The Potential for Development of an Automated System for Diagnosis of Acute Intra-Cranial Haemorrhage from CT scans

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A dissertation submitted to the University of Dublin in partial fulfilment of the requirements for the degree of Master of Science in Health Informatics

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Declaration

I declare that the work described in this dissertation is, except where otherwise stated, entirely my own work, and has not been submitted as an exercise for a degree at this or any other university.

Signed ____________________

Catherine McKenna

7th September 2007

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Summary

Information technology (IT) offers great potential to impact on the effectiveness of the health service. IT can improve outcomes but as yet the healthcare sector has failed to fully exploit these opportunities. However given that the volume of data produced by the health sector doubles every five years it is imperative that the healthcare sector makes strides to catch up with other domains in capitalising on opportunities provided by IT for management of this huge volume of information. This project attempts to evaluate the potential for the application of a computer program that would speed the diagnosis of the acute intra-cranial haemorrhage (ICH) from computer tomography (CT) scans.

The technology and techniques used in CAD systems are described. A theoretical description of a system that would diagnose ICH independently from a radiologist is described in light of those techniques.

Currently there is limited potential for application of such a system. The reasons why such a system does not exist are many. In terms of diagnosis of ICH the issues include technological and anatomical reasons. The technological reasons include difficulties in image registration, difficulties with the output type and the amount of computation required. The anatomical reasons include difficulties in disease classification, and the general nature of the brain as an organ.

The literature has shown that the application of CAD is still limited in clinical practice but that use and awareness is growing. CAD is most successfully used in diagnosis of specific abnormalities in localised regions of the body. With the volume of information that is been generated in the radiology department ever increasing it is necessary that new ways of managing that information are explored. Despite the current limitations of the technology there are definite benefits to be gained from the application of CAD in radiology in the diagnoses of diseases and conditions other than ICH.

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Abbreviations

ANN	Artificial Neural Network
CAD	Computer Aided Diagnosis
CADx	Completely Automated Diagnosis
CT	Computer Tomography
DSS	Decision Support System
ERHA	Eastern Regional Health Authority
HSE	Hospital Services Executive
HU	Hounsfield Unit
ICH	Intra cranial haemorrhage
IP	Image Processing
IT	Information Technology
KBS	Knowledge Based System
MRI	Magnetic Resonance Imaging
MSCT	Multislice Computer Tomography
MTANN	Multiple Massive Training Artificial Neural Network
PR	Pattern Recognition
RBS	Rule Based System
ROC	Receiver Operator Characteristics
ROI	Region of interest
RSNA	Radiological Society of North America

Chapter 1 Introduction

It is well documented that the application of information technology (IT) in the health services can dramatically impact on the effectiveness of the service and improve outcomes (Zviran 1992). It is evident that the use of IT offers great potential but as yet the healthcare sector has failed to fully exploit these opportunities. Stagnant environmental and cultural practices have held the health sector back in adopting IT. However given that the volume of data produced by the health sector doubles every five years it is imperative that the healthcare sector makes strides to catch up with other domains in capitalising on opportunities provided by IT for management of this huge volume of information. The volume of information that is generated in the radiology department is a considerable portion of this. The amount of clinical time that is required to analyse this information is growing and it would be foolhardy to overlook the potential that IT could bring to managing this information. This project attempts to evaluate the potential for the application of a computer program that would speed the diagnosis of the acute intra-cranial haemorrhage (ICH) from computer tomography (CT) scans.

Beaumont Hospital is located within Network 10 of the Health Service Executive (HSE) (formerly the Eastern Regional Health Authority). Beaumont Hospital provides acute care services across 54 medical specialties and is the national Irish referral centre for Neurosciences and Renal Transplantation. The hospital offers in-patient, day patient, outpatient and casualty services to the population that it serves. The hospital is Ireland’s national neurological referral centre and as such it receives a huge number of referrals for neurological consults from hospitals around the country. In 2005 the hospital had 2,048 neurosurgical admissions; this represents 10% of the total admission to the hospital for that year (Beaumont Hospital Annual Report 2005).

In the acute cases of head injury the primary method of contact with Beaumont Hospital from a regional hospital is via the telelinking of CT images to the neuro-telemedicine workstation from a regional hospital. A member of the neurosurgery team must review these images and a decision is then made on the course of treatment that the patient will undergo. The patient's condition may be deemed to be too mild to warrant intervention, too severe to benefit from intervention, or may be deemed as having the potential to benefit from intervention. This decision is often made on the basis of the reviewed CT images. If the patient is deemed to have potential to benefit from intervention he/she may be transferred to Beaumont for that treatment, subject to available resources.

The author proposes to look at the potential use of an image processing software system that would reside at the interface to the neurosurgical workstation. The system would classify and triage the incoming scans. The proposed system could prompt the neurosurgical team of the presence of an abnormality on the received scans. The purpose being to speed the rate at which a decision may be made and to reduce the amount of clinical time that radiologists and the neurosurgical team spend reviewing images.

Given that there are image processing techniques that are successfully employed in the diagnosis of disease and disorders in discrete organs, the author intends to explore the potential for image processing of the CT brain images in order to confidentially diagnosis acute brain conditions. The intended methodology is to look at how acute brain conditions are categorised, in particular how brain haemorrhages maybe classified. The nature of CT images and their suitability for image processing will be explored. The characteristics of existing pattern recognition systems in use in radiology will be reviewed, with a view to identifying the features that make them successful and looking at the potential for applying these features to a system that will successfully categorise brain haemorrhage in the clinical setting as described in this proposal.

There are a number of approaches that can be taken to the construction of a knowledge based learning system; Lovell et al (1997), and Tailor et al (1999) describe the use of artificial neural networks in the clinical environment. Bariess, Porter and Wier (1988) describe a hybrid system of case based and model based that is used in a clinical setting. The author will examine the options available and the types of computer based decision-making tools will be outlined. The author will consider which approach to machine learning may be most appropriate in the diagnosis of and classification of brain haemorrhage.

Currently an expert does the classification of brain haemorrhage on CT images. This expert may be a neuro-radiologist or a neuro-physician. The expert reviews the CT images and he/she gives verbal or written reports on their observations. The method of classification will be investigated in an attempt to understand if there are clear classifications of the types and severity of haemorrhage. The manner in which conditions are classified must be understood so that a proposed system can be taught to make the correct classification also.

Research Question

Is there potential for the use of pattern recognition in the automated diagnosis of intra cranial haemorrhages from CT images?

The aims of the study are as follows:

Primary Aims of the study

- To determine if any pattern recognition/image processing products that diagnosis ICH in CT scans exist.
- To identify techniques that might be applicable for the diagnosis.
- To look at the state of the art in pattern recognition of medical images, i.e. to identify what techniques, and approaches are most commonly used in IP (image Processing).

Secondary Aims of the study

- To determine the extent to which automated diagnosis is used in radiology.
- To understand the fundamentals of these existing systems, looking for factors that contribute to the success of such systems.

There is substantial background information to the subject that is being researched. This information is included in chapters two and three. Chapter 2 gives the reader a description of the basic acute neurological conditions and the fundamentals of CT.

Chapter 3 examines the basics of imaging processing including the development of computer aided diagnosis (CAD) systems are included in chapter 3. Chapter 3 also explores some definitions of CAD and explains which one is most applicable to this study.

The state of the art is reviewed in chapter four. Literature relating to the topics of automated diagnosis, computer aided diagnosis and imaging processing techniques in radiology and medicine is examined. The approach taken to searching for literature is described in this chapter. This is followed by a review of that literature. Chapter 4 describes techniques that are used in IP of radiology images. This is followed by an overview of the applications of CAD in radiology. A brief look is taken at uses of CAD in other areas of medicine.

In chapter 5 the process of diagnosing ICH from CT scans is described. This evaluation is followed by a description of how this process may be computerised. A structure for a system that would make a diagnosis of ICH is proposed in this chapter.

In chapter 6 the reasons why such a CAD system for diagnosis of ICH does not exist are discussed.

In chapter 7 the main observations and conclusions of the study are drawn. Limitations of the study are described. Potential for further study is then discussed.

Chapter 2 Neurological Disorders & CT

This chapter is included to give the reader the required background to identify with and comprehend the subject that is being researched. The first section of this chapter is an overview of diagnosis of acute neurological disorders resulting from trauma. This is followed by a description of the basics of CT and an explanation of the terminology that is used in subsequent chapters.

2.1 Diagnosis of neurological disorders

This section introduces the reader to the more common traumatic pathology affecting the head and brain that can be demonstrated radiologically. There are many types of tumours and infections that can affect the brain and skull but these are not described as they are beyond the remit of this dissertation. Traumatic conditions that affect the brain are described as this is the area that this study is concerned with. It is important to understand the nature of the conditions that are proposed for automated diagnosis so that the feasibility of that proposal can be fully appreciated.

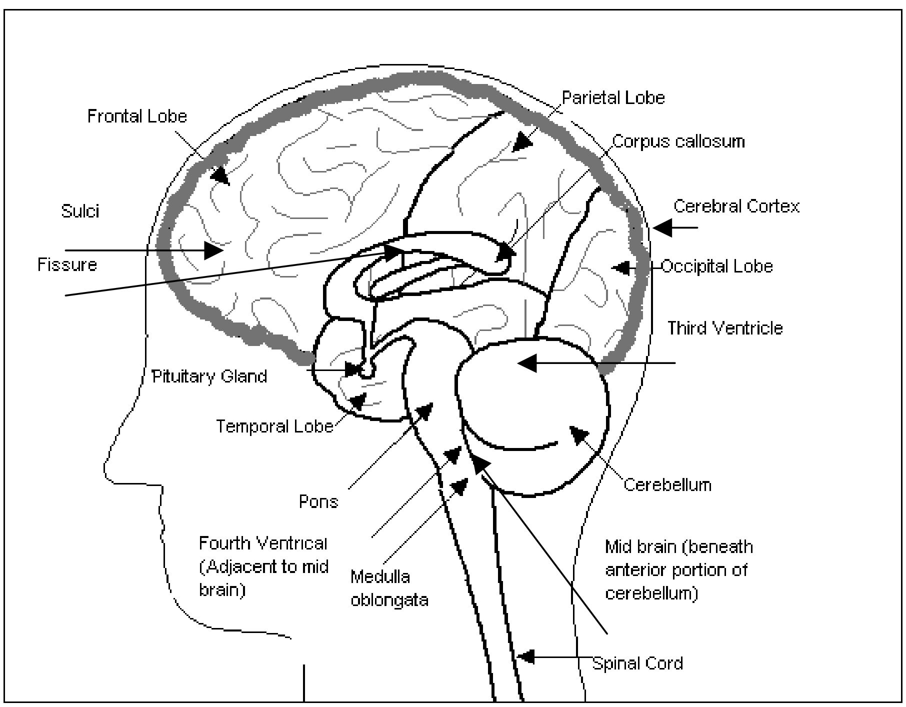
CT has virtually replaced all other imaging modalities in the investigation of patients with head injury (Eisenberg & Dennis 1995). For this reason and as CT is part of the subject of this study a description of how these conditions appear on a CT image is also included. The denser a structure is the brighter (whiter) it will appear on a CT scans, the less dense a substance is the darker it will appear. Air, which is not at all dense, will appear black; bone, which is very dense, will appear white on CT scans.

However to fully understand the pathology it is necessary to understand the basic anatomy and physiology of the brain. For that reason a brief description of the gross anatomy of the skull and brain are included in section 2.1.1.

2.1.1 Basic Anatomy & Physiology of the Brain

Together with the spinal cord the brain forms the central nervous system (CNS). The CNS is responsible for interpretation of sensory information and elicits responses based on past experience, reflexes and current conditions. The CNS together with the peripheral nervous system controls our sensory and motor functions (Marieb 1989).

The brain is composed of ventricles, the cerebral hemispheres, the cerebral cortex, the brain stem, cerebellum, and protective layers of meninges and bone. These components are shown in figure 2:1 and are then described briefly.



Taken from: http://www.enchantedlearning.com/subjects/anatomy/brain/index.shtml and adapted.

Figure 2:1 Lateral View of the Brain

There are four ventricles in the brain, two lateral ventricles, the narrow third ventricle and the fourth ventricle. The ventricles are interconnected and articulate with the spinal cord all of which contain central nervous fluid (CNF).

There are two cerebral hemisphere, left and right, each of which has elevated ridges of tissue called gyri. The shallow grooves between the gyri are called sulci. The deeper grooves are called fissures. The cranial bones that overlie the brain give name to the regions of the brain beneath. The two cerebral hemispheres are connected by a mass of white matter called the corpus callosum.

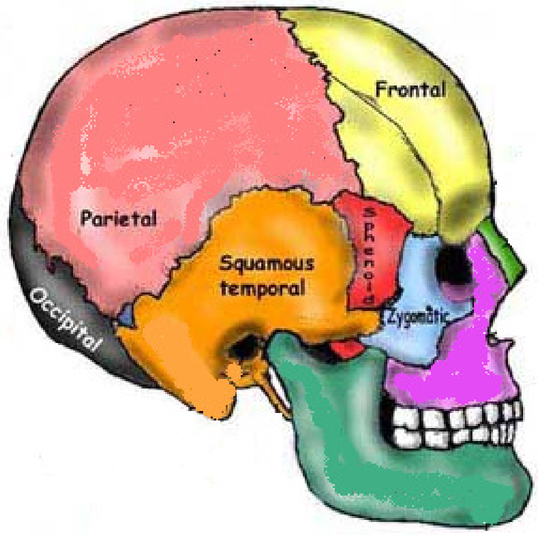
The outer layer of tissue that covers each hemisphere forms the cerebral cortex. The cerebral cortex is responsible for implementation of consciousness, memory, logic, perception, communication, and movement. Distinct areas of the cerebral cortex are associated with all sensory and motor ability that the body performs.

The brain stem lies between the brain and the spinal cord and is formed by the midbrain, pons, and medulla oblongata. The brain stem components produce the rigidly programmed behaviours necessary for our survival such as cardiac, vasomotor, and respiratory functions.

Beneath the cerebral hemispheres lies the cerebellum, which is responsible for our subconscious activity, it acts with the cortex to produce patterns of bodily movements.

Two layers protect the brain, a layer of meninges and the skull vault. The meninges consist of three layers, a layer of dura mater, arachnoid membrane and the pia mater. The dura mater extending to form the falx cerebri that separates the two hemispheres.

The skull vault is made up of eight separate bones, The bones of the skull are the frontal, occipital, sphenoid, ethmoid, right and left squamous temporal, and right and left parietal bones these are shown in figure 2:2. (the ethmoid is beneath the zygomatic bone). The articulating surfaces of these bones form suture lines.



Taken from: http://www.enchantedlearning.com/subjects/anatomy/brain/index.shtml and adapted

Figure 2:2 Lateral View of the Skull Bones

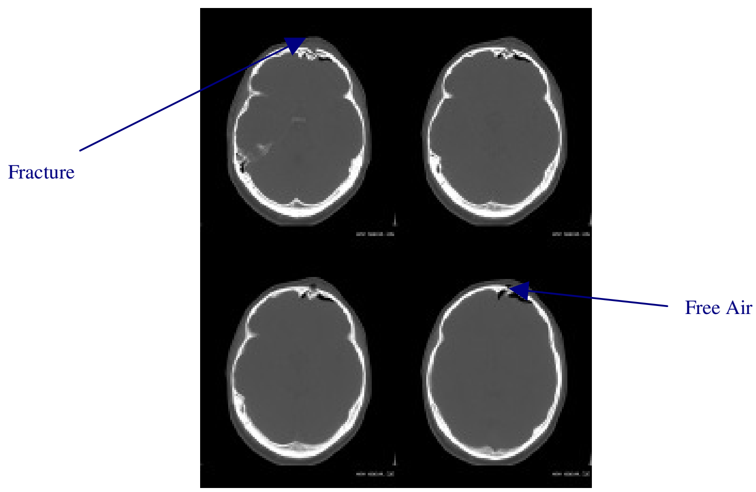
2.1.2 Traumatic Neurological Conditions

This section introduces the common traumatic conditions of the brain. Diseases that arise as a result of injury to the head are outlined. These conditions include skull fractures, epidural haematoma, subdural haematoma, cerebral contusion, intracerebral haematoma and subarachnoid haemorrhage.

The term haemorrhage refers to the rupture of a blood vessel. If a large artery or vein is ruptured the cause is almost always some form of injury such as trauma, atherosclerosis, or inflammation or erosion of the vessel wall by a neoplasm (Eisenberg & Dennis 1995). For the purpose of this study the causes other than trauma will not be considered as they are outside the concern of the study. The significance of the haemorrhage will depend on the site of the haemorrhage, volume of blood lost, and the rate of loss. A haematoma is formed following the accumulation of blood in an area of the body.

2.1.2.1 Skull Fractures

A skull fracture is a break in the cortex of the skull bones. The break may be linear or depressed. A linear fracture can be distinguished from a suture line in that suture are generally bilateral, symmetric, and have vascular grooves and serrated edges. Depressed fractures are often star shaped with multiple fracture lines radiating outwards from a central point. Fractures may be demonstrated with plain radiographs, but the presence of a skull fracture does not always correlate with intracranial abnormalities. The location of the fracture can however indicate possible complications. More severe trauma may result in a piece of the skull bone being detached and the underlining dura can be damaged as a result.



(Images courtesy of CT Dept. Beaumont Hospital)

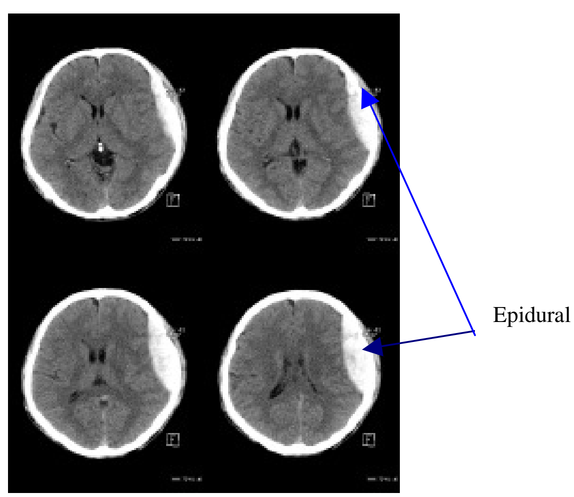
Figure 2:3 CT Images showing skull fracture

Figure 2:3 shows part of a CT brain series with a bone window applied so that the structure of the bone is detailed and focused. The soft tissue structures appear to have the same density in the image and are effectively muted from sight with the application of a bone window. The four images included show a depressed fracture in the frontal bone at different levels through the skull. The black area along side the fracture represents air in the skull. The presents of this air indicates that the fracture articulates with the skin surface or that the fracture extends to a sinus. This has implications for treatment and management of this case.

2.1.2.2 Epidural Haematoma

An epidural haematoma (also referred to as an extradural haematoma), results from acute arterial bleeding and most commonly forms over the parietotemporal convexity. As the dura is very adherent to the inner table of the skull the epidural haematoma generally appears lens shaped in outline. The high arterial pressure associated with epidural haematomas cause rapid mass effect, resulting in midline shift unless a contra balancing haematoma is present. An epidural haematoma that is left without prompt diagnosis can lead to rapid progressive loss of consciousness, dilation of the ipslateral pupil (pupil on the opposite side), compression of the upper midbrain, and eventually compression of the entire brainstem and death.

In figure 2:4 part of a series of CT brain images are shown. A soft tissue window had been applied in these images and therefore the detail of the soft tissue structures are apparent. The bone in theses images appears as a dense white outline surrounding the brain tissue. In these images a typical epidural acute haematoma is shown. It can be said that the haemaotoma is acute rather than chronic because the collection of blood appears as a dense white area. If the bleed were chronic this area would have reduced density. Note the dense lens shaped outline in the parietotemporal region and depression of the right lateral ventricle. There is some very mild midline shift present.



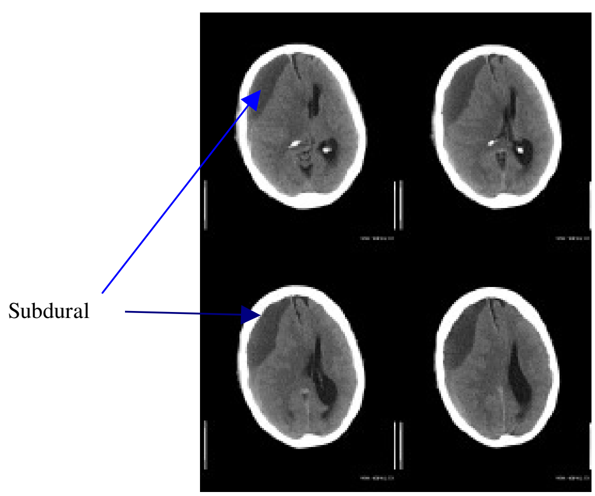
(Images courtesy of CT Dept. Beaumont Hospital)

Figure 2:4 CT Image showing an epidural haematoma

2.1.2.3 Subdural Haematoma

Subdural Haematoma occurs from venous bleeding and most commonly form between the dura and the meninges. Due to the low pressure of venous bleeding the onset of symptoms is generally at a slower pace than that of epidural haematoma. The symptoms are headache, drowsiness, confusion, and gradual neurological deficits.

On a CT scan an acute subdural haematoma typically appear as a peripheral zone of increased density that follows the surface of the brain and has a crescent shape adjacent to the inner table of the skull. A scan of a chronic subdural will show an area of decreased density. A mass effect is often seen in these cases with displacement of the midline structures, the sulci on the affected side may be obliterated. If there is no displacement then the presence of bilateral subdural haematoma should be considered a possibility. Scans taken after the initial onset will show an area of reduced density, there will be a gradual reduction in the attenuation of the subdural haematoma over a period of weeks. In figure 2:5 the appearance of a subdural after a number of days is shown. Note the low-density area of the frontal region of the brain. There is midline shift and associated depression of the left ventricle and dilation of the right ventricle. The bright areas within the ventricles represent fresh bleeding.



(Images courtesy of CT Dept. Beaumont Hospital)

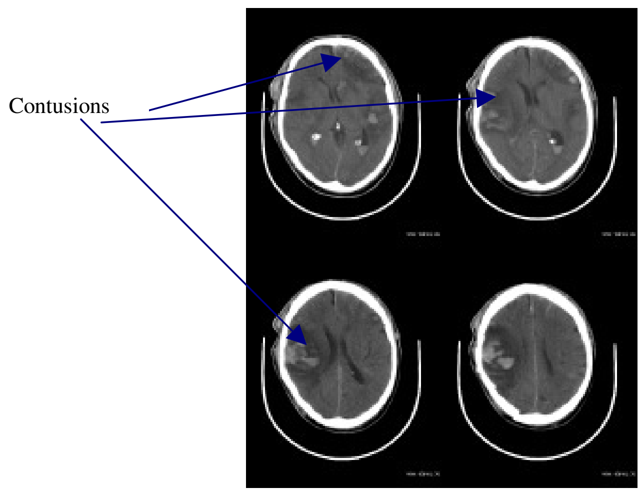
Figure 2:5 CT Images showing chronic subdural haematoma

2.1.2.4 Cerebral Contusion

When the brain tissue is involved in trauma that causes it to move within the skull vault a brain contusion can occur. If the brain hits against rough skull surfaces such as superior orbital roof or the petrous ridges the tissue can be damaged resulting in a cerebral contusion.

The typical appearance of a cerebral contusion on a CT scan is as areas of low-density oedema and tissue necrosis. There may also be areas of non-homogeneous high-density zones that represent multiple areas of haemorrhage.

Figure 2:6 shows part of a CT brain series from a young male patient. There are multiple contusions present with oedema surrounding the contusions. There are collections of blood within some of the contusion, blood in the right lateral ventricle,. There is compression of the left ventricle and midline shift.



(Images courtesy of CT Dept. Beaumont Hospital)

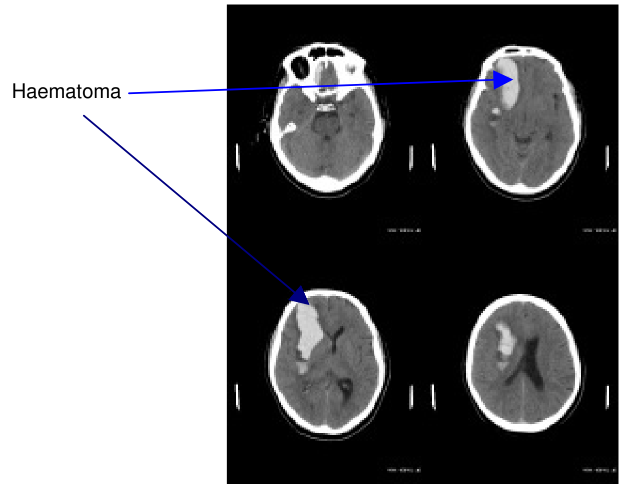
Figure 2:6 CT scans showing multiple brain contusions

2.1.2.5 Intracerebral haematoma

A shearing force on the intraparenchymal arteries can result in an intracerebral haemorrhage, this tends to occur at the interface between the grey and white matter. Damage to the intracranial vessels can cause aneurysms that can rupture resulting in intracerebral haematoma.

On a CT scan the intracerebral haematoma appears as a well-defined, homogeneous, high-density area that is typically encircled by an area of low-density oedema. As the haematoma disintegrates the density of the lesion's appearance on CT will become equal to that of normal brain tissue. The outline of the original haematoma will remain apparent. It is most common for intracerebral haemorrhage to happen at the time of injury but may also occur after the surgical evacuation of subdural haematoma that are compressing potential bleed sites.

In figure 2:7 a typical intracerebral haematoma is shown. The haematoma is dense in nature and so appears bright in colour. This haematoma occupies a large region of the brain extending from the sphenoid region through to the apex of the brain. There is compression of the ventricles and oedema surrounding the haematoma.



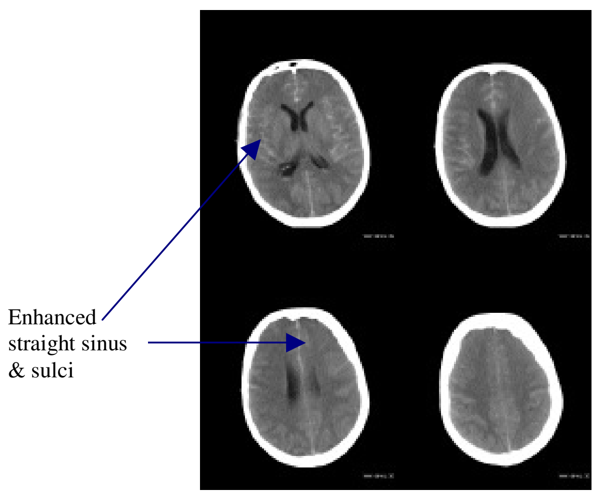
(Images courtesy of CT Dept. Beaumont Hospital)

Figure 2:7 CT Images showing intracerebral haematoma

2.1.2.6 Subarachnoid haemorrhage

Subarachnoid haemorrhage is characterised by bleeding into the ventricular system of the brain. The bleeding may be in the basilar cisterns, cerebral fissures, and sulci. If the falx cerebri, straight sinus, or the superior sagittal sinus appears enhanced on a non-contrast CT scan then a subarachnoid haemorrhage is often indicated. Care must be taken not to confuse traumatic pathology with normal variants such as calcified falx.

In figure 2:8 a typical subarachnoid is shown. The sulci and straight sinus appear enhanced due to the presence of fresh blood. The blood tracts along the ventricular system and appears to highlight the tract. The diffuse nature of the bleeding makes this condition easy for an inexperienced observer to overlook.



(Images courtesy of CT Dept. Beaumont Hospital)

Figure 2:8 CT images showing subarachnoid haemorrhage

2.2 Computed Tomography

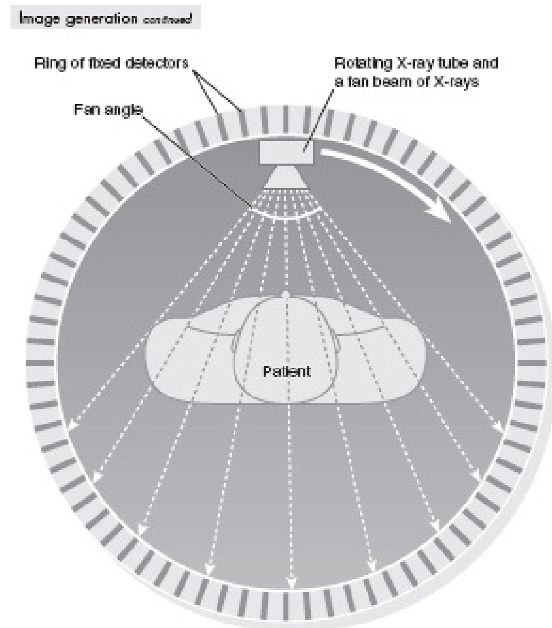
In this section the basic technical principles and common terminology of CT are explained. This is followed by a brief explanation of the application of CAD in the area of CT. A more detailed review of the application of CAD in radiology can be found in chapter three.

Tomography originates from the Greek word section. Computer tomography is a technique that allows the body to be imaged in sections or slices and employs a computer to display and manipulate the resulting digital images.

The origin of digital imaging began with the invention of the CT scanner in the 1970's (Imaginis 2006 online). Since its inception CT has been continuously adapted to the technical state of the art and to reflect the changes in radiology practice. Changes have been made to the user interface, image quality, image acquisition time etc.

2.2.1 CT Basic Technique

CT is a cross-sectional imaging modality that uses an x-ray tube and an array of receptors to create a digital image of the subject that is being imaged. Conventionally the x-ray tube and the receptors rotate around the subject using tomography to create the image. The image appears as a slice through the anatomy typically in the axial plane. The thickness of the slice is controlled by collimator, which limits the incident beam. The thinner the slice the more information is gained, but the scan time and the radiation dose will be increased with thinner collimation. A typical arrangement of a CT scanner can be seen in figure 2:9.



(Taken from Introduction to CT physics - elsevierhealth.com pg4)

Figure 2:9 Arrangement of component parts of a CT scanner

As the tube rotates the relative distribution of the detectors record the x-ray intensity. The relative linear attenuation coefficient[1] is calculated from the incident x-ray photons. The detectors convert the x-ray photons into an analog signal, which in turn is converted into a digital signal. The computer reconstructs a grey scale image from that data using reconstructive algorithms. This image is then displayed on the viewing monitor.

The images were acquired slice by slice until the onset of spiral scanning. Spiral scanning captures a volume of data while the patient is moved continuously through the scanner. The x-ray tube and the detectors move continuously for several revolutions.

In the late 1990's a new generation of scanners was introduced. This was the multislice CT (MSCT). The MSCT scanner used multiple stationary detectors to

[1] Relative linear attenuation coefficient is the amount of radiation that is absorbed in the tissue for the various elements in the section.

cover a much greater volume of the subject. The patient is scanned continuously as the table moves through the scanner along the z-axis. The result is a single volume of data. The scan time is dependant on the number of detectors and the collimation thickness.

2.2.2 Hounsfield unit

In order to allow a direct comparison between images obtained on different scanners with different voltages and filtrations a new unit of density was created for use in CT images, that is the Hounsfield unit (HU). This was necessary to ensure the consistency of the characteristics and appearance of CT images. The scanner is calibrated against the density of water and air. The resultant values are independent of the energy of the x-ray used during each scan, these then constitute fixed points with which create a CT value scale. The density of the target tissue in CT characterises the linear attenuation coefficient of the tissue in each volume relative to the CT value scale. This ensures the CT value or the Hounsfield unit (HU) value of a given structure is relatively unchanged regardless of the energy of the incoming x-ray beam.

Water and water equivalent tissues have a HU value of 0HU. Air has a negative HU value of –1000HU. Lung tissue and fat have negative HU value due to their low density and therefore their low attenuation value relative to water. Bone is dense in nature and therefore has a positive HU value in the order of 1000HU.

2.2.3 Windowing

Lung and fat have negative CT values, they are less dense than water so they have a HU less than water. Air has a HU value of –1000. There is however no upper limit on the Hounsfield scale, but medical scanners generally have a range of –1026 up to +3071. In practice over 4000 grey levels may be shown on a CT image. However the human eye can only distinguish 70 grey levels. On viewing the image the grey levels assigned to the structures of interest are applied, grey levels above this are displayed as white, and grey levels below this are displayed as black. This technique is called windowing. It allows the observer to focus attention on structures of a particular density range. The narrower the range the more contrast the image will have. This range is called the window width. Images of the brain have fewer variations in density and therefore a narrower window width is applied to images of the brain.

In figure 2:10 the window width for bone, mediastinum and lungs are shown relative to each other. The centre for each window is also shown. The centre is the value about which the width is applied. The centre value for bone is 1000. The centre is chosen as the mean value of the structures of interest. The window width for bone is 2500. The width will determine the contrast. The window width for bone is wide as spongey bone can have a very low HU value of 50 whereas compact bone can have a high HU value of +2000. To display very small attenuation differences in soft tissue structures such as the mediastinum or the brain, a narrow window width is chosen. The window centre and width values for a brain are typically of the order of 40 and 80.

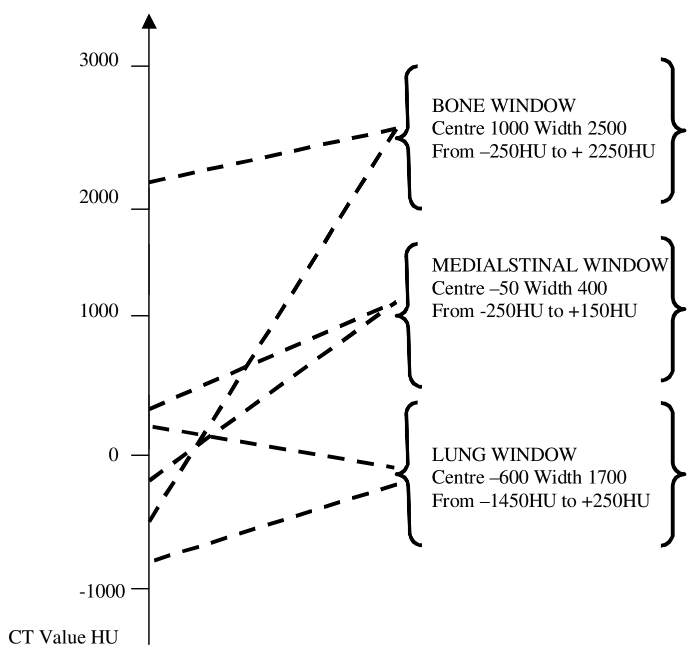


Figure 2:10 Windowing of CT Images

2.2.4 Contrast Agents

CT is very sensitive to the radiographic differences in soft tissue structures, sensing differences of 1% in tissue densities. Conventional screen-film radiography requires a tissue difference of at least 5% in order to differentiate between adjacent structures. Consequently CT is very useful for imaging soft tissue structures in the body cavities. In CT of the head it is possible to differentiate between white and grey matter, cerebral oedema, cerebrospinal fluid, blood clots and neoplastic structures. It is possible to alter the density of vascular structures artificially during the scan with the use of iodinated contrast agents. These contrast agents are injected intravenously during or immediately prior to the scan and the contrast permits the differentiation of vascular from nonvascular structures.

2.2.5 Computer Aided Diagnosis and CT

The introduction of MSCT has compelled the industry to provide alternative ways of managing the huge volume of data that is generated. CT as an imaging modality typically represents 7% of the total number of examinations performed in an Imaging Department but accounts for 30% of overall images produced in the department (Jennings 06). It is therefore responsible for the generation of a vast volume of the over all data generated in the radiology department. Using a single slice scanner an examination of the liver produced on average 140 images, using multi-slice this number rises to 360 (Tamm et al 2002). It is not practical for a Radiologist to sit and examine each of these axial images individually as this would be counter productive in the use of their time. This leads to the problem of finding alternative methods of viewing the data without loosing information. It is prudent to look at new ways of managing this huge volume of data.

The use of CAD and representation of these images and information in innovative ways that will reduce the amount of clinical time spent analysing them is growing in importance. Doi (2005) states that the use of CAD systems in the area of MSCT would assist radiologists in reducing reading time as well as improving diagnostic accuracy. The benefits of CAD are therefore twofold, in that reading time, and consequently time for delivery of results is reduced; and secondly that the accuracy of these results may be improved. In chapter 3 CAD will be discussed at length.

2.2.6 MRI & CT

In subsequent sections reference is made to the imaging modality Magnetic Resonance Imaging (MRI). This section is included to give the reader a simple explanation of the techniques used in MRI so a comparison may be made with techniques used in image processing of MRI and CT images.

Like CT MRI is a cross-sectional imaging modality. The technologies used in MRI are however quite different to those used in CT. The physics used in MRI is beyond the scope of this dissertation but the technique basically consists of inducing transitions between energy states by causing certain atoms to absorb and transfer energy. This is achieved by directing a radiofrequency pulse at a subject within a large magnetic field. A computer measures the time required for the subject material to return to its baseline energy state. The computer then processes the measurement using various algorithms and reconstitutes the data in the format of a digital image that is then displayed on a viewing monitor.

It important to note that two types of images are generally acquired during a MRI scan, these are a T_1 weighted scan and a T_2 weighted scan. In a T_1 weighted scan slow flowing blood, fresh haemorrhage and fat are some of the substances that cause a high signal. A high signal will appear bright on the final image. Water as in cerebral spinal fluid or in simple cysts will appear dark as water has a low signal. In a T_2 weighted scans the opposite is true, muscle and fat will have a low signal and will appear dark. Haemorrhage also appears bright on a T2 weighted scan as the age of the haemorrhage increases. MRI images of head infarction, oedema, tumour, infection and demyelinating disease all produce identical signal intensity on T2 weighted images. However only T1 weighted imaging is used after the administration of contrast in MRI.

The degree of signal intensity is dependant on a number of factors but some generalisations can be made about the resultant images. Both CT and MRI images are similar in that they are cross-sectional digital images. A MRI image provides excellent spatial resolution, equal to that of a CT image. However MRI images have better contrast resolution than CT images. The flood of blood during a scan will produce a signal and means that it is unnecessary to use contrast media in MRI to identify blood vessels. To image cerebral vascular structures a "time of flight" technique is used, this uses the flow of blood to produce a high signal while the background structures are saturated out. Therefore no contrast is needed in imaging of the arterial vessels in the brain. In imaging of arterial vessels in CT administration of contrast is necessary as described in section 2.2.4.

This chapter introduces the reader to the common concepts of acute traumatic neurological conditions and CT. The next chapter introduces the common concepts in the study of pattern recognition and image processing. Also in the chapter 3 the architecture of CAD systems and definitions of CAD are discussed.

Chapter 3 Pattern Recognition & Computer Aided Diagnosis

This dissertation examines the potential use of pattern recognition and image-processing techniques in the diagnosis of acute brain haemorrhage from CT scans. Pattern recognition and image processing are techniques that arise from the study of knowledge based decision support systems (DSS). This section is included to give the reader an insight into the basic principles and terminology used in the study of DSS and IP. A description of CAD architecture, CAD definitions and associated terminology are included in the section 3.2.

3.1 Pattern Recognition & Image Processing

Knowledge based system (KBS) development is the development of a computer system that will solve a real world problem. The initial problem must be analysed and represented in a way the computer can manipulate, this initial representation may result in the compilation a set of problem attributes. A reasoning mechanism often called an inference engine will then manipulate the problem or a representation of that problem and produce a solution.

An expert system is a knowledge-based program that provides expert quality solutions in a specific domain. The knowledge is gathered from the human experts. This knowledge is then encoded into formal language and the program is structured to emulate the experts' methodology and performance.

It is the processes that occur in the inference engine that are of interest in this dissertation. The process of training a computer may be described as supervised learning or it may be unsupervised. To train using supervised learning the training data is already classified, the result is already known and the computer is taught this result. Unsupervised learning is more useful if the training data is not easily categorised and the category is formed as a result of the machine learning. Data mining will commonly use this approach to machine learning. For the purpose of this study supervised learning is more pertinent and will therefore be described further.

Supervised machine learning depends on the useful generalisation of the possible problems and the associated outcomes. These generalisations must be presented concisely in order to allow machine to learn. The machines learns from a training set that presents generalisation of the problem allowing similarities to be found and outcomes to be present on the basis of finding those similarities. This approach is referred to as similarity based learning. There are a variety of techniques used to do this; these include Rule Based Expert Systems, Decision tree induction, k nearest neighbour and Artificial Neural Networks. The IP techniques Fourier analysis, wavelet transformation, morphological filtering and difference image technique are described.

3.1.1 Rule Based Expert Systems

A rule-based system (RBS) is an expert system that is particular model of computation that forms the basis of many expert systems. The rules may be used to generate new facts until the desired answer is reached. This approach is called forward chaining and is used in data driven RBS. The alternative to this is called backward chaining. Backward chaining attempts to prove a hypothesised goal by linking the fact back to initial facts. This approach is used in goal driven RBS and is more commonly used in medicine.

3.1.2 Decisions Tree Induction

A decision tree is induced from a set of training data. It is a set of rules that correctly classifies the training data and will correctly classify unseen cases. It is generally accepted that the simplest tree that achieves correct classification of the training data is most likely to correctly classify unseen cases.

A decision tree will test each feature serially and the reasoning of the system can be represented in a model. However if the test case does not match exactly with the first feature tried then the system will not find a match at all.

3.1.3 *k*-Nearest Neighbour Classification

K-nearest neighbour classification requires a database of previously classified cases. The test case is compared against this data and the category is decided according to the category of its *k* nearest neighbours. It is possible to weight certain features in the test case to increase the accuracy of the classification. The feature can be manipulated to pull or push the test case towards or away from a certain result. For example, in the diagnoses of coronary heart disease the patients' family history can influence the outcome. A person who has a strong family history of coronary heart disease is more likely to develop such a condition. The family history of that person could then be introduced as a weighted factor in the classification process.

3.1.4 Artificial Neural Networks

Artificial Neural Networks (ANN) are a form of pattern recognition that are different from decision trees and *k*-nearest neighbour. They are modelled on the human brain in that they have many neurons that produce outputs based upon weighting of multiple inputs possibly including inputs from multiple time points. They are unique in that they can alter the weighting of certain factors with training. During training, a set of inputs, in the case of radiology multiple diagnostic images, is provided along with the desired output (i.e. the correct diagnosis). After a number of such training examples the network is considered trained and is ready for production.

The degree of training that the ANN will require will depend on the number of possible outcomes and the numbers of factors that influence the outcome. The desired output for each training example is taught to the system. An algorithm called "backpropagation" is commonly used for training the system. The weights associated with the inputs are given an initial value, a sample of inputs are presented to the

ANN. The resulting outputs are compared with the desired outputs and the weights are altered to reduce the mean square error. This process is repeated until such time as the error is within an acceptable tolerance. However it is possible to over train an ANN, the result being that irrelevant feature in the training set is recognised rather than true abnormalities.

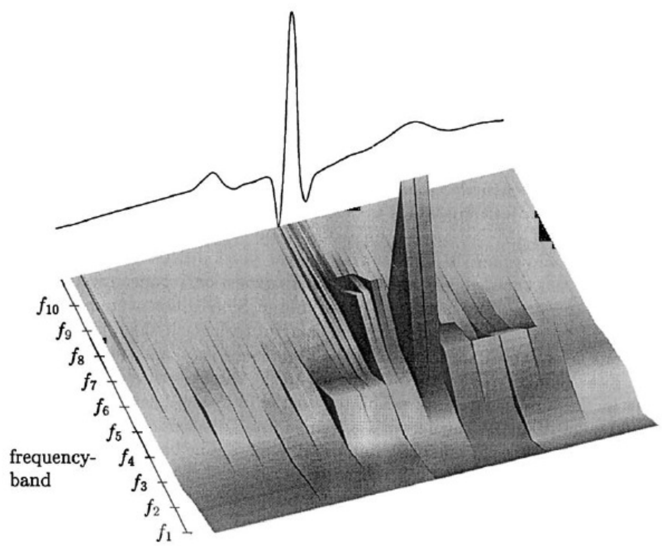
The use of ANN is particularly suited to pattern recognition due to the true similarity based learning of the system. These systems are flexible an easy to maintain and can handle noisy and incomplete data well.

3.1.5 Fourier analysis

Fourier analysis is a mathematical technique that has been developed to divide a waveform into a series of sine and cosine functions of different amplitudes. This technique is widely used in science and engineering as an analytical tool as it allows the waveforms to be transformed into to mathematical representations and manipulated. In radiology this technique is used in CT and more commonly in MRI for the transformation of the measured signal to a visual representation of that signal, i.e. an image. The signal in a frequency domain can be manipulated, edges enhanced or smoothed. The Fourier technique does not provide any information regarding when in time the frequency occurred.

3.1.6 Wavelet transform

Wavelet transformation is a process by which a discrete waveform is decomposed into time frequency three-dimensional representation. In figure 3:1 the transformation of an ECG tracing into it constituent frequencies is shown. This decomposition allows frequencies to be manipulated and filtered according to requirements. It shows the frequency and the time relative to other frequencies of occurrence.



(Taken from Sternickel (2002 pg110))

Figure 3:1 Wavelet Transformation

3.1.7 Morphological filtering

Morphological filtering of medical images is a collection of techniques based on the mathematical technique called mathematical morphology. Mathematical morphology is a theoretical model used to manipulate digital and binary images. The technique uses the relative ordering of the pixel value and not the numerical value. Morphological filtering is therefore very suitable for the use in manipulation of greyscale images. This technique allows the creation of algorithms for a variety of functions, such as image sharpening, image filtering, image segmentation or feature detection.

A common morphological filtering process is one in which a non linear transformation for sharpening digitised grey scale images is applied. The transformation replaces the grey scale value at a pixel by the minimum or the maximum of the grey scale values in the adjacent pixel. The choice to apply the maximum or the minimum will depend on which is closest to the original grey value. After a finite number of iterative applications the resulting image stabilises so that each pixel becomes either a local maximum or a local minimum. The structures in the resultant image appear shaper with more definite contours.

3.1.8 Difference image technique

Difference image technique is a technique used in image processing to determine changes or differences between images. The difference is calculated by finding the difference between each pixel in each image. An image that portrays the difference is then generated. The technique aligns the two images so that corresponding points coincide. The photometric values of both images must be compatible, this can be achieved with calibration or careful post processing. The amount of pre-processing required will vary with the type of image. This alignment can be achieved through a process called image registration in which the two different data sets are transformed onto the one coordinate system. Image registration allows integration of data and comparison of data from images from a variety of sources and dates.

3.2 Development of a CAD system

In this section the definition of CAD are examined. The general background of CAD is explored prior to looking at the typical architecture of a CAD system and examining the concept in more depth.

Computer Aided Diagnosis (CAD) was developed in the last twenty years from technology that was used by the military in defence programs (Gilbert & Lemke 2005). The technology that was previously employed by the military has been adapted for use in the medical setting, with a view to improving speed and accuracy of diagnosis (Crane et al (2006), Armato and Sensakovic (2004), and Li et al (2006)).

Doi (2005) reports the number of papers presented at the Annual Meetings of the Radiological Society of North America (RSNA) in Chicago, which is one of the major meetings in the field of diagnostic radiology, on subjects related to CAD has increased by approximately 50% per year, from 55 in 2000, to 86 in 2001, to 134 in 2002, and 191 in 2003. Various types of CAD designs are being developed for detection and/or characterisation of various lesions in medical imaging, including conventional projection radiography, computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound. Organs currently being subjected to research for CAD includes the breast, chest, colon, brain, liver, kidney, and the vascular and skeletal systems.

3.2.1 Definition of CAD

Kakeda et al (2003) states that computer-aided diagnosis (CAD) is a computer system, the purpose of which is to direct the radiologist's attention by identifying and indicating suspected focal opacities that may represent a cancerous growth on a radiograph. This description establishes the concept of the computer assisting the expert radiologist with diagnosis of malignant disease in a specific region of interest.

Lim Jeong and Ho (2005) define CAD as a diagnosis introduced by a radiologist who uses the output from a computerised analysis of medical images as a second opinion in detecting lesions. This definition broadens the concept of CAD beyond that of a system that solely diagnoses lesions other than cancer, but is similar in that it supports the idea of a computer assisting the radiologist final opinion. This definition introduces the concept that a CAD system incorporates the radiologist, the computer and the final diagnosis as components of the system. The system refers to a number of component elements that include not only the computer programme but also the radiologist, and the computer’s intermediate diagnosis, and the eventual diagnosis. This definition supposes that CAD is the complete diagnostic process rather than as a component of that process.

Doi et al (1999) states that CAD can be defined as computer output that provides a second opinion to assist radiologists in reading the image. This frank definition asserts that a CAD system is a computer output that provides a verdict that may prompt the diagnosis to be made by a radiologist. This description of CAD is more simplistic than Kakeda et al but the simplicity offers wider scope to the application and interpretation of a CAD system beyond diagnosis of malignant disease. Unlike the definition given by Lim Jeong and Ho (2005) the definition by Doi et al (1999) does not include the radiologist and the ultimate diagnosis as part of the system, but sees CAD as a part of a the diagnostic process rather than seeing it as the complete diagnostic process.

Typically CAD has been defined by a diagnosis made by physician who takes into account the computer output based on quantitative analysis of radiological images (Doi 2005, Doi et al 2000). The concept of *automated computer diagnosis* differs from *computer-aided diagnosis*, in that automated diagnosis seeks to replace radiologists. The clear purpose of CAD is therefore through the use of a computer to assist the radiologist in arriving at a diagnosis, thereby improving effectiveness and productivity by reducing image reading time.

All of the definitions place CAD in the domain of radiology although it is evident from the literature that computer aided diagnosis can be applied to fields other than radiology, such as neurology, otolaryngology, and optometry (Sternickel 2002,Verikas 2004, and Aisbett & Gibbon 2005). It is fair to say therefore that the definition of CAD will depend on the context.

In the reviewed literature the terms Computer Aided Diagnosis and Computer Aided Detection have been interchanged by authors in the field (Karssemeljer et al (2003) and Gur et al (2004)) and are therefore taken to refer to the same principle.

The exact components parts of the system proposed in this dissertation have not yet been determined. It needs to be differentiated from existing systems; therefore it will be referred to as CADx. The focus of this study is to examine the potential for a system that will detect and diagnose brain haemorrhage from CT scans. It is envisaged that the system will act in place of the radiologist. For the purpose of this study the Lim Jeong and Ho (2005) definition will be used as it most closely matches with the intended system proposed by this study. This definition reflects the broader application of the CAD system in the diagnosis of pathology other than malignancy that this study wishes to investigate. It views CAD as the complete diagnostic process including the radiologists' role.

In the following section the uses of CAD in radiology are examined. This section begins with an over view of the general nature of the application of that technology in radiology. The specific application of that technology in the diagnosis of particular disease is then reviewed. These specific applications are divided into the uses of CAD in diagnosis of breast, lung, liver and brain pathologies. The final section in thischapter reviews the use of automated diagnosis in medicine in general.

3.2.2 CAD Background

Computer aided diagnoses (CAD) is currently used in a number of imaging modalities, these include Magnetic Resonance Imaging (MRI), CT and mammography. Pattern recognition, which forms the basis for many CAD systems, is currently used successfully in the detection of abnormalities in the brain on MRI scans (Chen (1999), Sharman, Tyler and Pianykh (2000), Crane, Crawford and Nelson (2006)). Armato and Sensakovic (2004), and Li et al (2006) describe the use of CAD tools in the diagnosis of lung nodules on CT scans. Stoitsis et al (2006) present a paper on the use of CAD in the diagnosis of focal lesions on CT scans of the liver, the system has the ability to categorise the liver as normal, hepatic cyst, haemangioma, and hepatocellular carcinoma. Stoitsis et al (2006) conclude that the use of quantitive image analysis tools can improve diagnostic sensitivity and reduce interpretation time. Image processing techniques have successfully detected abnormalities in digital images of the breast (Hemminger 2001, Taylor 1997). The volume of information that is produced in the health sector doubles every five years, the imaging department is responsible for a huge volume of that information. It is necessary therefore to find and employ new and innovative ways of managing the data that is produced and reaping the benefit of the information that may be produced.

The application of CAD systems in the domain of radiology and while it is still in its infancy, it is certain to grow in use in time.

3.2.3 Architecture of a CAD system

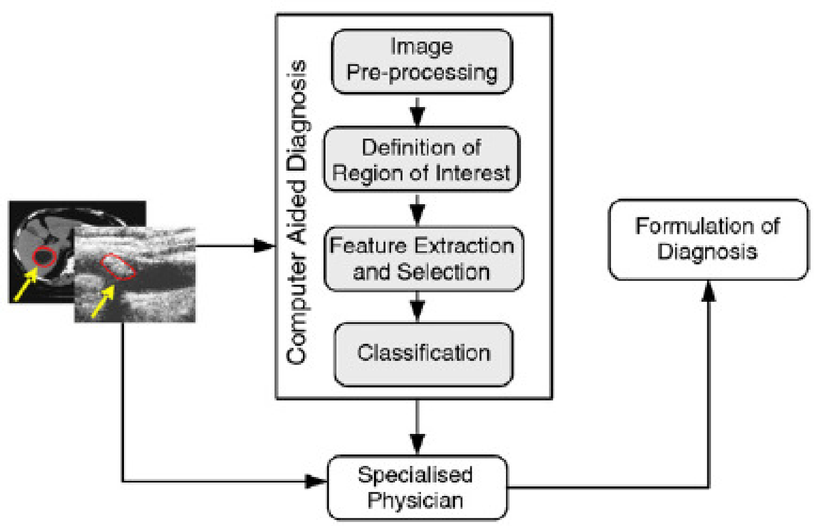
A CAD system will generally operate by locating a lesion and determining an estimate of the probability of a disease. In the development of a CAD system there are two general approaches that may be taken. The first to find suspicious lesions by searching for specific patterns that vary from what has been defined as normal, such as lung nodules in chest images. The second approach is to quantify the features within each image as normal and/or abnormal, such as lung texture of chest with interstitial disease. The approach taken will depend on the nature of the pathology been investigated. If the pathology is likely to be localised, such as a subdural then the first approach may be appropriate. However if the pathology is diffuse in nature, such as an arachnoid haemorrhage the second approach is more suitable.

Doi (2005) stated that a CAD system has three basic components. The first component is image processing that extracts and enhances lesions. The image processing that is done at this point is to facilitate the computer and not the human eye in identification of lesions. The image processing techniques that are commonly employed are Fourier analysis, wavelet transform, morphological filtering, the difference image technique, and artificial neural networks (ANNs).

According to Doi's suggested model the second component is the quantitation of image features, such as the contrast, size and shape of the candidates identified by the first module. The features within the image can be defined using heuristic techniques drawing on the radiologists' expertise to find unique features that will reliably distinguish a lesion from a normal anatomical structure. Further quantitation of features is possible using exhaustive and non-deterministic methods.

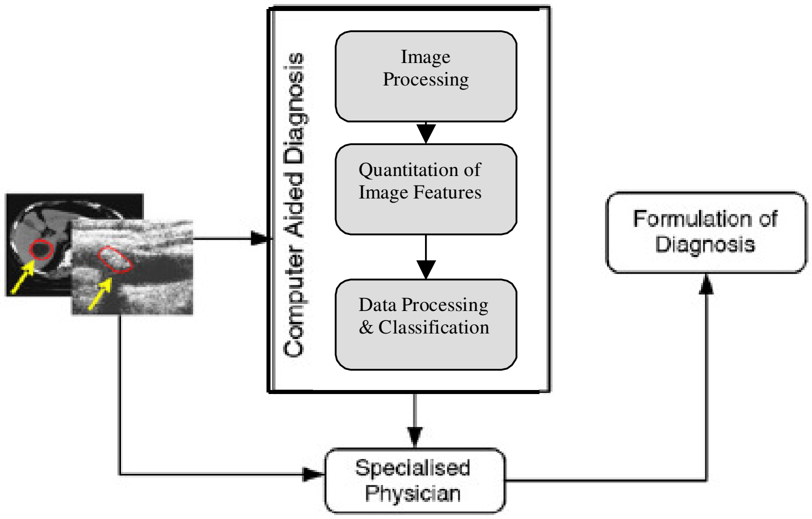
The third component involves processing the data generated by previous component and classifications of the findings. A common approach used in this component is a rule-based method. The rules can be established on basis of normal patterns and understanding the nature of lesions. Discriminate analysis, ANN and decision trees, or more commonly a hybrid system are also used in this component.

Stoitsis et al (2006) have stated that a CAD system has four basic components. Figure 3:2 depicts a representation of the system described by Stoitsis et al (2006). On comparison with the model suggested by Doi (2005) in Figure 3:3 it can be seen that Stoitsis et al have included an image pre-processing component, this component is inferred in Doi model in the image processing component.



(Taken from Stoitsis et al (2006 pg 592))

Figure 3:2 CAD Architecture as described by Stoitsis et al (2006)



(Taken from Stoitsis et al (2006 pg 592) and adapted)

Figure 3:3 CAD Architecture as described by Doi (2005)

There is another component that should be included in the development of any CAD system, that is the observer performance studies that will monitor and validate the work of the system. Doi (2005) states that the development of computer algorithms in the field of CAD must incorporate large-scale observer performance studies that use a reliable methodology such as Receiver Operating Characteristics (ROC) in order to determine the value and benefits of CAD.

A successful CAD system must therefore include not only computer algorithms, but also incorporate a measure of how useful the computer system would be in assisting in diagnoses, how to quantify the benefits of the CAD system, and how to maximise the effect of CAD. Bearing in mind the range of disciplines that are therefore required to create a successful system it is necessary to exploit experts from different backgrounds such as physicists, radiologists, computer scientists, engineers, psychologists and statisticians.

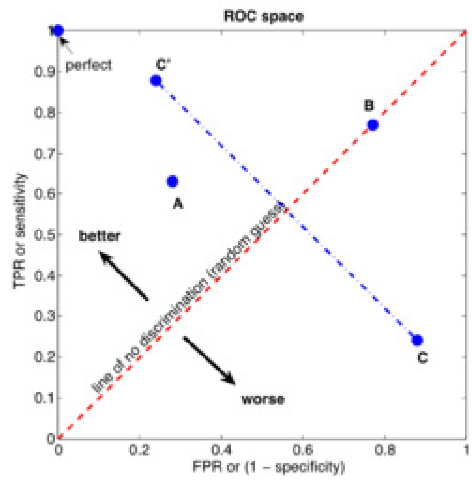
3.2.4 Receiver Operator Characteristics Analysis

The Receiver Operator Characteristics ROC analysis curve was originally created during the Second World War to assess the capabilities of the radar system in distinguishing random interference from genuine targets. Today the technique is successfully used in the medical field in particular in medical imaging (Tortorella 2005). The ROC curve estimates and reports all the combinations of sensitivity and specificity with comprehensive description of diagnostic accuracy. The National Council on Radiation Protection and Measurements in the USA have stated that the ROC curve provides the most comprehensive description of the accuracy of diagnostic systems when compared against other techniques for assessing accuracy (Metz 2006).

In the study of Pattern Recognition it is necessary to measure the suitability of particular approaches to problem solving. The ROC curve is useful for organising classifiers and visualising their performance. A classifier is also called a classification model and is mapping of an instance to predicted classes (Fawcett 2005). The ROC curve is used to depict the performance of two classifiers at different operating points and allows the researcher to select characteristics based on their performance. A classifier will have a threshold at which point to the classification changes. The ROC curve is created by plotting a true positive (sensitivity or benefits) against the true negative (specificity or costs); the decision threshold varies continuously to take into account the outcome.

Figure 3:4 shows a simple ROC curve. With reference to figure 3:4 classifiers to the left of and above the diagonal, those that lie more towards the true positive axis are said to have good diagnostic discrimination. A classifier that lies at the (0,1) coordinates is said to be perfect, giving a 100% accurate classification every time. The diagonal represents the divide between good and bad performance of classifiers. The classifier A produces more true positives than C. However if the results of the C classifications are reversed C^1 has better discrimination than A. The classifier B that lies on the diagonal represents the performance of a random guess.

The area under the ROC curve can be used as a measure of the sensitivity and specificity of a diagnostic system. The area under the ROC curve measures the probability of correct classification. An area of 0.9 for example indicates that a sequence chosen from the positive group has a probability of 0.9 of scoring higher than a sequence from the negative group. Representing the information in this way allows the quantitative performance of a particular classifier to be visualised and an analysis of that performance to be made.

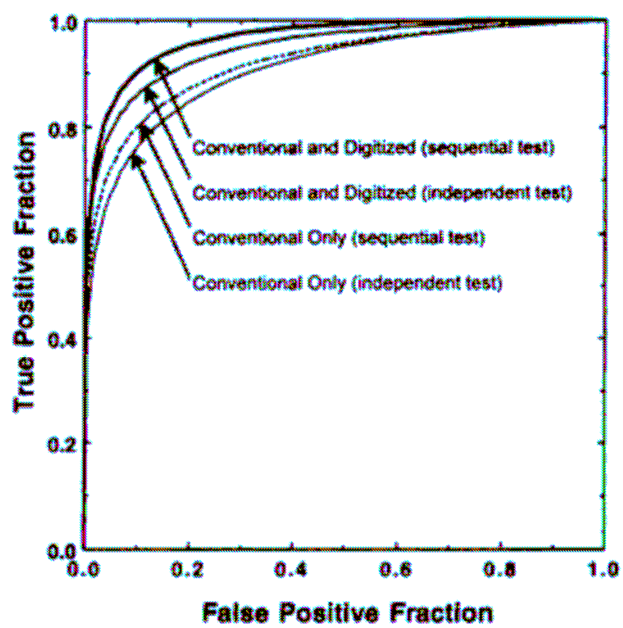


(Taken from http://en.wikipedia.org/wiki/Receiver_operating_characteristic)

Figure 3:4 A basic ROC Graph

Kobayashi et al (1996) used ROC curves in their analysis of the impact on a CAD system on radiologists' performance in the diagnoses of lung nodules. The Kobayashi et al (1996) measured performance in four circumstances; using the conventional observer tests without the CAD output (conventional independent), using conventional observer tests with the CAD (conventional sequential), output using conventional and digital images without CAD (conventional and digital independent), and using conventional and digital images with CAD (conventional and digital sequential). The results can be seen in figure 3:5

In figure 3:5 four ROC curves are plotted on the same axis. Plotting the curves on the same axis allows direct comparison of the reporting techniques. Looking at these curves it can be seen that the curve that has the greatest area beneath it will lie more towards the true positive axis. In this case the curve with the greatest area beneath it is the conventional and digital (sequential test) curve. This diagnostic method has therefore the best diagnostic discrimination of the four methods. The improvement in the radiologists' performance is clearly demonstrated, and is easily compared to the other methods of diagnosis. This demonstrates the strength of ROC curves in demonstrating quantitative performance of a particular approaches to diagnosis of lung nodules. The performance can be visualised and an analysis of that performance to be made simpler.



(Taken from Kobayashi et al (1996) Page 845)

Figure 3:5 Graph showing comparison of ROC Curves

This chapter introduces the reader to the basic principles of IP, pattern recognition and CAD. The next chapter is a review of literature significant to this study.

Chapter 4 The State of the Art

4.1 Literature Search

Prior to embarking on the search for literature the aims of the search where outlined so that the search could be structured to achieve the aims of the study as outlined in the introduction chapter. These aims are as outlined below:

Aims of the Literature Search.

- To find literature that looks at the state of the art in pattern recognition of medical images, i.e. to identify what techniques, and approaches are most commonly used in IP (image Processing) of medical images.
- To find literature that shows if any pattern recognition/image processing products that diagnosis ICH in CT scans exist
- To find literature that identifies techniques which might be applicable for the diagnosis of ICH from CT scans.

This research is concerned specifically with the computer-aided diagnosis of specific acute brain pathologies; in particular ICH on CT scans of the brain, and the use of pattern recognition and image processing techniques to achieve that diagnosis. The application of imaging processing and pattern recognition techniques in medicine is a huge area of study. It is not within the scope of this dissertation to examine these areas without exception. The aims are set to focus the study and to set appropriate boundaries for the study.

To begin the search was broadly focused with the primary aims in mind, the wide nature of the initial search was to give the author an overview of the topic. The search for literature began with using Google Scholar. This search of *grey literature* was primarily to identify if any of the manufacturers of CT scanners are promoting a software package that uses such technology. The key words used where "CT scanners manufacturers", and "computerised tomography scanner manufacturers". The results showed there to be five manufacturers of CT scanners in Europe, each of these manufacturers was *googled* individually including the phrases " CT scanner automated diagnostic tools" and "CT image processing tools". The results where searched for articles or promotional literature that indicated the existence of a diagnostic tool for brain haemorrhage.

The majority of the results related to scanner specifications and opinion articles from the manufacturers' perspective on the products that were being promoted. The quality of the information was generally poor and did not indicate the existence of software tools for the diagnosis of ICH.

The database Science Direct was searched for articles on the subject of CT images and image processing; the search was conducted using the keywords "radiology image processing", "computer aided diagnosis in CT", "image processing and CT head" and "image processing and CT Brain". The search resulted in 8137 articles. The results were refined by excluding articles prior to 1997. This resulted in 1735 articles. Of these articles that did not include the search terms in the title were excluded. This action resulted in the listing of 132 articles. The abstracts of these were examined to decide if the article was relevant. The full text of thirty articles was retrieved. The reference lists from the articles were explored and this approach yielded articles relevant to the subject.

The process of finding literature relevant to the topic was ongoing through the composition of the dissertation. During the course of writing the dissertation the databases CINAHL, Springerlink, BMJ Journal online and Pubmed was also accessed to search for articles and text on background material, on IP techniques, CT images and ICH.

The results of the initial search showed that there is no truly automated diagnostic system used in practice in radiology departments. However the use of computer-aided diagnosis is a tool that is employed in radiology but that the technique is in its infancy. Many of the studies that were reviewed seek to establish the potential usefulness of CAD in diagnosis of specific diseases in particular modalities. While its use in clinical practice is growing, many of the articles related to controlled and retrospective studies on the effectiveness of CAD in diagnosis of particular diseases and conditions. The exception to this is the use of CAD in mammography, which is widely accepted and used in practice. However overall the literature does support the idea that image processing and subsequent automated computer diagnosis technique are growing in use in the clinical setting.

The retrieved literature did not establish the existence of a system for specific diagnosis of brain haemorrhage in CT scans. Furthermore the literature does not illustrate that there is any truly automated diagnostic systems used in radiology, the systems that are used, are employed to aid in the diagnosis of conditions that range in nature.

The search for literature indicates that the use of CAD in diagnosis of brain conditions other than acute brain haemorrhage is limited. Some articles found review the use of computerised tools to diagnose very specific brain conditions. These conditions include middle cerebral artery stroke and unruptured intracranial aneurysms.

The general purpose of the radiology systems that have been reviewed is to prompt the radiologist in his or her diagnosis with a view to improving accuracy and speed of reporting time. The literature on the use of systems that aid diagnosis in radiology in particular and medicine in general is reviewed with a view to understanding the technology and its suitability or unsuitability, as the case maybe, for the proposed use of automated computer diagnosis in brain haemorrhage in CT scans.

In chapter 2 section 3 the definition, development and background for a CAD system was discussed. In this chapter the techniques used in development of a CAD system are reviewed. The techniques reviewed are not intended to be a comprehensive description of IP techniques as it is not with in the scope of this study to evaluate all the techniques that can be used. The section introduces the reader to the more common concepts and approaches used in processing of medical images. Following that, the current uses and potential uses of CAD in Radiology are reviewed. A brief consideration of CAD systems used in medical fields other than Radiology is made.

4.2 Image Processing and the State of the Art

This section is a review of the techniques used in image processing that are pertinent to this study. There are numerous techniques used in image processing but it is not within the capacity of this document to describe all of them. The techniques most pertinent to image processing of medical images and in radiology are discussed here. The techniques discussed are segmentation, image registration, rules based systems and ANN.

4.2.1 Segmentation

Segmentation is the process of dividing a digital image into multiple sets of pixels. The purpose of segmentation is to simplify the image into something easier to analyse. Segmentation is used to locate objects and outlines of structures in images. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. All of the pixels in a region share a common characteristic or characteristics such as colour, intensity or texture. Regions adjacent will have significantly different characteristics.

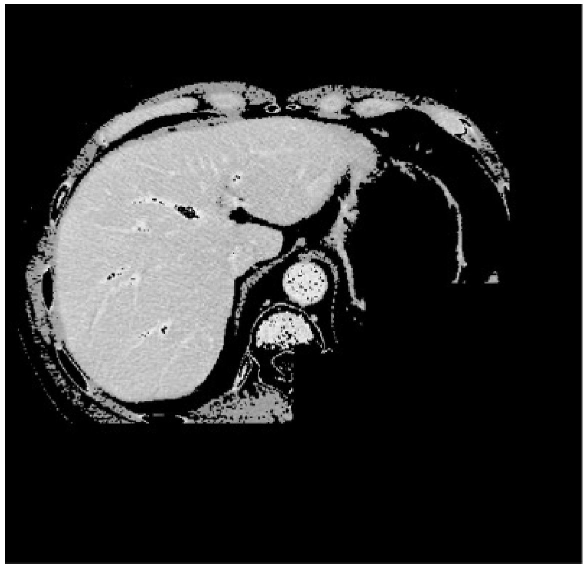
Several general-purpose algorithms and techniques have been developed for image segmentation. Since there is no general solution to the image segmentation problem, these techniques often have to be combined with domain knowledge in order to effectively solve an image segmentation problem for a problem domain (Wikipedia 2007a).

Lim, Jeong and Ho (2005) describe in their study how a liver is successfully segmented using a combination of approaches to contour and segment the organ. This study states that grey level thresholding, region growing, clustering, template matching, feature thresholding, and contour based techniques are all segmentation techniques that are used in medical imaging. These approaches can be broadly categorised as either a region based or as a contour based approach.

4.2.1.1 Region Based Techniques

Grey level thresholding is a region-based technique that can be used to identify organs or particular tissue types. Thresholding is the simplest method of image segmentation (Wikipedia 2007c). Each pixel in a greyscale image is assessed and marked as an object pixel if its value is greater than the threshold value, pixels lower than this value are pushed to the background. Typically, an object pixel is given a value of “1” while a background pixel is given a value of “0.”

Lim, Jeong and Ho (2005) used this grey level thresholding to aid in the segmentation of the liver. The Hounsfield number for muscle and liver is used to set a threshold value with the effect that elements outside that threshold are removed from the image. In figure 4:1 the effect of grey level thresholding can be seen. The organs other than the liver have been effectively blacken from the image. However some superfluous structures remain in the picture such as the abdominal wall and the spine. This highlights the need to use a sequence of segmentation tools for effective segmentation.



Taken from Lim, Jeong & Ho (2005 pg 863)

Figure 4:1 Threshold Image

Region growing is a region-based technique that is used for segmentation. A region is started with a single pixel. Flanking pixels are examined and added to the region if they are sufficiently similar to the region. If the pixel is dissimilar to the current region it is used to start a new region.

Clustering is an iterative technique that like region growing is used to partition an image into *k* clusters. A centre cluster *k* is selected either randomly or using some heuristic. Each pixel in the image is then assigned to a cluster centre that closest matches the pixel. The pixel values in any given cluster are then averaged and this average becomes the new cluster centre. The pixels in the image are then reassigned until the process becomes stable.

4.2.1.2 Feature thresholding & Contour Based Techniques

The terms “contour based techniques” and “feature thresholding” are terms used to refer to the same collection of methods by which various shapes (features) and contours can be isolated or detected in a digital image (Wikipedia 2007c). This collection of techniques is used to simplify an image with a view to making it easier to manipulate and process. These techniques include edge detection, blob detection and scale invariant features.

The aim of edge detection is to mark the points in a digital image at which there luminous intensity changes sharply. These changes usually represent a change in the nature of the object in the image, reflecting a change in the material matter or representation in the introduction of a new object in that area of the image.

Blob extraction is a technique that categorises the pixels in an image as belonging to one of many discrete regions. The terminology used to describe this process is inconsistent. The technique may also be called region labelling, connected component labelling, blob discovery or region extraction (Wikipedia 2007a). However blob extraction is related but distinct from blob detection.

Scale invariant features transform is a useful IP tool in that it allows segmentation of features invariant to scale, viewpoint, rotation or illumination. Features in an image can be successfully segmented regardless of zoom and image rotation. The differences in anatomy and patient positioning makes this particularly useful as this technique makes allowances for those variations.

The following section describes image registration techniques commonly used in processing of images in radiology.

4.2.2 Image registration

Sharman, Tyler and Pianykh (2000) describe image registration as the process aligning two somewhat similar images. The process may involve translating, rotating, magnifying, shrinking or cropping the images in order to align them. Due to the vast applications to which image registration can be applied, it's impossible to develop a general algorithm optimized for all uses (Wikipedia 2007b).

Image registration techniques fall broadly into two categories, area based or feature based methods. The initial image is referred to as the reference image and the image to be mapped is referred to as the target image. Area based (also referred to as region based) examines the structure of the image using structural analysis methods such as Fourier techniques and morphological filtering. Fourier techniques and morphological filtering are described in chapter 3 section 3:1.

Feature based methods examines the images' features such as the boundaries, curves, lines, texture as matching criteria.

In medical imaging it is useful to compare images taken from different modalities. Using multi-modality registration algorithms it is possible to compare images acquired from different modalities. Particular attention is needed for registration of data from the same patient taken at different times or registration of data from two different patients that are to be compared. The registration of the images must be flexible to allow for variations in the characteristics of the body parts imaged. *Elastic* or *non-rigid* transformations are techniques that give a system that flexibility. Linear transformations are exact in nature and are therefore not able to model local deformations.

In registration of medical images similarity based methods are commonly used. This method uses a transformation model that is applied to reference image coordinates to locate the corresponding coordinates in the target image space. The degree of similarity is optimised using an optimisation algorithm and measured. The technique used to measure the similarities of the images will depend on the nature of the image to be registered. Cross-correlation, Mean-square difference and Ratio Image Uniformity are commonly used for registration of images of the same modality. Mutual Information and Normailised Mutual Information are commonly used for registration of multimodality images.

The next section descibes the contribution made by rule based systems and artfical neural networks to image processing of radiology images. A general description of these processes can be found in chapter 3 section 3.1.

4.2.3 Rule Based Systems & ANN

In chapter 3 section 3.1.1 and section 3.1.4 Rule Based Systems (RBS) and Artificial Neural Networks (ANN) are described. The reviewed literature testifies to the importance of the use of ANN and RBS in CAD systems particularly in the classification component (Kakeda et al 2004, Doi 2005, Brem et al 2003, Arimura 2004a, Giger et al 1988, Xu et al 1997). It is evident from the literature that ANNs and RBS are widely used in IP.

In general the use of these techniques is best suited to manipulation of small sections of the image and will be used in conjunction with another technique to enhance results. The area will be processed by the ANN or RBS and will be categorised. ANN and RBS can be used in the pre-processing stage or in the feature extraction stage but are predominantly used in the classification stage of CAD (Kakeda et al 2004, Doi 2005). The general purposes of ANN and RBS in CAD system are to improve the overall sensitivity of the system by reducing false positives and false negatives.

Arimura et al (2004a) describes combining a rule-based system with a MTANN to reduce false positives in a system to diagnose lung nodules. This combination successfully reduced the overall inaccuracies in the systems. Giger et al (1988) and Xu et al (1997) also used combined RBS and ANN systems to improve classification accuracy.

The previous section is included to give the reader an introduction to the common terminology and techniques used in IP today. It sets the context for the next section so that the more common techniques that are used in IP can be appreciated. The next section looks at the use of CAD in radiology. The section begins with an over view of the use of CAD in radiology. Following this the application of CAD in the diagnoses of breast calcifications, lung nodules, liver nodules and brain pathology is reviewed. Section 4.4 is a brief evaluation of the uses of CAD in medicine in general. This is followed by a summary of the finding of the literature.

4.3 The Use of CAD in Radiology

Doi (2005) reports that the concept of CAD can be applied to all digital imaging modalities; these include plain radiography, CT, MRI, ultrasound, and nuclear medicine imaging. It may be used for all parts of the body, from the head, thorax, abdomen, and extremities. CAD may be used for skeletal imaging, soft tissue, functional imaging and angiography. Gilbert and Lemke (2005) state that CAD is likely to become part of daily practice in radiology departments as it has proven to be a clinically useful tool in a variety of areas and imaging modalities. CAD is therefore a technique that is adaptable and versatile, and is sure to grow in use and application in all areas of radiology. The literature supports the belief that the current status of CAD and its present applications is destined to explode in importance and range into all areas of clinical radiology in the future.

In the following sections the uses of CAD in diagnostic radiology departments are examined. These uses include application in imaging of the breast, chest, liver, and brain. As CAD is most commonly used and accepted in mammography this is reviewed first. The impact that CAD is having in clinical practice in mammography is examined.

4.3.1 CAD in Mammography

The evolution of CAD in mammography is at the point where its clinical effect and thereby its consistency and effect on clinical outcomes is the subject of real-time review. Recent papers on the use of CAD within this imaging modality focus on appraising the influence of CAD on radiologist performance and on clinical outcomes.

Brem et al (2003) have evaluated the improvement in sensitivity of screening mammography with CAD. They conclude that the use of the CAD system significantly improved the detection of breast cancer by increasing radiologist sensitivity by 21.2%. Therefore, for every 100,000 women with breast cancer identified without the use of computer-aided detection, an estimated additional 21,200 cancers would be found with the use of computer-aided detection. However, Gur et al (2004) report that in their study on the effects of CAD on the recall rate, (where recall rate refers to the number of cases that where found to warrant further investigation), that they found no statistically significant variation in recall rates.

Ikeda et al (2004) report in a retrospective study that a CAD system highlights non-specific areas that the reporting radiologist had failed to highlight. Some of these areas were found to be benign and some were found to be malignant in subsequent investigations. This demonstrates that a CAD system is more sensitive than a radiologist to small pathologies. However it is interesting that Ikeda et al (2004) conclude that the failure to act on the pathologies identified by CAD and not by the radiologists, do not represent a failure in acceptable standard of care. However, in the treatment of cancer the stage at which the diagnosis is made is crucial to the eventual outcome. Therefore if CAD systems can improve the detection rate by highlighting more subtle disease, then their clinical worth in mammography should surely be undisputed. It may be that the resources to act on each finding need to be made available and that the *standard of care* that Ikeda et al (2004) refer to can be improved upon.

Ikeda et al (2004) and Brem et al (2003) present conflicting opinions on the effectiveness of CAD in the clinical setting. If the success of CAD in mammography is to be determined for sure further studies and clinical trials are required in order to establish the effect of computer output on clinical outcome.

Hemminger et al (2001) reports on the effect of different image processing techniques on the detection of simulated masses in mammograms. They conclude that the success in detecting the masses depends on the image processing parameters used. It is fair to say that the reliability of a system for detection of masses will depend on the algorithms used and that to maximise effectiveness simulated trials can improve clinical consequence. The findings of Hemminger et al (2001) highlight the view that the usefulness of a system will depend on the sensitivity of the algorithms for the specific pathology being sought. Therefore in order to achieve a level of sensitivity that is clinically useful it is necessary to explore the requirements for diagnoses of each pathology type in depth. This would require extensive clinical trials or simulated trials, the benefits of such an endeavour need to outweigh the effort involved. It is necessary to under take a cost benefits analysis prior to embarking on developing such a system.

Gur et al (2004) state that the use of CAD in mammographic reporting is widely gaining clinical use and acceptance. There are a number of commercial systems for the detection of cancer in the breast currently in clinical use (Doi 2005). CAD has gained ground most quickly in this area of imaging. The reasons for this success are not immediately obviously from the literature, but may be inferred when the difficulties in applying CAD to other organs are examined. These reasons are explored and discussed in chapter 6.

The following section examines the use of CAD in the detection of lung nodules. A subsection of this looks at the diagnoses of lung nodules from CT scans.

4.3.2 CAD For Lung Nodules

The reviewed literature indicates that the use of CAD for the diagnosis of pulmonary lung nodules is established in clinical practice although not as widespread as the use of CAD in mammography. In this section the use of CAD in the diagnosis of lung nodules is examined. The literature that is reviewed deals in part with the impact of CAD on the diagnostic outcome and in part with the approaches taken to development of CAD systems. The diagnosis of lung nodules from chest radiographs is reviewed initially. A review of the use of CAD to diagnosis lung nodules from CT scan is also included within this section.

The National Cancer Registry of Ireland (2007) states that the survival rate from lung cancer can be dramatically improved if the cancer is detected early while the tumour is still small and localised. However Doi (2005) states that as many as 30% of lung nodules may be missed by radiologists on chest x-rays, many of these lung nodules can be easily identified in hindsight. The development of a CAD system that would assist in the identification of these nodules and early detection of disease would consequently increase survival rates from lung cancer.

The merit of such computer output has been investigated in observer performance studies using ROC analysis. Kobayashi et al (1996) describe how two sets of digital chest radiographs were presented to radiologists for reporting, one set had markers highlighting potential nodules the other set did not. The results showed an improvement in accuracy of reading from 89.4% detection rate to 94.0% detection rate when the computer output was used in reporting. Studies such as this demonstrate the impact that CAD can have in practice. Other such similar studies are reported on by Erickson and Bartholami (2002), and Summers (2003). These studies show that CAD systems with automated detection of lung nodules improve diagnostic accuracy in identifying lung nodules.

Giger et al (1988) describe the development of a CAD system, the function of which is the diagnosis of lung nodules. The system highlights the possible position of nodules as a prompt to the radiologist. The technique used is based on difference image technique in which nodules are enhanced and the majority of background normal structures are suppressed. The suspect areas are assessed by comparing the pixel values in the problem image with pixel values derived from a standard chest radiograph. Subsequent to this development Xu et al (1997) describe the introduction of a combined rule based and an artificial neural network component to this system, the purpose of which was to remove some of the false positive result and to improve the effectiveness of the system as a whole. The system indicates the site of potential nodules with markers such as arrows on the monitor on reporting station.

Manning et al (2005) studied the process of diagnosing lung nodules. They concluded that the “complexity of the visual information in chest imaging makes it difficult for observers to discriminate between normal anatomical structures and nodular pathological features, even when such features have been made visually obvious by the imaging process” (Manning et al, 2005 pg 12). They suggest that perceptual difficulties are responsible for the missed pathologies and not reader incompetence. The basis of the perceptual difficulty may lie in the similarity between normal or inconsequential structures and nodular pathological features so that one cannot differentiate reliably between the two. They go on to say that certain other tasks such as detection of micro-calcifications may not suffer this problem to the same extent because of the dissimilarity of calcification to normal tissue. They conclude that the use of artificial intelligence such as that provided by CAD would be beneficial.

The distinction made by Manning et al (2005) as to the suitability of CAD in assisting in the diagnoses of certain diseases as opposite to others is a point of note, in that it highlights that different approaches are required to diagnose different diseases. Being mindful of that the purpose of this research is to evaluate to potential use of CAD in diagnosis of ICH it is worth bearing this point in mind that the approach for diagnosing of ICH will be different also.

The following section looks at the use of CAD in the diagnosis of lung nodules from CT. The reasons for the importance of development of CAD in this area are reviewed. The approaches taken to the development of CAD by different authors are described and discussed.

4.3.2.1 CAD for Lung Nodules in CT

The use of CT in detecting cancer in the early stages is regarded as one of the most effective techniques (Diederich et al 1999). It is widely believed that CT images are superior to chest radiographs for detection of peripheral lung cancers. With the advent of the multi slice Computerise Tomography (MSCT) Scanner has resulted in the huge growth of the volume of images that are produced for each examination, and the number of images that radiologists are required to read has increased greatly (Tamm et al 2002). Therefore a CAD system would be useful in assisting radiologists in making a diagnosis of cancer from MSCT images. There have been several studies on the development of CAD systems for lung nodules and these propose a variety of methods and techniques.

Arimura et al (2004a) developed a CAD system based on difference image technique for enhancing lung nodules and suppressing the majority of background normal structures. The original image is passed through a *ring average filter* that suppresses the nodules, the resultant image is then subtracted from the original image and the difference is referred to as the difference image. The initial nodule candidates were identified by the application of a grey level thresholding technique to the original image. A rule-based schemes on localised image feature relating to morphology and grey levels is used to reduce the false positives. Some of the remaining false positives are reduced with the use of a *multiple massive training artificial neural network* (MTANN).

This description of the process of creating a CAD system is similar to the process described by Giger et al (1988) and Xu et al (1997) in the previous section 4.3.2. The images in both systems are processed in such a manner that the background structures are suppressed and the potential disease is highlighted. Both systems reduced the false positives with the introduction of a combined rule based and an artificial neural network ANN component. The exact algorithms used in the two systems will vary as the Hemminger et al (2001) has stated that the algorithms used needs to vary depending on the organ that is being processed and the disease that is to be identified.

In the next section the use of CAD in the diagnosis of liver nodules is examined. The reviewed literature indicates that the use of CAD in this area is still in its infancy. The principal difficulty that needs to be addressed is the segmentation of the liver from the surrounding tissue. The suggested approach is reviewed.

4.3.3 CAD in Diagnosis of Liver Lesions

Lim, Jeong and Ho (2005) describe the automatic segmentation of the liver and the automated process of diagnosing liver lesion. They state that research into the process of automatic segmentation of the liver is not as prevalent as CAD for mammograms and chest radiography because the process of segmentation of the liver from adjacent organs with similar densities is a complex one. This fact is exacerbated by the fact that the liver as an organ varies greatly in size and contour from patient to patient. They have proposed an algorithm for use in defining the liver from the surrounding tissue that uses a combination of region based and contour based approaches to image segmentation.

Lim, Jeong and Ho (2005) have describes how a combination of different image processing techniques can be used to address more complex issue associated with CAD. They have suggested that a region-based approach be used to simplify the image. Following this the organ is contoured using threshold values of the CT number (Hounsfield number) for the liver. They conclude that the algorithm used is effective in the segmentation of the liver in CT and that this can be used as a first step in developing a CAD system for liver nodules.

Stoitsis et al (2006) have published a study that reports to have successfully characterises liver tissue from CT scans. However the regions of interest (ROI), that is the liver outline is defined manually. This fact supports the view that the successful segmentation of the liver has yet to be achieved. As the use of CAD in more regions of the body is explored and understood the application of CAD will become easier. The approach suggested by Lim, Jeong and Ho (2005) and Stoitsis et al (2006) is evaluated in chapter five in light of development of CAD systems for diagnosis of ICH.

The following section looks at the use of CAD in the diagnoses of brain conditions.

4.3.4 Uses of CAD in Diagnosis of Brain conditions

This section examines literature relating to the automated diagnosis of brain pathologies in radiology. The subject of this dissertation is the automated diagnosis of ICH therefore the use of automated tools for diagnosis of brain conditions other than ICH are pertinent to this study. While the literature search did not indicate the existence of any truly automated systems for diagnosis of brain haemorrhage or any brain pathology in radiology it did indicate the existence of systems that aid in the diagnosis of particular brain conditions.

Maldjian et al (2001 pg 1050) state that they feel "that the quantitative nature of CT should make it amenable to automated analysis". This is a point of view that the author agrees with.

As with other organs such as the liver the process of segmentation and registration of anatomical features within the brain is the have proven difficult. Maldjian et al (2001) describe an automated method for identification of potential areas of acute ischemia on CT scans. The study by Maldjian et al (2001) reports excellent quality in the registration of anatomic regions of the brain. The study describes the approach taken to development of the system in which the brain was segmented, the image was normalised and the anatomical regions of the brain were registered. Madldjian et al

(2001) used a thresholding technique with bone as the threshold value to remove the skull vault from the images. This approach was combined with clustering to remove extraneous feature from the image.

A Talairach[2] atlas was used for image segmentation. A smoothing kernel was applied to the image to allow for the relationships of adjacent pixels. The study was limited in that it is semi automated and required manual intervention to initiate the scalp stripping, image normalisation and segmentation. The system is limited to diagnoses of disease in certain areas of the brain namely the lentiform nucleus and the insula. These areas are known to have the highest incidence of acute ischemia. This fact will impact on the system's effectiveness if use was extended to the brain as a whole.

Sha & Sutton (2001) describe the development of an algorithm for use in delineating regions of interest in MRI images of the brain. Sha and Sutton use an algorithm that was developed by Guan and Sutton initially and developed the algorithm further. They report that the resultant algorithm illustrates the success of the principle concepts in the evolution towards automated segmentation and classification of digital brain images. They state that the approach is applicable to other types of images within the medical domain. This piece of literature is pertinent to this present study as it indicates that image processing of the brain is a viable subject and the potential for developing a CAD system for diagnosis of brain haemorrhage exists.

The study by Sha & Sutton (2001) does however identify possible problems with the concept of image processing of brain images. The first problem that they mention is the variation in brain structure and function between individuals. The second problem is the variation in brain within one individual. The size and contour of the brain can vary greatly with the worsening or regression of disease. These problems have also

[2] Jean Talairach was a neurosurgeon developed a coordinate system of the human brain. This can be used to describe the location of brain structures regardless of the variation in size and shape from person to person. This coordinate system is commonly referred to as the Talairach Atlas.

been noted in imaging processing of the liver. Lim, Jeong and Ho (2005) suggested an algorithm that took in to account variations in the size of the liver. There may be merit in a similar approach for creating an algorithm for CT brain segmentation.

Arimura et al (2004b) have developed a system for automatic detection of unruptured intracranial aneurysms on MRI images of the brain. The initial candidate images were selected with the use of a multiple grey level thresholding technique on dot enhanced images and a region growing technique with monitoring of selected image features. All potential aneurysms are classified into one of four types according to the size and local structures and based on the effective diameter of each suspect vessel; these are one type of large candidate, and three small candidates, a short branch type, a single vessel type and a bifurcation type. In each group the number of false positives are removed using different rules on localised image features related to grey scale and morphology. Initial studies suggest the system would be of practical use in improving detection rates. The application of CAD to an area such as this is pertinent to this study as it relates specifically to the diagnosis of conditions of the neuro-vascular area of medicine. The ability of the system to classify aneurysms into four categories is significant in that the classification of brain haemorrhage may also be possible using a similar technique.

4.4 IP & Pattern Recognition in Medicine

In the absence of any truly automated diagnostic system in the domain of radiology it is worth exploring beyond the radiology domain to ascertain if automated diagnosis is used in any other medical field. The use of computer aided diagnosis is widely used in medicine, disease of the retina (Uloza et al 2003), myocardial diseases (Ohlsson 2004) are some of the diseases that are diagnosed with the use of automated systems. It is beyond the scope of this study to review all the retrieved literature. Therefore a brief review is made of literature that relates to automated diagnosis of ECG tracings, cortical activity and vocal cord diseases.

Sternickel (2002) describes an automated system of pattern recognition used in the analysis of ECG tracings. This study is worth reviewing because although ECG and radiological images may seem to be quite different in nature, they share some similar characteristics. Sternickel finds that an executable program was created for use in a clinical setting but writes that previous attempts had failed due to inappropriate selection of design. Two basic parts are used in the system, a feature extraction part and a classification component. These components are also found in a typical CAD system previously described in chapter two.

Aisbett & Gibbon (2005) describe an attempt to automatically categorise pictorial representations of cortical activity using an ANN. The attempt failed due to poor quality images. These images are very different in nature to those generated in most radiology modalities, these image are similar to thermal images. However the short comings of this study do highlight the importance of the quality of the input data. The practice of image pre-processing and image optimisation must not be underestimated.

Verikas et al (2006) describe a system that will diagnose and classify vocal cord diseases. The input into the system is a photograph of the vocal cords. The pre-processing techniques are quite different to those used in a CAD system in radiology. ANN and k-nearest neighbour are techniques used in the classification of the disease. The study reports an 87% correct classification. However the classification is simplistic in that the results are classified into three categories, namely healthy, nodular or diffuse. In radiology it would not be acceptable to simplify the results into such classes. A more definitive diagnosis is expected, a typical radiology report is in chapter 5 section 5.1.

4.5 Summation of findings of the literature

The techniques used in processing of medical images are varied and complex. The techniques for segmentation, image registration and classification have been examined. The reviewed literature illustrates that the success of a CAD system will depend on achieving the correct mix of these techniques in the right sequence.

The reviewed literature indicates that there is no completely automated diagnostic system in use in radiology. The outputs from the systems in the reviewed literature are in the form of an image that prompts the radiologist of the location of a possible abnormality. However the use of CAD in radiology in growing in importance as the health service strives to find new methods to optimise clinical results and harness the potential unleashed by new technology. There are however limits to the success that CAD has had to date.

The use of CAD in clinical practice is still limited to the diagnosis of specific diseases in particular modalities. The use of CAD in mammography is widely accepted and used in clinical practice. This practice is seconded by the use of CAD in the diagnosis of lung nodules both from plain film and high resolution CT scans. The issue of segmenting the liver from surrounding tissue have hampered the use of CAD in the diagnosis of liver nodules. Some authors have developed semi-automated tools in which the ROI is manually defined. There has been limited success in the application of CAD in the diagnosis of brain pathology but as yet have not been widely tested or implemented.

In this chapter the literature relevant to this dissertation are discussed. In the next chapter the process of diagnosing ICH from CT scans are described and discussed. Following that a theoretical system to make that diagnoses is described.

Chapter 5 Diagnosis from CT

The aim of this study it is to evaluate the potential for a computer system would automatically diagnose ICH and classify the ICH type from CT scans. The scans are those received by the neurosurgical team in Beaumont. If the task of making that diagnosis is to be computerised it is necessary first to look at how the diagnosis is currently made. In this chapter the process of diagnosis of ICH in radiology is discussed. This is followed by a description of an automated system that would in theory make that same diagnosis.

5.1 Diagnosing ICH in Radiology

The task of diagnosing ICH in radiology can be broken down into three essential parts: detection, description and differential diagnosis. The parts must then be related to functions that can be done effectively by a computer. Firstly lets consider the basic images series that is acquired.

A typical series of images obtained during a CT scan of a patient is shown in figure 5:1. There are twenty-four images in total in this series; the number of images may range from 18 to 34 depending on the slice thickness and the size of the patient's head. The patient is generally scanned upwards from the upper orbital margins to the apex of the skull vault at 4mm intervals through the petrous bones (for the first 10 images) and at 8mm intervals for the remainder of the brain. This variation in slice thickness in the posterior fossa and the supratentorial space is standard protocol in CT of the brain.

In chapter two it was explained that the detectors convert the x-ray photons into an analog signal, which in turn is converted into a digital signal. The incident radiation is measured by the detectors and is called the measurement data. This data is subject to pre-processing that eliminates erroneous or noisy data such as measurements from bad detectors readings or scattered radiation. This pre-processing is not to be confused with the pre-processing that happens in the CAD system. Raw data results from this process. It is the raw data that is the subject to the image reconstruction algorithm. These data sets are stored and subsequently retrieved as needed for further manipulation. The computer reconstructs a grey scale image from that data using reconstructive algorithms and techniques such as Fourier filtering and morphological filtering. This image is then displayed on the viewing monitor or used by a CAD system. The process of windowing these digital images was described in chapter 2 section 2.2.3. The manipulation of the grey scale range in these images is a form of image processing.

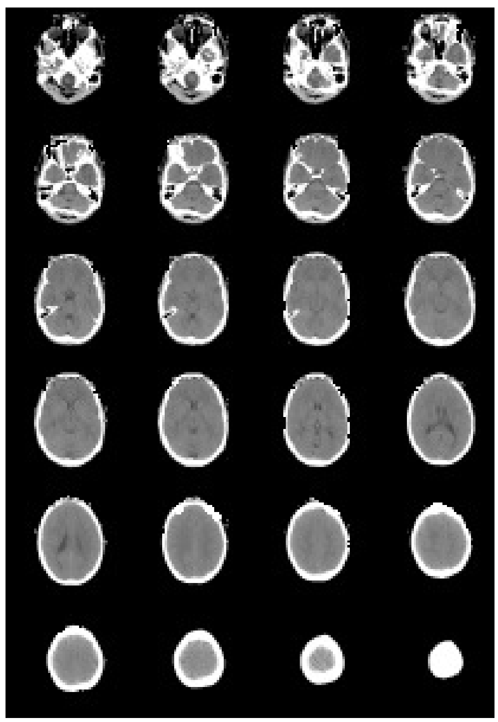


Figure 5:1 Typical CT Brain Series

Once the data has been reconstruction and presented in accordance with predetermined standards and protocols the images are then ready for analysis by a radiologist. The images are received by the radiologist via telelink at the neuro workstation in Beaumont Hospital. The analysis of the images is followed by characterisation of the images, and the final part of the process is a description of a differential diagnosis.

Detection involves the analysis of the images, looking for patterns or signs within the image that may indicate the presence of disease or abnormality. It can be said that pattern recognition forms the basis of radiological diagnosis. Training to become a radiologist involves review of many thousands of images that portray normal and abnormal anatomy. This process of training can be compared to the processing of teaching neural networks, described in chapter 3 section 3.1. Through this process the important patterns are reinforced in the mind of the radiologist and the noise is excluded. The images in the brain scan series are reviewed in sequence. If there is an abnormality noted in one slice the slices above and below are examined for further evidence of the same abnormality. It is possible but not usual to find an abnormality on one slice only. In the case of ICH this is highly unlikely to happen due to the systemic nature of ICH.

The detected findings must then be characterised as normal or abnormal. It is necessary to further describe the findings in terms of its visual properties; these properties include the extent, size, location, and texture of a lesion or region.

It is an educated evaluation of these properties that will allow the radiologist to make their final differential diagnosis. In arriving at the differential diagnosis the radiologist will usually take into account additional information such as the patients age, past medical history or a particular symptom. The radiologist's findings are presented in a written or dictated report. A typical radiology report for an ICH can be seen in figure 5:2.

HOSPITAL NAME

Patient Name:
Address: Consultant:
DOB Ward:
Radiology Number:

Findings of CT Brain Scan:

There is a hyperdense fluid collection in the right frontal parietal region. These finding are in keeping with acute epidural haemorrhage.

Reported by (radiogists name):
Typists initials :
Date of Report:

Figure 5:2 Typical radiology report for ICH

If the system proposed in this study was to be developed it is necessary to model this entire process in such a fashion that the computer can also make an accurate diagnosis. In the next section how this may be achieved in theory is described.

5.2 Diagnosing ICH Using CADx System

The primary aim of this study is to evaluate the potential for application of a computer program that would speed the diagnosis of the acute brain haemorrhage from computer tomography (CT) scans. In the previous section 5.1 the process of making a diagnosis of ICH from CT scans was described. In this section the potential for automating that process is described. In chapter 3 section 3.2 the typical architecture of a CAD system is described and the definition of CAD is discussed. In this section how the process of automating the processing of making a diagnosis of ICH is examined. A structure for the proposed system is described and will be referred to as CADx.

The typical architecture of a CAD system as described in chapter 3 lists four main components. The components are the pre-processing of images to match a predetermined standard, the segmentation of the ROI from other structures, the registration of the anatomy within the region of interest, the classification of the normal and abnormal, the classification of abnormal into distinct categories. The output is an image that highlights suspicious lesions on it. The proposal to automate the process of diagnosis of ICH needs considerably more application of proven technology. The most pertinent shortcoming of the current systems, in view of this proposal, is the failure of any radiology CAD system to arrive at a differential diagnosis autonomously.

If the typical CAD architecture is applied to ICH as it is to other pathologies the system will be as configured as in figure 5:3. It can be seen from this that the radiology report comes from the radiologist. The CAD systems that are in use currently are used as an aid in making a diagnosis. The CAD systems discussed in chapter 4 give the radiologist an image with suspicious lesions marked upon it. However if automated diagnostic systems are to be developed in the future the possible approaches that may be taken must be explored.

In theory it is possible to build a system that would correctly classify each type of ICH. The literature showed that the current CAD systems diagnose very specific pathology types. When computerising the process of making a diagnosis the process must be broken into elements that can be done by a computer.

The CADx system like the CAD system will require some pre-processing of the images. The techniques used for pre-posting are the same namely Fourier analysis, wavelet transformation and difference image technique. These techniques are described in chapter 3 section 3.1. The purpose of the pre-processing component is to standardise the image to allow application of the ensuing algorithms.

The second component is the definition of the ROI that extracts and enhances areas of interest within the image. The image processing that is done at this point is to facilitate the computer and not the human eye in identification of lesions. The image processing techniques that could be used are Fourier analysis, wavelet transform, morphological filtering, the difference image technique, and artificial neural networks (ANNs).

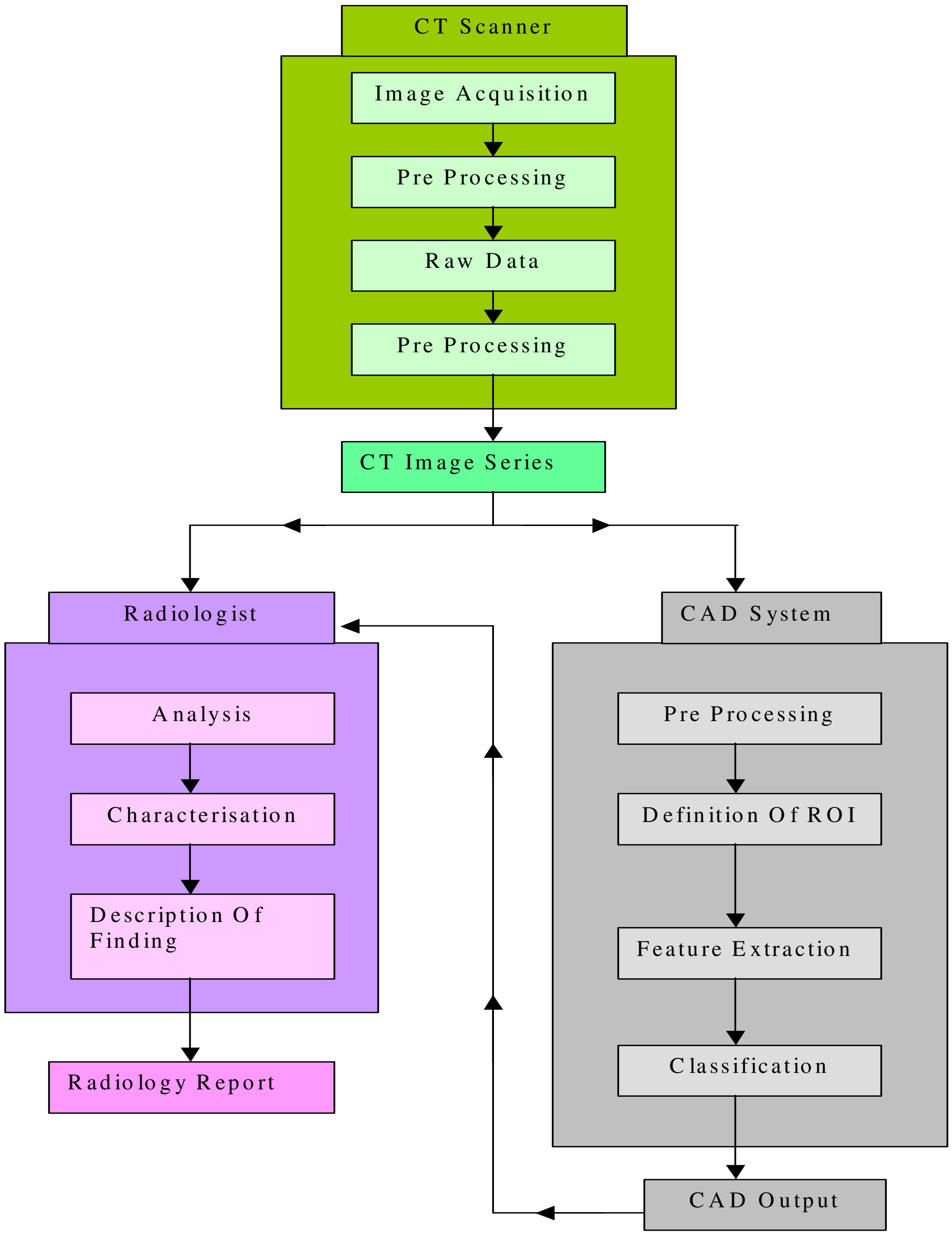


Figure 5:3 CAD & the current system for diagnoses of ICH

The third component is the quantitation of image features, such as the contrast, size and shape of the candidates identified by the first module. The features within the image can be defined using heuristic techniques drawing on the radiologists' expertise to find unique features that will reliably distinguish a lesion from a normal anatomical structure. The use of Talairach atlas has also proven successful in the registration of the image features of the brain (Maldjian et al 2001). Further quantitation of features is possible using exhaustive and non-deterministic methods.

The fourth component involves processing the data generated by previous component and classifications of the findings. The proposed system CADx is required to make an accurate diagnosis of ICH. It is envisaged that the CADx system would include all of the components of a CAD system but it needs to include a component or components that will classify the input scans into predefined categories. Normal and abnormal categories are required. The abnormal classification needs further division into classes that reflect the variety of ICH types and the other brain pathology.

If the CADx system is to succeed it is within the classification component that the most extensive work is required. The system needs to include a series of elements or systems at this point that have been designed to recognise and classify ICH, one for each ICH type. The CADx system requires components that recognise epidural haemorrhage, subdural haemorrhage, arachnoid haemorrhage, haematoma, and brain contusions. The ability of the system to diagnose other conditions would require additional components that would recognise the features of each particular condition. Bearing in mind that a patient may have more than one type of ICH the initial image series would need to be tested in sequence by each classification component. The result being that each ICH type can be ruled out or diagnosed with high degree of confidence.

The classification components can used a selection of techniques. One such approach used in this component is a rule-based method. The rules can be established on the basis of normal patterns and understanding the nature of lesions. Discriminate analysis, ANN and decision trees, or more commonly a hybrid system are also used in this component. These techniques are described in section 3.1.

On making diagnosis radiologists usually take into account clinical information that is provided by the referring clinician. If the CADx system is to duplicate the radiologists' role this information must be made available to the system through another component part. Various methods are presently employed to represent this information. Encoding disease and representation of this information in a way that allows accurate computation is a complex field and beyond the scope of this dissertation. However it is necessary to say that this information may impact on the final diagnosis and must be considered. One recent study describes how age was included as an input and did improve the performance of the system however the difference was not statistically significant (Ikeda et al 2004). The Bayes Theory may be used to give an indication of the probability of the presence of a certain disease, given a certain finding.

The output from the system needs to be in a format similar to a typical radiology report. It should be a description of the appearances within the image series together with a likely explanation for the presence of those appearances. The report should be emailed to both the referring team and to the neurosurgical team in Beaumont.

The CADx system would therefore be hybrid system that includes all of the components currently incorporated in a CAD system but requires extra components in order to replicate the role of the radiologist in the process. These extra components are extra classification components, encoding of clinical information and generation of a written diagnoses. A representation of the proposed system can be seen in figure 5:4.

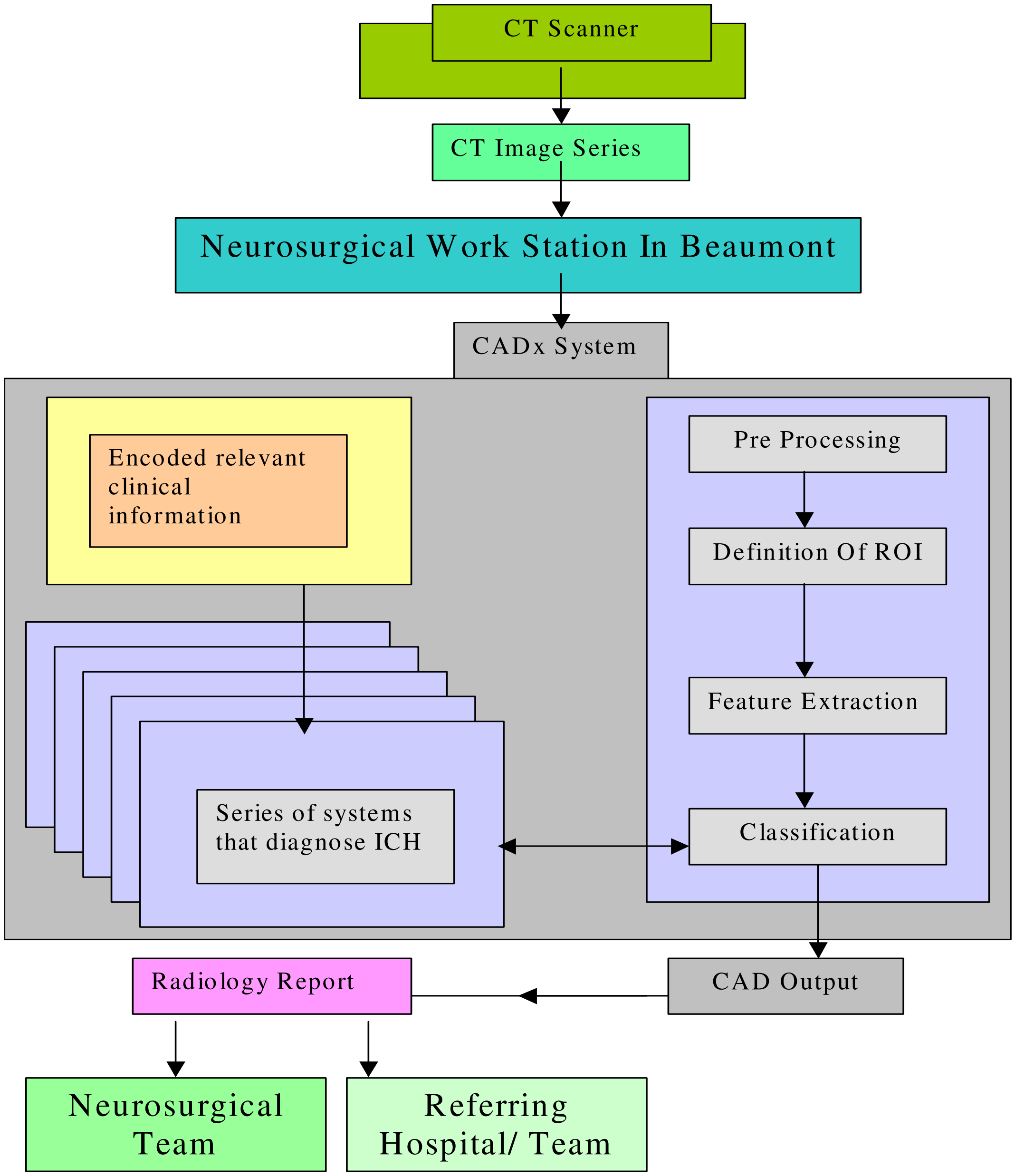


Figure 5:4 Proposed systems for diagnoses of ICH

In this chapter the current process of diagnosing ICH is described. The theoretical means by which this process could be automated is described. However no such system exists and the reasons for this are explored in chapter 6.

Chapter 6 Discussion

In the previous chapter the potential design of a system to diagnose ICH was described. In this chapter the reasons why that system does not exist are discussed. The reasons are broadly divided into technological reasons and anatomical-pathological reasons. The technological reasons include difficulties in image registration, difficulties with the output type, the amount of computation required. The anatomical reasons include difficulties in disease classification, and the general nature of the brain as an organ.

6.1 Technological Reasons

Having explored the CAD systems that are in use and proposed for use it can be said that the proposal to develop a system that would diagnose and classify ICH is not a viable option given the state of the art at present. If the process of diagnosis is to be automated it must be reduced to reproducible steps. The stages are the pre-processing of images to match a predetermined standard, the segmentation of the area of interest from other structures, the registration of the anatomy within the region of interest, the classification of the normal and abnormal, the classification of abnormal into distinct categories and the creation of a differential diagnosis. In this section the reason why the proposal is too ambition are explored in the context of the present state of the art.

6.1.1 Registration

The brain like the breast is a discrete organ and registration of the brain should theoretically be relatively simple. However the anatomical structure of the breast is far simpler than the brain. Breast tissue is generally homogenous in nature. The mammary glands are largely made up of connective tissue and fat. The blood supply to the organ is via small inconspicuous vessels that are not apparent on mammogram images. Similarly the lactiferous ducts are unremarkable on mammograms. In chapter 2 the structure of the brain is described. By comparison the structure of the brain is complex. The use of tools such as the Tairlaich atlas have aided in the registration of brain regions. This tool was successfully used in computer diagnosis of localised neurological conditions but the skill is not developed sufficiently to allow strictly automated diagnosis of extensive brain condition such as ICH.

6.1.2 Output

In the CADx system the output is a written description of the diagnosis. The literature has shown that the automated generation of a written report is not within the capability of the current technology. The outputs from the current CAD systems are images that have the suspicious lesion or lesions marked in some fashion. The generation of a set of images that identify the location of abnormalities is unhelpful as ICH do not tend to be inconspicuous in appearance. The neurological referrals that are received at Beaumont are urgent referrals for neurological consult. To reduce the mortality rate the need for early intervention in patients with ICH is crucial (Zimmerman et al 2006). Therefore output that is required is a decisive description of the findings on the CT scans.

6.1.3 Variety of Approaches Needed

A CAD system will generally operate by locating a lesion and determining an estimate of the probability of a disease system there are two general approaches that may be taken. The first to find suspicious lesions by searching for specific patterns that vary from what has been defined as normal, such as lung nodules in chest images. The second approach is to quantify the features within each image as normal and/or abnormal, such as lung texture of chest with interstitial disease. The approach taken will depend on the nature of the pathology been investigated. If the pathology is likely to be localised, such as a subdural then the first approach may be appropriate.

However if the pathology is diffuse in nature, such as an arachnoid haemorrhage the second approach is more suitable.

6.1.4 Amount of Computation Required

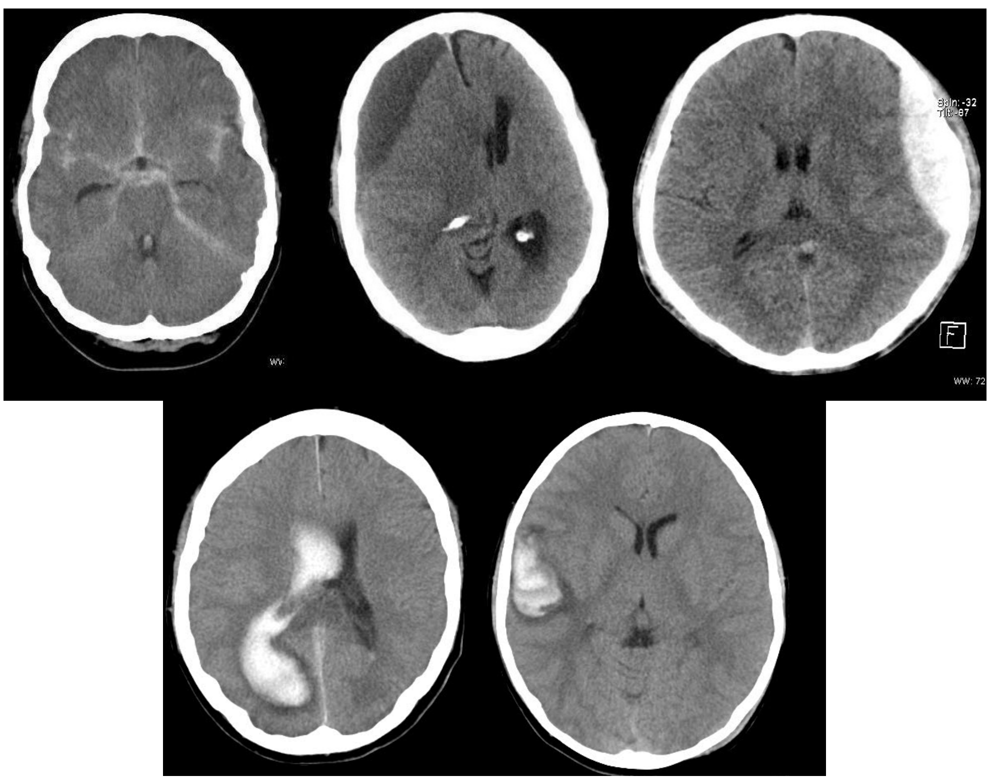
There is a range of types of ICH as described in chapter 2 section 2.1. To have a system that would only diagnose one type would not be helpful in practice as the presence of any type of ICH is significant clinically. One of the functions of the proposed system is to speed the process of decision-making based on the extent of ICH. The neuro radiologist would still therefore be required to view the scans to make that decision. In chapter 5 it was proposed that a series of systems that process the images series in sequence could in theory diagnosis ICH. This approach would be cumbersome and slow in practice and the convoluted approach is likely to make it prone to faults.

6.2 Anatomical & Pathological Reasons

In general the appearance of an ICH on a CT scan is conspicuous and unlike the subtle changes that are associated with breast lesions. While this may seem to favour the automation of the diagnostic process, it does so only up to a point. It is not helpful to report only that there is an abnormality on a scan. A differential diagnosis is required to facilitate correct management of the patient. Therefore the proposal of a system that simply marks the position of an abnormality is unhelpful. Given the current state of the art the reasons why ICH are not suited to automated diagnosis are described in the following sections. These reasons are the variety in the types of ICH, the variations in appearances of each type of ICH, the changes that can occur in an ICH over a period of time and the need to be able to determine the exact location of a ICH for correct diagnosis.

6.2.1 Variety of ICH

The systems that are in use are used to aid in the diagnoses of very specific diseases. The literature that was reviewed in chapter 3 described systems that diagnosed focal abnormalities in very exact locations in the brain and specific regions of the body. The variety of ICH haemorrhage types and diversity in appearance of each type of ICH makes the proposal unfeasible. Figure 6:1 shows five CT images, each images shows a different ICH type. This range of ICH makes the creation of a system that will correctly classify each type unrealistic.

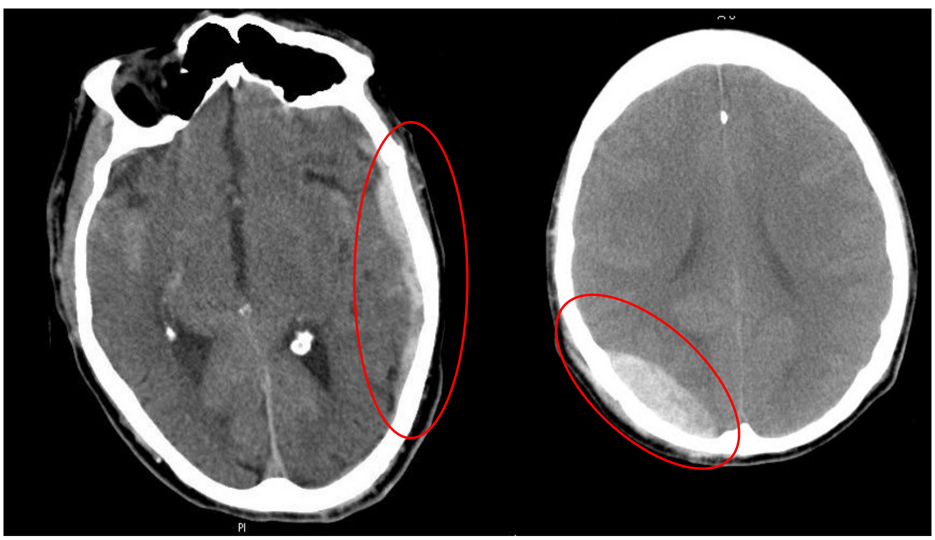


(Images courtesy of CT Dept. Beaumont Hospital)

Figure 6:1 ICH Haemorrhages

6.2.2 Variety of Appearance of Each ICH

The appearance of an ICH can vary greatly. For example the appearance of a subdural can vary substantially from patient to patient. This difference is shown in figure 6:2. Both of these CT images show a subdural haemorrhage that has been encircled for easy identification. However there are substantial differences in the volume and location of the bleeds. ICH haemorrhages may be focal in nature but may also be diffuse. The appearance of a subarachnoid haemorrhage can be very subtle and none of the systems discussed in the literature deal with pathology of a similar diffuse nature. Brain contusions may also be singular or multiple in number. This variety of appearance of each ICH makes the proposal impractical.



(Images courtesy of CT Dept. Beaumont Hospital)

Figure 6:2 Different Types of Subdural Haemorrhage

6.2.3 Changes that Occur in Haemorrhage.

The appearance of a haemorrhage can change over time. As a subdural haematoma ages the appearance changes, an acute subdural appears bright in colour on a scan as shown in figure 6:3. However as the blood collection ages the appearance changes so that the collection is then dark in colour as shown in figure 6:4. However the condition must still be classified as a subdural and requires neurological management. Correct diagnosis of these conditions is too complex when compared against the types of conditions that the current systems make. This has implications for image registration and classification and makes achieving the automation of the diagnosis a huge task.

(Image courtesy of CT Dept. Beaumont Hospital)

Figure 6:3 Acute Subdural haematoma

(Image courtesy of CT Dept. Beaumont Hospital)

Figure 6:4 Chronic Subdural Haematoma

6.2.4 Exact Identification of Location Required.

The appearance of blood on a CT scan is generally obvious however exact identification of the location within the brain is required in order to correctly classify the ICH type. However the positioning of blood within the brain is hugely significant in realising the correct diagnoses. The position of a bleed is significant in determining the correct classification of the haemorrhage type. Figure 6:5 shows two types of ICH; both on the left side of the brain; both have a random outline and changing range of densities within the abnormal area. However the image on the left is a large haematoma, the image on the right is a contusion. A contusion would never form in a ventricle as this haematoma has. The formulation of algorithms that recognise these subtle differences is an immense undertaking when compared to those required to recognise disease of other organs described in chapter 4.

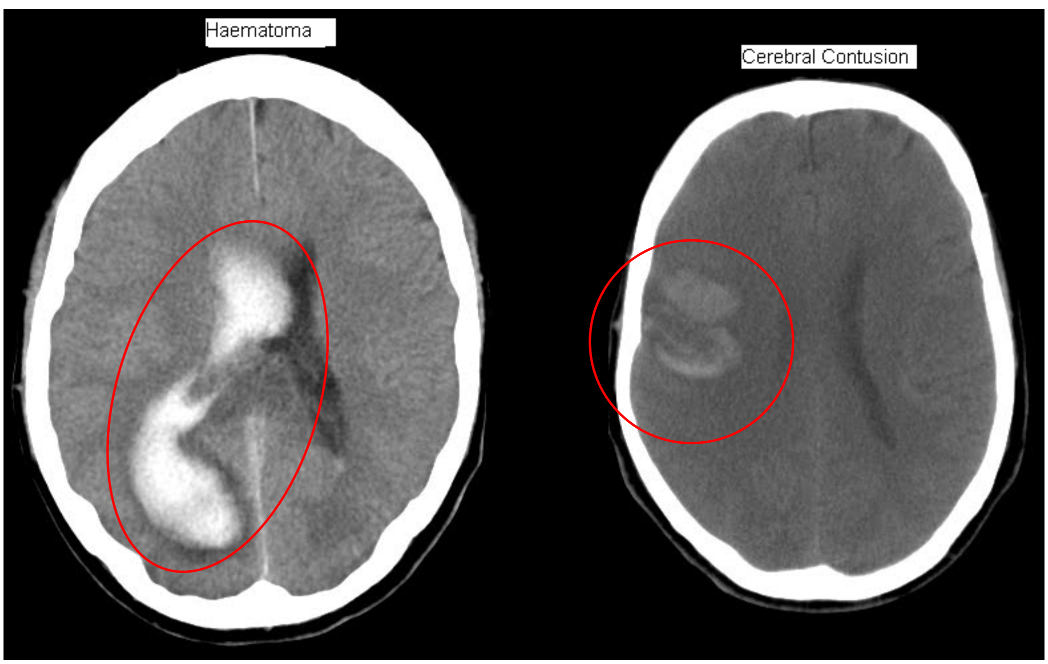


Figure 6:5 Location of ICH

Chapter 7 Conclusion

In this project the potential for a CAD system that would speed the diagnosis of the acute ICH from CT scans is examined. The potential use of such a system that would reside at the interface to the neurosurgical workstation in Beaumont with satellite hospitals is discussed.

There is no pattern recognition/image-processing product available to diagnosis ICH in CT scans. A radiologist or neuro-surgeon makes the diagnosis. However CT images by their nature are ideally suitable for use in CAD systems. The literature has shown that the application of CAD is still limited in clinical practice but that use and awareness is growing. CAD is most successfully used in diagnosis of specific abnormalities in localised regions of the body. CAD systems are successfully used to aid in the diagnosis of disease and disorders such as microcalcifications in the breast, lung nodules, liver nodule and unruptured intracranial aneurysm. There is however no automated diagnosis system in use in radiology.

The technology and techniques used in CAD systems are described. Techniques used for segmentation include feature thresholding and contour based thresholding. Image registration techniques are area based or feature based methods. RBS and ANN are also widely used in CAD systems. Fourier analysis, wavelet transform, morphological filtering and difference image technique are also widely used in image processing of CT images. The theoretical description of a system that would diagnose ICH independently from a radiologist is described in light of those techniques that can be found in chapter 5.

The question that was posed by this dissertation was to examine the potential for the use of pattern recognition in the automated diagnosis of intra cranial haemorrhages from CT images. It can be said that there is limited potential for application of such a system.

The reasons why such a system does not exist are many. In terms of diagnosis of ICH the issues include technological and anatomical reasons. The technological reasons include difficulties in image registration, difficulties with the output type and the amount of computation required. The anatomical reasons include difficulties in disease classification, and the general nature of the brain as an organ

7.1 Limitations of the Study & Future Study

Time constraints imposed limits to this dissertation. This dissertation was not intended to provide an extensive descriptions of techniques used in IP, nor a complete description of CT terminology, nor a comprehensive report of neurological terminology. The focus of the study was limited so that the aims of the study could be achieved. However there is ample scope for further study in the area of the application of CAD in radiology.

The application of CAD technology in aiding in the diagnoses of ICH may be beyond the remit of the current technology however the application of CAD to other pathologies should be considered. Imaging techniques that produce large volumes of images, techniques such as mammography screening programs and CT oncology staging scans, have the potential for reaping the greatest return for invested effort.

Following the identification of pathologies that are suited the algorithms needed for image segmentation and registration should be investigated.

The appropriate classification techniques or combination of techniques is also an area that warrants further study. Following the creation of any CAD system the accuracy of the system needs to be evaluated.

There are issues with duty of care to the patient and user confidence if a computer is making a clinical diagnosis in place of a radiologist. The legal and ethical implication of using a computer system for creation of differential diagnosis also needs to be considered.

With the volume of information that is been generated in the radiology department ever increasing it is necessary that new ways of managing that information are explored. Despite the current limitations of the technology there are definite benefits to be gained from the application of CAD in radiology. There is enormous scope for further applications of computer-aided diagnoses and in the future to automate diagnoses of particular diseases.

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