# Abalone Tag Detection and Recognition

by

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A dissertation submitted to the

School of Computing and Information System

in partial fulfilment of the requirements for the degree of

**Master of Computing**

UNIVERSITY
OF TASMANIA

**JUNE 2009**

## Declaration

I, Harpreet Kaur Gill, declare that this thesis contains no material which has been accepted for award of any other degree or diploma in any tertiary institution, and that, to my knowledge and belief , this thesis contains no material previously published or written by another person except where due reference is made in the text.

Harpreet Kaur

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## Abstract

In recent years, there have been serious concerns about the declining stocks of wild abalone combined with a rapidly increasing market demand and so aquaculture researchers are continuously investing in new methods for growing and monitoring cultured abalone. There are a number of new programs that have been planned for farmed abalone, such as selective breeding and genetic manipulation to meet world demand.

These methods can only be successful if abalone traits and behaviour can be identified properly. Therefore, physical tagging of abalone shells and DNA (Deoxyribonucleic Acid) pedigree markers have been developed to enable tracking and tracing of individuals. Researchers are continually finding more effective methods of physical tagging so that tags can be visualised more readily and will be retained on the abalone shell for a longer period of time. Identifying the tag and character information is also time and labour intensive. Therefore, automated image analysis of abalone tags may provide a solution for tracking abalone and for identifying abalone behaviour and pedigree information. After reviewing the broad field of computer vision, an image processing system was developed in MATLAB using appropriate image analysis and processing techniques, to automate the process of extracting sub-images of physical tags attached to the abalone shells, in preparation for input to an optical character recognition system, which would read the tags on the shells.

The image processing system developed was able to successfully identify a number of tags from digital images directly taken from land-based tanks on various abalone farms; tag colour and character recognition was achieved. In addition, this research

will help aquaculture researchers to study abalone movement, behaviour and performance traits in a cultured environment.

## Acknowledgments

I sincerely thank my supervisors, Dr. Ray Williams from UTAS, and Dr. Sharon Appleyard from CSIRO MAR. Dr. Ray Williams provided great support throughout the project, and I greatly appreciate his encouragement during the early difficulties with this project, and his accessibility and thoroughness in all aspects of work.

I thank, Dr. Sharon Appleyard for provided the image data and other information and also giving me the opportunity to visit an abalone farm during my project. I also really appreciate Dr. Sharon Appleyard efforts in providing valuable advice on the literature review on abalone aquaculture.

Special thanks go to Mrs. Jacky Hartnett, honours unit coordinator for provided valuable information from the beginning to the end of the research.

Finally, I thank those who are not directly connected to my work, and my family members, and my friends Ming, Saung, Linda for their excellent support during my years studying at UTAS.

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# Chapter 1

## Introduction

Abalone is an important single-shell shell-fish species found in Asia, Australia, United States, Mexico, New Zealand, Canada and South Africa (Selvamani et al. 2001, p.478). Australia is one of the major sources of the world's abalone. Tasmania supplies nearly 50% of Australian wild abalone and approximate 25% of abalone globally, to which the cultured abalone contributes only 2%, at approximately 500 – 600 tonnes (Elliot et al. 2004).

Cultured abalone farming is undertaken with appropriate planning and management to maximise the quality of the abalone for commercial purposes and for selective breeding purposes. Improving performance traits such as growth rates of cultured abalone will lead to significant cost savings in the abalone aquaculture industry. To obtain the desired results, researchers have suggested two genetic methods that could help to increase traits in farmed abalone (Li et al. 2008, p.15; Hulata 2001) – selective breeding and chromosome manipulation. In addition, non-genetic methods such as improved husbandry and nutrition can also be crucial in improving traits such as abalone growth.

To meet world demand for abalone, it is necessary to work on effective selective breeding techniques for farming cultured abalone. As part of successful breeding programs, tools are required that can identify individuals, groups or families of abalone. Currently this is achieved through physical tagging, DNA (Deoxyribonucleic Acid) marking and growing abalone families in different tanks. These are the most common techniques used in selective breeding programs. However, growing abalone families in separate tanks is not the most efficient method of culture for a breeding program due to the expense and time required for tank maintenance and tank effects can also limit the genetic gain.

Therefore, tagging and DNA markers provide effective avenues for individual identification in selective breeding programs, but on the other hand, molecular markers are not as cost effective as physical tags because amplifying the DNA markers in thousands of individuals can be very expensive (Appleyard et al. 2008). Physical tags are also still required for a visible method of identification – DNA markers can not be seen by eye (Appleyard et al. 2008).

However, physical tagging methods in abalone are also very labour and time-intensive, and there are a number of issues related to tag durability, including tag loss by dislodgment, fouling, and grazing. Therefore, some method is required to monitor growth and behaviour using individual tags that can enable researchers to find the same individual repeatedly throughout an animal's lifetime. However, manually monitoring abalone movement and behaviour in order to get the survival and heritability information is complex and time consuming. Therefore, this research focuses on the development of image analysis algorithms that can assist abalone farmers and researchers to track and trace individuals within a tank and monitor abalone behaviour more easily. The visualisation of the tags on animal surfaces is important for automatic tag recognition through image analysis. Automated image analysis is particularly important when the manual process is slow and expensive, as is the case for tracking of abalone with attached tags in image sequences.

Analysing tags on abalone shells using images can be an effective way to identify abalone pedigree information. The image analysis can be of benefit, not just in selective breeding programs, but also in the analysis and identification of the best characteristics of the abalone both for selection and commercial purposes. Currently, CSIRO and the Tasmanian abalone farms use Labview software to collect the images and then NI Vision to estimate abalone lengths. In addition, a Victorian farm uses digital callipers to obtain length data for various abalone species.

However, although it may be easy for humans to analyse the tags in images, again this process is a very time consuming process if it needs to be undertaken on a large set of images. On other hand, an automated system must have knowledge of the colour and shape of each tag in order to extract it from the image background. Therefore, this project involves the use of the Image Processing Toolbox from MATLAB, which is very suitable for work with colour images. It provides a comprehensive set of algorithms and graphical tools for processing digital images.

This project involves the development of suitable image processing techniques to identify tags and other parameters such as position, orientation and colour information of tags. The extraction of tag ID (identification) is important to derive the pedigree information of each abalone. The development of the application provided an initial confirmation of the hypothesis that image analysis is suitable for identifying and extracting the tags from abalone images. However, it is important to recognise that the success of image processing techniques can be affected by a number of factors such as image quality, how far away from the tank the images are taken and image size. Any input images presented to the current image analysis system need to be clearly human readable before the system is likely to produce acceptable results.

The system development process is divided into three main categories, which include pre-processing, shape comparison and extraction processes on abalone images and lastly preparation of characters from each tag for optical character recognition.

In this research, tagged abalone images were obtained from Victorian and Tasmanian farms. These farms use land-based tanks to grow abalone and the images were taken directly from these tanks. The images were in JPEG format and were approximately 2000 * 3000 pixels in size. Image quality and image size can make a major difference to the success of the image analysis system. The process for analysing the tags can suffer if the images are of poor quality, if the images are very large in size, if the abalone depicted in the images are very small or if the camera is poorly positioned with respect to the tank.

Once sub-images containing the tags had been extracted from the images, they were presented to an optical character recognition system, to enable the system to understand the characters on each tag. Currently, the system uses a template-matching algorithm to recognise the characters on binary sub-images of each tag, extracted from the surrounding image. In this process, the characters are passed through number of pre-processing steps before the optical character recognition process applied.

At last, the system accuracy is checked using two approaches. Firstly a comparison between manual evaluations and system-produced results for the position, width, height and orientation of each tag was carried out. Secondly, a manual analysis was used to determine the accuracy of the automated system when identifying tag colours and counting the number of tags as well as determining the number of times the system recognises an object as a tag when it is not a tag.

# Chapter 2

# Literature Review

The aim of this chapter is to briefly discuss the abalone aquaculture industry, and to explain how tagging techniques can be used to assist in the selection of the best traits in farmed abalone using selective breeding programes. In addition, some image analysis and automated recognition systems are discussed for identification and extraction of tags for further processing.

## 2.1 Abalone Aquaculture

Abalone is an important single-shell shell-fish species found in Asia, Australia, United States, Mexico, New Zealand, Canada and South Africa. Abalone species are marine gastropod mollusks, belonging to the family of Haliotidae and the genus Halitosis (Selvamani et al. 2001, p.478). Abalone are usually found in temperate locations worldwide, and are recognised as a highly prized animal in the consumer seafood industry (Elliot 2000). In recent years, abalone stocks have been declining due to a number of factors including overfishing, illegal harvesting and habitat destruction (Lee et al. 2007; Dixon et al 2006; Wilding 2007).

### 2.1.1 Production

The farming of abalone has rapidly risen in importance between 1992 and 2007 and now produces approximately 26000 tonnes globally, on an annual basis. In contrast, the wild harvest has declined to 9500 tonnes annually due to overfishing, illegal harvesting, habitat destruction, and diseases within the population (Lee et al. 2007; Dixon et al 2006; Wilding 2007). Therefore, cultured abalones are in high demand, with a wide diversity of abalone species available to offer to world markets and the industry can produce a more consistent supply of high quality farmed products.

A major component of the world's abalone fishery comes from Tasmania. Tasmania supplies nearly 50% of Australian wild abalone and approximate 25% globally (Elliot et al. 2004) with wild abalone taken directly from the sea. In contrast, cultured abalone farming is done inside land based tanks enabling proper planning and management to be undertaken to maximise the quality of the abalone for commercial purposes and selection purposes.

Australia currently farms two pure abalone species: *Haliotis rubra*, the blacklip abalone and *H. laevigata*, the greenlip abalone and their interspecies hybrid (Elliott 2000). The hybrid combines the market quality traits of the greenlip with the endurance and growth rates of the blacklip ablone (Appleyard 2008). Australia makes a profit of $A246 million each year exporting abalone to major markets in Hong Kong, China and Japan (Appleyard 2008).

### 2.1.2 Methods

#### 2.1.2.1Factors in Cultured Abalone Growth

To protect abalone species and to meet world demand for abalone, it is necessary to work on effective selective breeding techniques for farming cultured abalone. Abalone are generally slow growing gastropod mollusks with a five stage life cycle- embryo, larvae, postlarvae, juvenile and adult (Grubert 2005, p.8). The grow-out time to market size for cultured adult abalone in temperate Australian regions is approximately three to four years; it starts with one year of juvenile development. Given this, improvement in growth (i.e. faster growth or production of larger abalone in a four year time frame) is a very important trait for the abalone industry. For example, greenlip abalone have been shown to grow faster than blacklip abalone and so provide better returns on investment for farmers (Weston et al. 2001). The considerable time for growth to market size contributes to the high operating costs associated with culturing abalone (Appleyard 2008; Li et al. 2008). Consequently, improving growth rates of cultured abalone will lead to significant cost savings in the abalone aquaculutre industry.

To obtain the desired results, researchers have suggested two genetic methods that could help to increase the growth rates in farmed abalone (Li et al. 2008, p.15; Hulata 2001) – selective breeding and chromosome manipulation. Other non-genetic methods such as improved husbandry and nutrition can also play a major role in improving abalone growth.

Selective breeding uses targeted mating to produce a large number of abalone families and individuals with desirable commercial traits. Aquaculturists commonly use different types of breeding methods for intraspecific genetic improvement (Li et al. 2008, p.15; Hulata 2001) including mass selection, within and among family selection and multiple trait selection using selective indexes. For example, genetic variation in the red abalone (*H.rufescens*) can lead to a 50% to 100% increase in growth rate (Elliot 2000).

In all selective breeding programs, farmers need to select their broodstock from either farms or wild abalone stocks. Selecting individuals from the wild, farmers usually target abalone that are in reproductive condition. Farmers bring the ripe broodstock back to the farm, where the broodstock are induced to spawn. However, this approach is not suitable for all farmers because collecting the brood stock from the sea at different sites poses different problems such as the total absence of appropriate animals in some years and unreliable supply of abalone during the spawning season almost every year (Fleming 2001). In addition to selective breeding programs, ploidy or chromosome manipulations are the second type of genetic modification which can help improve abalone traits although this technique requires direct genetic modification of the abalone genome. Chromosome manipulations are best undertaken within a selective breeding program using known sires and dams and monitoring of performance on the farm alongside diploid controls (Appleyard 2008).

#### 2.1.2.2 Selective breeding

One of the key research challenges for the Australian abalone aquaculture industry is the development of selective breeding programs to improve the productivity of the farm populations. An important first phase in selective breeding is to measure the genetic variation in commercial traits and estimate a standard measure of the proportion of genetic variation in a population. A number of industry-based selective breeding programs currently concentrate on a number of commerical characteristics, including growth rate, foot meat, and disease resistance in pure abalone species and in hybrids (Kube et al. 2007).

An issue which needs to be considered in selective breeding is the high environmental variation that is introduced in the early stages of abalone development and which heavily impacts on the attainable genetic improvement. The age at which selections are made also needs to be considered carefully (Kube et al 2007, p.823). On other hand, the process of crossing from the best parents of each generation and explains that it was possible to achieve a gain of approximately 5% in total weight using this process. However, their research faced some limitations, such as frequent loss of tags, and significant environmental variation at in the early stages of the abalone life cycle, even for families that were raised in different tanks. The research project only recovered 17 families, out of a total of 21, due to poor durability of tags (Kube et al. 2007).

Alongside managing high environmental variation, success in breeding programs will rely on individually identifiable pedigreed abalone (Appleyard et al. 2006). To maintain the familial or pedigree information in abalone, farmers often grow the abalone in separate tanks so they can select appropriate family members for breeding. However, rearing families in separate tanks is not the most efficient method of culture for a breeding program due to the expense, labour and time required for maintaining multiple tanks. Tank effects can cause growth related differences due to different tank environments, and they can also limit the genetic gain made within a breeding program (Appleyard et al. 2008).

Controlling environmental variation by growing families within the same tank environment will help to increase the gains made in selective breeding programs for abalone. However, when different families are grown within the same tank environment, farmers and researchers must have the tools to be able to identify, monitor and track individuals and families at all stages of their life cycle from the juveniles to the adult broodstock (Kube et al. 2007). Repeated trait measurements across an individual's life-time are required - accurate trait data from both individuals and families will help to increase genetic gain and hence profit for the farmer. Therefore, a major challenge in selective breeding is to grow out a large number of families in a communal environment where families and individuals can be uniquely identified. However, overstocking/density of abalone in tanks may also affect on the abalone growth directly because competition of shelter space and indirectly because of degradation of water quality in tanks (Huchette et al. 2003; Weston et al 2001).

In cultured systems which use a communal grow-out environment, marking and tagging is regarded as the most effective way to acquire valuable information about abalone, from the larvae to the adult growth stage, and to obtain pedigree information. Using this approach, a researcher can also obtain other information on growth and mortality, as well as on movement and foraging behaviour. CSIRO is currently using several specific types of physical tags and DNA markers to provide pedigree information on abalone when they are grown in the same tanks (Appleyard et al. 2008).

### 2.1.2.3 Physical Tagging

Physical tagging enables researchers and farmers to repeatedly measure, track and trace the same individual over its life-time. A number of different types of tags have been used in cultured abalone breeding programs including nail polish, paint pens, small coloured beads, PIT tags, spring tags, and Hallprint shellfish tags (Appleyard et. al 2008) (see Figure 1).

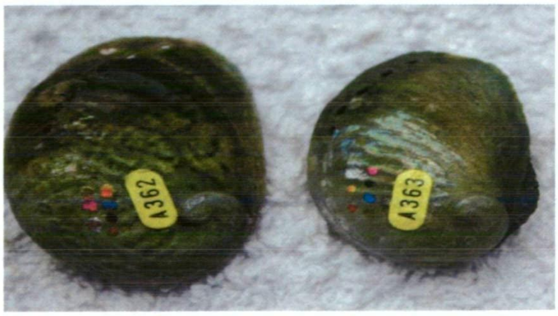



**Figure 1**: Tagged abalone (image provided by CSIRO Marine and Atmospheric Research (CMAR)

Prince (1991) also explained the different ways of tagging abalone, including the use of tags affixed to the abalone shell with adhesive and tagging using a wire or split pin. All of these techniques, however, increase the stress on the abalone because of the handling required and may cause mortality of some abalone.

Prince (1991) proposed a technique that uses central laminated numbered discs with a hole inside and nylon rivets, with the tags assembled prior to insertion into the abalone shell. This technique serves to minimise the stress associated with tagging. McShane et al. 1988 explained that attaching tags with adhesive produces more stress than attaching tags with stainless steel. This study shows that laminated numbers can be easily applied under the water without bringing the abalone to the surface, while the adhesive tags were difficult to apply under water.

#### 2.1.2.4 Effectiveness of Physical Tags and Tagging Issues

There are a number of issues related to tag durability, including tag loss by dislodgment, fouling, and grazing. In one experiment on greenlip abalone families, the tag recovery rate after eight months of monitoring varied from 21 to 100%. The experiment was affected by crushed shells, visualisation problems and tag fouling (Appleyard et al. 2008). Various kinds of tags have been used in an attempt to solve to these problems, but no one has yet found the perfect solution for tagging. Tagging is also very labour and time-intensive. Therefore, some method is required to monitor growth and behaviour using individual tags that can enable researchers to find the same individual repeatedly throughout an animal's life time. Similarly, the ability to visualise the tags and to retain the tag on the abalone shell is important for automatic tag recognition through image analysis.

#### 2.1.2.5 Alternative Methods

Researchers are currently searching for better methods of identifying individual abalone to provide solutions to some of these physical tagging difficulties. One alternative is the molecular marker which is a fragment of DNA which is inherited from both the sire and dam. Molecular markers can be used to assess stock diversity, broodstock relatedness and identification of pedigree information relating to the abalone (Carr et al. 2008). The molecular marker is amplified from an individual's DNA using the PCR (Polymerase Chain Reaction) technique (Semagn et al. 2006). The main advantage of molecular tagging is that it is determined at birth, the marker stays with the abalone for its entire life and can be amplified in young juveniles (as PCR techniques require only a small amount of tissue) (Appleyard et al. 2008). Importantly, if implemented correctly, molecular markers can be used to identify individual family members from a communal tank. Markers are amplified in the offspring and 'putative' broodstock. Using genetic software, offspring can then be assigned to their correct sires and dams; hence family information is retrieved. However, molecular markers are not as cost effective as physical tags because amplifying the DNA markers in thousands of individuals can be very expensive (Appleyard et al. 2008). Physical tags are also still required for a visible method of identification – DNA markers can not be seen by eye (Appleyard et al. 2008).

However, using stable oxygen isotopes is one of safest method to determining the age and growth of abalone, in contrast, to tagging methods which can create adverse effects on the abalone shell surface (Gurnery et al. 2005).

As highlighted above, the key challenge for the abalone aquaculture industry is to increase the growth rate (and other commercially important traits) in abalone species to reduce the cost of maintenance/grow-out and to increase profit for the industry. This challenge can only be addressed by thorough planning in the appropriate selection of abalone for broodstock, accurate trait monitoring and by using appropriate techniques for identification of abalone families. However, manually monitoring abalone movement and behaviour in order to get the survival information is complex and time consuming. Therefore, this research focuses on the development of image analysis algorithms that can assist abalone farmers and researchers to track and trace individuals within a tank and monitor abalone behaviour more easily.

## 2.2 Image Analysis

Image analysis is a field of the computer vision to give a meaningful description to physical objects in an image (Ballard & Brown 1982). The field of image analysis is a broad discipline. Therefore, it is important to focus on the actual requirements for image analysis techniques in this research. The main focus of the research is to develop image analysis techniques to automatically analyse abalone images to detect the tags attached to the abalone and to derive significant attributes relating to the tags, such as tag ID number (used for heritability information) and colour, as well as the position of the tag.

### 2.2.1 The MATLAB Image Processing Toolbox

The Image Processing Toolbox from MATLAB is very suitable for work with colour images. It provides a comprehensive set of algorithms and graphical tools for processing digital images. MATLAB also provides an analyser which can be used to inspect algorithms and to create source code. A user can restore noisy or degraded images, enhance images for improved intelligibility, extract features, and analyse shapes and textures.

### 2.2.2 Related work

Image processing work has been carried out for chromosome analysis on the Pacific red abalone (Kober et al. 2004) using rank order and digital morphologic filters to determine the total length of chromosomes and relative arm lengths in digitally enhanced images. These digital filters are very efficient in removing additive and impulsive noise, as well as enhancing and restoring the microscope images. The reason for their success in image processing is that they can suppress noise without destroying important image details, such as edges and fines lines (Kober et al. 2004).

### 2.2.3 Image Analysis Procedures

#### 2.2.3.1 Image Enhancement

The first step in analysis involves attempting to improve the quality of underwater images. One of the fundamental steps in the design of image processing techniques is to make sure that a given image is optimized for enhanced quality (Trussell 2005). Images can be degraded by two main factors, light absorption and scattering. The quality of the water controls and influences the filtering properties of the water. The reflected light is partly polarised horizontally and partly vertically. An important characteristic of the vertical polarisation is that it makes the object less shiny and therefore helps to capture deep colours which may not be possible to capture otherwise (Iqbal et al. 2007).

Some techniques, such as ACE (Automatic Colour Equalisation) enhance the image without supervision and reduce the loss of contrast in an image by applying contrast stretching to an RGB colour model. It also does saturation and intensity stretching on the HSI colour model. These two stretching techniques help to equalize the colour contrast in the images and at the same time solve the problem of lighting. Figure 2 shows the result after applying the two operations on an under water image (Iqbal et al. 2007).

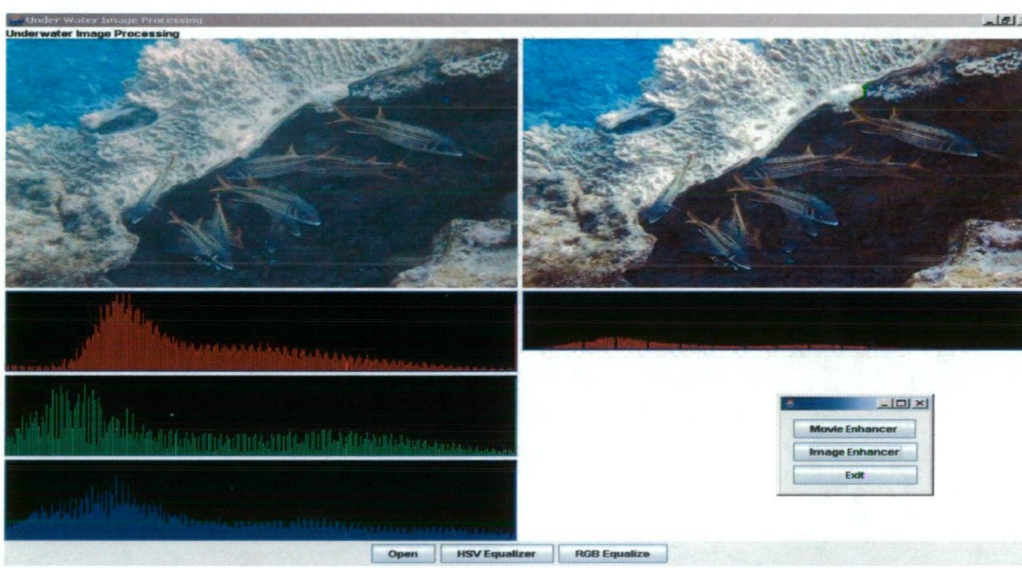
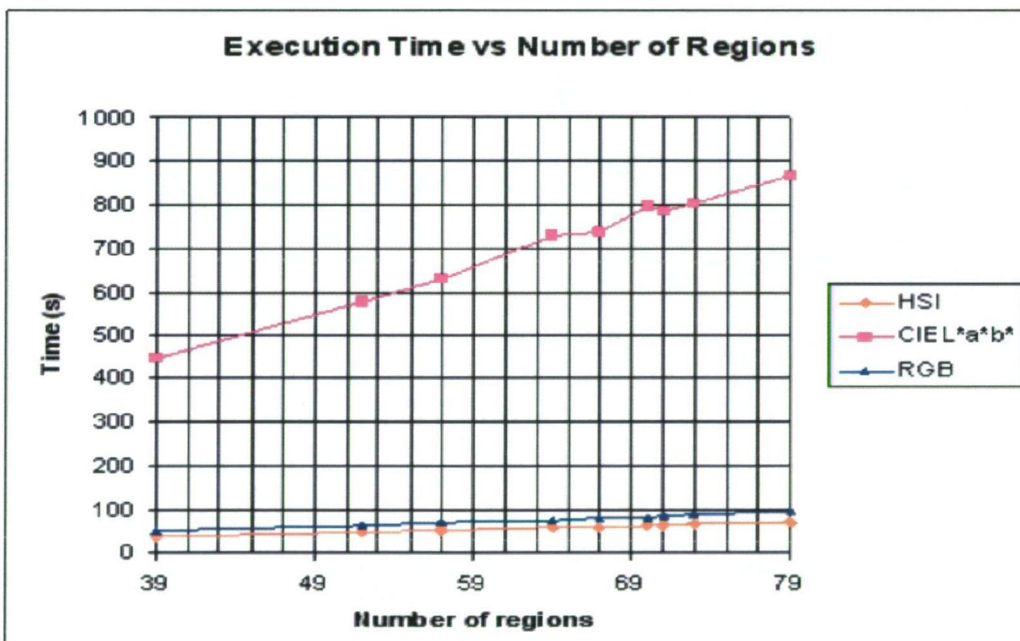



**Figure 2**: Enhancement in underwater image (Iqbal et al. 2007)

## 2.2.3.2 Colour models

The second step relates to the use of colour models such as HSI and CIE. This step converts the RGB images provided by the camera into an appropriate HSI or CIE colour space for colour analysis. Numerous methods for working with images are provided, including histogram methods, smoothing and sharpening operations, segmentation operations, and edge detection. These methods are designed specifically for grey scale image analysis. The RGB colour space is the most common model used for the display of colour images but the red, green and blue components within this model are highly correlated and so it is not the most appropriate model to use for processing colour images (Luijten 2005).

On the other hand the HSI and CIE colour spaces are appropriate for most work undertaken with colour images. Rasras, Emary and Skopin (2007) reported on a study in which they showed that the CIE model produced better results than the RGB and the HSI models when calculating the distance colour, a method applied between two colours, but the drawback of the CIE is that it is not as computationally efficient as RGB or HSI. This means that execution times in the CIE colour model are higher than in other colour models for producing the output result on each selected region (see Graph 1).




**Graph 1**: A comparison between colour Models (Bueno et al. 2008)

Therefore, the HSI model is generally used for controlling the various elements of a colour image individually. The Hue (H) determines the perceived colour of the image (for example blue) while the Saturation (S) determines the depth of the colour (from a pale blue to deep blue) and the Intensity (I) is the brightness of the colour (from dark to bright). Saturation and Intensity help to produce a wide range of colours. Therefore, it is easy to decrease or increase values to control the contrast ratio in an image. The process can be carried out by using a *histogram* of the digital values for an image, and redistributing the stretching value over the image to get the maximum possible values of colour variation ( Figure 3) (Iqbal *et al.* 2007).

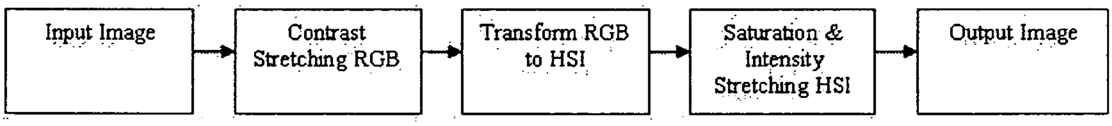



**Figure 3**: RGB to HSI image process (Iqbal et al. 2007)

In this research, it is the Hue value that enables an application to determine the colour of the tags; categorised as red, yellow, green, pink or white. According to the International Commission on Illumination (CIE), "*hue is the attribute of a visual sensation according to which an area appears to be similar to one of the perceived colours, red, yellow, green and blue, or a combination of two of them*" (Finlayson & Schaefer 2000)..

The calculation for the Hue, in terms of the R, G and B values of an RGB image is given by:

$$H = \cos^{-1} \frac{0.5[(R-G)+(R-B)]}{\sqrt{(R-G)(R-G)+(R-B)(G-B)}}$$

## 2.2.3.3The Segmentation Process

The third important step in image analysis is related to the separation of objects from the image background. Segmentation is the process of splitting an image into regions such that each region is characterised by having relatively uniform properties, such as grey level, hue or brightness. Segmentation methods can be broadly classified as grey level or texture-based and can make use of histogram features or edges identified in the image using an edge detector (such as a Sobel or Canny edge detector). Normally, medical image processing is based on grey-level segmentation methods, which sometimes do not produce very clear or relevant results. On the other hand texture-based analysis is still a complex and challenging problem for image segmentation (Sharma et al. 2008).

Cheriet, Said and Suen (1998), proposed using Ostu's algorithm, which uses a threshold value, to segment an image. This algorithm is used for computer vision and image processing. It uses the image histogram to predict the optimum threshold value for separating the two classes within an image and so is capable of separating a foreground from a background. At each recursion, the object with the lowest intensity is segmented from the given image. The recursive process continues until only the darkest element is left in the image. This method was trained on 220 real-life bank cheques and tested on another 505 cheques to eliminate their background to facilitate the processing of cheques (see Figure 4).

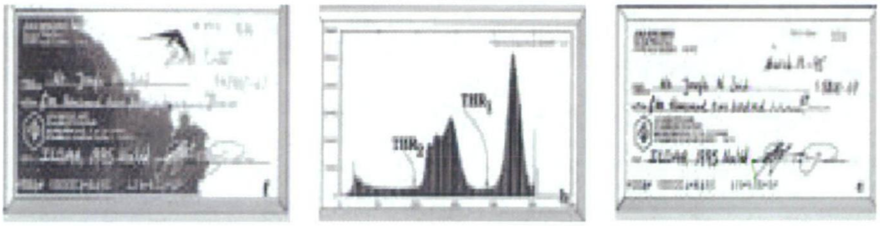


**Figure 4** a) Original image of bank cheque b) Two threshold values c) The output result (Cheriet, Said & Suen 1998)

Similarly, a novel algorithm is reported for analyzing tongue images for improving the effectiveness of tongue inspection. This algorithm used the HSI color model, as discussed in section 2.1, for converting the RGB color values into hue, saturation and intensity values and using its red hue to segment the tongue from the image background. Later, morphological operations were performed to fill small holes in the tongue area. Finally, the new generated image was combined with the original image to produce a successfully separated tongue image (see Figure 5). As result of this experiment, they segmented the tongue images correctly, but further research is required for cases where it is necessary to identify a white coating on tongue (Jian-qiang 2008).

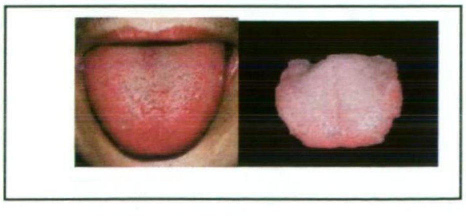


**Figure 5** : a) Before segmentation b) After segmentation (Jian-qiang 2008)

### 2.2.4 The Feature Extraction Process

This step is also very important for extracting tag-shaped objects from abalone RGB images. Feature extraction is a process for identifying an essential object in an image. This process is utilised in a number of fields such as robotics, computer technology and medical image analysis.

#### 2.2.4.1Feature extraction in the robotics industry

Guzman and Parra (2007) described the importance of feature extraction in the robotics and computer vision fields. With the help of feature extraction, it is possible to reduce unnecessary computation and speed up the process of analyzing images to detect selected objects from an image.

Guzman and Parra (2007) suggested that the robotics community could provide a mechanical automated solution for many problems if robots could clearly visualise path information. Their study explored different ways for analysing path information to assist in robot understanding. They analysed the path information from a selected region, calculating the centroid of the region, along with the direction of the path, to give useful information to the robot to find the path and guide the control system to plan and undertake autonomous navigation (Figure 6a and Figure 6b).

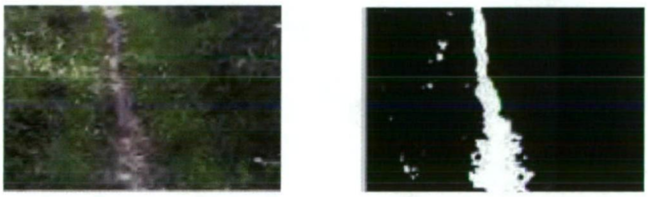


**Figure 6 a):** Original image **b):** Resulted Image (Guzman & Parra 2007)

A similar study (Kang et al. 1992) developed a technique for industrial robots that can recognize and classify industrial objects such as numbers on tires. From this study, they described the extraction of arcs which form parts of the digits, using a Hough transformation method, and subsequent use of these for recognition purposes (see Figure 7).

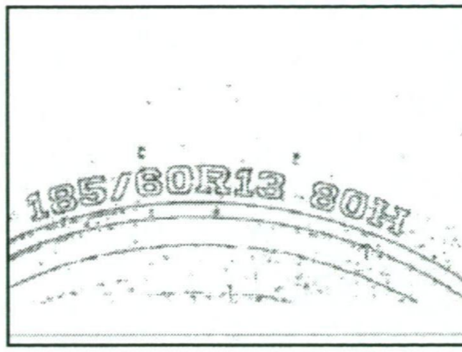



**Figure 7** : Segmentation on tire image with line operator (Kang et al. 1992)

### 2.2.4.2 Feature extraction for medical imaging analysis

Feature extraction has also been used to identify the hemorrhaged region of a patient's brain, enabling doctors to determine the position, shape and size of that region. The best method for identifying parts of the brain is by determining the position, size and shape of each part of the brain. Therefore, they developed an automatic image classification system to identify different syndrome types (head trauma types). Using this tool, doctors can now study different syndrome types and can educate other medical professionals in this field (Gong et al. 2007). In conclusion, the feature extraction process is based on extracting geometric features of each segment within the image, and so this process has potential for determining the position and orientation of abalone tags based on their centroid coordinates and their major and minor axes.

### 2.2.5 Optical Character Recognition

In this project, optical character recognition is an important step in enabling the machine to analyze the characters that appear on the tags attached to the abalone shells. This project aimed to extract the tag characters from the image in preparation for input into an OCR (optical character recognition) system.

There are three main types of methods used for optical character recognition. Template matching methods match characters from a reference character set with each of the input characters. Statistical methods perform the character recognition based on various attributes extracted from the input character and represented as N-dimensional vectors. The prototype character whose N-dimensional vector is most similar to that of the input character is matched to the character. Structural methods recognise the character on the basis of structural relationships between primitives (such as individual strokes) of the character (Kang et al. 1992).

A statistical method is used to match input characters to prototypes in Kang's system for recognising raised characters for rubber tire classification. In their studies, they proposed a recognition algorithm using sequentially designed rule-based methods.

The characters were divided into groups on the basis of partial width (the ratio of black pixels to the character width is used). Subsequently, these character groups were sub-divided using the cross-point and partial projections. Finally the distance feature (distance from enclosed rectangular window to black points of the character at several positions) was used to recognise the character among several candidates (Kang et al. 1992).

Optical character recognition can also be useful in analysing text and then synthesizing it into speech. This research is useful in enabling humans with impaired vision to read road signs by recognising the sign and providing a voice output alerting the driver (Haque et al. 2007). The automatic sign translation system used a digital camera to capture images of road signs, and then employed an adaptive threshold method to binarise the text block. The text recognition was done using a neural- network-based OCR. Finally, identified text was converted into a synthesized voice output. This study reported a success rate of 84.7%, which was considered reasonable. The 15.3% failure rate of the system resulted from complex backgrounds behind the text in some of the signs, low intensity signs and multiple sign boards appearing in the same image frame.

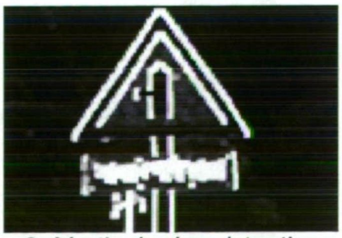


**Figure 8:** Original Image **Figure 9:** Vertical edge detection
(Haque et al. 2007)

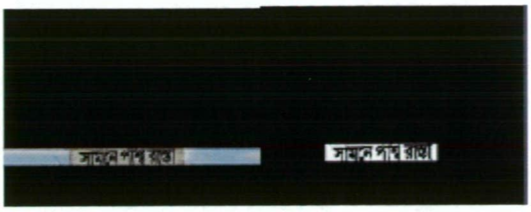


**Figure 10:** Extracted text area and Binary image (Haque et al. 2007)

| Modules | Correct | Error |
|---|---|---|
| Text Detection | 84.7% | 15.3% |
| Segmentation | 93.9% | 6.1% |
| Character Recognition | 95.7% | 4.3% |
| Whole system | 91.4% | 8.6% |

**Figure 11:** Test result of proposed System (Haque et al. 2007)

In summary, the classification and recognition of objects in images represents a broad sub-field within robotics and computer vision. Automated image analysis is particularly important when the manual process is slow and expensive, as in the case for tracking of abalone with attached tags in image sequences.

## Chapter 3

# Methodology

This chapter discuss the methodology for implementing the work undertaken in this project. The discussion is divided into four sections. Firstly, the platform, tools and the other requirements needed to develop the application are discussed. The second section discusses the pre-processing stage of the implementation work. The methods explained in this section are very important in ensuring the overall success of the application. The third of these discusses the development of image analysis techniques which extract individual tags from the image and present them to an optical character recognition. The final part discusses how the evaluations of the image analysis techniques are carried out.

### 3.1. Requirements and Work

The main aim of this research is to develop image-processing techniques for analysing underwater images to identify tags affixed to abalone shells. The techniques would enable abalone researchers to identify individual animals and to track their movement over time. The underwater images of tagged abalone are collected from Victorian and Tasmanian farms. These farms use land-based tanks to grow abalone and the images are taken directly from these tanks. The images are in JPEG format and are about 2000 * 3000 pixels in size, creating difficulties in handling because of their size. Therefore, the images are reduced in resolution before other pre-processing functions are carried out on them.

Currently, CSIRO and the Tasmanian abalone farms use Labview software to collect the images and then NI Vision to estimate abalone lengths. The Victorian farm work uses digital callipers to obtain length data. This software just gives size information and, for this process, they need to take each abalone out of its tank to be photographed. This is very labour intensive and time-consuming way to determine the growth and mortality rates in the abalone. Therefore, this image analysis application development is important because it will enable the images to be obtained directly from the tanks and then processed in order to monitor abalone behaviour. The techniques developed in this project could also be incorporated, in future, with other software to obtain the size of the abalone as well as the value (heritability information) of the tag attached to its shell.

The main aim of this research is to develop techniques for enhancing the images and detecting the tags; then determining the colour of each tag and segmenting it from the background. After the tags have been segmented from the background the techniques calculate the location of the centroid, and the orientation of each tag, enabling the tag information to be extracted for further processing.

### 3.1.2 Development Platform

The MATLAB Image Processing Toolbox is a suitable package for this application. It offers image-processing tools, which include a wide range of standard algorithms and graphical tools for image processing and visualisation. It is easy to get access to these standard algorithms in MATLAB, and it also provides a multi-platform capability to run programs on any operating system, including Windows or Mac OS X, that is supported by MATLAB.

### 3.1.3 Input Data

The input images used for this research are RGB images stored in JPEG format. There are three categories of images; images with rounded-rectangle tags in a wide variety of colours, images of abalone with pairs of tags all yellow in colour, and images with rounded-rectangle tags and round tags in a variety of colours. Each of these categories of images has tags with different size dimensions and other characteristics, such as colour and shape.

## 3.3 Pre-Processing for Tagged Abalone Images

### 3.3.1 Size classification

The dimensions of the input images are calculated using the **size ()** function and this can be used to classify the images into each of the three categories described above. The **size ()** function gives the value of XY dimension of images. The second value of **size (file, 2)** function is used in this process. As described in Table1, the images are categorised according to their sizes.

| Filename | Size | Category |
|---|---|---|
| Families_071.jpg | 3264 *2448 | I |
| Photo1.jpg | 2304 * 3456 | II |
| IMG_1126a.jpg | 778*1166 | III |

**Table 1:** Three categories of images

The next challenge is handling these large files. The main concern is the time it takes to process these very large images. Therefore, an analysis was done to determine ways of reducing the size of the images. Category I images could be handled easily with no significant reduction in quality by using the **imresize ()** function to resize the image, reducing it to a manageable level by reducing the resolution. However, the **imresize** function was found not only to be suitable for category II images, so these images were cropped into three equal sizes using the **imcrop ()** function before further processing was carried out. For category III images, there was no requirement to resize or crop the image, because they were small enough to be processed easily.

### 3.3.2 Colour Classification

As described in chapter 2, section 2.2.3.2, the colour values in an image can easily be calculated using the HSI colour space where the Hue value is important as an intuitive cue to identifying the tags' colours. Basically, the objective is to select tags of particular colours from the input image. Each tag colour is identified separately. The extracted images are then combined to make one image. For this project implementation, the HSI (Hue, Saturation, and Intensity) colour space was used for colour segmentation.

The first step involves identifying which colours in the image are associated with which Hue values in the histogram after converting the image from RGB to the HSI colour space. This process involves manually observing the values from the histogram. For example, the colour yellow is found between **hsiImage (:,:, 1)>0.17** && hsiImage (:,:, 1)<0.2. The histogram produced from a category I type image is shown in Figure 12.

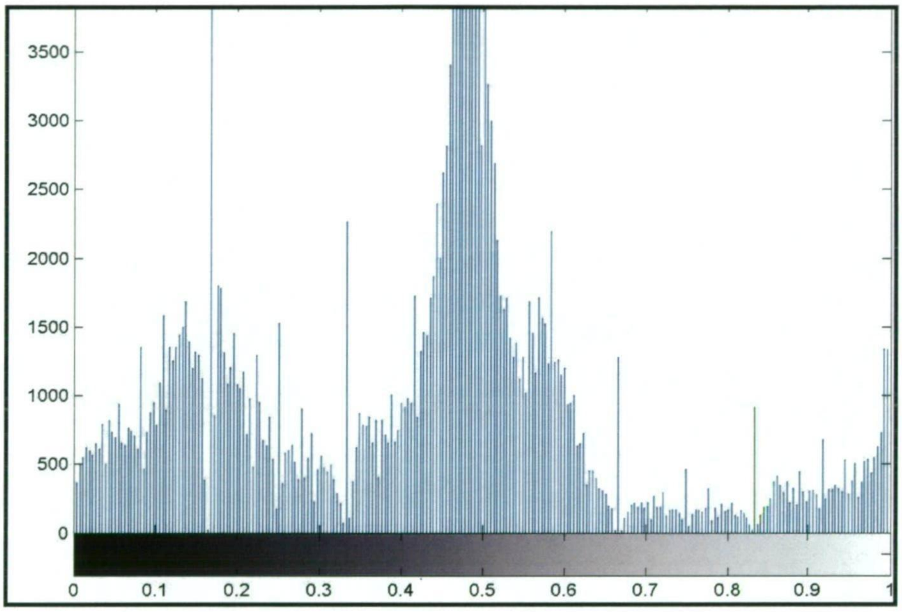



**Figure 12:** Hue values from HSI model Image

However, manually observing the colours associated with particular values of a single histogram are not suitable for all images. Therefore, selection on the basis of "angle of hue" provides more reliable results than analysing colour values via the histogram of hue values. Hue can be calculated from the RGB image using the following formula.

$$H = \cos^{-1} \frac{0.5[(R - G) + (R-B)]}{\sqrt{(R-G)(R-G)+(R-B)(G-B)}}$$

The HSI colour model uses a hue value of 0 degrees to 360 degrees, with the red

Colour at 0, yellow at 60, green at 120, cyan at 180, blue at 240 and magenta at 300 (see Figure 13).

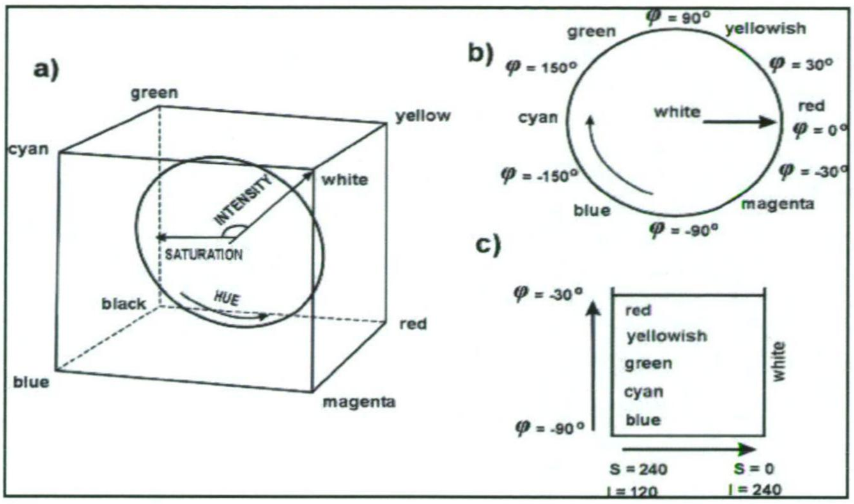



**Figure 13**: HSI Colour Space (Hengl 2003)

Therefore, it is possible to calculate threshold values that can operate on a combination of hue, saturation, and intensity by using different colour angles. For example, to identify yellow coloured tags in HSI images (see Figure 15), one would calculate the hue angle value H using the formula above and then extract all pixels for which:

((pi/3 <= H) & (H < 2*pi/4)));

Where Pi = $180^0$

**Figure 14:** Original Image (provided by CMAR)

**Figure 15:** Results of identifying Yellow tags

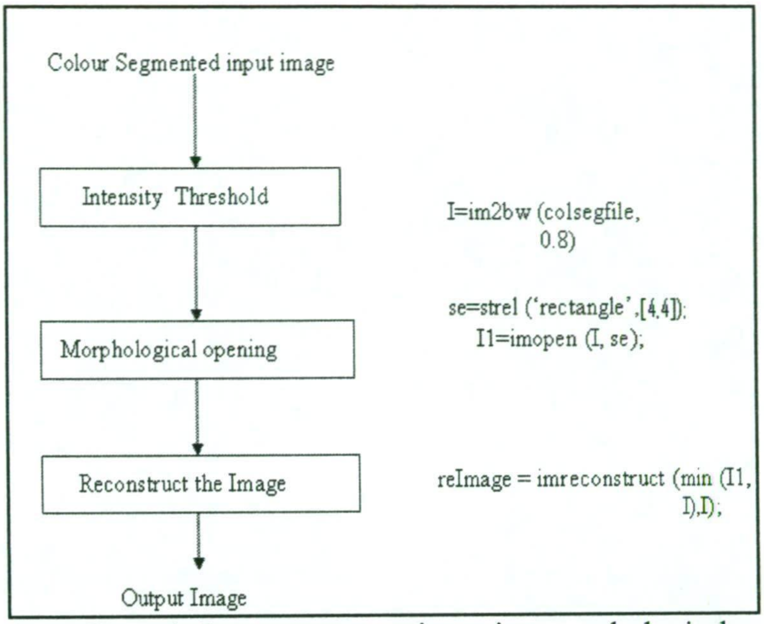
### 3.3.3 Noise Removal and Background Detection

After identifying pixels with a particular colour within the image, the next task is to remove all pixels that don't belong to a tag of that specified colour. The background in this image is tank concrete and that surface can produce yellow-coloured pixels that could be recognised as belonging to a yellow tag. To remove the pixels, the following method can be used.

This first step is completed using the **im2bw ()** function, which produces an output image in which all pixels in the input image with luminance greater than a specified threshold level are given the value 1 (white) and all other pixels are given the value 0 (black). The threshold level used here can be calculated using Ostu's Algorithm (Cheriet et al. 1998) as discussed in chapter 2.

### 3.3.4 Tag Segmentation

This processing task involves segmentation of the tags from the surface of the abalone (i.e. the background). Initially erosion and dilation operations are used to obtain more accurate and smoother images. The structuring element used for the dilation and erosion is a 4* 4 pixel rectangle. Flow chart 1, illustrates how this morphological processing is carried out for each image (Figure16 and 17).




**Flow Chart 1:** Image segmentation using morphological operators

**Figure 16:** Image after Colour Segmentation

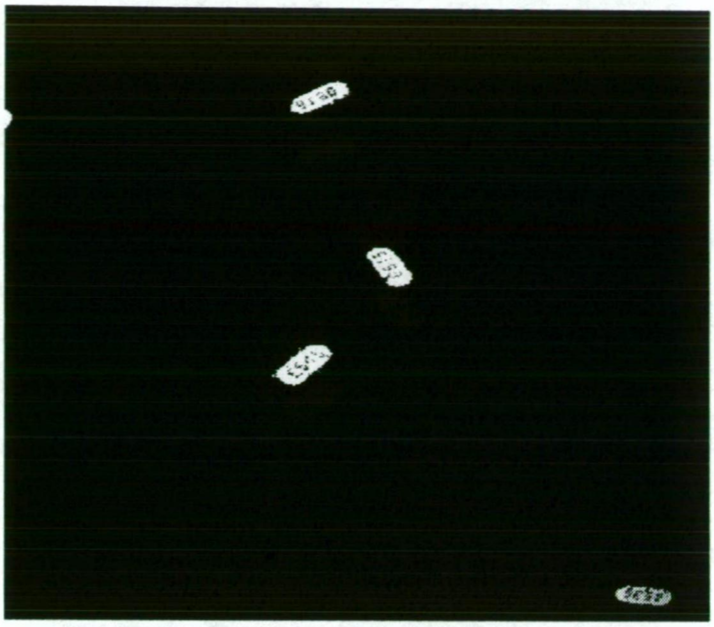


**Figure 17:** Image after Morphological Processing

The next step in this segmentation process involves labelling each separate object within the image. This process labels all groups of connected pixels in a binary image (with the option of setting the connectedness level to 4- connected or 8-connected). This process produces an image in which each pixel has a value that is the label of the group (or object) to which it belongs. It also gives the number of labelled objects in the image.

The final step in this process involves calculating the regional descriptors of each labelled object in the image. The information obtained from the region descriptor includes the area of the object region, the centroid, which provides the position of centre of mass of the object, the length of the major and minor axes of the region, and finally the orientation of the region.

## 3.4 Analysis

### 3.4.1 Area Estimation

Even after performing the segmentation process there are some objects in the images that do not represent tags. However, the area estimation process can remove those objects that do not have the same area as the tags. For this process, a minimum and a maximum area is estimated by manually analysing the tags in a range of images and any objects which fall outside this area range (either smaller or larger) are rejected as not being tags.

### 3.4.2 Rectangle Fitting and Rotation

The next step involves plotting a rectangle around each object that has been identified as a tag. The centroid location, the major axis and minor axis lengths and the object orientation can be used to do this, using the following equations:

x = Centroid (1) – MajorAxisLength/2
y = Centroid (1) – MinorAxisLength/2
Width = MajorAxisLength
Height = MinorAxisLength
xpoints=[x x+Width x+Width x x]
ypoints=[y y y+Height y+Height y]
plot(xpoints, ypoints).

The rectangle is rotated through the angle represented by the object orientation,

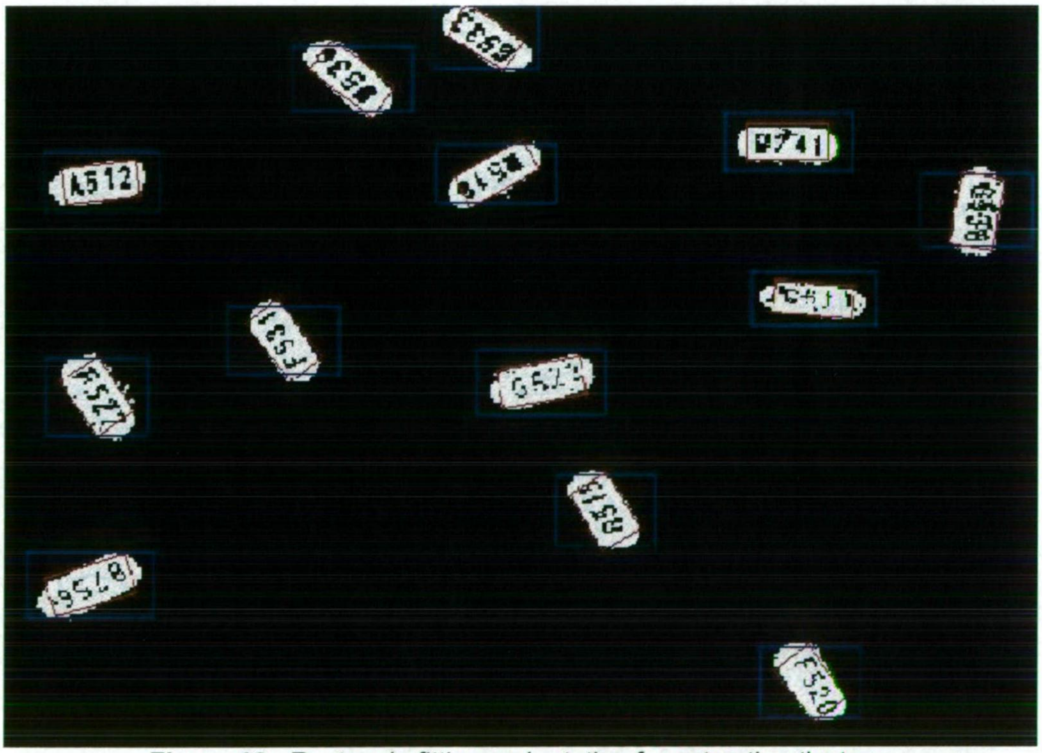


**Figure 18**: Rectangle fitting and rotation for extracting the tags

### 3.4.3 Extracting Tag Sub-images

This next step in the image analysis process is to extract a sub-image for each tag in the original image and prepare it for presentation to an optical character recognition system. The characters on extracted tag images are aligned in a horizontal direction. The orientation value can be obtained using the region descriptor function (regionprops).

As described in section 2.2.1, category III images include round tags and, in this case, it is not possible to compute the orientation from the outline of the tag. Therefore, these category images will require a different process to determine the orientation of the tag.

## 3.5 Optical Character Recognition

This is the final step in the image analysis process. Currently a template matching method is used to recognise the character from extracted tags. There are certain steps that need to be considered before applying a template matching operation to the characters. These are:

- removing the unwanted pixels around the border.
- creating a skeleton of the character
- performing an erosion operation to separate characters
- re-filling holes in the characters that are produced by the erosion operation.
- applying the template matching optical character recognition function to read the characters on the tag.

## 3.6. Evaluation

For the evaluation process, five images were selected for training and six for testing. The evaluation was carried out as follows:

Firstly, the positions and colours of all the tags in these images were observed manually and these subsequently compared with the system-generated output.

Secondly each tag was outlined manually using the region of interest tool in MATLAB. This produces a binary image of the manually selected region and with the selected region it is easy to identify the orientation, major axis and minor axis of each tag. These results can also be subsequently compared with results produced automatically by the image analysis system.

The methodology chapter described the tasks undertaken by the image analysis system and how the system was evaluated. The system produced some useful results. However, the results obtained vary significantly with the nature of the input data. For example, images obtained from dark areas or taken from too far away in the tank produce poorer results. In conclusion, any input images presented to the image analysis system need to be clearly human readable before the system is likely to produce acceptable results.

# Chapter 4

# Results and Discussion

This chapter presents the evaluation of the final application. The discussions are divided into three main sections. In the first section, the image classification and analysis results are discussed. The second section discusses the system accuracy and presents the tag extraction image output results, including a comparison of the accuracy of the system with manual analysis of the abalone images. The final section discusses the optical character recognition system.

## 4. 1 Image Analysis Process

The image analysis system was developed using five images, containing approximately 18-20 tags each, and four images, also with about the same number of tags in each, were set aside for testing. To achieve the desired results, the system uses a set of operations for identifying the colour values, segmenting the tags from the background, and finding the tag colour after extraction of each tag. Finally, the extracted tags are prepared for optical character recognition.

As described in Chapter 3, the images were divided into three categories according to size. After being classified, the images were either cropped or resized to contain approximately 500*500 pixels. The third category of images can easily be processed without resizing. The reason for resizing images is to increase the speed of processing to get the final output. **Table2** shows the times taken to process the three different categories of images.

| Filename | Size | Category | Total Time (sec) |
|---|---|---|---|
| Families_072.jpg | 3264 * 2448 | I | 18 |
| Photo4.jpg | 2304 * 3456 | II | 20 |
| IMG_1126a.jpg | 778*1166 | III | 20 |

**Table 2:** Time taken to process each Image

As described in Chapter 3, the colour values from an image can easily be identified within the HSI colour space. For this process, colour values were identified as described in **Table3.** The value of H (the Hue) was computed as **hsiImage (:, :, 1).** Similarly, the Saturation was computed as **hsiImage (:, :, 2),** and the Intensity as **hsiImage (:, :, 3).** The first step is to identify the colour values. Hue values were considered most appropriate for colour thresholding, not Saturation or Intensity, since these just provide the depth of the colour or the brightness of the object.

| **Colours** | Hue Colour Values |
|---|---|
| Yellow | `pi/4 <= H & H < pi/2` |
| Green | `2*pi/3 <= H & H < 3*pi/4` |
| White | `pi <= H & H < 1.2*pi` |
| Blue | `3.45*pi/3 <= H & H < 3.7*pi/3` |
| Pink | `5*pi/3 < H) & (H <= 5.5*pi/3)` |
| Red | `5.5 * pi/3 < H & H <2 * pi).` |
| Total Accuracy in Colours estimation | 99% |

**Table 3:** Colours and Hue Angle values Pi = $180^0$

## 4.2 Tag Segmentation

The segmentation process was carried out in three steps in order to get a better output result from the system. The first step involves the segmentation of the foreground object from background noise. This step was completed with the **im2bw()** function. This function replaces all pixels in the input image, with luminance greater than a selected level, with the value 1 (white) and all other pixels with the value 0 (black).

The next step was to label each region and to create a region descriptor for those regions. In addition, the width and height of an object was estimated using the minor and major axis lengths of each region, and then the area of each labelled object was calculated.

Table 3 describes the results from the segmentation. There were 50 objects in the test images that were identified manually as tags. Of these 50 tags, those that were successfully identified automatically by the system as tags are called "true positives". Those that were not identified as tags are called "false negatives" and objects that were identified as tags by the system but were not real tags in the image are called "false positives". The Overall Accuracy is defined as the number of true positives divided by the total number of tags (identified manually) while the False Positive Rate is defined as the number of false positives divided by the total number of tags (identified manually). The aim is to maximise the Overall Accuracy of the system, whilst still maintaining an acceptably low False Positive Rate. The images used for testing the system are shown in Figures 19, 20, 21 and 22.

As indicated in Table 4, the system identified 78% of the tags from the four images with a false positive rate of 14%.

| | |
|---|---|
| Total Number of Tags | 50 |
| Number of True positives | 39 |
| Number of False negatives | 11 |
| Number of False positives | 6 |
| Overall Accuracy (true positives/total tags) | 78.00% |
| False positive rate (false positives/total tags) | 22.00% |

**Table 4**: Final Result of the Tag Segmentation Process

**Figure 19:** Single Tagged Abalone Image (provided by CMAR)

**Figure 20:** Single Tagged Abalone Image (provided by CMAR)

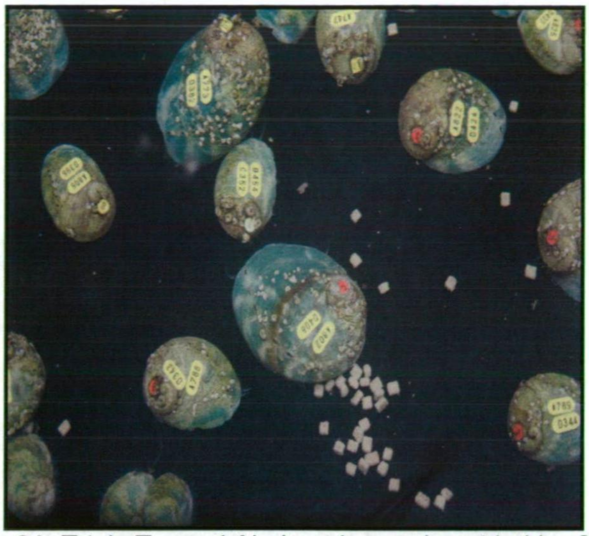


**Figure 21:** Triple Tagged Abalone Image (provided by CMAR)

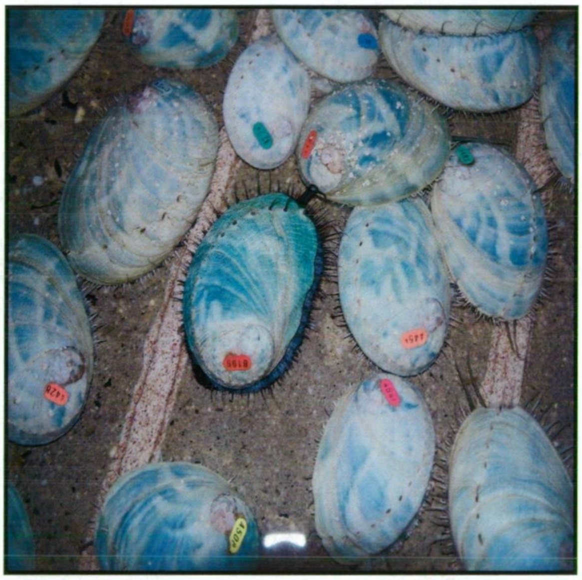


**Figure 22:** Single Tagged Abalone Image (provided by CMAR)

As far as system performance is concerned, there are a number of factors that reduce the accuracy of the system. These include the poor quality of some tags, the fact that some tags are on the border of the image and the fact that some tags have the same colour as the shell of the abalone (such as yellow or green).

## 4.3 Extraction of Tag Sub-images

This process involves the extraction of a rectangular sub-image, containing each tag, from the original RGB image. The reason for using the original image was because the quality of characters is low on the binary image after the dilation and erosion operations have been performed on it. The values retrieved from the binary image such as tag position, width and height, and orientation assist in extracting the tag object from the original image (Table 5, Table6, Table 7 and Table 8). The resulting extracted tag image is always oriented in a horizontal direction so it can be presented to the optical character recognition system in standard way. The centroid positions, heights, widths and orientations for all objects detected as tags in the four test images are presented in following tables.

| **Objectes geometric attributed identfied as Tags in image** | | | | | | **Manual object identification** |
|---|---|---|---|---|---|---|
| Tags | Width | Height | X | Y | Orientation | |
| 1 | 44 | 23 | 31 | 64 | 26.934 | **Tag** |
| 2 | 41 | 23 | 57 | 327 | 45.392 | **Tag** |
| 3 | 45 | 17 | 69 | 417 | 1.7153 | **Tag** |
| 4 | 49 | 22 | 105 | 100 | 12.8637 | **Tag** |
| 5 | 45 | 27 | 121 | 173 | 62.1772 | **Tag** |
| 6 | 45 | 27 | 131 | 281 | 33.6307 | **Tag** |
| 7 | 41 | 27 | 219 | 172 | 61.7583 | **Tag** |
| 8 | 50 | 22 | 272 | 116 | 11.7271 | **Tag** |
| 9 | 37 | 25 | 269 | 402 | 88.1213 | **Tag** |
| 10 | 35 | 28 | 323 | 360 | 71.1314 | **Tag** |
| 11 | 51 | 24 | 337 | 149 | 3.5596 | **Tag** |
| 12 | 39 | 23 | 356 | 80 | 55.7356 | **Tag** |
| 13 | 41 | 23 | 395 | 196 | 17.2988 | **Tag** |
| 14 | 44 | 26 | 448 | 413 | 64.4005 | **Tag** |

**Table 5:** Results on Object attributes (Figure 19)

| Objectes geometric attributed identfied as Tags in image | | | | | | Manual object identification |
|---|---|---|---|---|---|---|
| Tags | Width | Height | X | Y | Orientation | |
| 1 | 98 | 48 | 198 | 119 | 4.2652 | Tag |
| 2 | 78 | 32 | 418 | 15 | 3.8476 | Tag |
| 3 | 88 | 43 | 455 | 428 | 5.6566 | Tag |
| Tags | Width | Height | X | Y | Orientation | |
| 1 | 80 | 44 | 125 | 180 | 0.8872 | Tag |
| 2 | 102 | 46 | 293 | 341 | 4.4763 | Tag |
| Tags | Width | Height | X | Y | Orientation | |
| 1 | 77 | 42 | 167 | 176 | 4.444 | Tag |
| 2 | 112 | 40 | 441 | 388 | 4.4061 | Tag |
| 3 | 71 | 44 | 472 | 84 | 9.4398 | Tag |

**Table 6**: Results on Object attributes (Figure 20)

| Objectes geometric attributed identfied as Tags in image | | | | | | Manual object identification |
|---|---|---|---|---|---|---|
| Tags | Width | Height | X | Y | Orientation | |
| 1 | 56 | 30 | 17 | 363 | 56.2125 | Tag |
| 2 | 61 | 31 | 107 | 280 | 61.8033 | not Tag |
| 3 | 113 | 57 | 151 | 173 | 12.4856 | Tag |
| 4 | 67 | 30 | 141 | 49 | 32.5311 | Tag |
| 5 | 59 | 35 | 160 | 353 | 49.1255 | Tag |
| 6 | 75 | 30 | 173 | 444 | 14.5722 | Tag |
| 7 | 68 | 33 | 184 | 240 | 29.7932 | Tag |
| 8 | 78 | 28 | 253 | 111 | 3.9939 | Tag |
| 9 | 65 | 34 | 273 | 312 | 32.2869 | Tag |
| 10 | 69 | 36 | 304 | 57 | 26.3671 | Tag |
| 11 | 63 | 34 | 289 | 404 | 89.4371 | Tag |
| 12 | 58 | 33 | 352 | 253 | 82.5532 | Tag |
| 13 | 64 | 57 | 376 | 132 | 23.8396 | Tag |
| 14 | 54 | 35 | 373 | 472 | 46.5481 | Tag |
| 15 | 65 | 28 | 456 | 66 | 28.4658 | Tag |

**Table 7:** Results on Object attributes (Figure 21)

| Objectes geometric attributed identfied as Tags in image | | | | | | Manual object identification |
|---|---|---|---|---|---|---|
| Tags | Width | Height | X | Y | Orientation | |
| 1 | 32 | 20 | 42 | 343 | 18.5382 | Tag |
| 2 | 64 | 55 | 202 | 295 | 36.7512 | Tag |
| 3 | 58 | 40 | 214 | 86 | 89.3833 | not Tag |
| 4 | 44 | 21 | 324 | 215 | 5.175 | not Tag |
| 5 | 68 | 45 | 344 | 364 | 60.6919 | not Tag |
| 6 | 31 | 24 | 359 | 292 | 1.3348 | Tag |
| 7 | 34 | 27 | 402 | 161 | 30.8086 | not Tag |
| 8 | 79 | 33 | 434 | 317 | 76.5475 | not Tag |

**Table 8:** Results on Object attributes (Figure 22)

Using the results from these tables, images are extracted for further processing. Figures 23 and 24 showed the extracted tags from the original image, together with the colour information on those extracted tags. However, the resulting image after re-orientation is again resized with common values of length and width to display each extracted tag clearly.

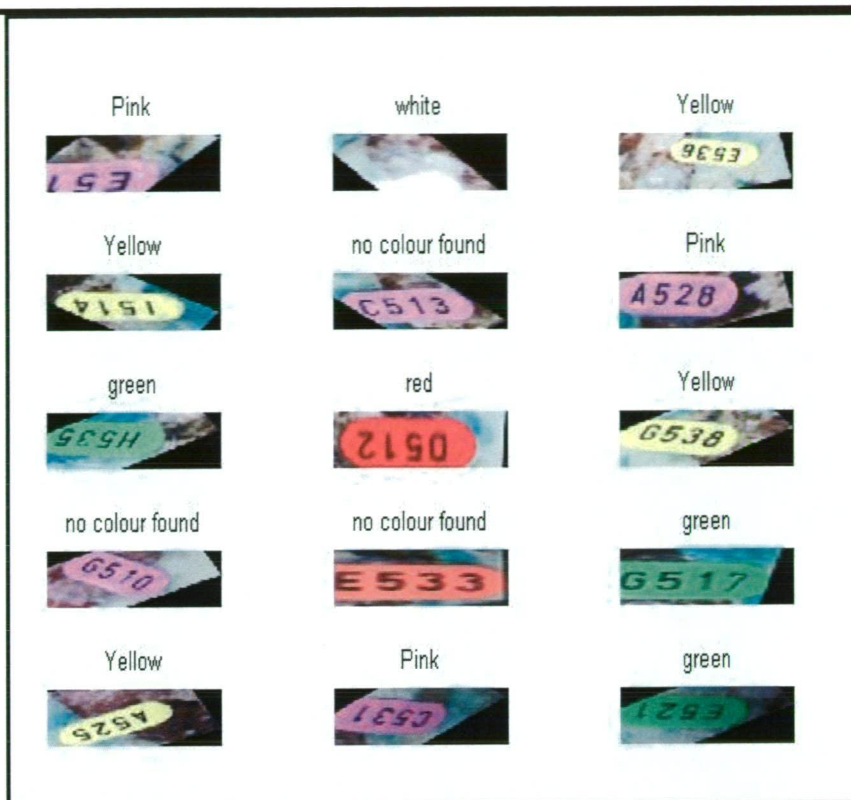



**Figure 23**: Single Tagged Image Tags Extraction Results

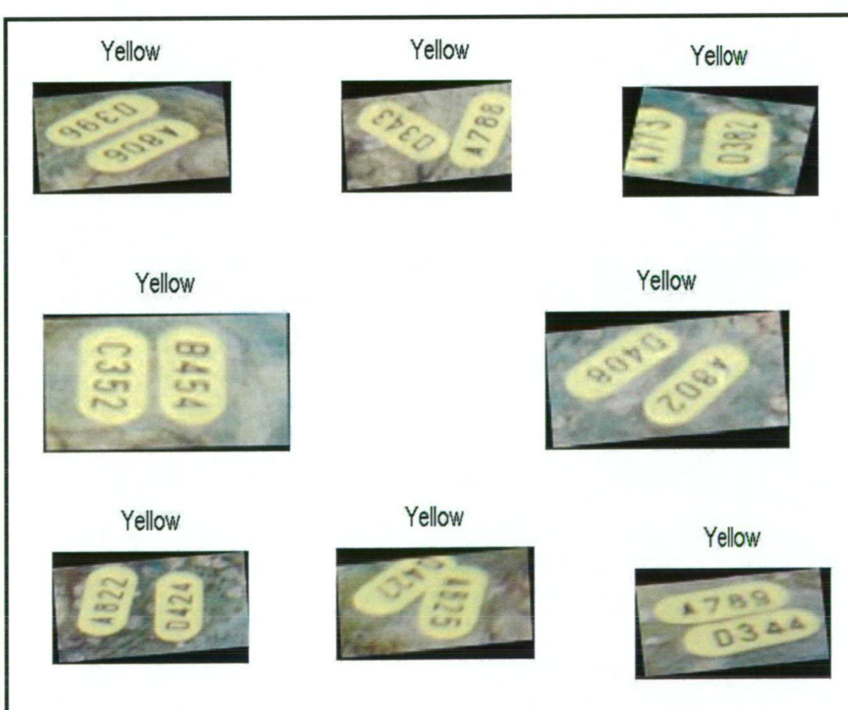



**Figure 24:** Triple Tagged image Tag Extraction Results

### 4.3.1 System Evaluation

The tag extraction system was evaluated by comparing the results obtained using the system with a manual analysis undertaken on the same test images. Two approaches were used to make the comparison. In this first approach, the images were analysed manually to estimate the X and Y positions of each of the tags in the original image using cursor positioning. These were then compared with system-generated X and Y positions (Chart 1). The results from the chart clearly showed that system generated values of (XY) position and (X",Y") tag position values from manual analysis were same.

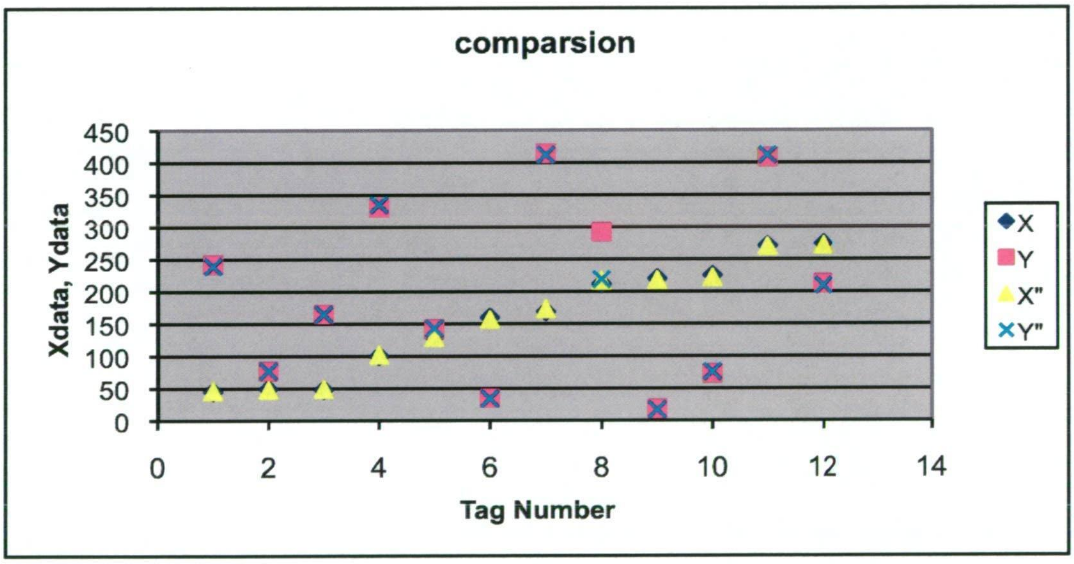



**Chart 1**: Comparison of Manual Analysis Data (X" and Y" values) with System Generated Data (XY values)

In the second approach, MATLAB's function **roipoly ()** was used to extract the tags from the images. This function will return a binary mask representing the shape of each tag and from which we can determine the width, height and orientation (angle) of the tag. This comparison was made with five tags (see Chart 2).

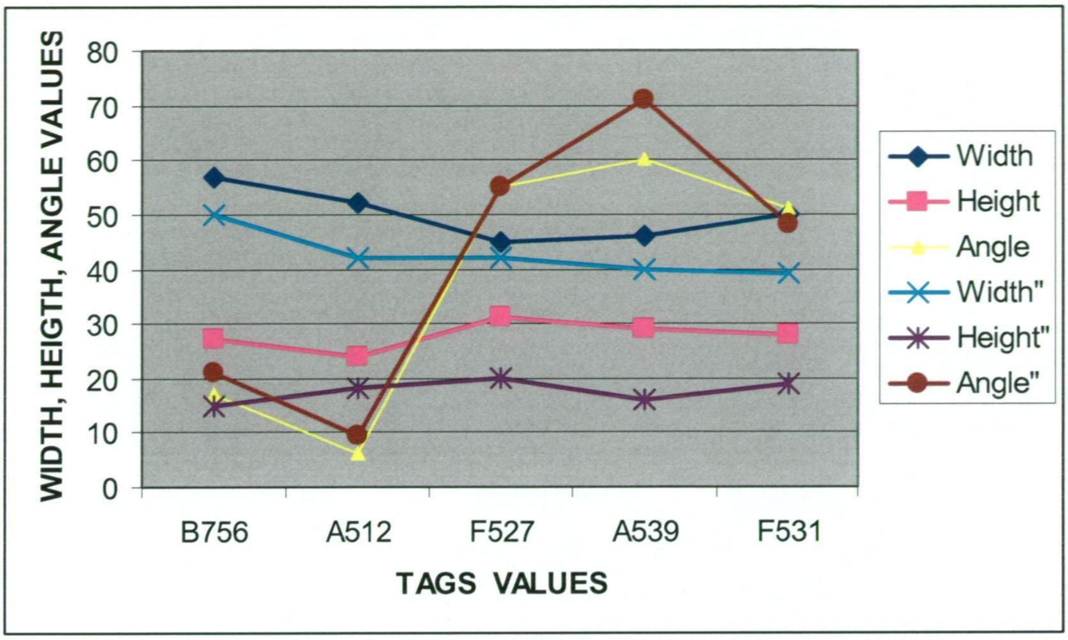



**Chart 2:** Comparison of Manual Analysis with System Data (Width, Height, Angle of tag)

Chart 2 results depict a comparison between values (Width, Height and Angle) produced by the system and the manual analysis data (Width", Height", Angle"). Some differences were found between system generated data and manual analysis data (e.g. A539). Possible reasons for this difference include inaccuracies in the segmentation process by which the system extracts the tags from the surrounding background and the possibility that the manual selection process did not extract a perfect representation of the shape of the tag.

### 4.5 Optical Character Recognition

This stage of the image analysis process involves preparing the characters on the tags for optical character recognition. Firstly the extracted tag sub-images were converted into binary images. For this conversion, two approaches were employed. The first makes use of the Ostu's algorithm (Cheriet et al. 1998), but this approach failed to provide a useful result for characters that are set on a light-coloured background, such as yellow and white.

In the second approach, the coloured tag sub-images were changed into greyscale images, after which the contrast function **imadjust ()** was used to improve the contrast between the characters on the tags and the tags themselves. After that, the Ostu's algorithm was used on some extracted tags but not all. The remaining coloured tags such as those that were yellow or white in colour were converted into binary images by manually observing the level value for **im2bw ()** function. This process obtained a better result than just using Ostu's algorithm.

To optimise the result, the MATLAB function **imclearborder ()** was used to remove unnecessary information, such as the border, from around the tag characters.

**Figure 25 and Figure 26** represent the final output as binary extracted tags.

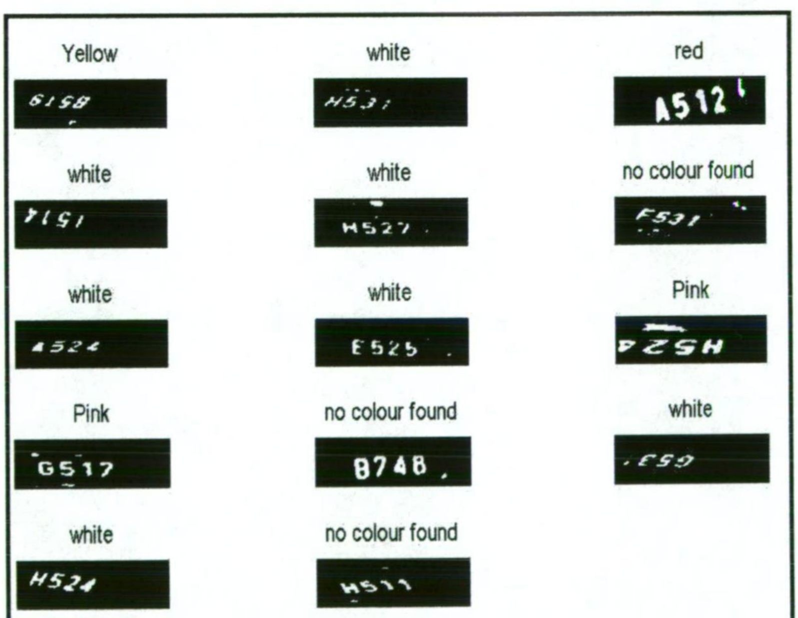



**Figure 25**: Single Tagged Binary Sub-images

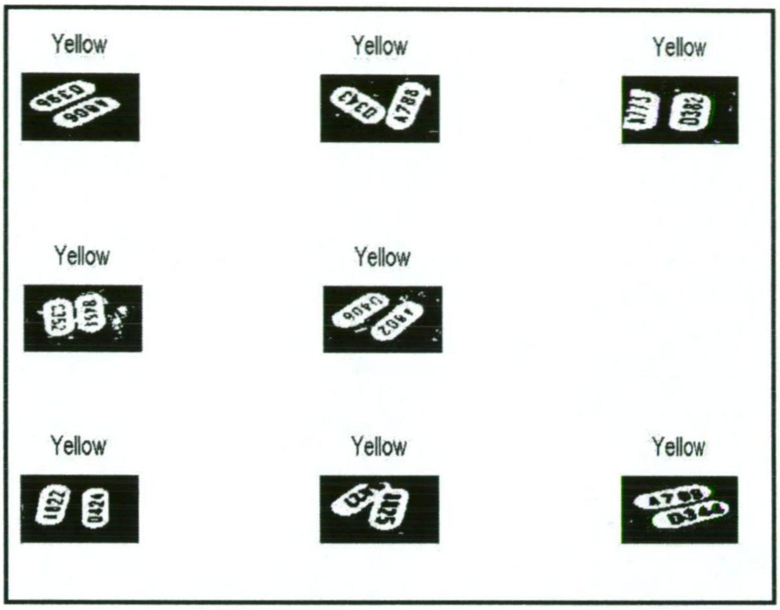



**Figure 26:** Double Tagged Binary Sub-images

These sub-images were then presented to a standard template-matching character recognition system but the results were disappointing and there is a need to consider use of a better optical character recognition system that can more accurately recognise the characters on the tags. Table 9, shows the optical character recognition system results compared with the original values of the tags, and it also compares the system generated colour information result of each tag with the actual colour of found tags in the four test images.

| Original Data | | System generated Data | |
|---|---|---|---|
| Tag Value | Tag Colour | Tag Value | Tag Colour |
| **Single Tagged Image** | | | |
| B519 | YELLOW | 7ZZ | YELLOW |
| H531 | WHITE | V4J2 | WHITE |
| A512 | RED | 90WJ | RED |
| I541 | WHITE | 71V | WHITE |
| H527 | WHITE | _H52V | WHITE |
| F531 | REDPINK | A574 | NO COLOUR FOUND |
| A524 | WHITE | 4424 | WHITE |
| E525 | WHITE | C545 | WHITE |
| H524 | PINK | ZZ14 | PINK |
| G517 | PINK | 664Y | PINK |
| B748 | PINK | 9744 | NO COLOUR FOUND |
| G531 | WHITE | 477 | WHITE |
| H524 | WHITE | VT7V | WHITE |
| **Single Tagged Image** | | | |
| H511 | PINK | A51X | NO COLOUR FOUND |
| E510 | PINK | - | PINK |
| - | - | - | - |
| E536 | YELLOW | T5727 | YELLOW |
| I541 | YELLOW | TQ | YELLOW |
| CS13 | PINK | C4X3 | NOCOLOUR FOUND |
| A528 | PINK | 4524 | PINK |
| H535 | GREEN | T727 | GREEN |
| O512 | RED | O593 | RED |
| G538 | YELLOW | 4744 | YELLOW |
| G510 | PINK | 44X7 | NO COLOUR FOUND |
| E533 | REDPINK | 633 | NO COLOUR FOUND |
| G517 | GREEN | 5V2 | GREEN |
| A525 | YELLOW | X435 | YELLOW |
| CS31 | PINK | 227 | PINK |
| E521 | GREEN | 47 | GREEN |
| **Triple Tagged Image** | | | |
| A806 | | XTA42 | |
| O396 | YELLOW | 0 95 | YELLOW |
| O343 | | SX9H | |
| A788 | YELLOW | Q10 | YELLOW |

| | | | |
|---|---|---|---|
| A773 | | I5T | |
| 0382 | YELLOW | 43 | YELLOW |
| B454 | | | |
| C352 | YELLOW | X1283 | YELLOW |
| A802 | | JUILIS7 | |
| 0408 | YELLOW | 402D | YELLOW |
| A822 | | TU7 | |
| 0424 | YELLOW | JW | YELLOW |
| A325 | | SDQTA | |
| 0427 | YELLOW | 2202 | YELLOW |
| A789 | | Q7Q1OED | |
| 0344 | YELLOW | K044 | YELLOW |
| **Single Tagged Image** | | | |
| A428 | REDPINK | LLT | WHITE |
| B195 | RED | -- | GREEN |
| A454 | REDPINK | 444 | WHITE |

**Table 9 :** OCR system an Image Analysis System Results

In summary, the research described here has been successful in developing image analysis techniques to extract the tags from the abalone images, determine their colour, location, height, width and orientation and use that information to extract sub-images containing the tags and present them to an optical character recognition system. However, more advanced techniques in optical character recognition will be needed to recognise and classify the characters on the tags accurately.

## Chapter 5

# Conclusion and Future Development

This research sought to develop an automated system for tracking and analysing tagged abalone in images, a task that is difficult and time consuming if the process has to be done manually. The classification and recognition of objects in images also represents a broad sub-field within robotics and computer vision.

For this project, images were collected from Tasmanian and Victorian abalone farms and used to design and implement an image analysis system that allowed the hypothesis to be tested directly on images taken from abalone farm tanks. In system development, significant progress has been made. The pre-processing techniques contribute to the overall success of the system not just in terms of identifying the object but also in reducing the execution time of the overall analysis process. The segmentation analysis is also an essential component in extracting and preparing the object for the optical character recognition system.

The results reported in this research confirm the hypothesis that image-processing techniques can successfully detect tags in the image. The pre-processing and segmentation results reported show that an acceptable number of tags can be identified with an acceptably low false positive rate.

The research described here has been successful in developing image analysis techniques to extract tags from abalone images, determine their colour, location, height, width and orientation and use that information to extract sub-images containing the tags, subsequently presenting them to an optical character recognition system.

Furthermore, the research results also confirm that appropriate image processing techniques can be applied in order to prepare the characters for optical character recognition and make them ready for the application of the template matching optical character recognition process. However, the results from template matching optical character recognition were not as effective as required. More advanced techniques in optical character recognition will be needed to recognise and classify the characters on the tags accurately.

For shape analysis, further image processing is needed in order to address issues such as tag orientation and the existence of double tags on an abalone. The present system tries to handle this problem to some extent. However, an assumption has been made that the double tag can be separated with a dilation process. If that can be done then the two tags can be identified separately and the second tag can be identified at a pre-defined distance from the first tag.

For further system development, there is a need to consider an optical character recognition system that can better understand the characters on tags. Instead of using the template matching system, a neural network may provide more accurate results. A change in the camera position may provide further benefits for the image processing techniques used, which in turn will benefit the whole system. It is clear that an increase in distance between the camera and the abalone leads to lower image quality, because it is harder to read the characters on the tags in a long distant picture. In addition, future work can be undertaken to identify the size of abalone thus helping to understand the growth rate in the abalone species.

The current version of the image analysis system that has been developed is flexible enough to accept new changes in order to support the future research and development work discussed above.

Finally, the research concludes that tracking and extraction of tags from images is achievable. Automatic image processing techniques for abalone image analysis will help researchers to identify individuals, monitor their behaviour in slab tanks and assess the performance traits of cultured abalone in breeding programs.

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# Appendix

## A.1 Application CD

There are four directories available on the sample CD: 'Images', Results', 'Source code' and 'Data'.

The 'Images' folder contains the Testing image and Training image directories containing images obtained from CSIRO Marine and Atmospheric Research.(CMAR).

The 'Results' folder contains the results of training and testing images in the Results-Training-Images and Result -Testing Images directories respectively.

The 'Source code' folder contains the MATLAB source code for the image analysis and tag recognition system.

The 'Data' folder contains system evaluation results and optical character recognition results.

## A.2 Application File List

### A.2.1 ALLOPERATION.M

The main file to run the system, and it performs initial size classification function and converts the images from the RGB model to the HSI model. Once this is performed the results are passed to the colour segmentation stage of the application.

### A.2.2 HSI2RGB.M

This stage performs the initial colour segmentation to identify the tag colours (such as green, pink, yellow, white etc.), and the output images are then passed to the segment analysis stage.

#### A.2.2.1 YELLOW.M, GREEN.M, WHITE.M, PINK.M, RED.M, BLUE.M, REDPINK.M

The code in these files identifies the colour in images with Hue and colour variation with Saturation and Intensity. The name of the file represents the colour it can identify.

### A.2.3 TAGS.M

This stage performs the detection of tags. The unwanted pixels are removed using the erosion operation, and then shape analysis is performed to detect the tags. The output images are then passed to the extraction stage.

### A.2.4 TRANFORMATION_ON_TAGS.M

In this stage, the value of tag's position and size are retrieved in order to extract sub-images, containing the tags, from the original image. The sub-images are then oriented in a horizontal position. Once this is performed, the RGB colour sub-images are then converted into binary images. This is the first step to prepare the character for the optical character recognition system.

### A.2.5 CHARACTER_READER.M

Performs the morphological operation to improve the character quality on the tag sub-images and the result is passed to a template matching optical character recognition system.

### A.2.6 OCR.M

This code performs the template matching optical character recognition on the characters depicted in the tag sub-images The output results are then displayed on the MATLAB output screen.