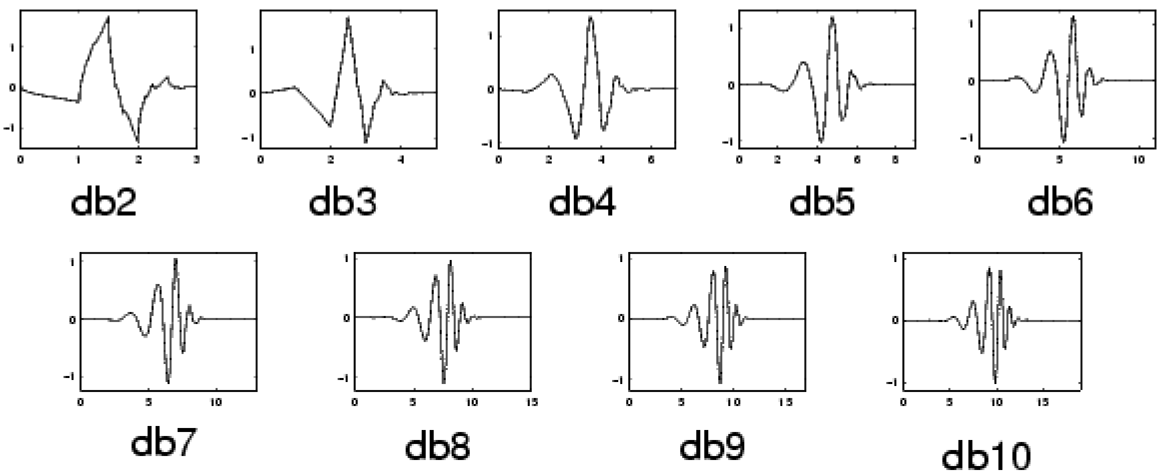

Fig. 4.3 The Daubechies family

4.3.2 Approximations and details of the wavelet analysis

For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavour or nuance. Consider the human voice, if the high-frequency components are removed, the voice sounds different, but what is being told is understood. However, if the low-frequency components are removed, only gibberish is heard.

In wavelet analysis, this is known as peaks of *approximations* and *details*. The approximations are the high-scale, low frequency components of the signal. The details are the low-scale, high frequency components. The low-scale solution contains the smooth part of the structure, while the high-scale solution provides the information for edge detection. The filtering process, at its most basic level, can be explained as follows: if X denotes the original image, and it is decomposed into a first level approximation $\mathbf{X_a^1}$, and detail components $\mathbf{X_h^1}$, $\mathbf{X_v^1}$ and $\mathbf{X_d^1}$, corresponding to the horizontal, vertical and diagonal details. Thus,

$$\mathbf{X = X_a^1 + \{ X_h^1 + X_v^1 + X_d^1 \}} \qquad (1)$$

Iterating the process to N levels,

$$\mathbf{X = X_a^N + \sum_{i=1}^{N} \{ X_h^i + X_v^i + X_d^i \}} \qquad (2)$$

Equation (1) when applied to the study, resulted in the following images;

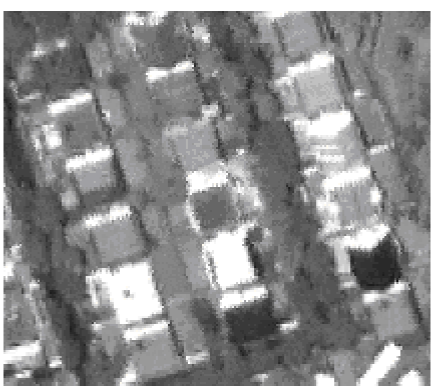

Fig. 4.4.a Approximation X_a^1

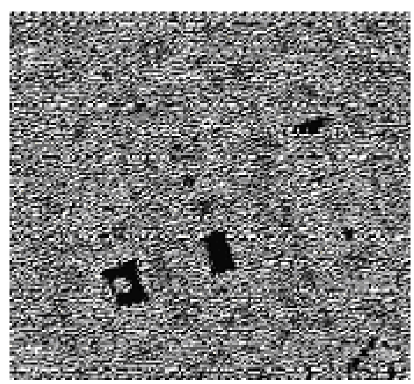

Fig. 4.4.b Horizontal Detail X_h

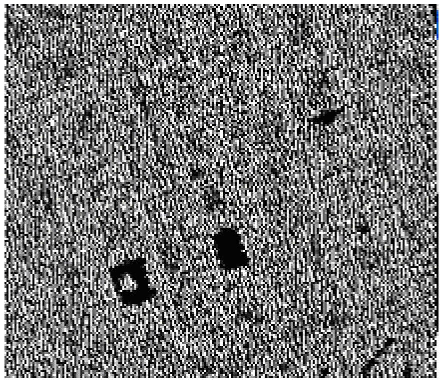

Fig. 4.4.c Vertical Detail X_v1

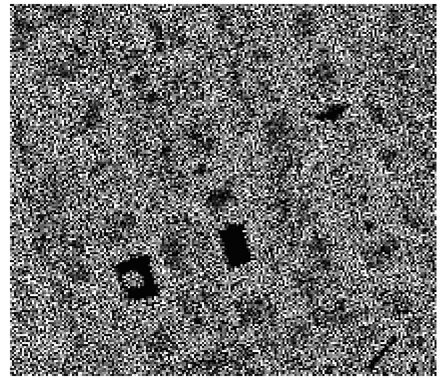

Fig. 4.4.d Diagonal Detail X_d1

For this particular study, the approximations are used for further analysis due to the high information content in it.

4.3.3 Wavelet Resolution

Wavelet resolution is the next most important parameter for any wavelet analysis. Only upon deciding the optimal resolution will the objects of interest be best pictured. For this particular study, many levels were tried, it was found that at lower levels (larger scale), the building features are detected with more contrast. The first level decomposition discussed in the previous sub-section is re-repeated, with successive approximations giving lower resolution components. The effect of this is that man-made features are detected at lower resolutions and other features namely, vegetation, water, etc. at other resolutions, depending on the feature type and resolution of the imagery. To see the effect of resolution, a simple edge detection test was applied and the results visually evaluated to assist in choosing the resolution for the study.

From the images below, it is noted that edges become straighter as level increases. At level 3, details are introduced which are uncharacteristic of the image object.

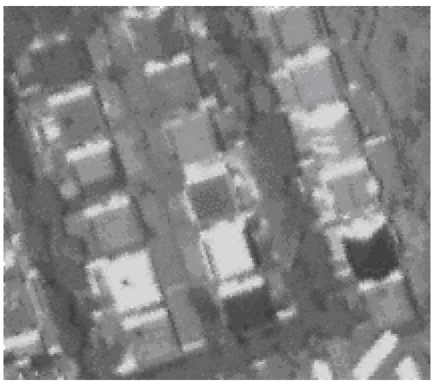

Fig. 4.5.a Level 1 image

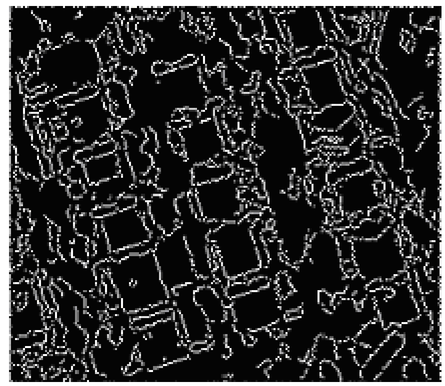

Fig. 4.5.b Edges detected at level 1

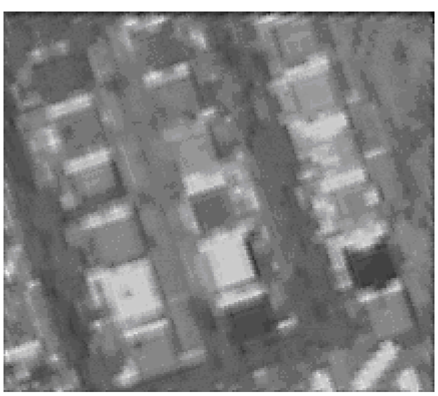

Fig. 4.6.a Level 2 image

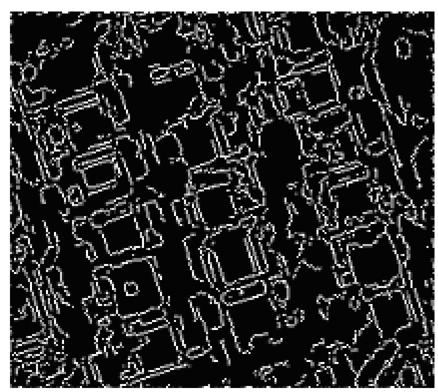

Fig. 4.6.b Edges detected at level 2

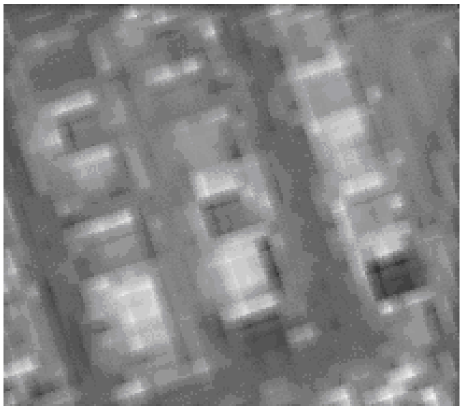

Fig. 4.7.a Level 3 image

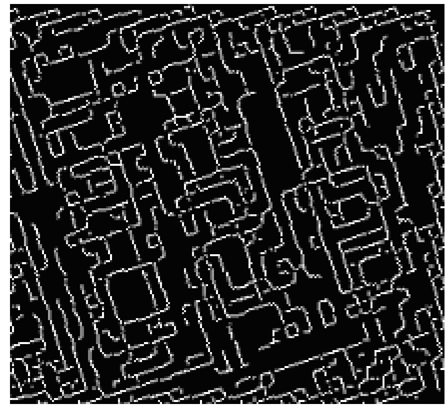

Fig. 4.7.b Edges detected at level 3

It is apparent that the first and second levels are more appropriate for the detection of building outlines. At both the lower levels, the building edges are picked up. The second level, gives a much better visualisation: the edges are straight lines and at the later stages of the study, these straight edges play an important role in the template matching step.

4.4 Parameters of the Canny edge detection

The Canny operator works in a multi-stage process. First of all, the image is smoothed using a Gaussian convolution. Then a simple 2-D first derivative operator is applied to the smoothed image to highlight regions of the image with high first spatial derivatives. Edges give rise to ridges in the gradient magnitude image. The algorithm then tracks the top of these ridges and sets to zero all pixels that are not actually on the ridge top so as to give a thin line in the output in a process known as *non-maximal suppression*. The tracking process is controlled by two thresholds: *T1* and *T2*, with *T1 > T2*. Tracking can only begin at a point on a ridge with a gradient higher than *T1*. Tracking then continues in both directions out from that point until the height of the ridge falls below *T2*. The two threshold process helps to ensure that noisy edges are not broken up into multiple edge fragments. The second parameter is the standard deviation which decides the width of the Gaussian kernel used in the smoothing phase and also to suppress the noise.

4.4.1 Threshold parameter

Thresholding is one of the most important parameters of the Canny edge detection, which belongs to the class of gradient operators. A successful choice of value for this parameter enables many weak edges to be picked up, which then gives meaning to the edge map when connected to strong edges. The upper tracking threshold should be set quite high and the lower threshold low for better results. Setting the lower threshold too high will cause noisy edges to break up. Setting the upper threshold too low increases the number of spurious and undesirable edge fragments appearing in the output. The threshold plays an important role in the performance of the edge detector as the probability of missing an edge and probability of marking a false edge depends on the thresholds. The thresholds are based on the amount of noise in the image. The following experiments were conducted to choose the optimal threshold.

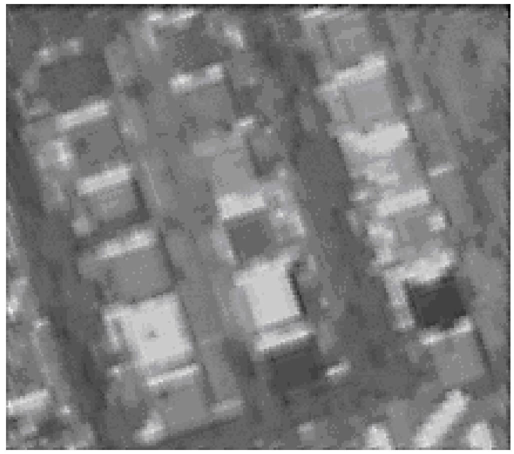

Fig. 4.8 Decomposed 2nd level Wavelet image

High threshold:

A very high threshold results in fewer number of edges being detected as seen in Fig. 4.9 and Fig. 4.10. The threshold value shown is the lower threshold T1. The upper threshold T2 is calculated as four times T1.

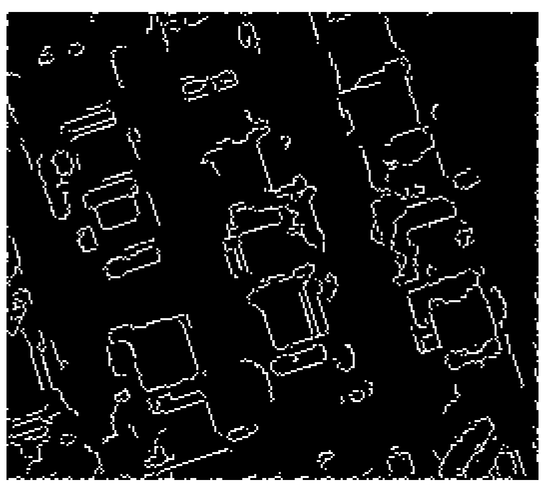

Fig. 4.9 Edge map at 0.25 threshold

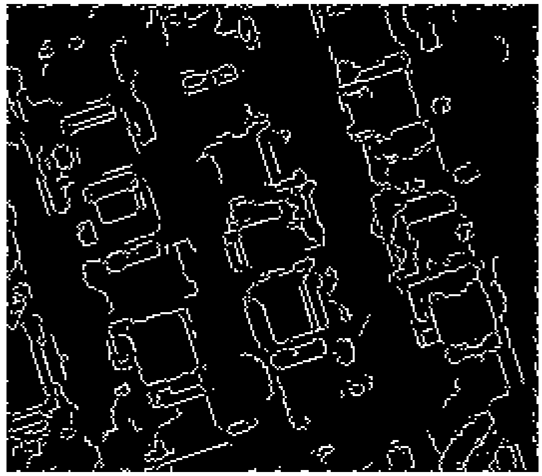

Fig. 4.10 Edge map from Canny edge algorithm (Threshold = 0.2)

Low threshold:

Setting the upper threshold too low increases the number of spurious and undesirable edge fragments appearing in the output as seen in Fig. 4.11.

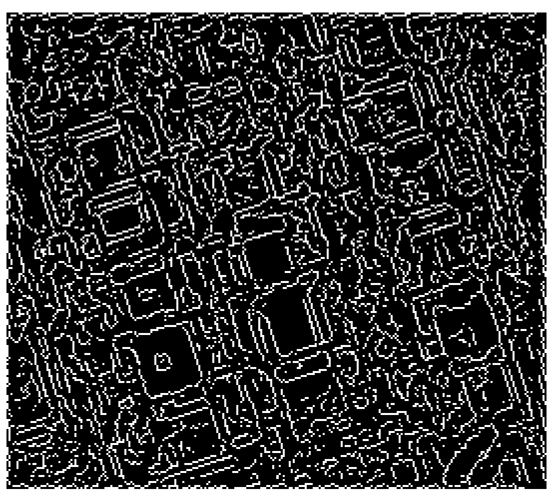

Fig. 4.11 Edge map from Canny edge algorithm (Threshold = 0.01)

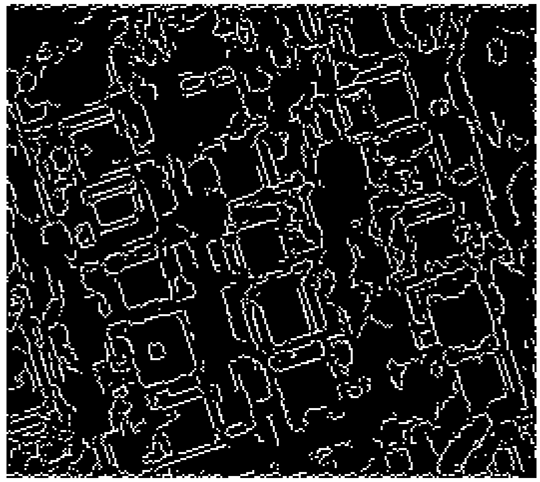

Fig. 4.12 Edge map from Canny edge algorithm (Threshold = 0.07)

The appropriate threshold for this study was determined to be as shown in Fig. 4.13. The threshold was selected depending by noting the number of straight edges detected as straight edges facilitate better template matching in the next step.

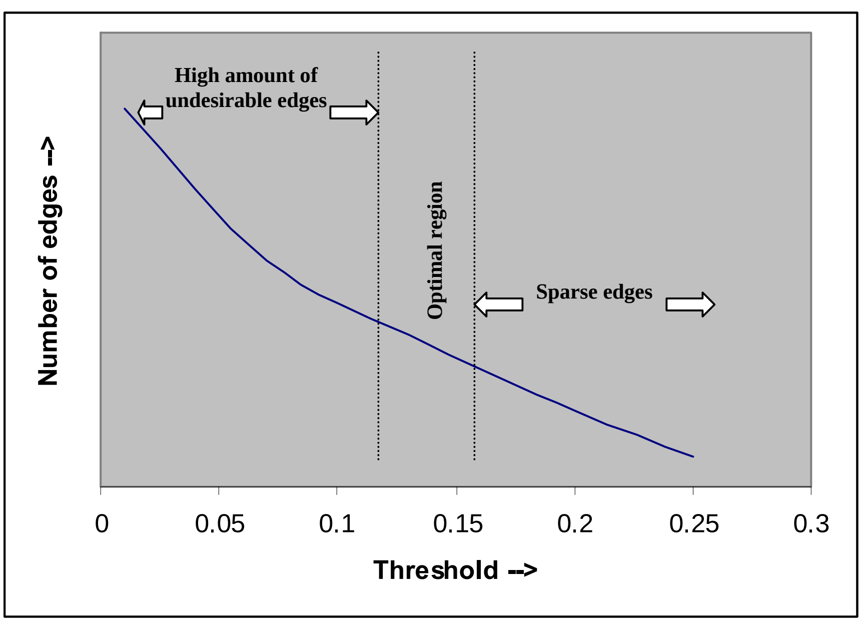

Fig. 4.13 Threshold Plot

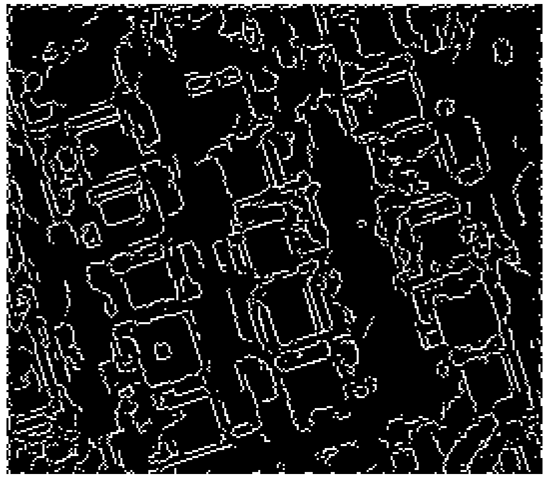

Fig. 4.14 Edge map from Canny edge algorithm (Threshold = 0.13)

4.4.2. Standard Deviation

The standard deviation of the Gaussian filter also plays an important role in the Canny edge detection algorithm, but not as much as the threshold. The results as shown in the following figures where the threshold has been held constant at 0.13.

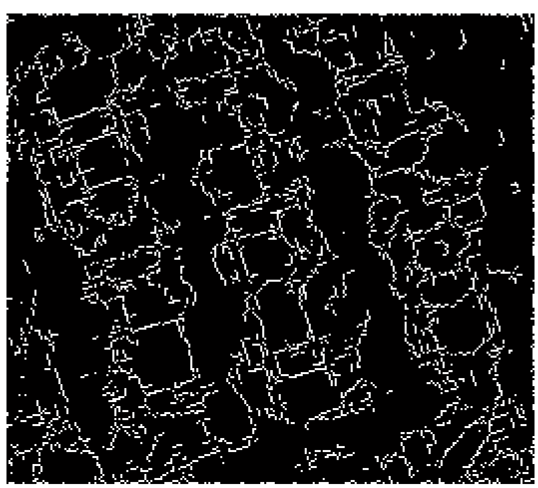

Fig. 4.15 Edge map from Canny edge algorithm (standard deviation = 4)

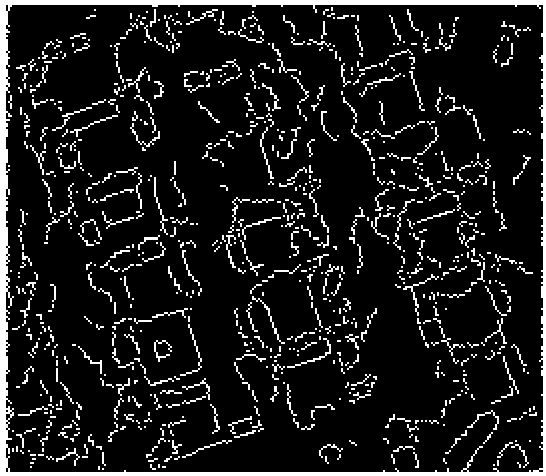

Fig. 4.16 Edge map from Canny edge algorithm (standard deviation = 2)

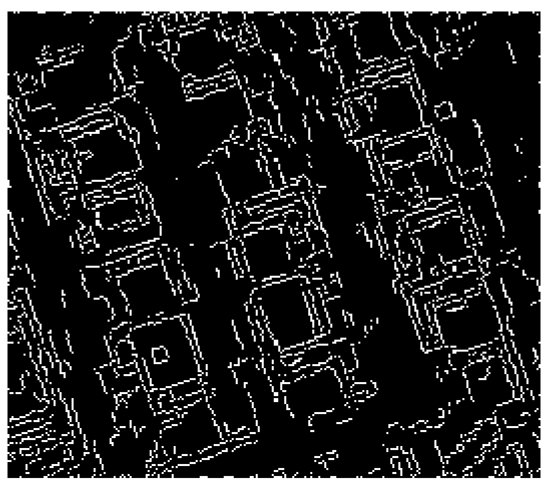

Fig. 4.17 Edge map from Canny edge algorithm (standard deviation = 0.2)

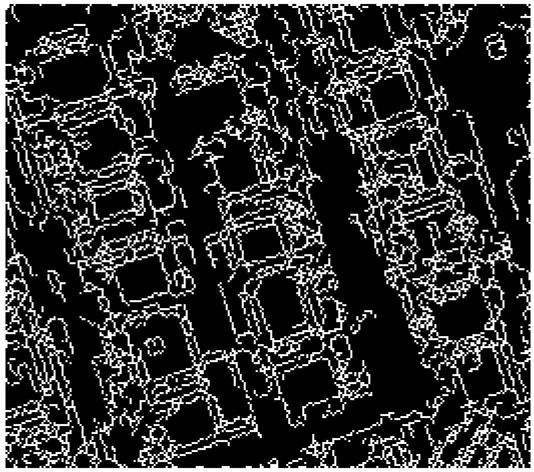

Fig. 4.18 Edge map from Canny edge algorithm (standard deviation = 0.05)

A high value for the standard deviation parameter leads to fewer number of edges. Much of the detail on the image is no longer detected but most of the strong edges remain. The edges also tend to be smoother and less noisy. In the case of a low value for the standard deviation, most of the major edges are detected and lots of detail has been picked out well but this may be too much for subsequent processing.

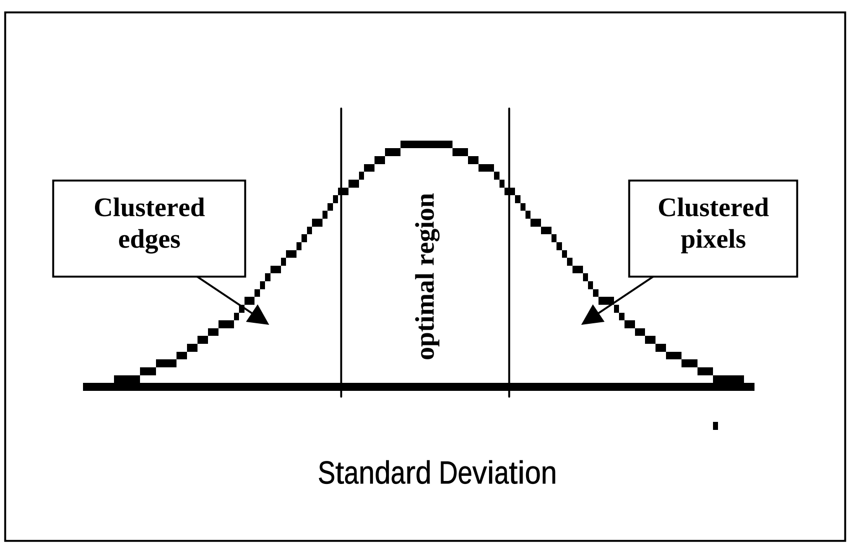

Fig. 4.19 Standard deviation plot

The appropriate standard deviation and threshold, when applied to the decomposed wavelet image results in the following edge map.

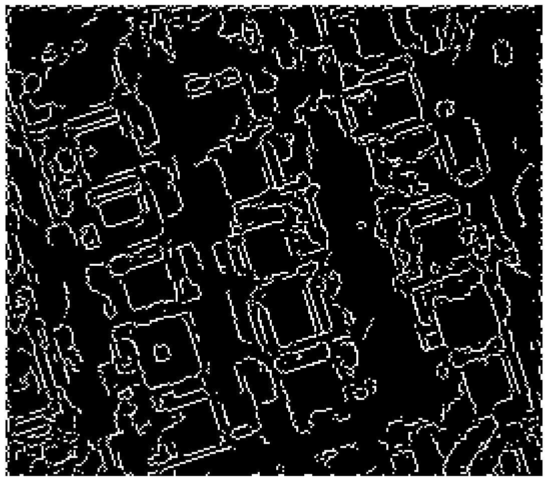

Fig. 4.20 Edge map

4.5 Morphological Operations

Morphological operations are used to understand the structure or form of an image. This usually means identifying objects or boundaries within an image. Morphological operations play a key role in applications such as machine vision and automatic object detection. Morphological operations are usually performed on binary images where the pixel values are either 0 or 1. A morphological operation is applied to the edge map to remove isolated pixels. The morphologic operation is performed by mapping small square pixel neighbourhoods for removing the isolated pixels. Morphological functions operate on 3 x 3 pixel neighborhoods. This operation helps in establishing connected boundary edges, which facilitates the template matching process.

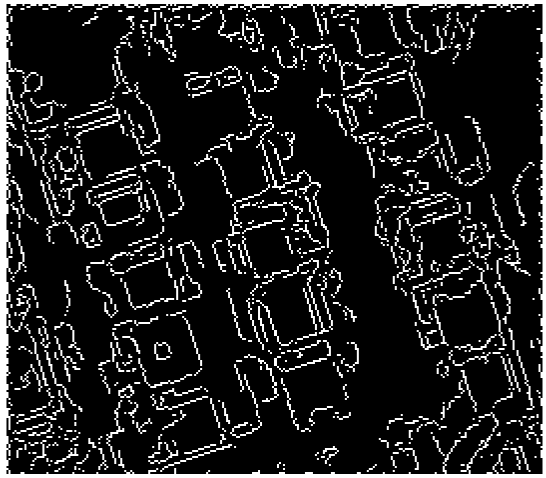

Fig. 4.21 Final edge map

4.6 Parameters for template matching

4.6.1 Shape Models

Pre-defined regular and sometimes even irregular shape models represent the main requirement for an object matching procedure. The basis of such a procedure can be a simple matching algorithm or a very complex non-linear regression model like a neural network. In the neural network, learning typically occurs by example through training, or exposure to a set of exemplar input/output data where the training algorithm iteratively adjusts the connection weights (synapses). These connection weights store the knowledge necessary to solve specific problems. This is often used in the numerical approach. The neural networks are often good at solving problems that are too complex for conventional technologies.

In this study the simple template matching procedure is used as it deals with the identification of simple shapes. Creating such a database is the most tedious part of the procedure. During the template matching process, the model is fitted on the extracted pattern. Due to factors such as object size, rotation, and image distortions, a large number of models are often necessary. Therefore, this procedure is limited to the detection of simple figures with few and simple shape variations. Squares and rectangles of different sizes constitute the main shapes used in the study. These models vary in size from 20 to 40 pixels.

The operator placed the initial match. The first template was decided based on the study of the site and running different templates. The size and shape of the template was saved and tried on the other objects. From then, the size, shape and rotation was changed and modified from the saved template and matching was carried out for the entire map.

4.6.2 Block template matching

Block template matching takes into consideration all the edges simultaneously. Not all edges can be detected, due to the existence of some broken edges resulting from the Canny edge detection. So an accuracy parameter is chosen such that most of the buildings are detected. The accuracy parameter is defined as the minimum number of pixels on the edges to be present for a plot to be identified. For the block template matching, all the edges put together has to satisfy the accuracy parameter. The results are shown with different template sizes and with different accuracy parameters.

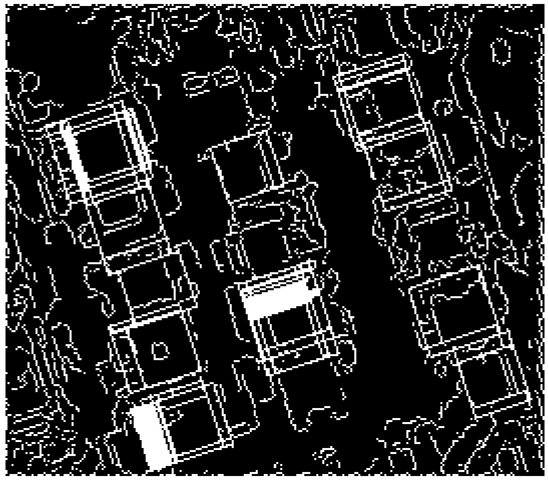

Fig. 4.22 Block template matching – pixels 30 to 40
Accuracy parameter: 92%

When the accuracy parameter is set high at 92% as in Fig. 4.22, few edges are identified resulting in very few building outlines being detected.

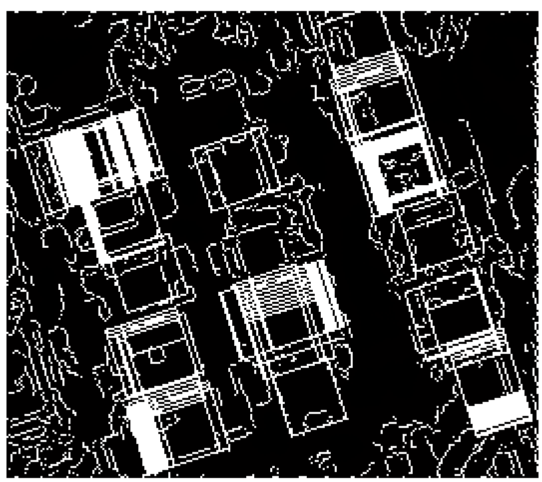

Fig. 4.23 Block template matching – pixels 20 to 40
Accuracy parameter: 75%

From Fig. 4.23 it can be seen that many building outlines are identified, compared to the Fig. 4.20. All building outlines were picked up except for one particular building that was not identified since none of the four edges meet the accuracy parameter set. If the accuracy parameter is decreased, then non-building edges are detected.

4.6.3 Edge template matching

In contrast to block template matching, patterns to be matched are broken into component templates. Edge template matching finds the building outline edge by edge. There are four accuracy parameters, one for each edge with same value. Unlike in the previous matching technique, if an edge is broken or has a fewer number of continuous pixels, a building outline is still found if the accuracy parameter is satisfied. The accuracy parameter is set at 80 % for this technique.

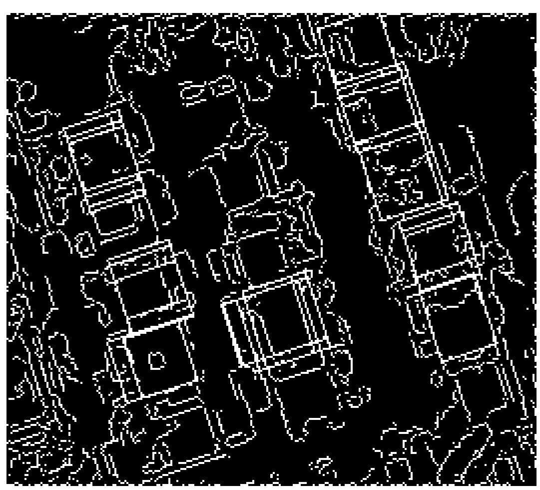

Fig. 4.24 Edge template matching – pixels 30 to 40
Accuracy parameter: 95%

Fig. 4.25 Edge template matching – pixels 20 to 40
Accuracy parameter: 90%

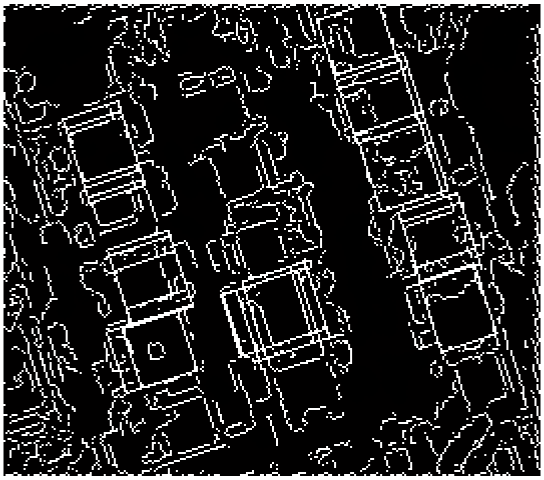

Fig. 4.26 Edge template matching – pixels 35 to 40
Accuracy parameter: 80%

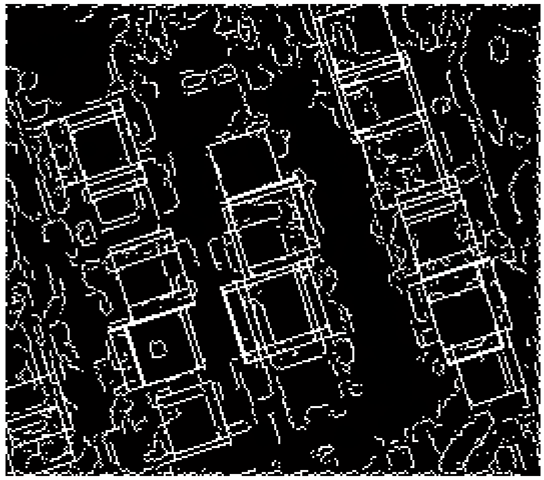

Fig. 4.27 Edge template matching – pixels 30 to 40
Accuracy parameter: 80%

From the Fig. 4.27, it is seen that 14 buildings are identified. In the next chapter, the results obtained are compared and discussed.

CHAPTER5. RESULTS AND DISCUSSIONS

5.1 Results of Feature Extraction

The test site for the detection of buildings was chosen from IKONOS panchromatic image data. IKONOS is a high spatial resolution, multi-spectral earth observing system. The pixel size of the high resolution panchromatic channel is 1m. The test site shows a part of the residential area near the East Coast Park (ECP) in Singapore fig. 5.1. The size of the house plots varies from 5m to 10m and allows a good visual interpretation due to the good spectral contrast.

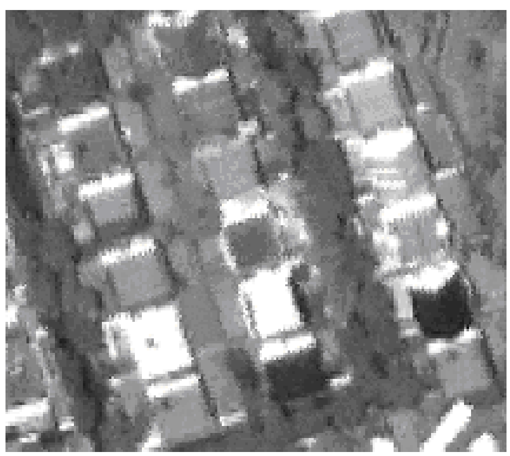

Fig. 5.1 Test site

The following picture provides more information about the test site. This is just to provide a good comparison of the real world scenario. The chosen house plots belong to the category of private housing. Each plot is a two storey building. From the picture, the shape of the roof top is seen, but it does not provide the accurate shape of each plot. As compared to the imagery and the below picture, it is clearly seen that shape of a few plots are not the same.

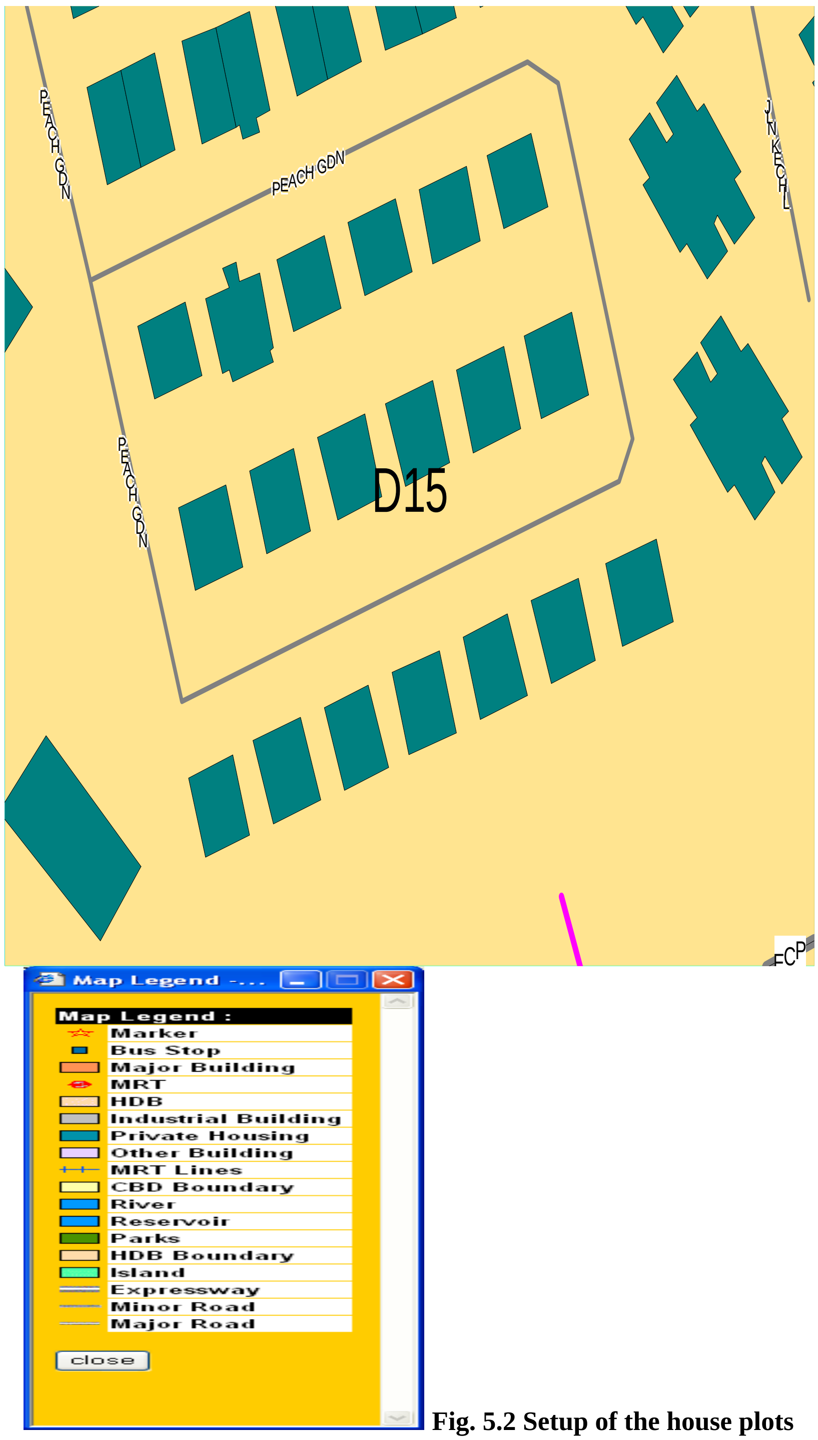

Fig. 5.2 Setup of the house plots

(Courtesy: www.can.com.sg)

As discussed in the previous chapter, the proposed technique detects the edges from the wavelet-analyzed test site as the first step and finally the classification is a simple template matching. Two methods are adopted in the classification stage: block template matching and edge template matching. The results of the two detection process are shown below. The white straight outlines show the detected buildings.

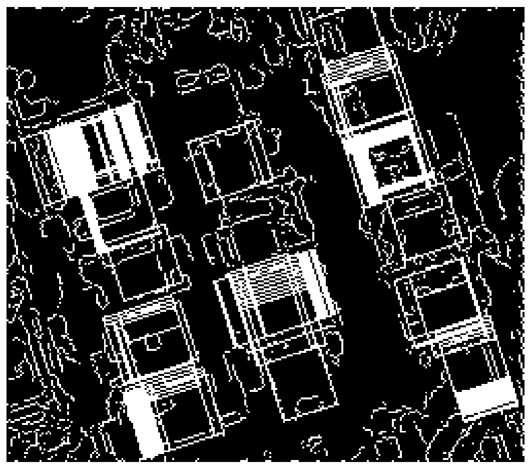

Fig. 5.3 Block Template Matching

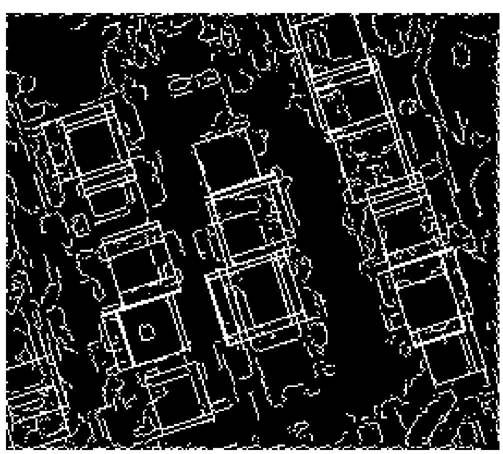

Fig. 5.4 Edge template matching

All the programs are implemented in MATLAB 6.0, running under the Windows NT 4.0 operating system, a language that offers an interpreter command interface and debugging facilities. All the images were stored in the grey-level tagged image file format (tiff), a widely used bitmap file format.

The template matching approach for finding buildings is computationally expensive. For the main testing image used which is approximately, 317 x 333 pixels in size and approximately 1 to 1.5 square meters per pixel. Running MATLAB on a Pentium III processor, this computation took nearly three hours. Much could be done to improve the efficiency and the speed of the programs.

5.2 Assessment of Accuracy

The accuracy assessment is performed by visual comparison with the satellite imagery for the building detection. The results of the validation are presented in table 1.

method	detected	total	true	false	missing
Block template matching	14	17	14 (82%)	0 (0%)	3 (18%)
Edge template matching	15	17	13 (88%)	2 (12%)	4 (24%)

Table 1: Accuracy Assessment of Buildings

The results are split into two methods that are characterized by the different numbers of successful model matches or classifications. The test data in figure 5.1 is covered by approximately 17 house plots. Accurate shape detection is only possible for objects with a high spectral spatial contrast. Since only the spatial content is taken into consideration here in this study, templates are created and fitted over the edge detected image map. Apparently, a high accuracy of 82% - 88% for a correct decision is achieved. In addition to the correct result, two errors (false and missing building plots) are also listed. The latter shows that 18% and 24% of the plots were not detected by the block and edge template matching respectively. If the accuracy parameter (discussed in Chapter 4) is decreased even further, more houses are found but also misclassifications. The repetition of the outlines (seen most in the block template matching) results from inefficiency of the edge detector which led to a partial overlap between the edges. Using only one successful accuracy parameter as in the edge template matching, nearly all plots are recognized but also the highest error rate (12%) occurs. Based on this, more or less reliable results are achieved.

Few plots were missed during the template matching operation. The reason was due to the absence of two or more edge sides. If a compromise has to be done, then the number of misclassifications increases by double. By the block template matching, three plots were missed out, due to the absence of validity of the edges. The undetected edges resulted from darker roofs. In the case of the edge template matching, though the detection of building outlines were based on individual edge lengths, the absence of two edge sides will lead to an undetected plot. And hence, four plots were missed out and two false plots.

With the help of the human visual interpretation, more reliable plots are identified using the additional information about shadow or the regular patterns, which they form in the densely settled areas.

5. 3 Key Features of the proposed method

By using the new wavelet-based edge detector recommended in this study to extract image edges from a satellite imagery, and comparing the results with the well known edge operators such as Sobel, Prewitt or even Canny, the following conclusions can be drawn. Fig. 5.3 shows an original satellite with 317 x 333 pixels. Fig. 5.9 provides the wavelet analyzed edge map. Compared with Prewitt, Sobel and Zero-crossing's of which the results are shown in figures fig.5.5, fig. 5.6 and fig. 5.7 for the same image, the new approach has obvious advantages. The proposed approach is very similar to the Canny operator (Canny, 1986) (fig. 5.8), but the wavelet theory is well known for its good multi-resolution and multi-scale properties which are extremely important for image processing, computer vision and modern GIS. The wavelet transform method can change the size of window corresponding to the frequency parameter. Because of the good localization properties of wavelet transform in both frequency and spatial domain we can extract the regular features with added advantage. According to the above mentioned investigation, the edge operator based on wavelet (fig. 5.9) has obviously many advantages.

The simple classification scheme used in this study has resulted in a faster and less complex matching process. The model database together with shape variations can be easily established and updated.

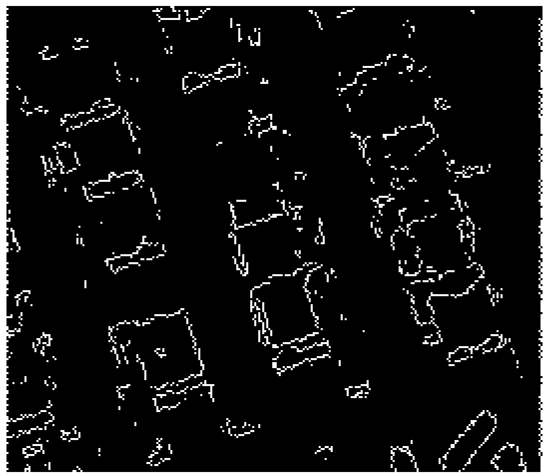

Fig. 5.5 Prewitt Edge Detector

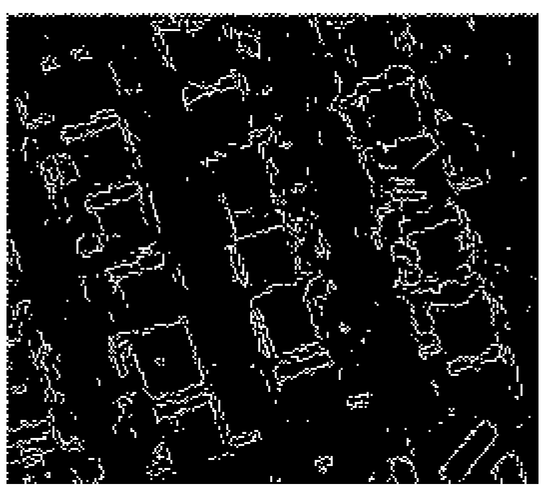

Fig. 5.6 Sobel Edge Detector

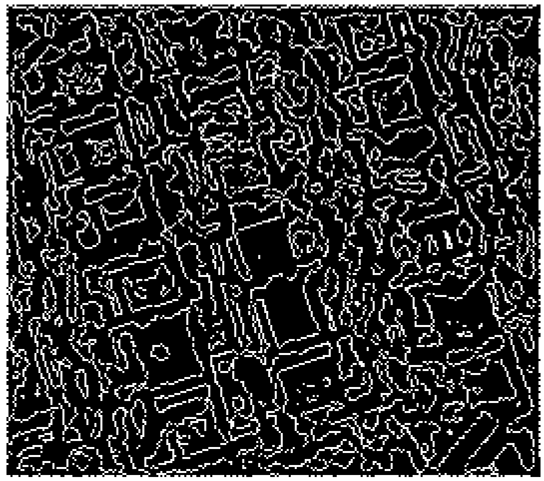

Fig. 5.7 Zero-crossing Edge Detector

The edges detected with Prewitt operator, Sobel operator and zero-crossings operator for the same original image as in Fig 5.1.

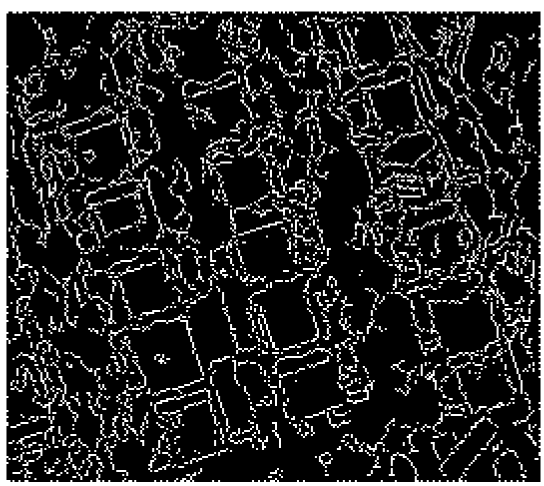

Fig. 5.8 Canny Edge Detector

Edges detected with Canny edge detector without wavelet analysis

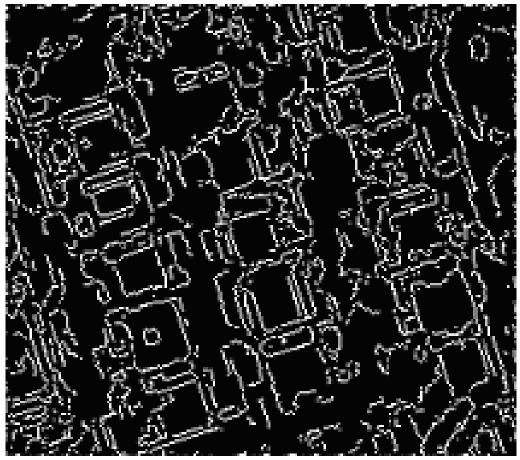

Fig. 5.9 Canny Edge Detector

Edges detected with Canny edge detector with wavelet analysis

Another testing has been done below. The table 5.2 below shows the comparison between the Canny edge detector and the Sobel edge detector with and without the application of wavelets (the Sobel edge detector was chosen as an example to compare against the Canny edge detector). An interesting result is seen. With the application of wavelets, more number of house plots has been detected by the Canny edge detector. But, the reverse is noted with the Sobel edge detector. The wavelets try to localize the signals which in turn tend to decrease the number of spurious edges. In most cases, the spurious edges are those which help to connect the weak and strong edges. As seen in fig.5.10 the Sobel edge detector has detected only few edges as compared to the Canny edge detector (fig.5.8).

total number of house plots: 17	**canny edge detector + template matching**	**sobel edge detector + template matching**
without wavelets	8	4
with wavelets	14	2

Table 5.2: Comparison between Canny & Sobel Edge Detectors

The following figures show the results on the same test (fig. 5.1) site with the application of the Sobel edge detector instead of the Canny edge detector.

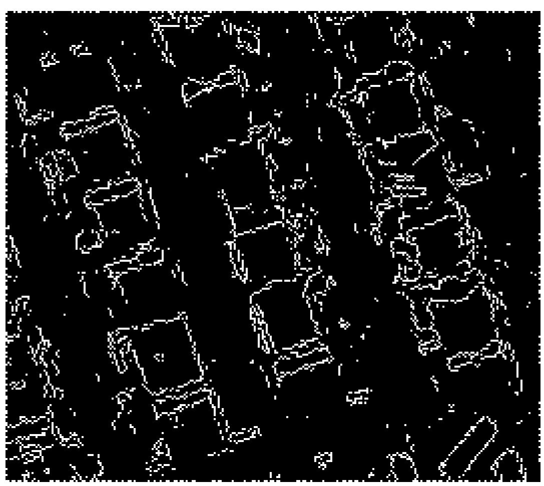

Fig. 5. 10 Sobel Edge Map

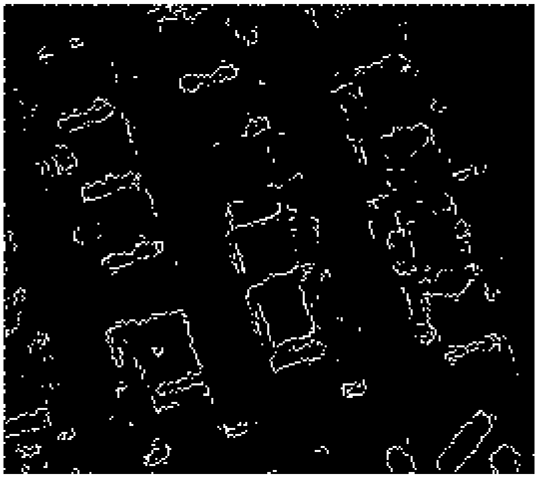

Fig. 5. 11 Wavelets + Sobel Edge Map

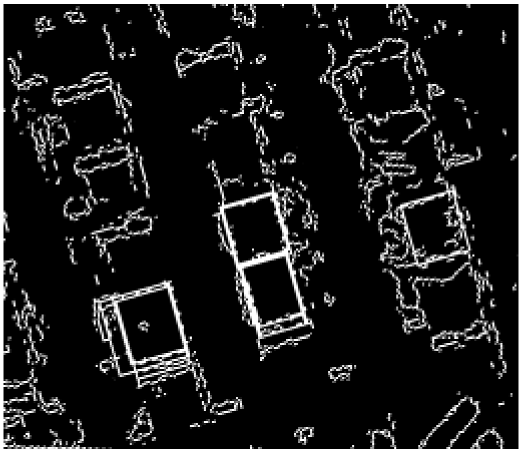

Fig. 5. 12 Sobel Edge Detector + Template Matching

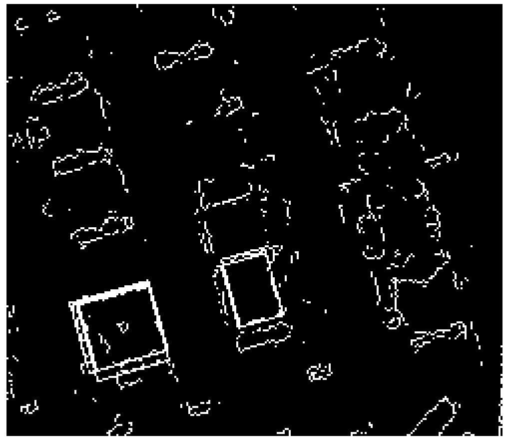

Fig. 5. 13 Wavelets + Sobel Edge Detector + Template Matching

The result of the template matching on a Canny edge map without the application of wavelets is shown below in fig. 5. 14.

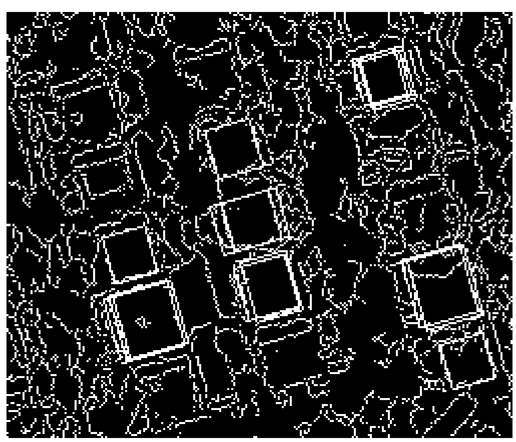

Fig. 5. 14 Canny Edge Detector + Template Matching

5.4 Validation of the Algorithm

The proposed technique was tested on two experimental data. The first test data was a similar patch to the test site. This was experimented first to check if the algorithm works fine. As seen in the fig. 5.15, in this patch the house plots are very close to each other. With the help of the WavEDIS technique, the unwanted features were removed and final edge map is shown (fig. 5.16) with only the house plots. Problems were not encountered during the template matching stage. The same template sizes with little modifications were used. The final image (fig. 5.17) shows that 6 house plots were identified. All the plots were successfully extracted since all the plots look alike and template shapes were also not needed to be changed.

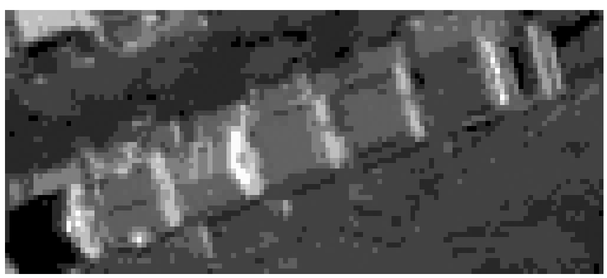

Fig. 5.15 Experiment Site 1

Similar house plots as test site

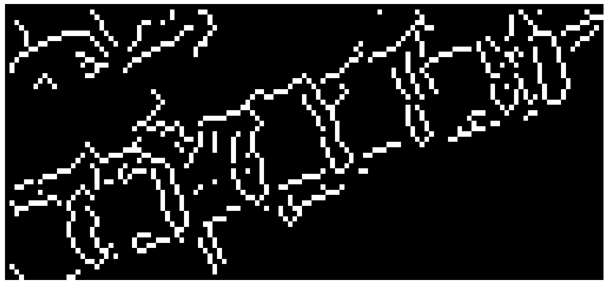

Figure 5. 16 Edge Map

Figure 5. 17 Final Map

The next data used was different from the above tested or experimented data. A patch of tall buildings were now tested. The main aim of the study is to detect/count the number of buildings, so the proposed technique was applied on the following site to check the algorithm's validity. As seen in the fig. 5.18, high amount of relief displacement is seen. Many difficulties were encountered during this testing. Unlike the previous patches, were the roof tops were only seen and the house plots were of regular shape and low-rise, here the buildings are tall and its facets are also seen. Fig. 5.19 shows the setup of the tall buildings in a map. These are categorized under the private housing section. Each building has 14 floors.

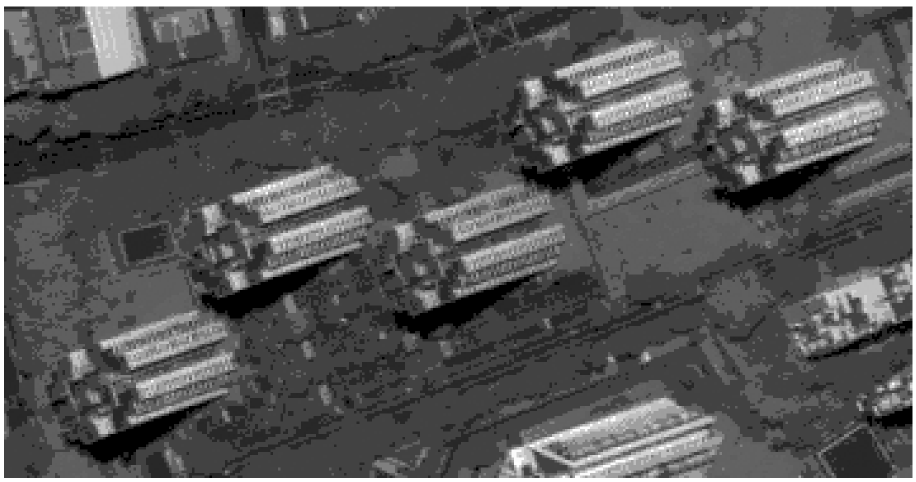

Fig. 5. 18 Experiment Site 2

Patch of tall buildings

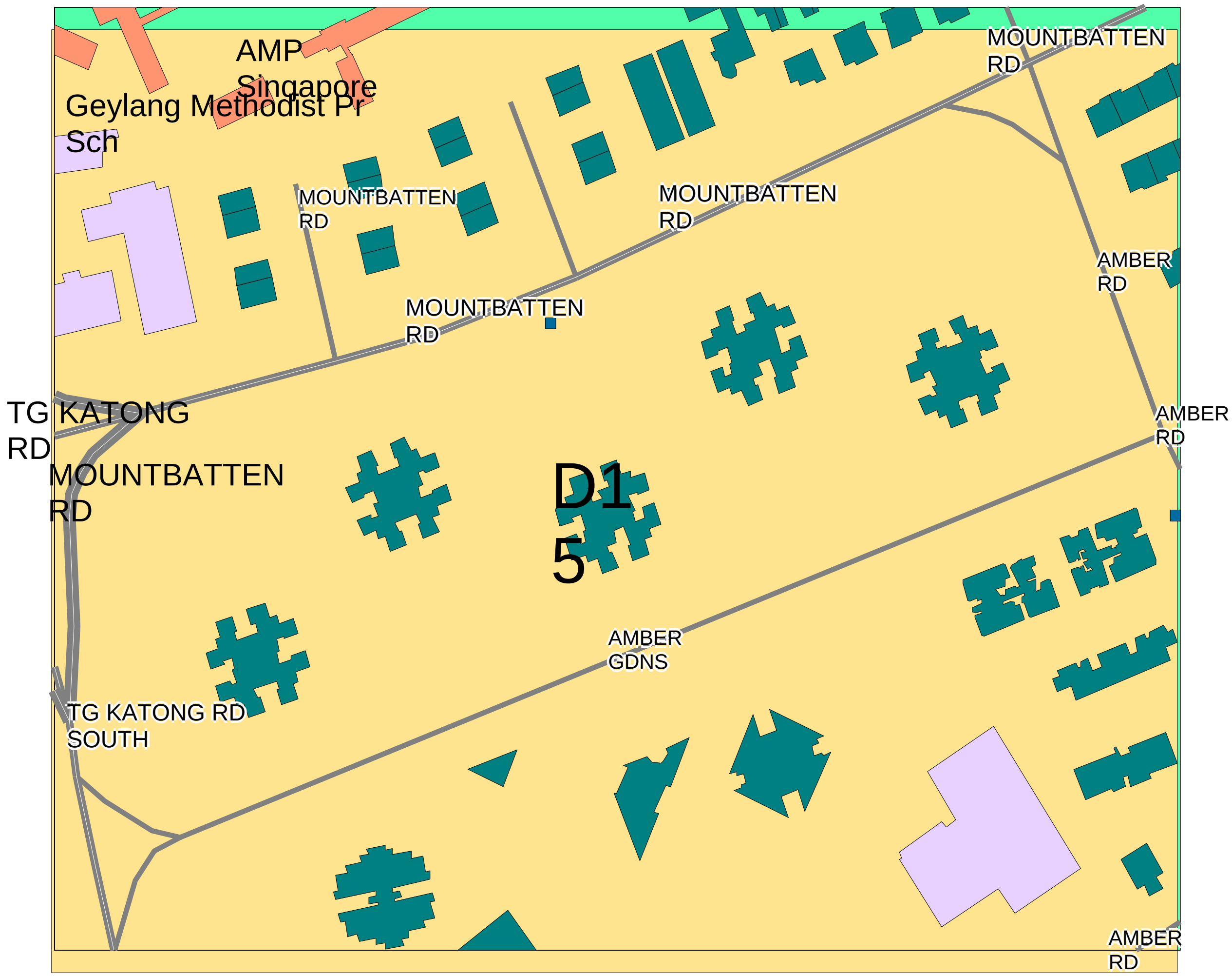

Fig. 5. 19 Setup of the Experiment Site 2 as seen on a map

The resulting edge map is seen in fig. 5.20. The next problem was choosing a template shape and size for this patch. Due to the problem of un-ortho-rectified imagery, resulting in the non-rectification of the relief displacement, the templates to be chosen are different from the previous examples. After many attempts the templates were chosen and applied on the scene. The resulting image is shown in fig. 5.21. It shows that all buildings were identified along with one more template matched. The error was due to a half building seen in the scene. Since its face is also in a similar shape, the technique identified the face also as a building. The sixth building (half part of the tall building) was introduced to see the algorithm's affect and as expected, it identified the sixth building also. The other small building seen in the scene is not extracted, due to the template size.

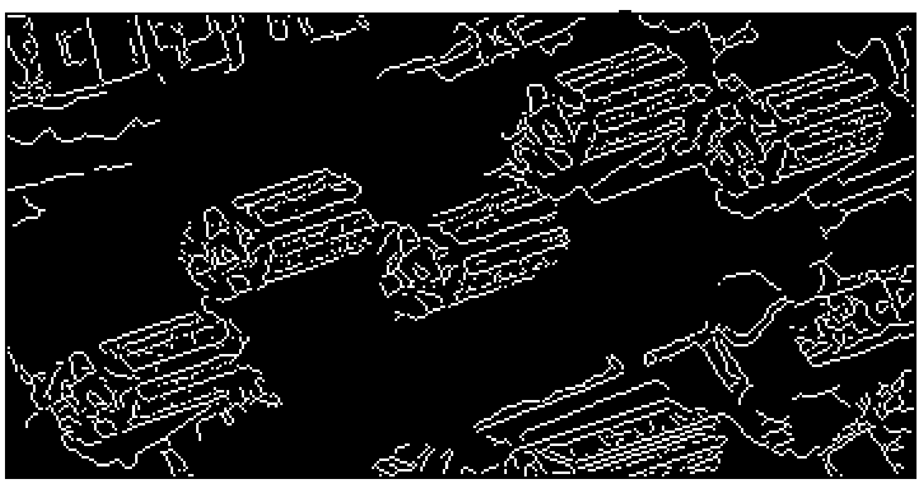

Fig. 5. 20 Edge Map

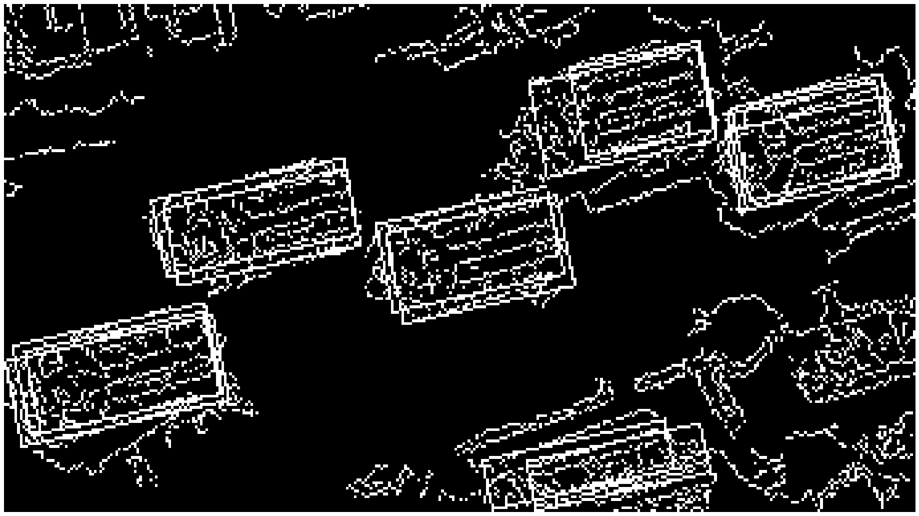

Fig. 5. 21 Final Map

Concluding all the above experiments, it is noted that the proposed WavEDIS and template matching algorithm has successfully extracted the buildings. Further conclusions are discussed in detail in the next chapter.

CHAPTER 6. CONCLUSIONS

6.1 Conclusions

An algorithm for finding building outlines in high resolution satellite imagery such as IKONOS was implemented and tested on an urban area. The proposed technique can be used to detect objects in the imagery in semi-automated way. The application of wavelet based edge detection and template matching was successfully demonstrated on building detection.

The application of wavelets brings about a better change in the recognition of the characteristics of the edges. A possible explanation is that the wavelets try to localize the signals which in turn tend to decrease the number of spurious edges. In most cases, the spurious edges are those which help to connect the weak and strong edges. Comparing the results of the Sobel edge detector and the Canny edge detector, the latter produced much better results than the former. The Sobel method finds edges using the Sobel approximation to the derivative and it returns edges at those points where the gradient of image is the maximum. The Sobel edge detection algorithms convolves masks with the image to detect both the horizontal and vertical edge components; the resulting outputs are simply added to give a gradient map. The Canny method finds edges by looking for local maxima of the gradient of the image. The gradient is calculated using the derivative of a Gaussian filter. The method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. This method is therefore less likely to be "fooled" by noise, and more likely to detect true weak edges.

There are also a few shortcomings to be noted. The imagery is an un-orthorectified imagery, which results in relief displacement for high rise buildings and other tall features. Simpler template shapes can be used on low rise buildings. More complicated shapes are used for tall condominiums and Housing Development Board (HDB) flats if ortho-rectified images are not used. If such images are available, then simpler shapes can be used.

Automating the entire image analysis process is a complex problem. In the tests conducted, the main cause for the false figures was the edge detection algorithm. Though the edge detector used was one of the best available, a few edges were still missed. Although the number of edges missed may be small, the effect could be significant. This error was compromised by using templates for matching objects. It can be concluded that the proposed edge-based recognition of man-made features will produce better results if combined with region-based techniques.

The computational time of the algorithm is quite lengthy, due to the number of operations involved and the computing equipment used. However there is much opportunity for parallelism to be exploited and this could make the computation much shorter. With the increased availability of high resolution imagery, better resolutions than

1-meter will soon be abundantly available. Since the proposed algorithm can detect buildings even at coarser resolution, it should be able to recognize additional details within buildings and other man-made features when using higher-resolution imagery. As the study is a preliminary one, the results of the present study cannot be generalized due to the small training area. But the results are definitely promising and pave way for future studies.

6.2 Future Improvements

Future improvements to make the algorithm more useful and practical include:

- <u>Combining edge maps</u>

  The edge detection algorithm can be further modified as to combine edge maps from different threshold hysteresis. This will enable to accommodate edges from different thresholds and lead to a better edge map than from a single threshold.

- <u>Using more template shapes and sizes</u>

  In the shape classification technique, more template shapes and sizes can be added to the database. This would allow for a wider range of building object matches.

Improvising on the above areas will make the project a powerful and practically useful algorithm to detect building features from high spatial resolution imagery.

REFERENCES

1. Abyoto Kun Wardana, Wirdjosoedirdjo Sri Jatno, Tadashi Watanabe, *'Unsupervised Segmentation using Multiresolution Analysis for Feature Extraction'*.

2. Bergholm, F., *'Edge Focusing'*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 9, 1987, pp. 726-741.

3. Canny, J., *'A Computational Approach to Edge Detection'*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 8, no. 6, 1986, pp. 679-678.

4. Clark, J. J., '*Authenticating Edges Produced by Zero Crossing Algorithms'*, IEEE Trans. Pattern and Analysis and Machine Intelligence, vol. 11, no. 1, 1989, pp. 43-57.

5. Daubechies, I., '*Ten Lectures on Wavelets'*, SIAM, 1992.

6. Draper, B.A., *'Modeling object recognition as a Markov decision process'*, Proceedings of the 13th International Conference on Pattern Recognition, 1996, vol. 4, pp. 95 -99.

7. Dunn, D., Higgin, W.E., Wakeley, J., *'Texture Segmentation Using 2-D Gabor Elementary Functions'*, IEEE Trans. on Pattern Analysis and Machine Intelligence, Feb.1994, vol.16, no.2, pp.130-149.

8. Elder, J. H., Zucker, S. W, *'Local Scale Control for Edge Detection and Blur Estimation'*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 20, no. 7, 1998, pp. 699-716.

9. Fatemi-Ghomi, N., Palmer, P. L., Petrou, M., *'Performance Evaluation of Texture Segmentation Algorithms based on Wavelets'*, Paper presented at the Workshop on Performance Characteristics of Vision Algorithms, Cambridge, April 19, 1996.

10. Friha, S., Boulemden, M., *'Meteorological Image Processing with Wavelets'*, System Theory, 1998. Proceedings of the Thirtieth Southeastern Symposium, 1998, pp. 208 -212.

11. Goshtasby, A, Shyu, H-L, '*Edge Detection by Curve Fitting'*, Image and Vision Computing, vol. 13, no. 3, 1995, pp. 169-177.

12. Haralick, R., *'Digital Step Edges from Zero Crossing of Second Directional Derivatives'*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 6, 1984, pp. 58-68.

13. Jawerth, B., Sweldens, W., '*An overview of wavelet based multiresolution analyses'*, SIAM Review, 36 (1994), pp. 377-412.

14. Jothimani, P., *'Operational Urban Sprawl Monitoring using Satellite Remote Sensing: Excerpts from the Studies of Ahmedabad, Vadodara and Surat, India'* – Proceedings of the 18^{th} Asian Conference on Remote Sensing.

15. Karras, D.A.; Karkanis, S.A.; Mertzios, B.G., *'A classification approach to image structure segmentation based on the wavelet transform***',** EUROMICRO 97. Proceedings of the 23rd Euromicro Conference on 'New Frontiers of Information Technology'. Short Contributions, 1997, pp. 56 -59.

16. Li Deren, Shao Juliang, *'The Wavelet and its Application in Image Edge Detection'*, ISPRS Journal of Photogrammetry and Remote Sensing, 1994, vol. 49, no. 3, pp. 4-11.

17. Li, S. Z., *'Closed-Form Solution and Parameter Selection for Convex Minimization-Based Edge Preserving Smoothing'*, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 20, no. 9, 1998, pp. 916-932.

18. Lijun Ding, Goshtasby Ardeshir, *'On the Canny edge detector'*, Pattern Recognition, vol. 34 issue (3) March 2001 pp. 721-725.

19. Luiz Alberto Lisoba da Silva Cardoso, *'Computer Aided Recognition of Man-made Structures in Aerial Photography'*, Master's Thesis, Naval Postgraduate School, Monterey, CA. 1999.

20. Mah Abdullam, *'Urban planning and monitoring changes using ER Mapper'* – Proceedings of the 21st Asian Conference on Remote Sensing.

21. Mallat, S., Zhong, S., *'Characterization of Signals from Multiscale Edges'*, IEEE Trans. on Pattern Analysis and Machine Intelligence, July 1992, vol.14, no.7, pp.710-732.

22. Mandal, D.P.; Murthy, C.A.; Pal, S.K., *'Analysis of IRS imagery for detecting man-made objects with a multivalued recognition system'*, IEEE Transactions on Systems, Man and Cybernetics, Part A, March 1996, vol. 26, issue. 2, pp. 241 - 247.

23. Manjunath, B.S., Ma, W.Y., *'Texture Features for Browsing and Retrieval of Image Data'*, IEEE Trans. on Pattern Analysis and Machine Intelligence, Aug.1996, vol.18, no.8, pp.837-842.

24. Marr, D., Hildreth, E., *'Theory of Edge Detection'*, Proc. Royal Society of London, vol. B-207, 1980, pp. 187-217.

25. Mueller, M. and Segl, K., *'Object recognition based on high spatial resolution panchromatic satellite imagery'*, Joint workshop of ISPRS on Sensors and Mapping from Space September 1999, 27-30, Hannover, Proceedings as electronic publication.

26. Pereira, M.S.; Manolakos, E.S. *'Hierarchical neural network for multiresolution image analysis'*, International Conference on Image Processing, 1996, Proceedings, 1996, vol.1, pp. 261 -264.

27. Rifaat, R., Kinsner, W., *'Experiments with Wavelet and other Edge Detection Techniques'*, 1997 Conference on Communications, Power and Computing Proceedings, Winnipeg, MB, May 22-23, 1997, pp. 322-326.

28. Rowe Neil C., Grewe Lynne L., *'Change Detection for Linear Features in Aerial Photographs Using Edge-Finding'*, IEEE Transactions On Geoscience And Remote Sensing, vol. 39, no. 7, July 2001, pp. 1608-1612.

29. Rusyn, B., *'The investigation of singling algorithms for small-dimensioned object recognition for remote Earth sensing'*, 6th International Conference on Mathematical Methods in Electromagnetic Theory, 1996, pp. 136 -138.

30. Mallat, S.G., *'A Theory for Multiresolution Signal Decomposition: The Wavelet Representation'*, IEEE Trans. on Pattern Analysis and Machine Intelligence, July 1989, vol.11, no.7, pp.674-693.

31. Shi, Z.; Shibasaki, R., *'An approach to image segmentation using multiresolution analysis of wavelets'*, SMC '99 Conference Proceedings, IEEE International Conference on Systems, Man, and Cybernetics, 1999, vol. 6, pp. 810 -815.

32. Siddique, J.I.; Barner, K.E, *'Wavelet-based multiresolution edge detection utilizing gray level edge maps'*, Image Processing, ICIP 98. Proceedings. 1998 International Conference, vol. 2, pp. 550-554.

33. Singh, S.; Markou, M.; Haddon, J., *'FLIR image segmentation and natural object classification'*, Pattern Recognition, 2000. Proceedings. 15th International Conference, vol. 1, pp. 681 -684.

34. Ulupinar, F., Medioni, G., *'Redefining Edges Detected by a LoG Operator'*, Computer Vision, Graphics, and Image Processing, vol. 51, 1990, pp. 275-298.

35. Wu Xiuqing; Zhou Rong; Xu Yunxiang, *'A method of wavelet-based edge detection with data fusion for multiple images'*, Intelligent Control and Automation, Proceedings of the 3rd World Congress, vol. 4, 2000, pp. 2691 - 2694.

36. Xiuwen Liu; Ke Chen; DeLiang Wang, *'Extraction of hydrographic regions from remote sensing images using an oscillator network with weight adaptation'*, IEEE Transactions on Geoscience and Remote Sensing, vol. 39, issue. 1, Jan. 2001, pp. 207 -211.

37. Yingcheng Li, Liangcal Chu, Tongying Guo, Yanli Xue, Xueyou Li, Xiaobo Ding, Xiaolong Liu, *'Landuse Change and Urban Growing Monitoring in China'*, Proceedings of the 20th Asian Conference on Remote Sensing.

38. HongJiang Zhang, *'Automatic Tracking Ice Floe from Satellite Imagery Abstract via Invariant Moment Matching'*, IGARSS '92. International Geoscience and Remote Sensing Symposium, 1992, pp. 582 -584.

APPENDIX 1

Orthonormal compactly supported wavelets

A brief description of orthonormal, compactly supported wavelet bases is discussed here; detailed information can be found, for example, in Daubechies [38] and Jawerth and Sweldens [39].

An orthonormal, compactly supported wavelet basis of $\mathbf{L}^2(\mathbf{R})$ is formed by the dilation and translation of a single function $\psi(x)$, called the wavelet function:

$$\psi_{j,k}(x) = 2^{-j/2}\psi(2^{-j}x - k); \quad j,k \in \mathbf{Z}, \tag{1}$$

where $\mathbf{Z}$ is the set of integers. In equation (1), the function ψ has M vanishing moments up to order $M-1$, and it satisfies the following ``two-scale" difference equation,

$$\psi(x) = \sqrt{2}\sum_{k=0}^{L-1} g_k \psi(2x - k). \tag{2}$$

The wavelet function $\psi(x)$ has a companion, the scaling function $\phi(x)$, which also forms a set of orthonormal bases of $\mathbf{L}^2(\mathbf{R})$,

$$\phi_{j,k}(x) = 2^{-j/2}\phi(2^{-j}x - k); \quad j,k \in \mathbf{Z}. \tag{3}$$

The scaling function $\phi(x)$ satisfies,

$$\int_{-\infty}^{+\infty} \phi(x)dx = 1. \tag{4}$$

and the ``two-scale difference" equation,

$$\phi(x) = \sqrt{2}\sum_{k=0}^{L-1} h_k\phi(2x-k). \tag{5}$$

In equations (2) and (5), two coefficient sets $\{g_k\}$and $\{h_k\}$have the same finite length $L$for a certain basis, where $L$is related to the number of vanishing moments M in $\psi(x)$. For example, Lequals $2M$in the Daubechies wavelets. In the wavelet representation of signals, $\{h_k\}_{k=0,...,L-1}$behaves as a low-pass filter and $\{g_k\}_{k=0,...,L-1}$ behaves as a high-pass filter to signals. These two filters are related by

$$g_k = (-1)^k h_{L-k}; \quad k = 0,..., L-1, \tag{6}$$

Dilated wavelets are related by a scaling equation. Rescaling can be interpreted as discrete filtering. Vanishing moments, support, regularity and symmetry of the wavelet and scaling function are determined by the scaling filter. A wavelet has m vanishing moments if and only if its scaling function can generate polynomials of degree smaller than or equal to M. While this property is used to describe the approximating power of scaling functions, in the wavelet case it has a "dual" usage, e.g. the possibility to characterize the order of isolated singularities. The number of vanishing moments is entirely determined by the coefficients h[n] of the filter h which is featured in the scaling equation.

The scaling function is compactly supported if and only if the filter h has a finite support, and their supports are the same. If the support of the scaling function is [N1, N2], then the wavelet support is [(N1-N2+1)/2,(N2-N1+1)2]. Daubechies has proved that, to generate an orthogonal wavelet with p vanishing moment, a filter h with minimum length 2p had to be used. Daubechies filters, which generate Daubechies wavelets, have a length of 2p.