CASE-BASED REASONING – AN EFFECTIVE PARADIGM FOR PROVIDING DIAGNOSTIC SUPPORT FOR STROKE PATIENTS

By

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Abstract

A Stroke can affect different parts of the human body depending on the area of brain affected; our research focuses on upper limb motor dysfunction for stroke patients. In current practice, ordinal scale systems are used for conducting physical assessment of upper limb impairment. The reliability of these assessments is questionable, since their coarse ratings cannot reliably distinguish between the different levels of performance. This thesis describes the design, implementation and evaluation of a novel system to facilitate stroke diagnosis which relies on data collected with an innovative KINARM robotic tool. This robotic tool allows for an objective quantification of motor function and performance assessment for stroke patients.

The main methodology for the research is Case Based Reasoning (CBR) - an effective paradigm of artificial intelligence that relies on the principle that a new problem is solved by observing similar, previously encountered problems and adapting their known solutions. A CBR system was designed and implemented for a repository of stroke subjects who had an explicit diagnosis and prognosis. For a new stroke patient, whose diagnosis was yet to be confirmed and who had an indefinite prognosis, the CBR model was effectively used to retrieve analogous cases of previous stroke patients. These similar cases provide useful information to the clinicians, facilitating them in reaching a potential solution for stroke diagnosis and also a means to validate other imaging tests and clinical assessments to confirm the diagnosis and prognosis.

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Glossary

Stroke	Medically known as Paralysis, Apoplexy, or (CVA) Cerebrovascular Accident. A stroke occurs when the blood supply to a part of the brain is suddenly interrupted, due to a clot or when a blood vessel in the brain bursts, spilling blood into the spaces surrounding brain cells. Brain cells (neurons) die in the affected area when they no longer receive oxygen and nutrients from the blood or there is sudden bleeding into or around the brain.
Stroke Rehabilitation:	It is restorative learning phenomenon that intends to improve and maximize recovery from stroke by treating the activity limitations (Impairments) due to stroke and to enable the survivor to reintegrate into the daily life as much as possible.
Hemiplegia	Complete paralysis on one side of the body.
Hemiparesis	One-sided weakness -which is not as debilitating as paralysis is.
Prognosis	A prediction of the probable course and outcome of a disease, the likelihood of recovery from a disease.
Stenosis	Narrowing of an artery or a valve.
Atrophy	A wasting or decrease in size of a body organ, tissue, or part owing to disease, injury, or lack of use: muscular atrophy of a person affected with paralysis.
Infarction	An area of tissue that undergoes necrosis (die out) as a result of obstruction of local blood supply, as by a thrombus or embolus.

Spasticity	A disorder of the body's motor system in which certain muscles are continuously contracted. This contraction causes stiffness or tightness of the muscles and may interfere with gait, movement, and speech.
Kinematics	Kinematics is a branch of mechanics which describes the motion of objects without the consideration of the masses or forces that bring about the motion. In contrast, dynamics is concerned with the forces and interactions that produce or affect the motion.
DB2	Short for Database 2, a family of relational database products offered by IBM. DB2 provides an open database environment that runs on a wide variety of computing platforms. A DB2 database can grow from a small single-user application to a large multi-user system. Using SQL, users can obtain data simultaneously from DB2 and other databases. DB2 includes a range of application development and management tools. (http://publib.boulder.ibm.com/infocenter/db2luw/v8//index.jsp)

Chapter 1

Introduction

"If we knew what we were doing, it wouldn't be called research, would it?"

(Albert Einstein)

According to the Heart and Stroke Foundation of Canada, stroke is the fourth leading cause of death or long-term disability in the world. Eighty percent of strokes occur when the blood supply to a part of the brain is suddenly interrupted (Ischemic stroke), usually due to a clot in an artery leading to the brain. The remaining 20% are caused by uncontrolled bleeding in the brain, due to a ruptured blood vessel (Hemorrhagic stroke). Of every 100 people who have a stroke, 10 recover completely, 25 recover with a minor impairment or disability, 40 are left with a moderate to severe impairment, 10 are so severely disabled that they require long-term care and 15 are unable to survive [1]. The research carried out for this thesis focuses on the 85 % of people who survive stroke and may potentially benefit from rehabilitation therapy and regain their lost independence.

1.1 Case Based Reasoning

When we talk about magnitude of healthcare resources used to diagnose and recuperate stroke survivors, significant efforts are involved; however, there is still a need for a standardized and comprehensive classification system in order to document the resultant impairment and disability. The diagnosis and prognosis of stroke patients is therefore a complex domain because of the fact that a multitude of varying factors are involved with each patient. In addition, keeping track of all the different experiences during their treatment is an intricate phenomenon for even adept neurologists. Case Based Reasoning (CBR) is an effective paradigm of Artificial Intelligence (AI) that has proved to be a prolific landmark in healthcare for its diagnostic and therapeutic support [2]. This research describes yet another progressive role of CBR in healthcare applications, with the innovation that now we are applying it to the stroke domain.

CBR is based on the principle that a new problem is solved by observing similar, previously encountered problems, and adapting their known solutions. It is analogous to the human mind as it solves new problems based on previous experiences [20, 21]. Choosing this paradigm of AI as our main methodology for this research, my hypothesis is that:

CBR can be utilized to create a repository of information, of the stroke patients who have an explicit diagnosis and prognosis and are receiving subsequent rehabilitation. For a new stroke patient, whose diagnosis is yet to be confirmed and has an indefinite prognosis, by applying CBR, similar cases can be retrieved from the case base which may provide useful information to the clinicians, hence facilitating them in reaching a potential solution for stroke diagnosis and assessment.

The main components of CBR cycle can be described as four processes that are also referred to as the mnemonic, “the four REs” [3]. They are: *Retrieve* the most similar case(s); *Reuse* the information from the retrieved case(s) to propose a new solution; *Revise* the proposed solution to solve the new problem, and *Retain* this problem as a new solved case in the case base. Another reason to use CBR for this domain in particular, is the assumption that patients with analogous sensory and motor deficits have similar impairments; therefore they may have similar prognoses and may lead to not only the diagnosis of impairment but to the quantification of the impairment as well.

1.2 Conventional Stroke Assessment Protocols

Once a cerebrovascular accident has taken place, proper diagnosis and accurate prognosis is the next critical step, followed by effective rehabilitation therapies. There are numerous conventional assessment tests performed by clinicians and therapists in order to confirm the occurrence of a stroke and measure the degree of impairment. However the lack of quantifiable constructs in these protocols makes them all subjective in nature. Based on the evaluation of psychometric standards, there is no assessment scale that can be regarded as perfect, although they are partially reliable [4]. Normally, an early diagnosis is made by assessing the symptoms, reviewing medical history, conducting tests to confirm the occurrence of a brain attack, and measuring the degree of impairment.

Conventional stroke assessment scales usually convert motor status to a score along an ordinal scale. In a usual assessment setup, the patient is asked to perform a task where the main emphasis is laid on task completion rather than specific details. Therefore it is a non-qualitative scoring. In a qualitative scoring other factors are considered as well, like measurement of the amount of assistance required, alteration in the normal (gross) position, and time utilized to complete a test [5].

There has recently been an explosion in the usage of robotic technology for quantifying motor function, because of the fact that they are objectively sensitive to small changes in neurological status, and are of value for studying and quantifying stroke impairment [6]. For these reasons, we have incorporated a robotic device, KINARM, as our main assessment protocol in this research, besides other assessment methods.

1.3 KINARM - Kinesiological Instrument for Normal and Altered Reaching Movements

One of the most commonly associated ailments caused by stroke is that of limited upper limb movement. The KINARM monitors and manipulates arm motion in the horizontal plane [7]. It is a robotic exoskeleton, developed by Dr. Stephen H. Scott and his colleagues at the Neuroscience Centre of Queen's University. KINARM calculates kinetic / kinematic data, such as reaction time, velocity, joint torque and hand trajectories of both stroke and control subjects for specific motor and sensory tasks. This data is saved in a database for later reference, thus providing for an efficient means of data access and a standardized way to keep track of a patient's recovery as a result of rehabilitation therapy.

1.4 Thesis Objectives

The purpose of this research is to apply strategies of automated reasoning in order to simplify the complex phenomenon of motor and sensory dysfunction assessment in stroke patients. This may potentially facilitate clinicians in prognoses and rehabilitation of future stroke patients.

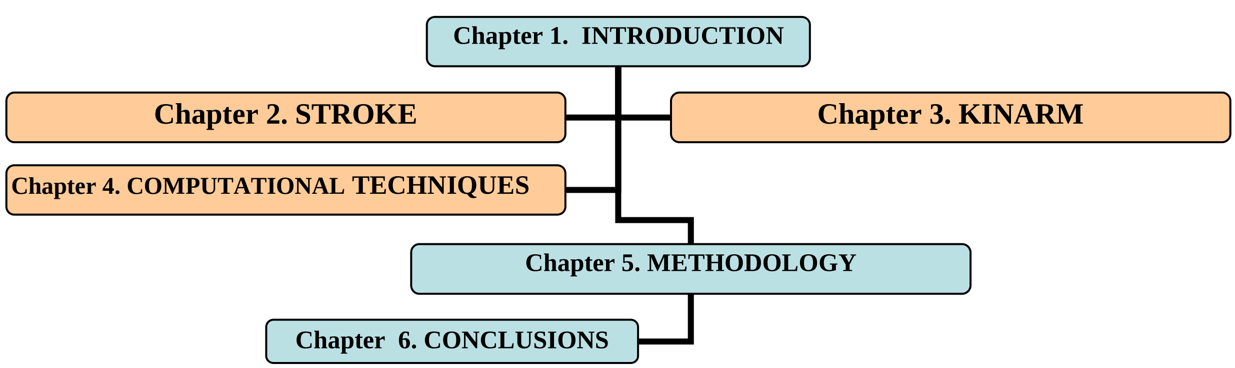
The main objectives of this research are to:

1. Develop a case structure comprising of relevant attributes of stroke patients that have a direct impact on diagnosis and prognosis.
2. Construct a case base system comprising of various stroke patients' cases in order to implement the CBR model.
3. Define a similarity criterion for retrieval of relevant cases given a new stroke case.
4. Determine the diagnostic support measures that can be taken in order to propose the potential motor and/or sensory deficit, based on the previous known impairments (solutions).
5. Test and evaluate the CBR system to retrieve the most relevant cases with useful diagnostic information that can facilitate the prognosis of the new patient.

6. Scrutinize the validity of results.

1.5 Thesis Outline

In Chapter 2, background information is presented in order to elaborate on concepts about the neuro-scientific domain – stroke – its causes, effects and rehabilitation methods presently used. Besides this, there is a brief description of significant concepts used later in the following chapters. Chapter 3 gives information about the use of robotic technology in the field of medicine, with an emphasis on its use for stroke subjects and giving details about the functioning, and the assessment procedure carried out by KINARM. Chapter 4 describes the computational techniques CBR and TA-3. It provides the literature review of CBR and its diverse applications highlighting the ones in healthcare. It also elaborates on the architecture of TA-3, its functionality and how it was used as a framework to develop the CBR system for stroke domain. Chapter 5 emphasizes the main methodology of CBR, the procedural details of how we made use of this paradigm as a distinct approach in merging neuroscience with AI. It also illustrates the experiments performed on data used and the corresponding results obtained. Chapter 6 describes the contributions that were made with this thesis, justification of hypothesis and limitations of the present system leading to the future directions. The following flowchart further clarifies the organization of various chapters and their interdependence. The components in pink refer to the background chapters where as the ones in blue refer to the other fundamental chapters for the thesis organization.



Chapter 2

Problem Domain – Stroke

"Wisdom is knowing what to do next; virtue is doing it."

(David Starr Jordan – American Scientist 1851-1931)

This chapter presents relevant background information about the domain of the research - stroke. The main aim behind writing this chapter was to provide information for the reader to understand the concepts later used in this thesis. It gives an overview of stroke, its pathophysiology and various impairments caused by it, specifically the motor and sensory deficits of upper limbs. This chapter also elaborates on current tests and assessments used for stroke diagnosis and how rehabilitation and care is brought into the picture of stroke patients.

2.1 What is Stroke?

Stroke, medically also known as paralysis, apoplexy, or hemiparesis, is a sudden damage to a part of the brain due to an interruption in the normal blood supply [1]. Stroke can be categorized into two types depending on the cause. 80% of strokes are *ischemic,* meaning they result from a blockage, usually a clot (thrombus) in an artery leading to the brain. 20% of strokes are *hemorrhagic*. They are less common but with severe effects, due to uncontrolled bleeding in the brain. In ischemic stroke, if the clot is formed in the artery directly leading to the brain it is called *thrombotic*, whereas if the clot travels from some other part of the body into the brain then it is referred to as an *embolic* stroke. A hemorrhagic stroke can be *subarachnoid*, leaking blood in the space around the brain in the area between the brain and skull, or an *intracerebral* hemorrhage, where rupturing of a deep artery in the brain tissue causes bleeding. Irrespective of the cause of stroke, the interruption in the blood supply causes depletion of oxygen and glucose in the affected area. This immediately reduces or abolishes neuronal function, and initiates an ischemic cascade which causes neurons to die or be seriously damaged, further impairing brain function [8].

2.2 Pathophysiology of Stroke

Stroke causes a depletion of blood to the brain or a part of the brain. In the absence of oxygen, the brain tissue ceases to function if deprived for more than 60 to 90 seconds and after a few hours it will undergo irreversible injury that may lead to death of the tissue referred to as infarction [8]. Due to collateral circulation, within the region of brain tissue affected by ischemia, there is a spectrum of severity. Thus, part of the tissue may immediately die while other parts may only be injured and could potentially recover. The ischemic area where tissue might recover is referred to as the “ischemic penumbra”. Therefore, for clinicians it is essential to diagnose which areas of the brain have been fully affected and which can be recovered.

A secondary effect of loss of blood in ischemic brain tissue is the deficiency of oxygen or glucose. As a result, the production of adenine triphosphate (a high energy phosphate compound) fails leading to the failure of energy dependent processes necessary for tissue cell survival [8]. This sets off a series of interrelated events that result in damage to cellular organelles such as the failure of mitochondria (the power house of a cell), which can further lead to energy depletion and ultimately trigger cell death. Other processes that may take place are the loss of membrane ion pump function, leading to electrolyte imbalances in brain cells and the release of excitatory neurotransmitters, which have toxic effects if released in excessive concentrations.

2.3 Potential effects of stroke

The effects of stroke vary depending on the type, severity, and location in the brain affected. The brain is an extremely complex structure within the human body and each area is responsible for a specific function. When an area of the brain is affected by stroke, it results in a corresponding potential loss of normal function associated with that particular part. The brain is divided into three main areas: Brain stem, Cerebellum and Cerebrum (consisting of the right and left sides or hemispheres) [1].

The brain stem, as the name explains, constitutes the base of the brain. It creates a bridge between the brain and the top of the spine. It is responsible for involuntary actions like heart beat, breathing, digestion, swallowing, and eye movement. A stroke resulting in a lesion of the brain stem may be fatal since it will interrupt the functioning of these vital involuntary processes.

The cerebellum looks like a miniature brain attached to the bottom of the brain. On the back, it is attached to the brain stem. It controls the important task of maintaining balance as well as managing some automatic responses and behavior. A stroke resulting in a lesion of cerebellum may potentially result in movement disorders, lack of coordination and cause clumsiness.

The cerebrum is referred to as the “thinking brain” and mainly constitutes the central bulky part. It not only controls the motor function but this is the main part where thinking and intelligence takes place. The cerebrum is subdivided into right and left hemispheres. The right hemisphere controls the left side of the body where as the left controls the right side. The right hemisphere is associated with the artistic abilities of a person, music, spatial relationship, recognizing faces etc. The left hemisphere is responsible for scientific functions, mathematical skills and reasoning. It also controls the ability to understand written and spoken language.

The entire cerebrum is composed of two layers, the outer being the cerebral cortex, gray matter composed of neurons and their unmyelinated fibers, while the white matter below the grey matter of the cortex is predominantly composed of myelinated axons that interconnect different regions of the central nervous system. The cortex is deeply convoluted into folds and is hypothetically divided on the basis of functionality into four distinct lobes.

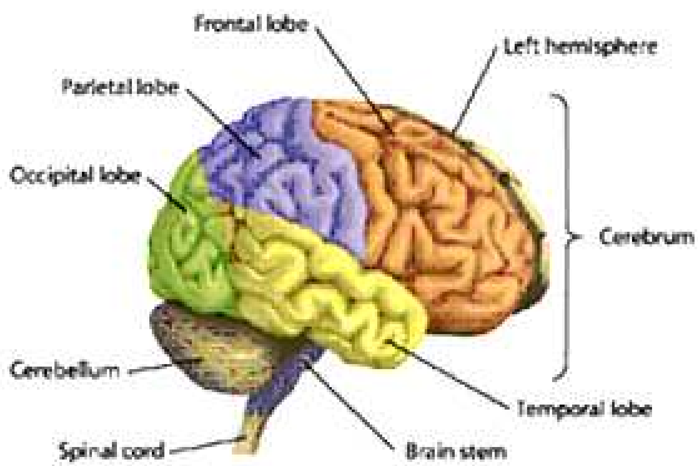


Figure 2.1: Right hemisphere of the brain. Different colors represent the labeled parts. Graphic Courtesy of: www.heartandstroke.ca (used with permission)

The frontal lobe is the anterior part of the brain and controls movement and higher cognitive processes. So a stroke patient with affected right frontal lobe would have movement affected on the left side and with affected left lobe, the right side would be affected. The parietal lobe, which is behind the frontal lobe, is mainly responsible for sensory activities such as receiving and interpreting information from all parts of the body. Stroke affecting the parietal lobe in the right hemisphere can result in a strange kind of disorder called "agnosia". Stroke survivors with Agnosia can feel, see and hear, but may not be able to comprehend what they perceive. In some cases, a condition "Neglect" may develop in which the patient may ignore everything on the affected side.

The temporal lobe controls the auditory functions and memory. A lesion in the temporal lobe of the dominant hemisphere (usually the left one) may cause a speech disorder known as "Wernicke's Aphasia". Memories are stored in the inner part of the temporal lobe therefore memory loss after stroke is usually temporary unless both the left and right lobes are damaged. The o*ccipital lobe,* located at the posterior end of the cerebrum, is responsible for visual perception. A stroke affecting the left occipital lobe can result in loss of right side vision although the eyes are functioning normally. The problem lies within the brain's processing of the information from the eyes.

2.4 Effects of Stroke on Upper Limbs

Stroke can cause varied impairments depending on the area of lesion. In majority of stroke patients, upper limbs are more affected than lower limbs [9]. The middle cerebral artery is one of the three major paired arteries which is responsible for supplying blood to the brain. The occlusion of this artery may result in the paralysis and sensory loss of the contra lateral face side and arm [8]. Stroke affecting an upper limb can cause various sensori-motor deficits in the patient, such as weakness of muscle [10], abnormal muscle tone [11], spasticity and abnormal movement synergies [12].

After the onset of a stroke, the impaired muscles of the affected limb become weak within a span of few weeks. These flaccid muscles become hyper-reflexive [11]. Research has revealed that during the recovery of upper limb function, stereotypic multi-joint movement patterns are observed that reflect the loss of independent joint control, referred to as spasticity [13]. This spasticity hinders the normal movement and results in slower response during movement.

2.5 Stroke diagnosis

Physicians have several diagnostic techniques and imaging tools to help diagnose the cause of stroke quickly and accurately. An early diagnosis can be made by assessing the symptoms and reviewing medical history. Once a neurological examination is performed along with the stroke onset details, the occurrence of a brain attack is confirmed. Having that confirmed, the next step is to identify the location of the lesion (area of brain or vascular territory in brain affected) and assess the degree of impairment caused. There are a number of assessment protocols used to measure the neurological deficits caused by stroke. These include Chedoke McMaster, Perdue pegboard, Fugl Myer test, Glasgow Coma Scale, NIH and many more [64]. Some of them are discussed later in the chapter, in detail. The idea of providing this information here is to set the context of stroke diagnosis. It indirectly refers to the objective of this research and that is to simplify the stroke assessment procedure and to be able to computationally analyze the sensory and motor deficits. Following are some of the routine screening tests performed to confirm the occurrence and analyze the degree of damage caused by the stroke [1-a].

2.5.1 Imaging Tests:

- *An echocardiogram* uses sound waves (ultrasound) to create a picture of the heart. The recorded waves show the shape, texture and movement of the valves, as well as the size of the heart chambers and how well they are working. This test is carried out to assess any abnormalities in the functioning of heart that can possibly be a cause of the stroke.
- *An electrocardiogram* measures the electrical activity in the heart and determines any irregularity in the rhythmic motion of the heart that may result in a stroke.
- *An electroencephalogram* monitors the electrical activity in the brain in order to assess the damage caused by stroke. It involves placing of small metal discs (electrodes) on a

person's scalp to pick up electrical impulses. These electrical signals are printed out as brain waves.

- *Cerebral / Carotid angiography* examines the blood flowing in the arteries of neck (carotids) and brain. The test involves injecting a dye into an artery and a series of rapid-image x-rays are taken as the dye travels through the arteries. By examining the flow of blood, the size and location of any blockages can be marked. This procedure is also sometimes used to help identify problems or malformations in blood vessels.
- *A Computerized tomography scan* is a special imaging technique that uses X-rays to produce a 3-dimensional series of cross-sectional slices of the brain. These images can determine whether the stroke was ischemic or hemorrhagic. They are also helpful to rule out other processes in the brain that can mimic the effects of a stroke.
- A *Magnetic Resonance Imaging* test works on the principle of low energy radio waves emitted by a large magnet and presents a detailed view on a monitor to produce 2 or 3-D images of the brain. An MRI is used to detect bleeding in the brain, tumors or stroke. It is also an excellent device for detecting smaller strokes or strokes in the back of the brain, which other imaging devices can miss. The image produced by MRI is sharper and more detailed than a CT scan so it's often used to diagnose small, deep injuries.

2.5.2 Clinical Assessment of Upper Limbs

There are numerous clinical assessments performed, in addition to the imaging tests carried out, not only to assess the level of upper limb impairment but also to identify the stage of recovery. Following are some of these included in our research work and are also included in this project.

The *Chedoke-McMaster test* [17] consists of two main inventories, an impairment inventory and an activity inventory. The activity inventory test is used to assess the patient’s functional level. It is focused on task completion rather than task performance. The Impairment

Inventory focuses on analyzing the stage of recovery of the shoulder, postural (positional) control, the arm, the hand, the leg and the foot. There are 7 defined stages of recovery and based on patient's response, the clinician derives the assessment.

In the Impairment Inventory test, the clinician starts by assessing the degree of shoulder pain in order to assess the stage of recovery of the shoulder. At first the patient is seated with his/her feet on the floor while the clinician carefully examines the position of the shoulder. The clinician then physically abducts (takes away from body) and adducts (brings towards body) the patient's shoulder and notes whether there is less than 90 degrees of pain free range. The Impairment Inventory has seven stages defined for shoulder, arm, hand, leg, foot and postural control. The clinician then looks at the description of each of the 7 defined stages of recovery and matches the description with his/her evaluation of the patient's pain.

The *Fugl-Meyer* test is a well-designed, practical and efficient clinical examination method that has been tested widely in the stroke population. It was developed by Twitchell and Brunnstrom [13] as the first quantitative evaluative instrument for measuring sensori-motor stroke recovery. Fugl Meyer assessment includes a scale comprising of 226 points and was developed to assess patients recovering from hemiplegic (one sided lesion) stroke. It is divided into five domains: motor function, sensory function, balance, joint range of motion and joint pain. Each domain consists of many items and each item is scored on a 3 point scale (0, 1, 2) [14]. A score of zero implies inability to perform, a score of one, partial performance, and a score of two suggests full performance. Similar to the Chedoke-McMaster, the Fugl-Meyer test involves physical and observational assessment by clinicians.

Numerous studies carried out to understand the sensori-motor deficits and recovery from stroke have used the Fugl-Meyer test as the primary clinical assessment tool [5, 9, 12]. Other studies focusing on the use of robotic devices in rehabilitation have also used the Fugl-Meyer test, to assess improvements in patients after robotic assisted rehabilitation [15, 16].

The *Perdue Pegboard* test is a simple board test used to objectively assess finger and hand dexterity. It has been shown that the Perdue Pegboard test can correctly predict the presence and laterality of cerebral lesions with 90% accuracy [18]. The Perdue Pegboard consists of pins, collars and washers located in four cups at the top of a board. Below the cups and in the center of the board are two columns of holes, one for the right arm and the other for the left arm. There are different tests involved in assessment of stroke patients. For each test, the examiner verbally provides the subject with a set of standardized instructions on how to proceed in placing pegs, pins, collars and washers and based on their performance they are scored.

Figure 2.2: Perdue Pegboard Graphic Courtesy of: www.rasmedical.com/1363/Dexterity-Tests.html (Incorporated with permission)

2.6 Stroke patients – Care and Rehabilitation

According to Heart and Stroke Foundation statistics (carried out in Feb, 2002), the cost of stroke treatment and rehabilitation is approximately $2.7 billion per year in Canada [1]. The average acute care cost per stroke is about $27,500. Stroke rehabilitation is the process by which patients that have had disabling stroke, are treated in order to assist them in adapting to a normal life as much as possible. This can be done by relearning and regaining the skills in a different way to continue with their life. The reason to incorporate this information in the thesis is to include as much knowledge about the domain as possible in order to enhance the functionality of our case based system. Successful rehabilitation of stroke patients is a vital multidisciplinary phenomenon since the main goal and output of diagnosis and prognosis is ultimately to what level did the patient improve? This phenomenon is comprehensive, and is based on various factors, a few of which are:

- extent of brain damage
- timing of rehabilitation
- support and patience of family and friends
- patient's positive attitude towards recovery and
- the adeptness of the rehabilitation team, which includes the nursing staff, therapists, social workers, pharmacists and/or psychologists.

Good nursing care plays an imperative role in feeding, hydration, maintaining skin care, positioning the patient, as well as monitoring the vitals like temperature, pulse and blood pressure. Rehabilitation may involve different therapies as required by the patient as follows:

Physiotherapy is a rehabilitation therapy for patients with stroke affecting the frontal lobe of the cerebrum, primarily resulting in motor functional anarchy. Since the general body movement is affected, this therapy tends to improve the muscle control, co-ordination and balance in movement of the body.

Speech therapy is usually required by patients whose temporal lobes of the brain are affected by stroke, resulting in speech disorder. With this therapy the facial muscles are retrained to regain speech, to improve feeding, and to recover from swallowing disorders.

Occupational therapy is for patients who need to improve their hand-eye-co-ordination and regain the skills required for daily living tasks, such as bathing, cooking, getting dressed, and carrying out vocation competency (reading, writing, driving), which are the tasks affected after the patient has gone through a stroke. For stroke patients, often the existing skills are lost or diminished to the extent that they need to be taught to adapt to their present circumstance [19].

Figure 2.3: Physiotherapy performed by rehabilitation team at Saint Mary's of the Lake Hospital. Graphic courtesy of: http://www.pccchealth.org/Default.aspx?tabid=150 (Incorporated with permission)

2.7 Summary

The main objective behind this chapter was to provide a detailed background of the problem domain–stroke. The sections; pathophysiology, the effects of stroke, the diagnostic tests and the care and rehabilitation, they were intended to provide the reader with a vivid idea, about the process of stroke. A gradual and systematic procedure from occurrence to rehabilitation. The goal was to set up a clear backdrop of stroke without including any irrelevant details, but at the same time enabling the reader to get adequate knowledge to be able to correspond with chapters to follow.

CHAPTER 3

KINARM - Kinesiological Instrument for Normal and Altered Reaching Movement

"I never think of the Future - it comes soon enough" (Albert Einstein)

This chapter elaborates on the robotic devices used in the assessment and rehabilitation of upper limbs with an emphasis on KINARM as an innovative means of quantifying upper limb impairments. It also describes the setup and method of how KINARM assessment was incorporated in the CBR system.

3.1 Use of Robotic Technology in Assessment and Rehabilitation

Recently, there has been an explosion in the application of robotic technologies for quantifying motor function. These devices have significantly made a difference in contributing to the knowledge of neural and mechanical basis of motor control [7]. The successful use of such robots in research has shown potential for their use in a clinical setting. With an increased demand on the healthcare system and limited resources, researchers are motivated to think about ways in which to optimize the quality and cost- effectiveness of healthcare. Many robots have been designed with a focus on rehabilitation uses. The robots were developed, not to replace therapists, but to assist and support them in their efforts to facilitate a disabled individual's functional recovery.

The *MIME* (*M*irror-*I*mage *M*otion *E*nabler) robot is used to move the affected arm in straight lines or in complex patterns, along a tabletop surface or in a 3-dimensional space [72]. The subject's forearm movement is passive when the subject is unable to move by himself, therefore, the movement is facilitated by the robot. On the other hand, the action is active when the subject initiates the movement. The robot provides any necessary assistance to the impaired arm if required to complete the movement. MIME takes commands from the unaffected arm to help move the affected arm in a mirror-image pattern. This permits practice of bi-manual movements to aid in the recovery of muscle control. Research studies with MIME show that both robot-assisted and unassisted stroke groups improved their ability to move the affected arm, but the robot-assisted group showed a faster recovery [72]. The MIME project used the Fugl-Meyer test to assess the improvements in motor performance.

ARM Guide (*A*ssisted *R*ehabilitation and *M*easurement *G*uide) is used to assist in recovery [73]. The aim is to examine whether the mechanical assistance provided by the robot or the repetitive movement attempts made by the patients is the primary cause of recovery. Experiment results showed comparable results between subjects who performed free reaching and subjects that underwent robot assisted reaching. ARM Guide uses Chedoke-Mcmaster for assessment.

3.2 Visually Guided Reaching Movements in Stroke Patients

Several studies have examined the kinesiology of patients following stroke. It was seen that patients with hemiparesis produce hand movements that are less smooth, more variable, slower and more segmented with a greater number of velocity peaks, than neurologically intact subjects [92], [93], [94]. Along with these differences in hand kinematics, stroke subjects can also be characterized by high within-subject variability on repeated performance [95], [96]. In a recent study early this year [97] it was observed that "directional deviation", or the difference between the initial hand movement direction and target location, was anisotropic and greatest to targets farther away from the subjects. It was also noted, through an analysis of joint kinetics, that these directional deviations were associated with abnormal spatial tuning of the muscle torque at the elbow. Another research reported that hemiparetic patients exhibited a deficit in inter joint coordination, as characterized by a lag in elbow rotation with respect to that of the shoulder [12].

The goal of most upper limb studies on stroke patients was generally focused on quantifying recovery after stroke, or on showing quantitative differences between neurologically intact subjects and a group of stroke patients. In most cases, the populations of stroke patients chosen for the studies were relatively homogeneous such as in this study [98], 15 stroke patients were chosen, 14 of which had a single ischemic stroke in the territory of the middle cerebral artery. Another study [10] had only 8 subjects, out of which 6 exhibited similar deficits. Therefore, while they can identify clear differences between stroke and control subjects, the experiments were not developed to create quantitative assessment tools.

3.3 Bi-lateral KINARM Setup

Robots have been used extensively in rehabilitation [15, 16, 76]. There have been limited attempts, so far, for their use as clinical assessment tools [40]. One of the particular interests is the robot's ability to quantify even subtle variations in motor performance during different

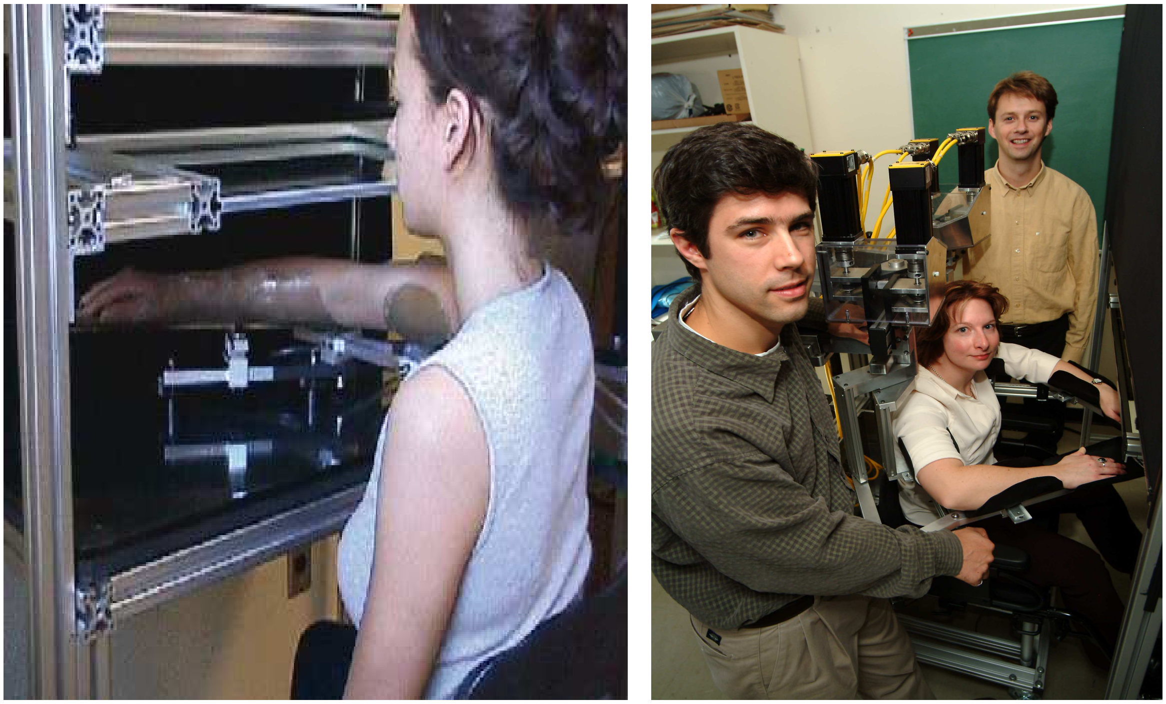


Figure 3.1 Bilateral KINARM device used in this study.

experimental trials. Such differences are not visible to the naked eye as observed in most of the clinical assessment settings.

In this research, the dual-arm robotic device KINARM was used to collect data for stroke assessment besides the other conventional assessment measures. KINARM, which stands for Kinesiological Instrument for Normal and Altered Reaching Movement, is a robotic bilateral-arm system (BKIN Technologies Ltd., Kingston, Canada; Scott 1999). It is the only device of its kind that measures multi-joint movement at the shoulder, elbow and hand, leading to new findings about how the brain coordinates limb movements. It is an exoskeleton comprising of hinge joints that align the subject’s shoulder and elbow in a way that enables arm movement on a horizontal plane. The subject's arm (including the upper and forearm) is attached to the mechanical linkage by fiberglass braces (see Figure 3.1). Motors attached to the mechanical linkage provide angular position of the joints and can apply torques either to the shoulder or elbow, or both.

Although many studies were aimed at understanding upper limb impairments in stroke subjects, very few incorporated motion analysis [12, 74, 75]. KINARM is used in combination with a computer projection system that uses a graphical development environment, LabView, which manipulates and analyzes the entire data. The same computer also controls eight virtual targets in the plane of the arm, such that the index finger tip and target positions are projected as small circles on a semi-transparent mirror.

3.4 KINARM Tasks

KINARM is being used to study the sensory and motor functioning in upper limbs; therefore, several tasks are designed that are performed by the stroke subjects as well as the controls in order to study the phenomenon. For details of the KINARM tasks please refer to Appendix A. Figure 3.2 shows the sensory matching task.

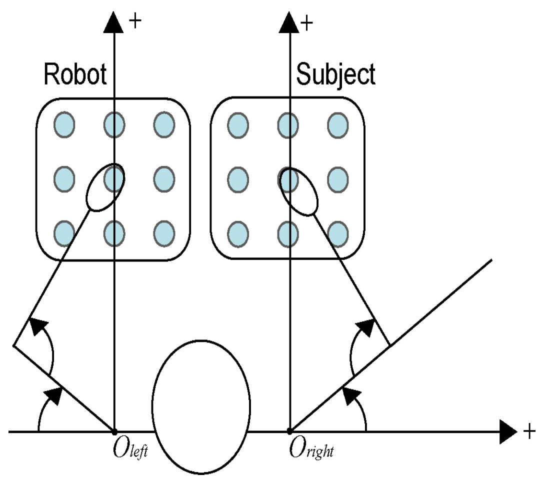


Figure 3.2: Sensory Matching Task. The subject is supposed to match the right arm to the left arm that is moved by the robot.

3.4.1 Sensory-Matching Task (Position Matching)

In the sensory matching task, the subject cannot see his/her arms. There are nine different spatial locations. One arm is moved passively by the KINARM to one of these nine spatial locations in the horizontal plane and then the subject is required to actively move the other arm to a mirrored location in space. Data for the actively moving arm is collected in terms of joint angles and hand position. There is no visual feedback during the task [85].

Figure3.3: Centre-out reaching task. Finger tip position is marked by the green circle.

3.4.2 Center-Out reaching Task

For each center out-reaching task the subject is required to match their finger tip position with a target position as soon as the target illuminates. Figure 3.3 clearly shows the green circle marking the finger tip position. The subject moves his/her hand to one of eight targets from the center-hold position. Once the target light comes on and after it is turned off the subject moves back to the central position and waits for the next random target light to be turned on. The position of the finger tip and the velocity during a reaching task are recorded. Eight repeat trials are performed for each target as seen in Figure 3.4. The order of target presentation is random. Three seconds are given to complete a single reaching trial and data recording stops after three seconds are over. If a subject completes the trial in a time frame less than three seconds then they are required to maintain their hand in the peripheral target location until the peripheral target light goes off.

In order to further elaborate how the performance of different subjects can be visually distinguished by the center-out reaching task, some results are shown in Figure 3.5.

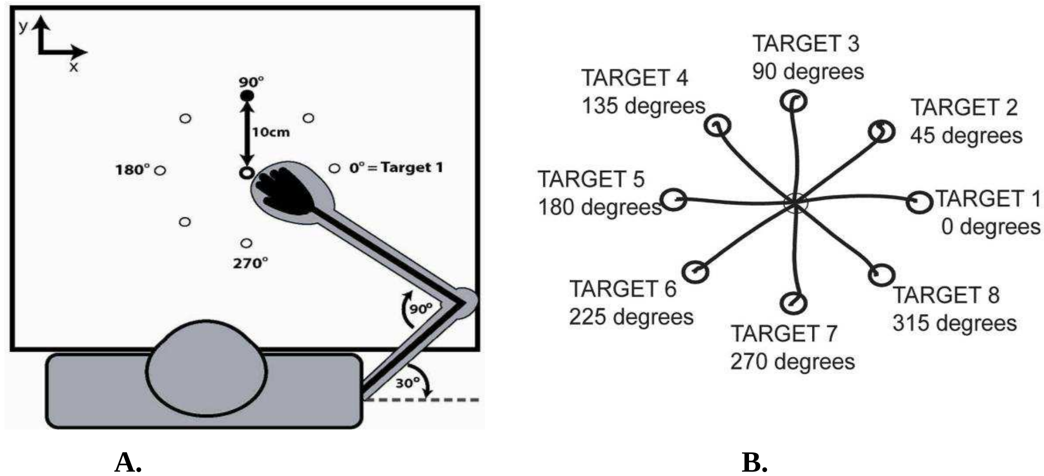


Figure 3.4: Target positions on the KINARM device. A. The subject moves his/her hand to one of eight targets from the center hold position (fingertip) once the target light comes on. B. Targets in terms of angular design on the bilateral system

The figure displays hand trajectories of three subjects in three different colors, *blue* for the *control subject*, *red* for the *stroke subject* with *right side* of brain affected and *green* for the *stroke subject* with lesion on the *left side* of the brain. The results are visually significant and distinct as for the control subject (*DB*), it can be clearly observed that the hand performance is quite smooth for both the arms. However for the subject with right side of the brain affected (*AJ*) the irregularity is seen in the left hand performance whereas for the subject with left side of the brain affected (*FC*), the hand trajectory of the contra-lateral side (right side) exhibits irregularity. This also corresponds to the information provided earlier (Chapter 2, Section 2.3), that right side of the cerebrum controls the left side of the body and left side controls the right side of body.

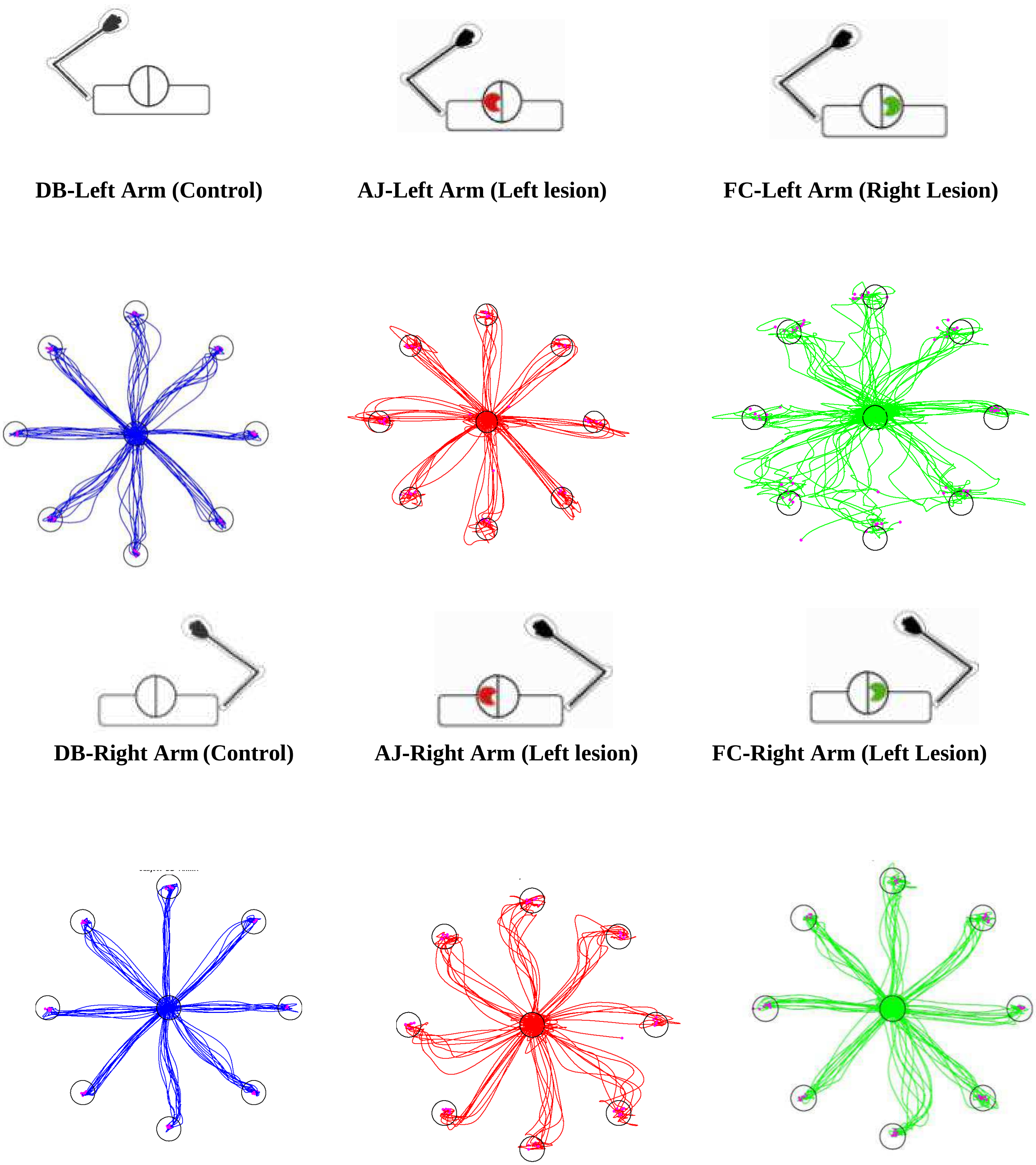


Figure 3.5 Reaching tasks performed by a control subject (DB) and two stroke subjects (AJ with left cerebral lesion) and (FC with right cerebral lesion) (used with permission [78])

3.5 Parameters Selection

There are many variables and parameters to clarify motion analysis by KINARM that were studied by previous students such as hand path length, number of first peak velocities, hand path distance ratio and tangential velocity [6]. The parameters that are chosen for this research to be used in the CBR system are enumerated as follows:

- **RT_mean (s):** the subject's reaction time i.e. the length of the interval between when the target light appeared and first volitional movement was detected.
- **PostureSP_mean (m/s):** Posture speed is the average hand speed.
- **TMT_mean**(s)**:** Total movement time is the total time of movement from start till the end.
- **PathLenRatio_mean (m):** Path length ratio is the estimated length of the hand path during the total movement.
- **MTMaxSP_mean (m/s):** Movement maximum speed, MTMaxSP_mean refers to the maximum hand speed between the movement onset and offset
- **FMTMaxSP_mean (m/s):** First movement max speed indicates the *first* local maximum hand speed found after the target light came on.
- **FMTDisErr_mean (m):** First movement distance error is the distance between the hand position after the first movement (at the minimum hand speed subsequent to FMTmaxSP) and the centre of the peripheral target (T2).
- **FMTDirErr_mean (rad):** First movement direction error is the difference in angle between the optimal reach path and the subject's initial reach direction.

For each parameter the mean for all trials (for each target) was used, reason being that it is insensitive to the noise that may be caused by inattention of the subjects. These eight parameters are particularly given preference over the others because each of them possessed important information that was later utilized in classification of stroke subjects. Please refer to Chapter 5, Section 5.3.2 for details. For instance, FMTMaxSP_mean refers to the maximum hand speed between the movement onset and offset. In classifying stroke impairment this is a fundamental piece of information since stroke subjects reveal greater variability in the kinematics/kinetics of their movements than controls. RT_mean on the other hand measures the response time of a subject to a stimulus that is the length of the interval between when the target light appeared and first volitional movement was detected. However, it was chosen because theoretically it reflects the sensory capacity of brain to detect a stimulus, and the processing time involved in planning and initiating a response. This mechanism of brain processing is referred to as open loop processing [77].

An algorithm for the automated detection of movement onset has been developed by Scott's group [6]. This allows for the calculation of reaction time (See Figure 3.5). Now with the latest development of movement offset algorithm, recently developed, parameters that can measure the closed loop components can be calculated (example, total movement time that could not be calculated before, in the absence of movement off set.). It is expected that stroke subjects with a lesion affecting the open loop processing will present a higher reaction time value, meaning a slower response. FMTMaxSP_mean of the hand measures the speed of the initial movement; therefore, if a subject can only initiate slow movements, it can be clearly identified by this parameter.

3.6 Research Conclusions

The data analysis that has been carried so far, regarding this research by fellow researchers have concluded that although control subjects show variability in the magnitude of reaction time, they tend to show symmetry in reaction time values for both arms and both movement directions [78]. Although some stroke subjects had shown a longer reaction time than control subjects, a stronger observation that was reflected in the results was that of the difference in reaction time for both arms caused by single arm impairments. Symmetry in reaction time for both arms and both movement directions could therefore be incorporated as part of a new clinical score on reaction time.

Analysis of FMTMaxSP_mean for different muscle groups proved to be more difficult as symmetry of both arms for control subjects was only observed on shoulder extension and shoulder flexion. Many stroke subjects also showed similarity in FMTMaxSP_mean for the shoulder muscle groups. For elbow extension and elbow flexion the only notable difference between control and stroke subjects was that of magnitude as some stroke subjects (with affected left arm) presented a lower value for FMTMaxSP_mean [78].

3.7 Correlation of Summarized Parameters with Clinical Scores

The results of RT_mean and FMTMaxSP_mean were compared with the Chedoke Arm scores and the Purdue Pegboard scores that revealed that some correlation was observed but each measure has its own advantage. For instance, RT_mean and FMTMaxSP_mean are parameters that are capable of capturing delayed response time which the other two clinical protocols are unable to capture. Clinical measures on the contrary, are able to capture impairments not detected by the KINARM parameters. For example, the Purdue Pegboard score can measure hand dexterity problems. Therefore it is suggested that the KINARM system should not replace current assessment measures; rather its use could provide new additional information that could assist in rehabilitation [78]. In our research we incorporated KINARM assessment as well as the assessments done with Chedoke McMaster and Purdue pegboard protocols.

Chapter 4

Background - The Computational Techniques

"I have but one lamp by which my feet are guided, and that is the lamp of experience. I know no way of judging the future but by the past". (Patrick Henry)

This chapter consists of two main parts, referring to the main computational technique - CBR and the particular framework that was applied – *TA-3*. The first part provides a synopsis of CBR elaborating on the main principle of this AI paradigm, its architecture, previous work carried out in this area and its diverse applications, with a special emphasis on its significance in health informatics. The second part presents the background of *TA-3* (tatry), its design, functionality and its diverse applications that provided motivation to use it in this research.

4.1 What is CBR?

We humans are strong problem-solvers. We solve every day problems ranging from a simple task like a change of recipe (to alter the taste), avoidance of heavy traffic hours and routes, to complex tasks like troubleshooting locomotive problems of an airplane. In all the scenarios the objective is to improve the performance and efficiency with the utilization of experience and that's what the objective of AI is as well. In our day to day living, we observe that carrying out human expertise using a machine is much more precise, accurate and time-efficient.

Theoretically speaking, CBR is an important paradigm of artificial intelligence mainly used for problem-solving [3]. It tends to apply efficient methods to define descriptive patterns and explanations within an enormous amount of data. The basic idea behind CBR is to solve a new problem by remembering and reusing information from a previous similar experience. It can be applied in a variety of ways based on the intended use of the reasoning, such as to adapt and combine old solutions to solve a new problem, to critique new solutions based on old cases or, to classify entities based on the criterion of similar features.

The roots of CBR in AI can be traced from the theories of concept formation, problem solving and experiential learning within philosophy and psychology [23, 24]. Their objective was to develop decision-support systems that help to solve problems in open and weak theory domains. In other words, hard problems need improved methods to ground their models in real world situations. The field was further enhanced with the contributions of Roger Schank by his research in dynamic memory and situation patterns in problem solving and learning [25]. His idea of a problem-solving system comprised of a problem-solution criterion, in which the reasoner solves new problems by adapting relevant cases from the problem library.

Analogy-making, refers to our ability to see a particular object or situation in one context as being "the same as" another object or situation in another context. It plays a significant role in problem solving, decision making, perception, and communication just like CBR. Gentner performed investigations that are attributed to analogical reasoning [26]. He developed a theoretical framework for analogy. Carbonell explored the role of analogy in learning and plan generalization [33]. CBR has also been applied to the field of legal reasoning, which requires a lot of expertise and involves multiple factors. Rissland was the pioneer who applied CBR to this field [34].

The first system that is considered as a case-based reasoner can be attributed to Janet Kolodner at Yale University and was named CYRUS [22]. It was based on Schank's dynamic memory model. CYRUS contained knowledge, in the form of cases, and was basically a question-answering system with information of the various travels and meetings of former US Secretary-of-State Cyrus Vance. Subsequently, with an increasing number of research papers and diverse applications, CBR has grown into a field of widespread interest. It has proven itself to be a methodology suited to solve “weak theory” domains, which are the areas in which it is difficult or impossible to educe first principle rules to obtain solutions.

4.1.1 Significance of CBR

Humans and computers can interact in a prolific manner in order to solve problems with the application of CBR. Looking at the CBR phenomenon, some processes are easier to perform, for humans where as others are more appropriate for computers. People for instance can perform creative adaptation very well but might not remember the complete range of applicable cases due to being biased in their memory or for novices they still do not have the adequate experience to solve a variety of problems. Previous work has shown that CBR provides a number of advantages over alternative approaches [22].

- CBR does not require extensive analysis of domain knowledge. It permits problem solving even if the reasoner does not have full domain knowledge. The main requirement is to be able to compare two cases.

- CBR allows shortcuts in reasoning. If a suitable case is found, a solution can be promptly proposed.
- CBR can lead to improved explanation capability in situations where the most comprehensible explanations are those that involve specific instances [62].
- CBR can help in avoiding previous errors and in facilitating learning. In fact the system keeps a record of each situation that occurred for future reference.

4.1.2 Architecture of CBR

CBR methods can be divided into four main steps, *retrieve* - find the best matching case(s), *reuse* - information and solution of the matched case(s), *revise* - make changes to the proposed solution in order to best suit the present problem, and *retain* - add to the case base for later use and learn from this problem solving experience. This decomposition of the CBR cycle is derived from the contributions of Aamodt and Plaza [3] and shown as follows:

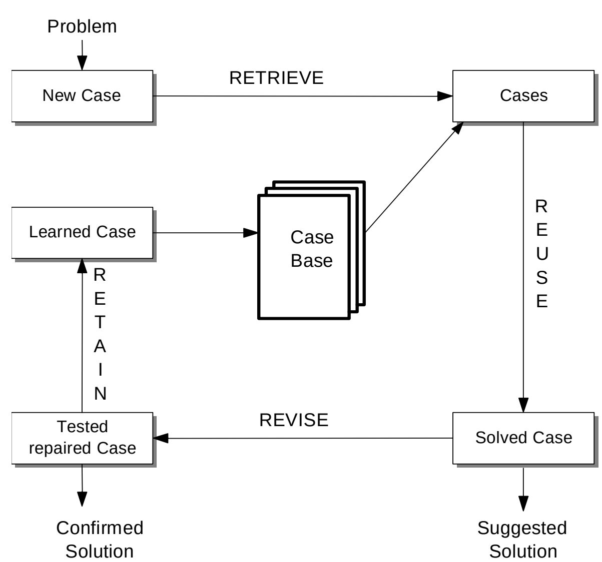


Figure 4.1: Graphical representation of CBR Cycle (Aamodt and Plaza) [3].

4.1.3 Case Representation

A case refers to a real-world experience in a certain set of circumstances. Generally a case is composed of three main parts: a problem, its solution and the corresponding outcome that can make it a positive or a negative experience [22]. A *case* should not be misunderstood with a simple *record*. Let us consider a library database, containing hundreds of *records* (books, journals and articles). In order to change one of these simple records into a case, it is required to associate an experience to the record, such as a student accessing the library database with a goal, (e.g. find a fiction novel), with a situation context (e.g., Thursday afternoon), with a strategy (e.g., book of a particular year, by an author) and with an outcome/feedback (e.g., specific record accessed or student's satisfaction/dissatisfaction).

A record is static information with no particular goal, task or action associated to it. On the other hand, a case comprises of active information - active in the sense that there is real time experience associated with it. A case has been defined as "A contextualized piece of knowledge representing an experience that teaches a lesson fundamental to achieving the goals of the reasoner" [22].

Example: A case comprises of three main parts: problem, solution and the outcome. *Problem* in some cases is further divided into goal, description and constraints, depending on the reasoner. CHEF which is a case-based planner used for recipe creation can be used as an example [28]. Let's take an example of making a dish with chicken and corn that should be sour and spicy. The case components for this case would be; the *goal* – making a dish, the *problem description* - should have the constraints that it should have chicken and corn as ingredients and have a sour and spicy taste. *Solution* for this case will be 'Chicken corn soup' which is the dish that satisfies all the constraints, and the *outcome*/feedback is how the taste was. Was it too sour or perfect? Was it too thick, too watery or perfect?

Case Representation in various CBR Systems

There are numerous ways to represent a case. Previous case-based systems have adapted various methods to represent cases. They can be as simple as database records, as in *Battle planner* (Goodman 1989) that consisted of 600 cases, or it may have a complex frame-based representation as in *Mediator* [69] which was used for dispute resolution area. CHEF [28] which was a simple meal planning system, represented cases in the format of a goal, a situation, a solution and a feedback.

Cardie [67] presented his case-based system and represented cases in the form of a single open-class word and the corresponding context. In this case base, cases were described by 38 attribute-value pairs. PROTOS that was developed in the domain of clinical audiology was used to classify hearing disorders. It comprised of 200 cases in 24 categories, from a speech and hearing clinic [43]. Figure 4.2 shows the visual representation of a case designed by Cardie, case representation in CHEF and in PROTOS. Before we proceed to the first main step of CBR cycle; case-retrieval, some important concepts about indexing are elaborated that play an important role during case retrieval.

4.1.4 Case Retrieval

The goal of case retrieval is to return the best matching case(s) from the case base. The process of retrieving a case or a set of cases from the case base is also termed out as '*remembering*'. It basically involves two steps: [22]

i. Recalling previous cases: The main aim of this step is to retrieve those cases that have the potential to make relevant predictions about the new case. This step is carried out by using *features* of the *new case* as *indexes;* based on which a match is generated from the case library.

ii. Selecting the best subset: The most promising case(s) is (are) selected in this step. The main aim of this step is to minimize the number of relevant cases to a few most closely matched-ones. Sometimes only one case is selected; sometimes a small set is chosen.

Example: In planning a meal for a group of friends, the host might *remember* (refers to retrieval) how she did the planning for the previous get-together (*referring to case-library*). Her experience (*refers to one of the relevant cases*) would help her plan the dishes such as she remembered one of her friends is a vegetarian and one is allergic to nuts.

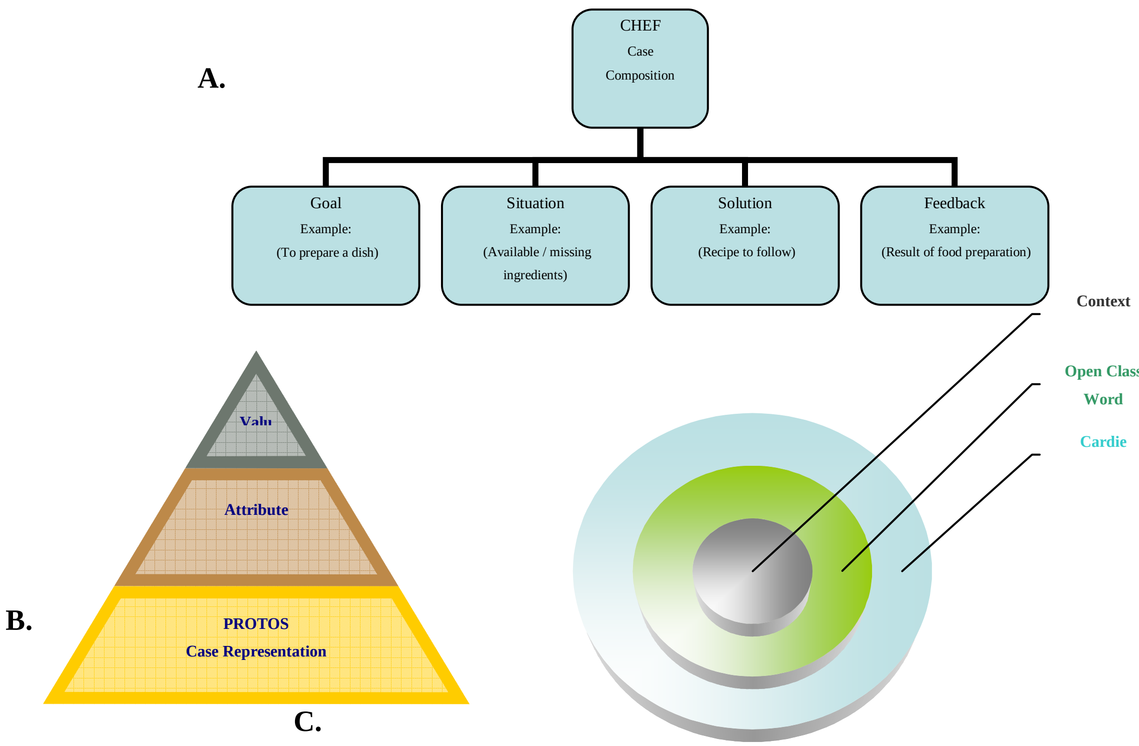


Figure 4.2: Representation of Cases in different Case-Based Systems A.CHEF [28], B. PROTOS [43] and C. CARDIE [67].

Therefore, keeping both of them in mind she would try to include some vegetarian dishes and avoid any nuts in the desserts or dishes that she prepares. Similarly, in CBR, cases that satisfy the similarity criterion are retrieved and information contained in them is used to solve the situation.

Case Retrieval in various CBR Systems

There are several retrieval algorithms that have been applied by different reasoners. Case retrieval takes place as a combination of searching and matching. The case base is searched in order to find the matching cases, which can be analyzed for their potential usefulness. This analysis of potential usefulness is performed with the help of 'matching functions'. In some CBR systems, search and matching is a sequential method, where as in some it is interleaved [22].

Similarity and Matching

The degree of match refers to how well the values of the corresponding attributes match. It is an important parameter pertaining to measuring the distance between two values, on a qualitative scale [22]. Two main concepts that require importance with regards to matching are: importance of a *dimension* (descriptor/attribute) in analyzing the similarity and *degree of match* of the *values*, along a certain dimension.

Dimension: Some dimensions (descriptors/attributes) of a case are more important in judging the usefulness than others, therefore, an efficient retrieval algorithm takes into account which features/attributes of a case are more important and categorizes (scores) the cases accordingly. For example, if the reasoner is attempting to choose a diagnosis based on the age, then a match between the current case's age and value of age in an old case are most important. Next in importance are matches between the constraints that guide how the range of symptoms must match; next in importance are matches of the descriptive features which assisted in choosing the plan previously. If two values are within the same qualitative range, they are considered a match, for example age 60 and up is considered as old age, therefore, 62 and 75 are a good match, 40 through 59 is middle age and 20 through 39 is considered as young adult. Therefore, ages 41 and 63 are one qualitative region apart where as 33 and 63 are two qualitative regions apart. This concept is reflected later in Chapter 5 for the retrieval algorithm for this case base system.

Degree of match: Sometimes, dimensions (attributes) match each other partially. For example in one case the dimension *color* is specified as *red* and another as *orange*. *Red* and *orange* match better than *red* and *blue* but not as well as *red* and *red*. Therefore, an efficient matching algorithm also takes into account the degree of match along with the dimension (attribute). However, cases that match well on important dimensions (attributes) are considered as better matches than those that match well on less important dimensions [22]. For example, for a reasoner to diagnose a disease, a case that matches the symptoms (heart rate, pulse, and temperature) would be a better match than the one that has same height, weight or hair color. Following are a few of the algorithms used by various reasoners [22]:

i. *Serial search on a flat memory:* This algorithm is easy to implement and performs a full search of the case library by applying a matching function sequentially to each case in the library and returning the best matching ones, but the problem arises when the case library gets larger and eventually the search becomes slower. In order to deal with this problem the memory should be partitioned so that the search algorithm can work efficiently.

ii. *Shared–feature networks partition:* It divides the case library according to the sizes of the sets of features shared by cases. Searching such networks is more efficient than a serial search but it has a disadvantage of missing even well-matching cases if the network is not prioritized.

iii. *Prioritized discrimination networks*: In such networks the case library is divided into one dimension at a time, the one being the most important dimension being the first. However this algorithm has problems dealing with missing features in a new case and also if the system is used for several tasks that have to be prioritized separately.

iv. *Redundant discrimination networks*: This overcomes one of the problems faced by prioritized discrimination networks because it can deal with the missing features in a new case. Multiple discriminations are performed at each level of the network. This has been one of the most commonly used algorithms in most of the popular systems. The reason being that this approach provides the best matching cases, but on the other hand it also returns barely-matching cases, therefore a second phase of matching has to be performed. Several variations have been performed on this algorithm; however, this method allows for a better and more accurate retrieval.

v. *Parallel retrieval algorithms*: In parallel retrieval, unlike serial search, a matching function is applied to all the cases in the library which makes the search far more efficient than serial search. However, the main significance of parallel approach is not in terms of efficiency but rather it is meant to allow indexing as a label-assignment process rather than a process of pointer assignment [22]. Parallelism tends to speed up the process but the need to partition the case library will have its own significance. Table 4.1 shows some of the retrieval algorithms applied by different case base systems:

Case-based System	**Retrieval Algorithm**
CHEF[28]	Discrimination net search
CASEY [42]	Redundant discrimination network
PROTOS [43]	Classification algorithm
CYCLOPS [27]	Serial search

Table 4.1 A few case base systems with their retrieval algorithms [22].

4.1.5 Attribute Selection

In a CBR system, attributes are the key features used to classify cases and develop a basis for the similarity criterion. Since case-based classifiers and nearest-neighbor algorithms are very sensitive to their input features, irrelevant attributes may cause an increase in the classification error. The classification of attributes is a complex and important phenomenon because the main goal here is not to include *any* attributes/features; but i*nformative attributes/features*. The significance of removing the irrelevant attributes/features (non-informative) ones is to overcome the curse of dimensionality [79]. The term refers to the problem caused in scenarios, where there are tens of thousands of attributes but only a few hundred cases/samples, such as in domains like micro array data sets measuring thousands of genes simultaneously. The potential benefits of attribute selection may include: enhancement of CBR performance, facilitation in data visualization and data understanding; reduction in storage requirements and improvement of prediction performance.

Attribute Selection Techniques

There are various attribute selection techniques which can be categorized according to a number of criteria. One popular categorization is in terms of "filter and wrapper" to describe the nature of the metric used to evaluate the worth of attributes [106]. Wrappers evaluate attributes by using accuracy estimates provided by the actual target learning algorithm. Filters, on the other hand, use general characteristics of the data to evaluate attributes and operate independently of any learning algorithm. Another useful taxonomy used for attribute selection is dividing algorithms into those which evaluate and hence rank individual attributes and those which evaluate and rank subsets of attributes. We consider three methods that evaluate individual attributes (*Information gain attribute ranking, relief & principal components analysis)* and produce a ranking unassisted, and a further three methods (*Correlation-based feature selection, consistency-based subset evaluation & wrapper subset evaluation)* which evaluate subsets of attributes. Following are some of the popular attributes selection techniques:

- *Information Gain Attribute Ranking:* This is one of the simplest (and fastest) attribute ranking methods and is often used in text categorization applications where the sheer dimensionality of the data precludes more sophisticated attribute selection techniques [111]. If A is an attribute and C is the class, the amount by which the entropy of the class decreases reflects the additional information about the class provided by the attribute and is called 'information gain'. Each attribute is assigned a score based on the information gain between itself and the class.

- *Relief:* Relief is an instance based attribute ranking scheme introduced by Kira and Rendell [107]. Relief works by randomly sampling an instance from the data and then locating its nearest neighbor from the same and opposite class. The values of the attributes of the nearest neighbors are compared to the sampled instance and used to update relevance scores for each attribute.
- *PCA - Principal Component Analysis*: Principal component analysis is a statistical technique that can reduce the dimensionality of data as a by-product of transforming the original attribute space. Transformed attributes are formed by first computing the *covariance matrix* of the original attributes, and then extracting its *eigenvectors*. Eigenvectors can be ranked according to the amount of variation in the original data that they account for. Typically the first few transformed attributes account for most of the variation in the data and are retained, while the remainder are discarded [108].

Following are the methods that evaluate the subsets of attributes:

- *CFS - Correlation-based Feature Selection*: This is the first of the methods that evaluate *subsets of attributes* rather than *individual attributes*. At the heart of the algorithm is a subset evaluation heuristic that takes into account the usefulness of individual features for predicting the class along with the level of inter-correlation among them. The heuristic assigns high scores to subsets containing attributes that are highly correlated with the class and have low inter-correlation with each other [109].
- *Consistency-based subset evaluation*: Several approaches to attribute subset selection use class consistency as an evaluation metric method. These methods look for combinations of attributes whose values divide the data into subsets containing a strong single class majority [110]. What usually happens in this technique is that the search is biased in favor of small feature subsets with high class consistency. Data sets with numeric attributes are first

discretized and then a modified forward selection search is used to produce a list of attributes, ranked according to their overall contribution to the consistency of the attribute set.

- *Wrapper Subset Evaluation*: Wrapper attribute selection uses a target learning algorithm to estimate the worth of attribute subsets. Cross-validation is used to provide an estimate for the accuracy of a classifier on novel data when using only the attributes in a given subset. Wrappers generally give better results than filters because of the interaction between the search and the learning scheme's inductive bias [108]. But improved performance is attained at the cost of computational expense; a result of having to invoke the learning algorithm for every attribute subset considered during the search.

Machine learning using WEKA

Baker and Jain reported experiments comparing eleven feature evaluation criteria and concluded that the feature rankings induced by various rules are very similar [102]. The conclusions are that no feature selection rule is superior to the others, and that no specific strategy for alternating different rules seems to be significantly more effective. Mingers compared several attribute selection criteria, and concluded that the quality of selected attributes is independent of a specific criterion [103]. He even claimed that random attribute selection criteria are as good as measures such as *information gain ranking method* described in the last section [104]. Although, the later claim was refuted [105], where the authors argued that random attribute selection criteria fail when there are several noisy attributes.

For the CBR system in this research, the tool that was used is based on all of the techniques explained above. In order to perform attribute selection, we applied "*WEKA*" (Waikato Environment for Knowledge Analysis), which is a powerful open-source Java-based, machine learning workbench [112]. *WEKA* is comprised of numerous machine learning algorithms and tools under a common framework along with an intuitive graphical user interface. *WEKA* has two primary modes: a data exploration mode, and an experimental mode. The experimental mode, ‘e*xperimenter’* allows large scale experiments to be run with results stored in a database for later retrieval and analysis where as the data exploration mode ‘e*xplorer’* provides easy access to *WEKA's* various modules to explore data, which include data pre-processing, clustering, classification, association, attribute selection and data visualization. These actions can be performed by the respective tabs at the top as seen in Figure 4.3 and 4.4:

1. *Preprocess*: To choose and modify the data being used.
2. *Classify*: To train and test learning schemes that classify or perform regression.
3. *Cluster*: To Learn clusters for the data.
4. *Associate*: To learn association rules for the data.
5. *Select Attributes*: To select the most relevant attributes in the data.
6. *Visualize*: To view an interactive 2D plot of the data.

Attribute Selection in WEKA

Attribute selection in *WEKA* involves searching through all possible combinations of attributes in the data to find the best subset of attributes that can be used for prediction. This requires two steps: to select an attribute *evaluator* and to choose a *search method*. The *evaluator* determines which method to be used in order to assign worth to each subset of attributes, where as the *search method* decides the style of search performed.

Evaluator Methods: Section 4.1.5.1 provides a detail of various popular attribute selection techniques. *WEKA* incorporates all of those as well as few more described as follows [112]:

1. *CfsSubsetEval e*valuates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them.
2. *ChiSquaredAttributeEval* evaluates the worth of an attribute by computing the value of the chi-squared statistic with respect to the class.
3. *Classifier subset evaluator* evaluates attribute subsets on training data or a separate hold out testing set.

4. *ConsistencySubsetEval* evaluates the worth of a subset of attributes by the level of consistency in the class values when the training instances are projected onto the subset of attributes.
5. *GainRatioAttributeEval* evaluates the worth of an attribute by measuring the gain ratio with respect to the class.
6. *InfoGainAttributeEval* evaluates the worth of an attribute by measuring the information gain with respect to the class.
7. *OneRAttributeEval* evaluates the worth of an attribute by using the OneR classifier.
8. *PrincipalComponents*: It performs a principal components analysis and transformation of the data.
9. *ReliefFAttributeEval* evaluates the worth of an attribute by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same and different class. In other words it searches for nearest neighbors of examples with different class labels, and hence the features are weighed according to how well they differentiate these examples.
10. *SVMAttributeEval* evaluates the worth of an attribute by using an SVM classifier.
11. *SymmetricalUncertAttributeEval* evaluates the worth of an attribute by measuring the symmetrical uncertainty with respect to the class.
12. *WrapperSubsetEval* evaluates attribute sets by using a learning scheme.

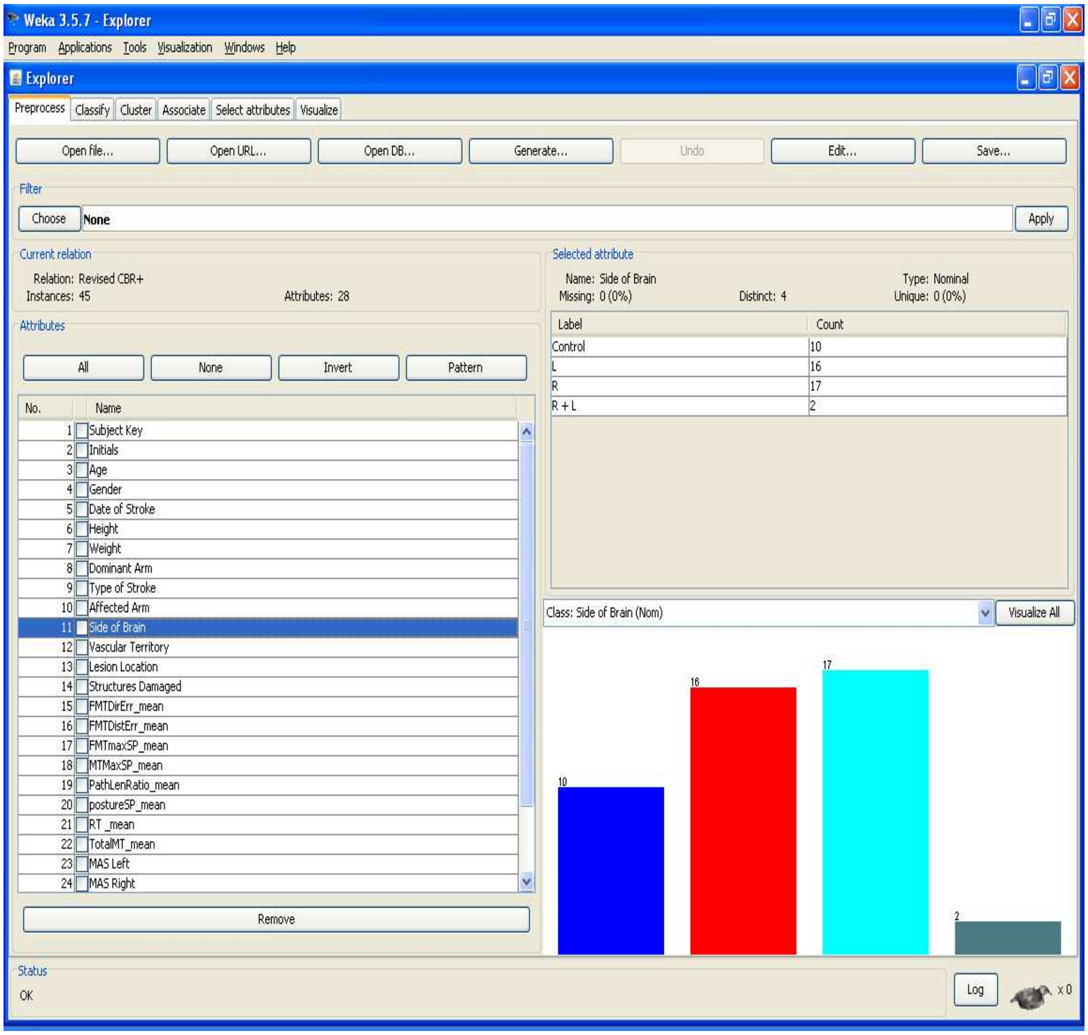


Figure 4.3: Screen shot of WEKA showing data preprocessing of the selected attribute left (Side of Brain), further details at right top (Control 10, Left side affected 26, Right side affected 17 and both sides affected 2. Right bottom shows the corresponding visualization represented by different colors.

Search Methods: There are numerous search methods that can be chosen for attribute selection in *WEKA*. A brief description of each is given as follows [112]:

1. *BestFirst s*earches the space of attribute subsets by greedy hill climbing augmented with a backtracking facility. Setting the number of consecutive non-improving nodes allowed controls the level of backtracking done. *BestFirst* may start with the empty set of attributes and search forward, or start with the full set of attributes and search backward, or start at any point and search in both directions [112].

2. *ExhaustiveSearch* performs an exhaustive search through the space of attribute subsets starting from the empty set of attributes. It reports the best subset found.

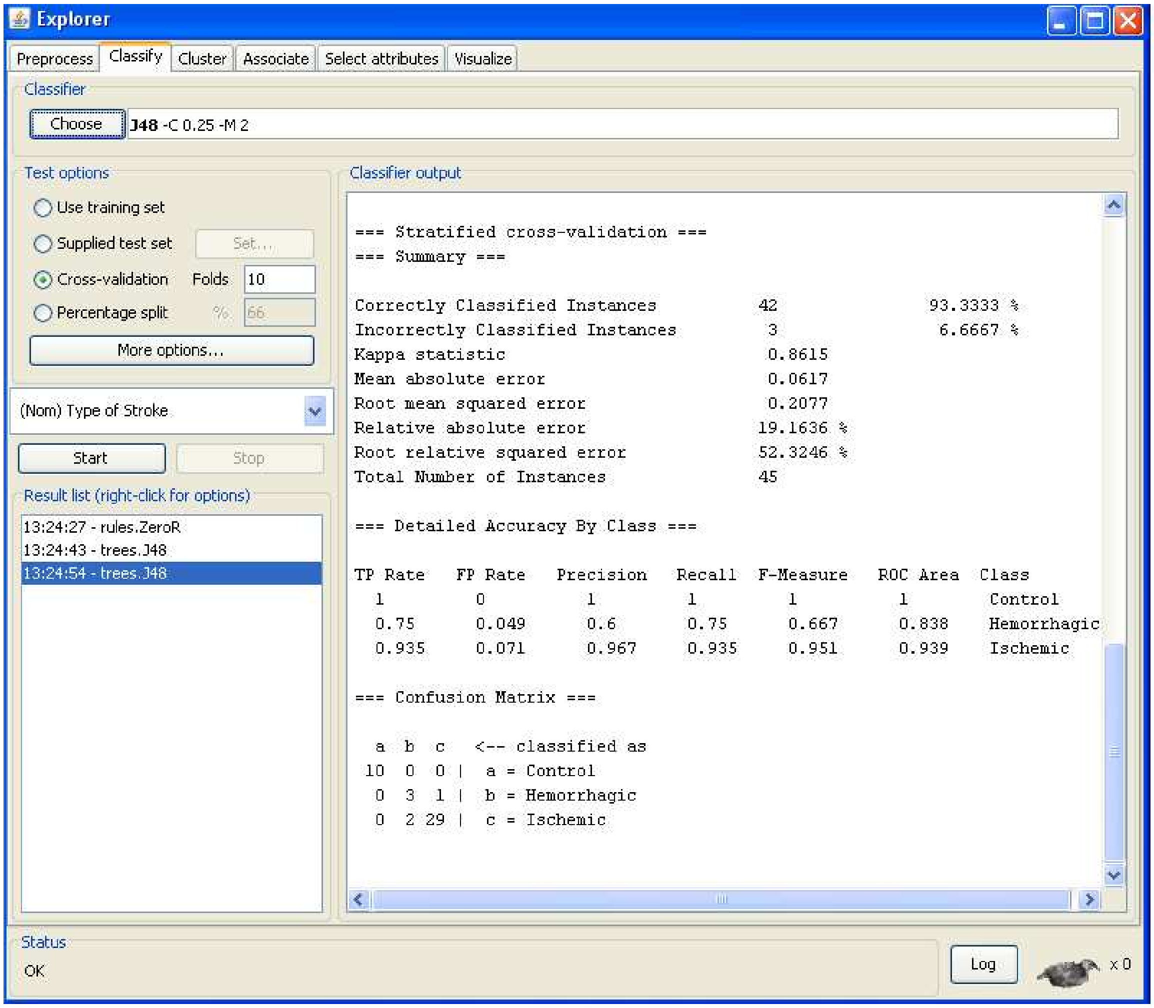


Figure 4.4: Screen shots of WEKA showing Classify tab high-lighted showing the classification of' type of stroke'. The classifier output area on the right gives the details of correctly classified (93.3 %) and incorrectly classified (6.6%) instance.

3. *FCBF (FastCorrelationBasedFilter)* is a feature selection method based on correlation measure and relevance and redundancy analysis. It is use in conjunction with an attribute set evaluator (SymmetricalUncertAttributeEval).

4. *GeneticSearch* performs a search using the simple genetic algorithm described in Goldberg (1989) [113].

5. *GreedyStepwise* performs a greedy forward or backward search through the space of attribute subsets.
6. *LinearForwardSelection* is an extension of BestFirst.
7. *RaceSearch* determines the cross validation error of competing attribute subsets.
8. *RandomSearch* performs a random search in the space of attribute subsets.
9. *Ranker* ranks attributes by their individual evaluations.
10. *RankSearch* uses an attribute/subset evaluator to rank all attributes.
11. *SubsetSizeForwardSelection* is an extension of LinearForwardSelection.

Once the *evaluator* and *search methods* are chosen, the next step is to choose one of the *attribute selection* modes. One possibility is the *Full Training set* in which the worth of the attribute subset is determined using the full set of training data. The other is *Cross-validation* that uses a process of cross-validation to determine the worth of the attribute subset. Besides these two modes there is another option of *Classify* to be used to specify the attribute that can be used as a class. In Section 5.2.2.1 Chapter 5, further details follow where *WEKA* has been applied in conjunction with the expert advice to determine the ranking of attributes for our proposed CBR system. The main case structure (Section 5.2.2.3 Chapter 5) was based on these selected attributes.

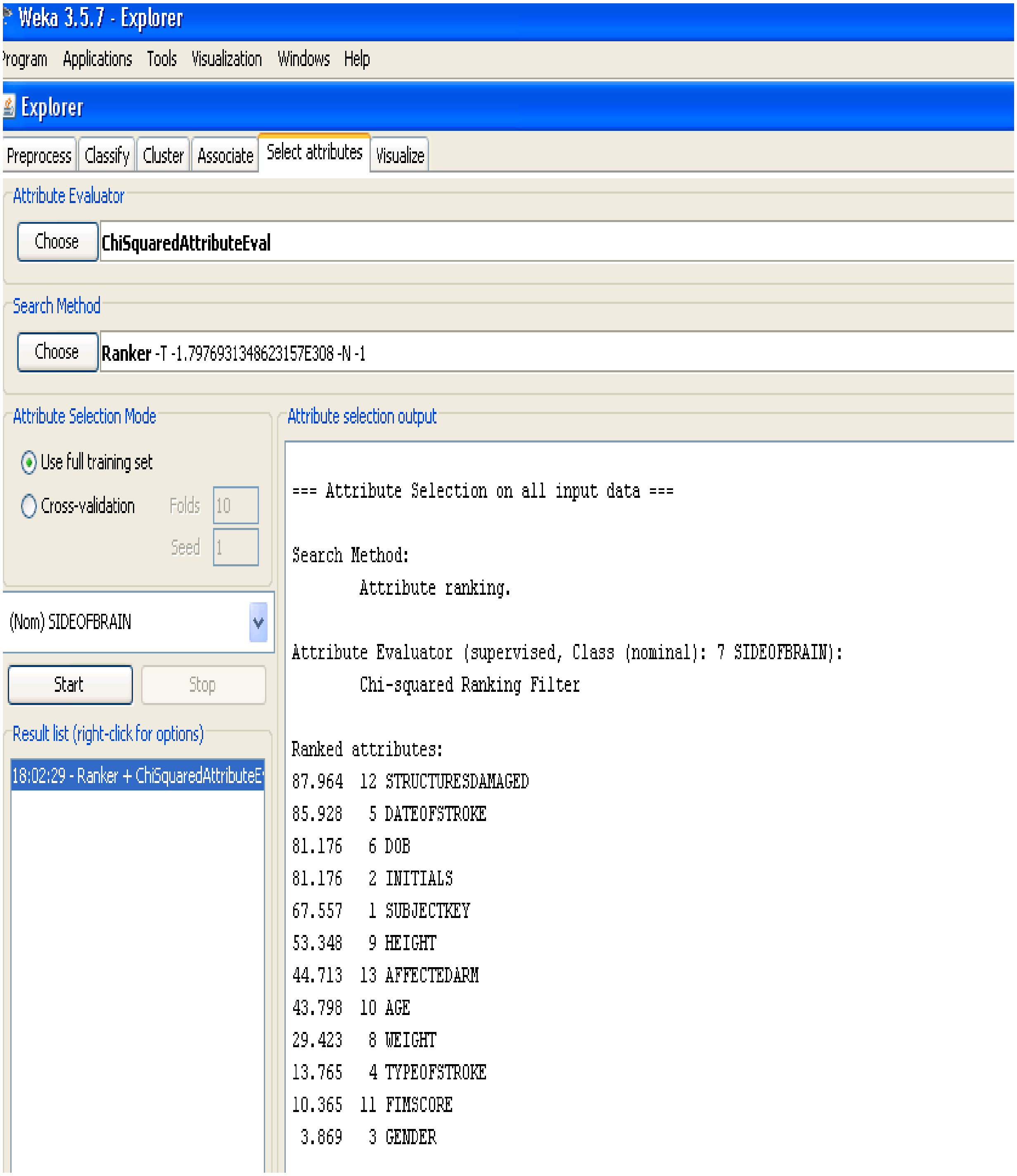


Figure 4.5: Screen shots of WEKA showing Attribute selection tab high-lighted showing the ranked attributes.

4.1.6 Reuse – Adaptation

The goal of case adaptation is to use the solution of similar retrieved *Source Case(s)* in solving the new problem *Target Case*, by applying some modifications to the retrieved- case solution. A good adaptation of Source Case (s) to fit the *Target Case* can reduce the amount of work required, significantly. In other words, adaptation is the phenomenon of fixing up an old solution to meet the requirements of a new situation. It can be considered as simple as substituting one component of a solution for another, or as complex as modifying the entire structure of a solution such as something new might be inserted or something can be eliminated from the old solution or in some cases a certain part of the solution might be transformed. Adaptation can be sub-divided into two main steps: [22]

i. Figuring out what needs to be adapted: One way to identify what needs to be adapted can be achieved by observing inconsistencies between new needs and old solutions. Some of the methods used in AI such as reason-maintenance and constraint propagation can be useful in finding these variations.

ii. Performing the adaptation: For any particular task or domain a set of its own specific adaptation strategies or heuristics can be developed, which is a rather ad hoc approach. However, the main idea is to identify a *general set* of adaptation strategies that provide guidelines for *specialized* adaptation strategies.

Example: If one of the guests attending the party is a vegetarian, the meat can be taken out of a recipe in order to make the dish vegetarian. This is a specialization of a more general adaptation strategy that is referred to as *delete secondary component strategy*. According to this general strategy, a secondary component of an item can be deleted if it is not performing an essential function.

Although there are many adaptation strategies available, the responsibility of many case-based reasoners ends at the retrieval phase [70]. The main goal is to be able to retrieve the appropriate cases. Once the goal is achieved the case solutions can be reused in whatever manner that is workable and practical by the domain experts. This is referred to as *null adaptation* [70]. Since CBR is usually applied on weak theory domains, the knowledge required to make adjustments is not available (as in ADHD domain) or if that knowledge is available, it is not standardized (as in stroke domain). In the absence of adaptation rules, it is better not to use them at all on the CBR system.

Another approach that is referred to as *CBR adaptation* is to store the adaptation strategies and outcomes as part of the CBR system [70]. After the retrieval phase, a second round of retrieval can take place in order to retrieve similar adaptation strategies. If the result of retrieval is no adaptation strategy, default is set to null adaptation. The justification for this is that, ability to adapt also improves over the period of time just like reasoning does.

Case Adaptation in various CBR Systems

There are a number of strategies that are used by CBR systems for case adaptation. Some of them are: s*ubstitution methods*, *transformation method*s and *special-purpose methods [22]:*

i. Substitution methods: Substitution is the method by which a certain part of an old solution is chosen and replaced. There are various kinds of substitution methods such as, *reinstantiation;* where new objects are instantiated in the old solution. *Parameter adjustment*; is another one used to adjust numerical parameters, of the old solution. L*ocal search*; provides a means for finding an auxiliary knowledge structure, as a substitute for some old value, inappropriate for the new situation. Another method known as *query memory;* either asks for auxiliary knowledge structures or the case memory to return something with a given description. In s*pecialized search;* both auxiliary knowledge structures and case memory are queried, in addition to the search heuristics for guiding memory search and *case-based substitution* utilizes other cases to suggest substitutions.

ii. Transformation methods: Transformation methods provide strategies, which transform an old solution in a way that it can work for the new situation. A commonsense heuristic known as *delete secondary component* (used in the example in Section 4.1.6) is an example of transformation. *Model-guided repair* is another transformation method used by a causal model (for diagnosis, or designing of devices).

iii. Special-purpose adaptation: Special-purpose repair heuristics are used to carry out domain-specific and structure-modifying adaptations that are not covered by the other two methods. These heuristics are indexed according to situations in which they are applicable. The following table shows various adaptation strategies applied by some of the CBR systems:

Case-based System	**Adaptation Strategy**
CHEF [28]	Reinstantiation
JULIA [31]	Specialized adaptation heuristics
CLAVIER [36]	Case-based Substitution
CASEY [42]	Model-guided repair (Transformation)

Table 4.2 CBR systems with their adaptation strategies [22].

4.1.7 Revise – Evaluation

The main goal of case evaluation is to provide *feedback* to the case-based reasoner system, whether or not the new case was solved adequately. Evaluation is the process of acquiring feedback. Feedback is an essential requirement in order to learn from experience and to be able to interpret, what was right and what was wrong with its solutions. In the absence of feedback, the CBR system may become faster at solving problems but it is at a higher potential to repeat its mistakes and would not be able to improve its capabilities.

"Interpretive case-based reasoning is a process of evaluating situations or solutions, in the context of previous experience" [22]. The main feature of interpretive case-based reasoning is the comparison and contrast of new situations to the old ones. *Example*: Members of the admission committees in universities *evaluate* the potential of applicants (to make it in their school) by comparing them with similar students who have, or have not done well. Based on this *feedback/evaluation*, the committee members are able to decide, whether they should be accepted or not.

Evaluation can be further categorized as *exemplar-based classification*, *case-based argumentation* and *case-based projection of outcome*. Case-based classification is best exemplified by PROTOS [43] which diagnoses hearing disorders by looking for the case in the case base that is the most similar to the new one and assigning the new case, the same classification.

In case of inadequate solution, the retrieval of additional cases may be required, that may result in the need of "repair" – an additional adaptation or cardinality relaxation /restriction procedure. With the relaxation of context, the number of similar cases is increased. More relaxed the context, more matching cases in retrieval.

4.1.8 Retain – Memory Update

This step refers to the storage of a new case in the case base, appropriately for future use. This case now comprises of the problem, its solution plus any facts supporting the reasoning. The most important step in this phase of memory update is choosing the ways to index the new case in the case library. This is the most important step because if the case is indexed properly, it would be able to recalled and retrieved during later reasoning when it can be most helpful. At the same time it should not be over indexed to avoid being retrieved indiscriminately which means that the reasoner must be able to anticipate the importance of the case for later reasoning.

Performance evaluation in CBR goes beyond error assessment due to the dynamic nature of the process. Task-contexts keep changing over time along with the addition of more cases in the case base. But this does not give a reason for inability to assess the CBR system's performance. Following are some guidelines that were proposed, in order to ensure the accuracy of retrieval and analyze the performance of the CBR system [70]

1. Individual accuracy - Is the case able to retrieve itself during a retrieval request?
2. Retrieval requests - Are the retrieval requests consistent?
3. Repeated Requests - Are same cases retrieved when attempting repeated requests?
4. Cross-validation test - Is the error rate same, when performing a cross-validation test?
5. Duplicate elimination- Are the duplicates scanned for?

The answer to all these questions should be a 'Yes'. A 'No' to any one of them might reflect a problem in the design. However, in case of assessing consistency, in some systems, a chance of a small variation is permissible, due to randomness in the retrieval process. Duplication should be taken into account when adding a new case to the case base.

Over all Coverage: This is another important feature to take into consideration during case base assessment. Over all coverage is not an issue till the case base becomes too big. When tasks change, the case base may not cover the essential cases that are useful for that task. Case utilization statistics can play important role at this point. According to case utilization statistics, cases that were never retrieved can be discovered. Sometimes these unusual cases need to be retained since they may refer to a rare situation and might be useful in future.

Granularity: If a case seems to be retrieved too frequently, that refers to the condition that the domain lacks sufficient granularity; therefore, more cases need to be added surrounding this popular case. With an increase in the number of cases to the CBR system, the accuracy of the system may improve but on the contrary it might diminish the speed. This depends on the discretion of user, if accuracy should be given priority over time consumed or vice-versa. If the CBR system is used a decision support tool, (like in stroke domain) where an expert can make the final determination, the system may be more successful if it gives a fast response in contrary to utilizing hours to present decision support. On the other hand, when the CBR system is used as diagnostic tool, accuracy has to be the most important feature so that even if the reasoner takes a long time to get an answer, it may be worth as compared to the consequences of a wrong diagnosis.

CBM (Case-based Maintenance) is a field that has recently flourished in the area of CBR. It deals with improvement of performance and increases the integrity of the entire system not just the case base [87].The work in this area focuses on the development of systematic strategies that enable the user to measure and maintain the quality of system, without the constant intervention of the expert.

4.1.9 A Classification of CBR Applications

There are two main reasons to incorporate applications of CBR in this chapter. First because it emphasizes the importance of CBR and its diversity and second, because it depicts the thorough research about CBR, manifesting the fact that it has not been applied to the stroke domain. However, there have been many diagnostic tools and shells, but not for stroke.

CBR has diverse applications that are widely used. Althoff and his colleagues suggested a classification method of CBR applications [63] as shown in Figure 3.3. According to this classification scheme, CBR applications can be classified into two main categories, *Classification* and *Synthesis* tasks. This dichotomy is at the conceptual level, however most of the times a blend of both types is seen. This is the reason why a combination of both methods is observed in most effective case-based situations. For instance, the labor mediation application SYCARA [29] makes use of both the methodologies, interpreting the situation and then deriving a solution based on precedents. The classification hierarchy is presented in the Figure 4.6.

Classification tasks

These CBR applications are common in business and everyday life. A new case is assigned to a specific class in the case-base from which a solution can be derived. In fact, most commercial CBR tools support classification tasks. One of their representative applications for maintenance is CASELINE [44], which is used for aero-plane maintenance and airplane trouble shooting in order to reduce airplane downtime [59].

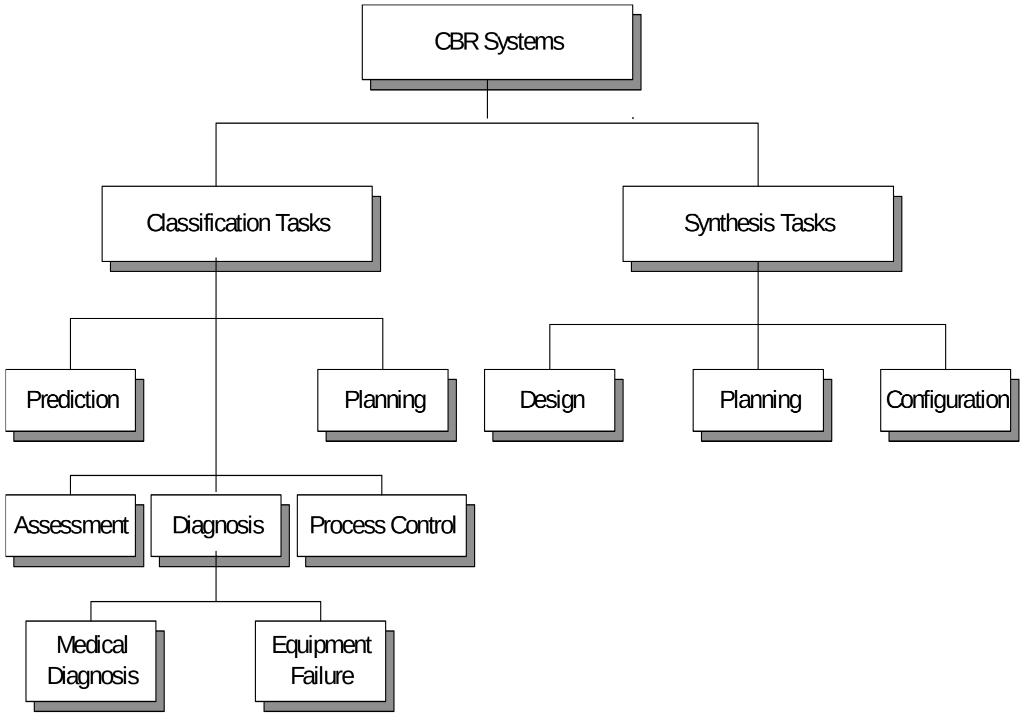


Figure 4.6: A Classification hierarchy of CBR Applications [63]

Maintenance systems for telecommunication networks [45] and engineering applications such as detecting locomotive faults [58] are a few more in this category. Legal and medical knowledge management and diagnosis [47, 48] also fall in this category. Product recommendation in e-commerce (online self service color selection for paint) [60] and efficient helpdesks and customer support systems (Compaq computers) [61] are additional novel classification applications of CBR.

Synthesis Tasks

Synthesis tasks attempt to get a new solution by combining previous solutions. There are a variety of constraints during this process. Comparatively, they are harder to implement. CBR systems that perform synthesis tasks must make use of adaptation and are usually hybrid systems. They combine CBR with other techniques. Recently, within the problem solving type of CBR, several systems have been built to do case-based planning and design. Among them are CYCLOPS used for landscape design [27], CHEF [28] and JULIA [31] for planning meals, and KRITIK [29, 35] which combines case-based and model-based reasoning for the design of mechanical assemblies. In addition, CLAVIER [36] is used to arrange compounds in an autoclave, SMART memory model [37] to improve the efficiency of the system PRODIGY [38], and then there are ARCHIE [39] and CADRE [30] to facilitate architects in understanding and solving conceptual design problems.

4.1.10 CBR in Medical Informatics

The medical domain has always been an area of ever-emerging challenges; therefore medical professionals are facing new problems and dealing with a need for better dynamic resources every day. This is one of the underlying reasons for improvement of the healthcare market and a requirement to support physicians in order to facilitate them [47]. Effective knowledge management is another driving force for health care organizations to ensure cost effectiveness, efficiency and justification of cost containment and better quality of care. The cost of healthcare is increasing accordingly because there is a demand of better service from patients [46]. Therefore the need for knowledge management is becoming an important requirement these days. The applications of CBR in medical domain can be classified into the following two groups: diagnostic and prognostic.

Diagnostic Applications

Diagnosis, in medical terminology refers to the act or process of identifying or determining the nature and cause of a disease. Diagnostic applications constitute an important branch of problem-solving CBR. The idea of applying knowledge-based systems to facilitate health professionals in diagnosis goes back to about three and a half decades in the 1970's. This involved statistical methods to support diagnosis but unfortunately did not get significant solutions [48]. There were various underlying reasons for being unsuccessful such as complexity of domain, enormous amount of data, inconsistency in data and parameters, missing information and significant outliers.

In diagnosis, just as in planning or design, it is necessary to adapt an old case to fit a new problem. CASEY [42] is a popular example of a case-based system for diagnosing problems of patients suffering with heart disease. This is also based on the principle of adaptation of the known diagnoses of previous patients. Another early case-based diagnosis system is PROTOS [43], which was used to diagnose hearing disorders applying a learning apprentice approach. FLORENCE [49] is a system that deals with health care planning for nursing. MEDIC [50], which is a schema-based diagnostic reasoner, is specialized for pulmonology. This memory organization and retrieval allows a reasoner to determine the most specific problem-solving procedures available.

GS.52 [51] differs from typical CBR systems in a way that cases are clustered into prototypes. It is used to diagnose dysmorphic syndrome (a morphological disorder by birth). It is another domain with incomplete knowledge and experts themselves have only seen a few syndromes during their entire lifetime. TROPIX [52] is an application to diagnose tropical diseases that are infectious and more widespread in the tropics. NIMON [53] is a renal function monitoring system to facilitate kidney dysfunctional diagnosis. ICONS [54] is another renal diagnostic tool that provides an automatic interpretation of the present state of intensive care patients and presents a suitable calculated antibiotic therapy as well.

Prognostic Applications

Prognosis, referring to the medical concept comprising of patient data, medical intervention, outcome, utilities and probabilities, is another area which came into the limelight in recent years. There have been CBR tools in this classification as well, such as TeCoMED [56], which is used to generate forecasts of epidemics and infectious diseases. CIM [57] is another application used for the prevention of clinical incidents in general practice. TA-3, the framework that we used for this research, is also a significant prognostic tool that had been used before to increase the success rate of in-vitro fertilization [55]. In the next section the role and function of this tool is elaborated in detail.

4.1.11 Is CBR the right choice?

Most knowledge-based systems perform problem-solving by acting on certain generalized rules that are based on facts. Rule-based systems rely on 'explicit knowledge of the domain', which is not only agreed upon by the experts, but also is used to construct a comprehensive set of rules [71]. This works well in genres where there are fixed rules and defined features such as weather prediction, equipment maintenance, and troubleshooting. But, if there is not enough knowledge available or there is a lack of standardization in defining criteria or the procedure for a knowledge engineer to practically create a model-based reasoning system, is enormously time consuming; CBR is often the best alternative.

In accordance to this fact, there are problem domains such as diagnosis of ADHD (Attention-Deficit Hyperactivity Disorder) [83] and diagnosis of patients suffering with heart disease [42], where rules cannot be simply derived based on a set of facts. Analogously, the stroke domain cannot be characterized as a set of explicit rules with regards to symptoms and diagnosis, due to the lack of an objective approach in stroke assessment, and a lack of standardization in rehabilitational techniques that clinicians can agree upon unanimously [90]. According to a recent study carried out by clinical practice committee of American Geriatrics

Society, it is necessary to implement some guidelines which should be used by hospitals, sub acute-care units and providers of long-term care in order to implement a structured approach to improve rehabilitational practices and by clinicians to determine best interventions to achieve improved patient outcomes [90].

There are some underlying reasons for this lack of standardization, the protocols for clinical assessments vary, the modes of diagnoses vary and the approaches towards rehabilitational therapies vary. CBR is a unique and prolific approach in problem-solving, with which the above-mentioned reasons for lack of standardization can be overcome in stroke diagnosis and rehabilitation. Instead of relying on generally accepted domain knowledge, CBR builds a system based on the specific knowledge contained in previously experienced problems and their solutions. This is one of the exclusive reasons for applying CBR to the stroke domain. The next section further elaborates on the significance of using CBR.

4.2 What is *TA- 3*

The comprehensive framework that we are using in this research (pronounced as tah-tree) is based on a research collaboration [82]. *TA-3* stands for *The Advisor 3* where the 3 refers to the three main components of *The Advisor* – representation, reasoning and presentation [55]. These three components are the main functionality of the CBR in terms of representing the cases, retrieving similar cases, reusing information for adaptation and ultimately retaining the learned case for presentation.

4.2.1 *TA-3* Architecture

The case-base repository uses either a relational database or a simple file system. Cases are represented as attribute/value pairs and their domains are defined in a case description (for details please see Chapter 5). Case description contains three classes of data (i) *Description*, which is non-predictive; (ii) *Problem*, which contains predictive data and (iii) *Solution*, which is also non-predictive and provides the classification of the case. To further elaborate the *TA-3* case structure, an example from *Attention Deficit Hyperactivity Disorder* (ADHD) diagnosis case can be used, where the *description* portion comprised of the *patient initials,* and *sex,* (non predictive data), the *problem* part consisted of *age,* the *direction error* and *saccade reaction time* (predictive data) and the *solution* part is made up of the diagnosis as a *control* or *ADHD* (non-predictive) [83].

The reason behind dividing the *case description* into these classes is that it allows the application of different constraints and priorities, to particular entities and these constraints have to be satisfied in order to perform a successful case-retrieval. It also diminishes the effect of irrelevant or less-relevant attributes on the system performance and presents complex information in a more comprehensible manner.

4.2.2 Retrieval in *TA-3*

The retrieval process takes place by the application of nearest-neighbor matching [80]. The goal of retrieval in the CBR system is to retrieve not only exact matches (equivalent cases) but partial matches (similar cases) as well. During the similarity assessment, an explicit *context* is used; therefore, the retrieval algorithm is based on incremental *context transformations*. The details for context–based retrieval are explained in the next section.

4.2.3 Context

In various research areas, *context* is defined differently. In *databases* it is referred to as *views* where as in *pattern recognition* it is mentioned as *aspects.* A *Context* can be defined as a subset of the problem class data with applied constraints (range of allowable values). A *Context* is a view of a case, which comprises of a finite set of attributes with associated constraints on the attribute values. The function for discovering context is an attribute-oriented clustering algorithm. The function maps a set of cases and a case base into a context, which guarantees the relevance of cases [114]. It is an efficient query relaxation algorithm which is based on incremental context transformations [82]. The following expression will further elaborate the relation between the context, the attributes and their allowable values. In this equation, Ω refers to the context, a_0 refers to the attribute and cv_0 refers to the set of allowable values for matching the attribute. Any values other than the constraint will not be considered.

Equation 1. $$\Omega = \{<a_0:cv_0>, <a_1:cv_1>, <a_2:cv_2>, \ldots, <a_n:cv_n>\}$$

A general example will further simplify the concept expressed in Equation 1. For instance, 'a_0' refers to the 'age' and the constraint on the value specifies the range of 40 to 60.

a – Attribute		**v – Value**	
a_0	Age	cv_0	40-60 (yrs)
a_1	Height	cv_1	150-180 (cm)
a_2	Weight	cv_2	60-90 (kg)

Table 4.3: Attribute / value reference.

Constraints can be applied to individual attributes or categories on the whole and can be of two types: *Value* and *Cardinality*. *Value* refers to the range of allowable values, where as *cardinality* refers to the number of attributes that must be satisfied for the entire category to be satisfied. A case C, *satisfies* a context Ω, denoted as *sat* (C, Ω), if and only if for all pairs $<a_i:Cv_i> \in \Omega$, there exists a pair $<a_i:v_i> \in$ C such that v_i is in Cv_i:

Equation 2.

$$sat(C,\ \Omega) \text{ iff } \forall a_i \langle a_i : CV_i \rangle \in \Omega \rightarrow \exists V_i \langle a_i : V_i \rangle \in C \wedge V_i \in CV_i.$$

Two cases are considered *similar* if they both satisfy the same *context* and a *case* would be considered to *satisfy* a *context*, if every *attribute value* in the case satisfies the *constraints* (range of allowable values provided). Retrieval for the CBR system is further explained in (Section 5.4.2). A case C_1 is *similar* to a case C_2 with respect to a given context Ω, denoted: $C_1 \sim_\Omega C_2$, if and only if both C_1 and C_2 satisfy context Ω:

$$C1 \sim_\Omega C_2 \longleftrightarrow sat(C_1, \Omega) \wedge sat(C_2, \Omega)$$

Equation3.

$$sat(C, \Omega) \text{ iff } \forall a_i \langle a_i : CV_i \rangle \in \Omega \rightarrow \exists V_i \langle a_i : V_i \rangle \in C \wedge V_i \in CV_i.$$

TA-3 being a decision support system reflects optimum performance when used interactively, as a conversational CBR system. The similar retrieved cases are presented to the user and the query can be subsequently modified with relaxation and restriction transformations. Following are the two transformations that can be applied:

Relaxation

Context *A* is said to be a relaxation of context *B* if *A* contains a subset of the attributes in *B* and the constraints on the attributes in *A* are a subset of the constraints on the attributes in *B*. Relaxation can be further sub-divided into two implementations: *reduction* and *generalization*. *Reduction* (also referred to as m_of_n matching), reduces the number of attributes needed for the match as the name implies. Generalization, on the other hand, increases the range of allowable values that the attributes may have. Both these transformations tend to relax the constraints in a way that, more cases are retrieved.

Restriction

If context *A* is a *relaxation* of *B*, then context *B* will be a *restriction* of *A*. Restriction can be further sub-divided into *expansion* and *specialization* which are opposite in effect to reduction and generalization respectively. So expansion increases the number of attributes (in contrast to reduction) while specialization decreases the range of allowable values. These concepts will be recalled in section 5.4.2 (Figure 5.5) By applying restriction, fewer cases are expected to be retrieved since it intends to restrict the constraints.

4.2.4 *TA - 3* Functional Specifications

TA-3 is regarded as a flexible framework in the sense that its responsibility is over at the retrieval process. It is the expert's, user's or possibly another program's job from there to use the set of cases retrieved appropriately. There is no specific module to perform adaptation in the system. For knowledge mining, *TA-3* provides limited support and that is through an *explain* function. The *explain* function automatically creates a context (a case interpretation) which is satisfied by the set of retrieved cases or the entire case base, meaning that a minimal context is created in a way that all cases in the returned set are similar. It is a useful function for the categorization of cases. For example, in *in vitro fertilization* (IVF) study [55] two contexts were created, one for pregnancy with abortion and the other without abortion, in order to make a comparison between both the contexts and determine the significantly predictive attributes among the two.

Recently, a *context refinement function* [83} was created and added to maximize the potential to produce a context with best fitness. This function makes use of a genetic algorithm iteratively creating, mutating and evaluating the fitness of hundreds of contexts. The genetic algorithm manipulates a context in a way that it increases the inter-class distance (between two classes) and decreases the intra-class distance (within the same class). The inter-class and intra-class distance is based on the distance between two cases, which is defined in equation 2:

Equation 2.

Distance between two cases = Number of relaxations required to make the cases similar.

The main advantage of this process is the significant information it yields, which is useful in determining unknown relations in the data and may provide a new context that can potentially improve the retrieval phase and achieve better prediction accuracy. Therefore, this process is iterative and user-guided.

4.2.5 *TA-3* Applications

The effectiveness of *TA-3* has been proved in many complex domains such as robotics [84]], molecular biology [66], protein crystallography [65] and for ADHD diagnosis [83]. The novel feature of *TA-3* is its flexibility in knowledge representation and efficient case retrieval. When we talk about prediction in medicine, *TA-3* has been applied as a cost-effective treatment for IVF [55]. IVF is an assisted reproductive technology affecting success of pregnancy. Because there are so many variables involved, even for adept physicians, it is a challenge to perform decision-making and improve the pregnancy rates. A complex domain with numerous variables and an enormous collection of previous treatment experiences is the perfect situation to apply CBR and this was the foundation of *TA-3*. The procedure followed the organization of a case base which comprised of previous IVF patient-treatments. This case base was used for the prediction of hormonal stimulation in new patients to increase the likelihood of a successful pregnancy and further the case base was used for knowledge mining, in order to derive innovative and interesting relationships for future reference.

Another non-linear study was carried out in the field of *robotics* [84]. The aim was to predict the joint angles on a 3-hinged robot such that the end-effector could be placed at a specific co-ordinate in 3-space. A large case-base was available for this task. Each case was comprised of 9 attributes that described the arm lengths, joint angles, and end co-ordinates. The attributes were divided into 3 categories and two retrieval techniques were applied, one based on value relaxation and the other based on m_of_n matching.

Recently, *TA-3* had been applied to the *protein crystal growth* domain [65]. The aim of this study was to speed up the process of determining protein structure with single crystal X-ray diffraction by providing decision support in novel crystal growth experiments. High-throughput crystallization techniques were used to develop the case base, which had the capacity of performing 40,000 crystallization experiments per day. The goal was to retrieve similar precipitation experiments given a novel experiment and guide a successful outcome by suggesting possible parameters and warning of any potential problems.

TA-3 had also been used for the prediction of ADHD [83]. The neurophysiological data used is multidimensional and its complex correlation with neurological dysfunction is not well understood. However, the success of CBR in complex domains suggested the potential for this application. *TA-3* was used as an effective decision support system for the diagnosis of ADHD.

4.2.6 Summary

The purpose of this chapter was to present the basic concepts that were adopted for this research in order to implement CBR using the *TA-3* framework. Having these concepts well-explained, we move on to the next phase of applying them for the problem domain-stroke. The next chapter will demonstrate how the mechanism of CBR was carried out, starting from the preliminary steps of data collection and database organization, to the final steps of case representation, case base organization and case retrieval.

Chapter 5

The Modus Operandi – Development of Case Based Reasoning System for Stroke Patients

"Computers have promised us a fountain of wisdom but delivered a flood of data"

(A frustrated MIS executive)

This chapter gives an overview of the methodology of the research. It describes the main components of the experiments conducted to apply CBR in the stroke domain. It gives a brief description of data collection, case base management issues and the *TA-3* functional implementations. Following is the hypothesis of the thesis, restated in order to verify that the goals which were set in the beginning are fulfilled adequately.

> *CBR can be utilized to create a repository of information of the stroke patients who have an explicit diagnosis and prognosis and who are receiving subsequent rehabilitation. For a new stroke patient, whose diagnosis is yet to be confirmed and who has an indefinite prognosis, similar cases can be retrieved from the case base, to*

provide useful information. These potential solutions can assist the clinician for stroke diagnosis and assessment.

5.1 Stroke Data

The database currently has data for 80 controls and 108 stroke subjects, who are (or were) under treatment at Saint Mary's of the Lake Hospital. The stroke subjects were provided with a detailed questionnaire related to the KINARM assessment and were included in the study by clinicians, given that they fulfilled the following selection criteria:

1) Hemiparesis resulting from stroke occurring at most 3-4 weeks prior to participation in the study.
2) Absence of severe cognitive or effective dysfunction (mental health).
3) Absence of severe concurrent medical problems.
4) Absence of dysphasia – the inability to understand and follow the given instructions due to impairment of speech comprehension.
5) Endurance to complete the experimental protocol.

Due to severe impairments, muscle atrophy and weakness of the upper limb could occur as a result of prolonged and in-sufficient use by the subject. Eventually, this may masquerade the underlying deficits of the sensorimotor system that need to be fully understood by a clinician to plan an effective rehabilitation therapy [88]. Thus, as opposed to an earlier study with a unilateral-KINARM device [89], where subjects were admitted at least 6 months after the occurrence of stroke, this study aims at capturing the upper limb impairments at their earliest stage.

5.1.1 Raw Data

Experimental (KINARM) Data: The data from KINARM is collected for each Center-Out reaching trial (for details please refer to Section 3.4, Chapter 3). About 40 different data parameters are recorded each millisecond for the length of the trial (three seconds). These data parameters are stored in various tables of the database. Table 5.1 provides further details of these tables and their corresponding parameters. Other KINARM tasks have already been discussed in Section 3.4. For the scope of this research, in case base development, only the Center-Out reaching task is considered.

TABLES	KINARM PARAMETERS
SETS	• Task Number • Task Code • Task Description • Main Arm • Task Variant
CONDITIONS	• Reach angle • Reach magnitude • Target id sequence
TARGETS	• Target id • x and y coordinates relative to origin at centre hold target • Radius of target displayed (virtual) • Accepted radius of target (logical)
FEATURES	• End position of hand (x, y) and joint angles (elbow and shoulder) • First peak tangential velocity • Max tangential velocity • Movement onset • Movement offset • Reaction time • Total movement time • Name of method or algorithm used to derive the feature • Error codes output by the derivation algorithm

Table 5.1: Tables and their corresponding KINARM parameters that constitute the KINARM database (Courtesy of LIMB- Laboratory of Integrative Motor Behavior).

Clinical Data: The clinical data is collected manually on assessment forms (refer to the Appendix for the detailed Forms A and B) by the physiotherapist (Mary Jo Demmers at Saint Mary's of the Lake Hospital). The data from the forms is entered manually in the database (by Helen Bretzke, the database administrator, and Kim Moore, the lab technologist).

TABLES	**CLINICAL PARAMETERS**
FEATURES	• Trial key • Arm • Feature • Method • Time • Feature Value • Units
ASSESSMENTS	• Subject key • Height • Weight • CT/MRI(Dates) • Handedness • Reflex Biceps Left and Right • Folstein scores • Ashworth Left and Right • ROM Left and Right • Dynaheld Left and Right • Thumb Left and Right • Chedoke Left and Right • Vision Left and Right • …
STROKE_ SUBJECT_VISITS	• Date • Subject Key • Date of Birth • Type of Stroke • Side of Brain • Lesion Location • Vascular Territory • Structures Damaged • …

Table 5.2: Tables and their corresponding clinical parameters that constitute the clinical data in the database. (Courtesy of LIMB- Laboratory of Integrative Motor Behavior).

The clinical data is comprised of two types of information, the subject's biographical information (age, sex, weight, height etc.), and physical information (strength scores, reflexes, tone, proprioception, grip and pinch strength scores, Purdue pegboard scores, Chedoke-McMaster scores, vision, FIM scores etc.). This information is stored in the database in corresponding tables. Table 5.2 further elaborates the storage of data with respect to a few of the database tables.

5.1.2 Database

The previous sub-section described the data stored in the tables. The next step is to introduce the actual database of this research. HUMAN2 (alias CLINICAL) is a DB2 [100] database that stores experimental (KINARM) as well as clinical data. This database is currently under development. Drivers for connecting to DB2 and executing SQL queries in a Mat lab running environment have been developed earlier [99]. Figure 5.1 demonstrates how the structure of the database has been organized. Table 5.3 shows the various data entities and their corresponding units in which they are measured and are stored in the database.

Data Entities:	**Units**
Distance	Metres
Angle	Radians
Load	Nanometres(Nm)
Date Format	YYYY-MM-DD
Time Format	HH:MM:SS
Time	Seconds(s)

Table 5.3 Data entities and their units as used for storing data in the database.

5.1.3 Views of the Clinical Database

In the CLINICAL database, a special feature of '*views*' has been created by the database manager. A *view* can be referred to as a read-only table. As a result of generating queries (using SELECT statements), the results of expressions returned from a query is stored in them. They are also significant because the data can be presented conveniently from multiple tables which are linked by their primary and foreign keys.

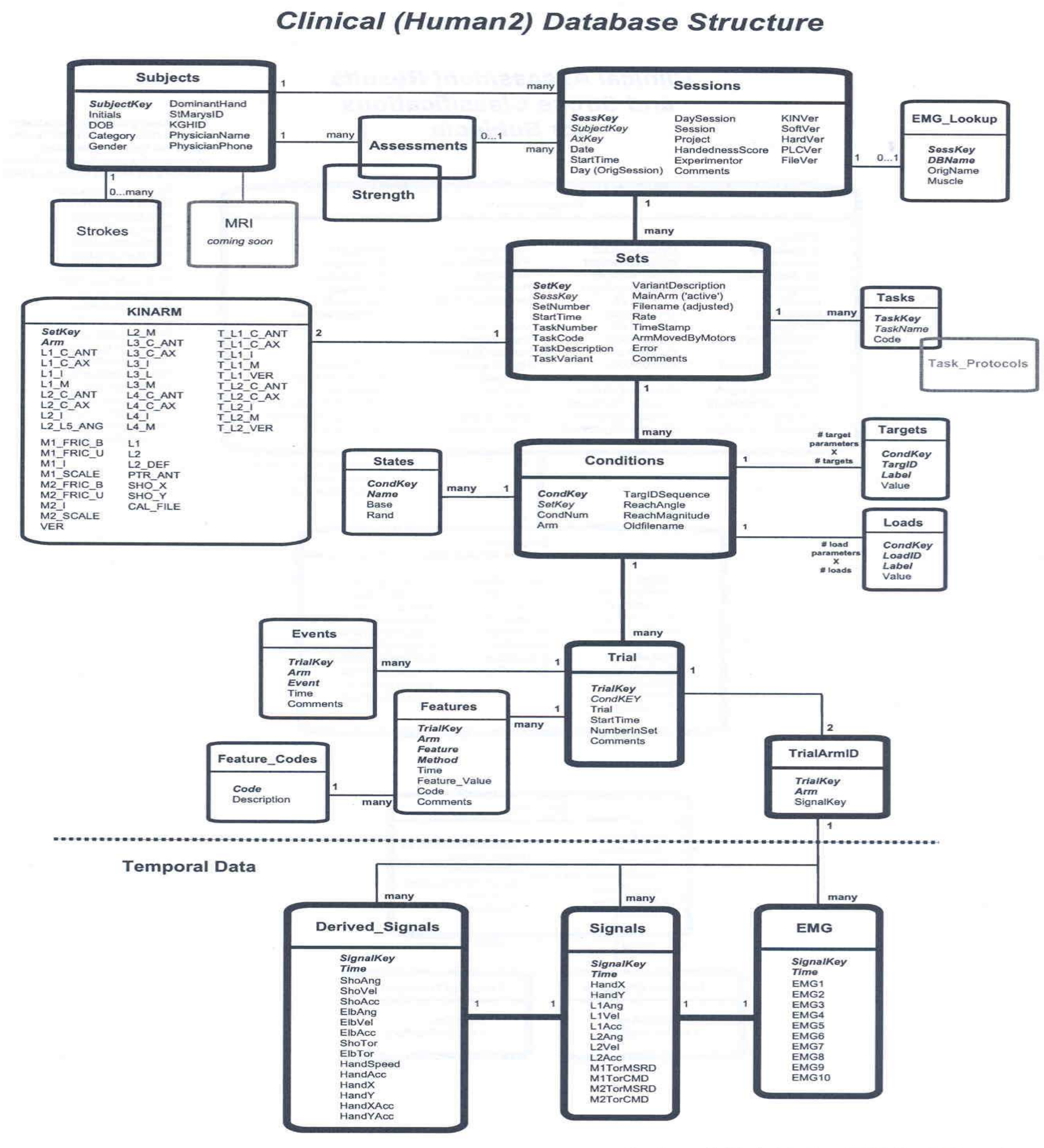


Figure 5.1: A demonstration of the Clinical database structure showing various tables constituting the database, their features and the relationships among them.(Courtesy of LIMB)

This feature has been effective in accessing the data for the case base. Following is a list of examples illustrating various views and presenting data by linking multiple related tables:

- STROKES_FOR_SUBJECTS: This view was created by linking STROKES and SUBJECTS tables.
- STROKE_SUBJECT_VISITS: This view is the result of linking existing view, STROKES_FOR_SUBJECTS, with the SESSIONS table.
- KEYS_LOOKUP: This is a convenience table which links all of the tables in the hierarchy by their primary and foreign keys. Using this view, for instance, the user can ask for al trial keys for a given subject, session (day) and set.
- SESSIONS_AND_SUBJECTS: As the name explains, this view is created by linking SESSIONS taken and the SUBJECTS table.

5.2 Case Base

The database described in the previous subsection provides most of the information necessary for populating our case base. But before continuing, its appropriate to distinguish the main difference between a database and a case base. A database is a structured collection of records or data that is stored in a computer system [101]. A database usually contains software (database management system) so that a person or program can use it to *answer queries,* or *extract the desired information*. On the other hand, a case base is a collection of previous cases or problems that are stored as a repository in order to be utilized for *solving a new case or a new problem*. Secondly, in databases queries extract information from the database on the basis of a word-for-word match or according to the provided statement conditions, whereas in our case base, there's a context-based retrieval. A context is defined as explicitly comprising of a set of allowable range of attribute values, therefore, cases that fulfill the criteria in a context, are retrieved as matching cases.

A case base is composed of cases that contain quantitative, textual or categorical information, whereas a database structure (e.g. relational database) consists of one or more tables contained in files, and each table defined by rows and columns. However, as a matter of fact, both the data structures are meant for storage but the utilization and the mechanism of data retrieval are the features that explicitly distinguish one from the other.

For this research, from the database we selected 35 stroke subjects and 10 controls for our case base. Out of these 45 subjects, 19 were female and 26 were male. The number of cases could have been increased, but at this point, these were the only cases that were complete, without any missing data. The stroke and control subjects included in the study varied in age (22-90 years old). Out of 35 stroke subjects, 17 were with lesion on the right hemisphere of the brain, 16 with lesion on the left hemisphere, and 2 with both the left and right side affected.

For the purpose of simplicity, the development of the CBR system was sub-divided into five main phases, which are in accordance with the objectives of this research as well. Figure 5.2 gives a picturesque demonstration of the entire procedure from entering data into the database, to accessing data and transforming it into a case base and achieving the corresponding results.

Phase I – Representation of cases – Case Structure

Phase II – Retrieval of Cases – Context–based criterion

Phase III – Experiments and Results

Phase IV – Testing and Validation of Results

Phase V – Adaptation

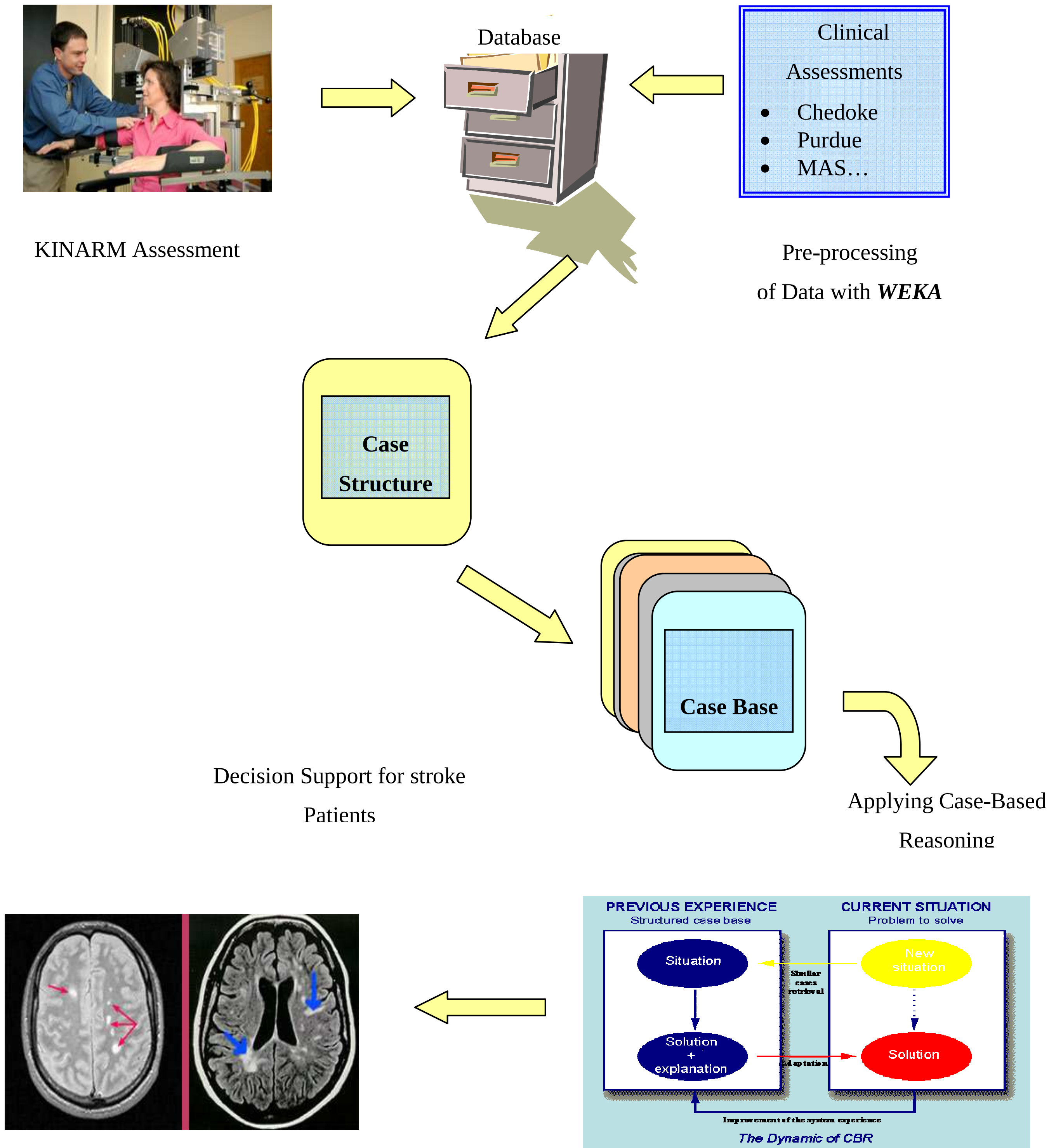


Figure 5.2 Pictorial demonstration of CBR system for stroke-patient data.

5.3 Phase I – Representation of Cases

The first phase in building the case base commences with the first objective of the thesis and that is to represent the cases by building an appropriate case structure from the pre-screened data. During the screening of data, it was ensured that the data used was complete. This was an important step because any missing data might lead to uncertain consequences; therefore, all those cases that had any missing data were not included in the study. The following three steps were employed to accomplish this phase:

- Step I – Attribute Selection
- Step II – Classification
- Step III – Case Structure in $\mathcal{TA}$ - $\mathcal{3}$

5.3.1 Step I - Attribute Selection

Attribute selection is an important step in this research due to the fact that with an enormous amount of data being produced by KINARM at a frequency of 1000 Hertz, there are 1000 time values generated per second. Each trial of KINARM (Center-Out reaching task only), takes maximum 10 seconds. As mentioned earlier (Section 3.4), there are 8 targets and 8-10 trials per target. This adds up to about 64-80 trials for a single session, and multiplying it by two for both the left and right hand, makes it almost a million values per session. Therefore, attribute selection played a major role and is a significant contribution of this thesis.

In Section 4.3.1.2, we explained the structure and functionality of *WEKA* [112]. *WEKA* has played an important role in determining the selection and ranking of attributes, using machine learning algorithms in order to construct the case structure for the CBR. Please refer to the Appendix, for a detailed list of all the attributes before attribute selection was performed. Table 5.4 demonstrates the lists of attributes selected by the evaluator methods to *classify type of stroke*. One important thing to be mentioned here is the *goal of classification*. In this case, the goal was *type of stroke*, with change in the goal of classification, different sets of attributes with different ranking would be generated but it was noticed that principal components selected the same attributes regardless of the classification criterion.

Sr. No.	Evaluator Method Used	Search Method Used	Attributes Selected and Ranked
1.	Cfs Subset Eval	BestFirst	15,19
2.	ChiSquared Attribute Eval:	Ranker	18,5,2,15,6,19,11,9,20,10,21,8,4,1,7,3, 23,22,25,24,13,12,17,14,16
3.	Classifier subset Evaluator:	Greedy Step wise	None
4.	Gain Ratio Attribute Eval :	Ranker	15,9,11,18,5,2,6,19,10,21,8,20,4,1,3,7, 23,22,25,24,13,12,17,14,16
5.	Info Gain Attribute Eval :	Ranker	18,5,2,15,6,9,11,19,20,10,21,8,4,1,7,3, 23,22,25,24,13,12,17,14,16 : 25
6.	One RAttribute Eval :	Ranker	10,8,9,13,11,12,3,1,2,7,4,5,23,24,21,22 ,15,14,18,25,17,19,16,6,20
7.	Principal Components	Ranker	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16, 17,18
8.	ReliefF Attribute Eval :	Ranker	9,11,24,15,19,14,16,12,17,18,25,13,20, 22,7,6,2,5,23,21,4,10,3,1,8
9.	Symmetrical Uncert Attribute :Eval:	Ranker	15,18,5,2,9,11,6,19,10,20,21,8,4,3,7,1, 23,22,25,24,13,12,17,14,16
10.	SymmetricalUncertAttribute SetEval :	Greedy Step wise	None
11.	Wrapper SubsetEval:	Greedy Step wise	None

Table 5.4: Ranked list of attributes attained by using the corresponding evaluator and search methods in WEKA. Column 3 shows the respective number of the attribute as selected and ranked by the corresponding search and evaluator method.

Having a number of selected attribute-lists, in order to choose the most appropriate one, a scheme was defined which is referred to as “SAS” (Scheme for-Attribute-Selection). According to SAS, the ranking of each attribute was aggregated as the sum of ranking, based on each evaluator method. The attributes with the smallest sum value are the ones with highest ranks. A constant (n+1) is added every time an attribute does not appear in a list; ‘n’ being the total number of attributes selected (27+1). Due to this addition, the rank would increase by a value of 28 and the less important attributes would be maintained at a lower rank. For further details of selected attributes, please refer to the appendix.

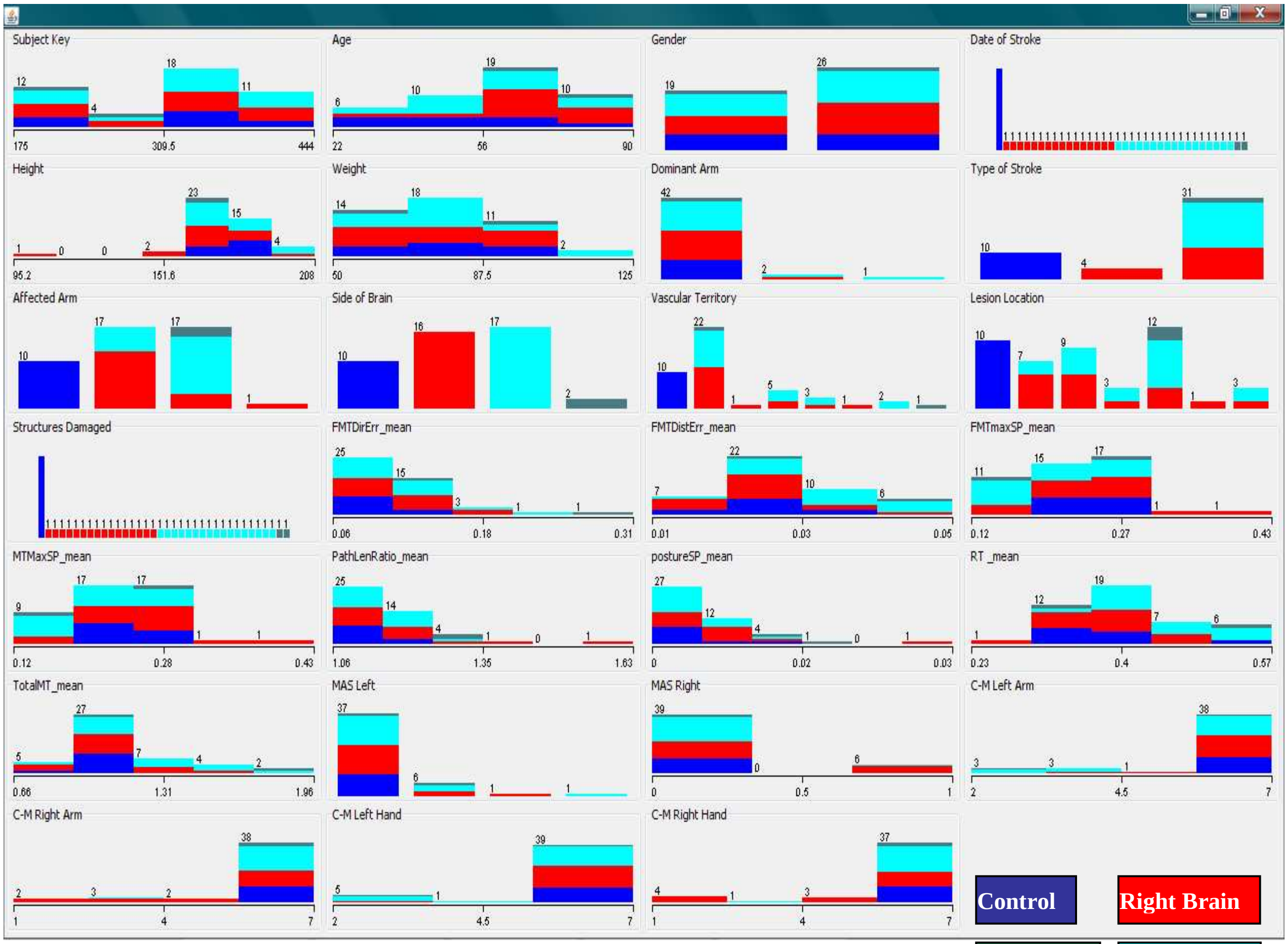


Figure 5.3 Visualizations of various attributes in WEKA.

5.3.2 Step II – Classification in *WEKA*

Classification is another important and significant automated function of WEKA that was used to identify predictor attributes for CBR. The application itself is not very complicated but the results obtained are quite significant. WEKA has a number of classifiers including *bayes, functions, lazy, meta, mi, misc, trees* and *rules*. Each one of the classifiers further has numerous functions. One thing to be noted here is that these classification results have been an important milestone in defining the retrieval criterion for context–based retrieval. Further details follow in the next section, in retrieval.

Feature	**Classification Algorithm**	**Correctly Classified**	**Incorrectly Classified**
Type of Stroke	Trees-J-48-C 0.25-M2	44/45 97.70%	1/45 2.22%
Side of Brain	Trees-J-48-C 0.25-M2	40/45 88.89%	5/45 11.11%

Table 5.5: Classification results performed in WEKA.

The following figures will further elaborate this process of classification in terms of the important attributes that reflect the results shown in the table 5.5.

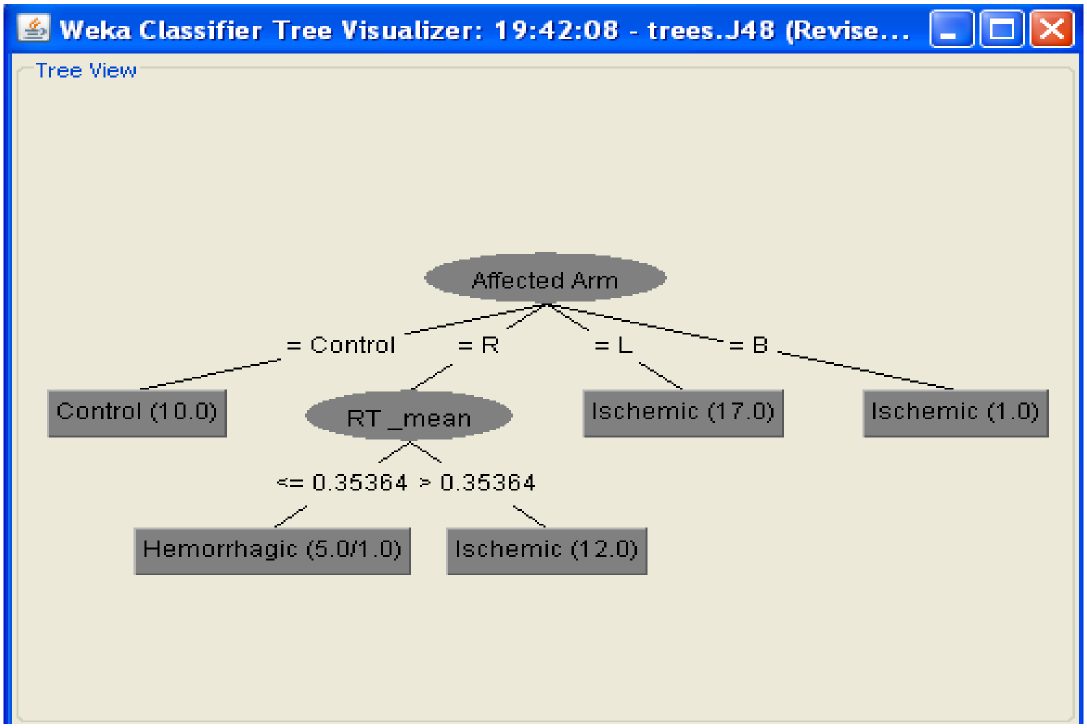


Figure 5.4: Classification for Type of Stroke: Control / Hemorrhagic / Ischemic Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2 Correctly Classified Instances 44 (97.78 %) Incorrectly Classified Instances 1 (2.22 %)

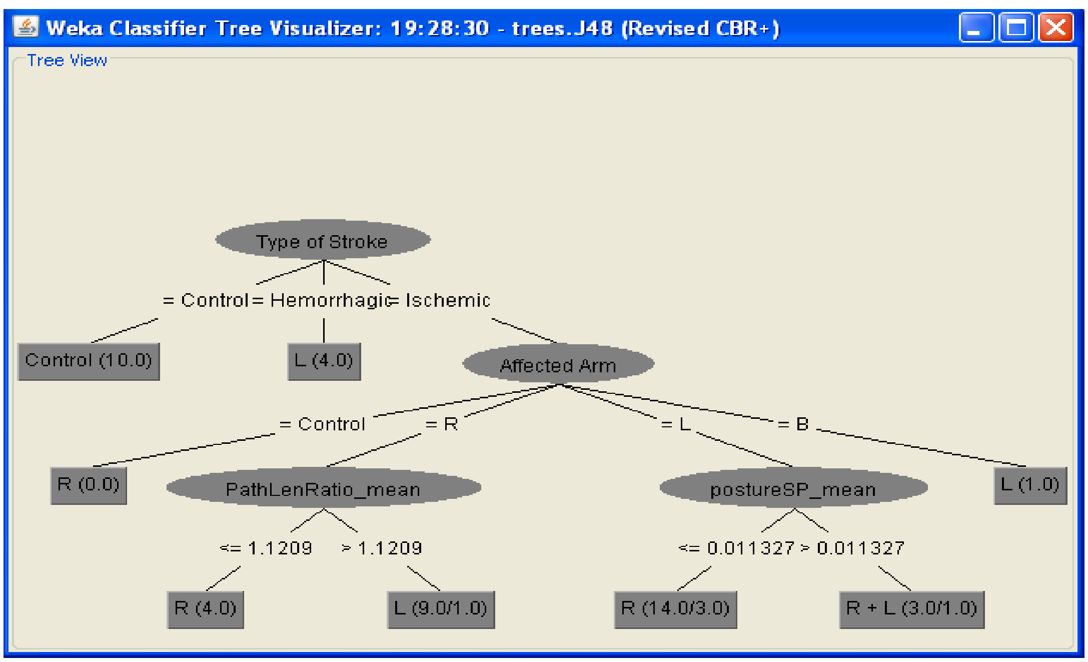


Figure 5.5: Classification for Side of Brain: Control / L / R/ B Scheme: weka.classifiers.trees. J48 -C 0.25 -M 2 Correctly Classified Instances 40 (88.89 %) Incorrectly Classified Instances 5 (11.11%)

5.3.3 Step III - Case Structure in TA - 3

TA-3 is a versatile framework for implementing a CBR system, as it can handle both quantitative and qualitative data. As explained in Section 4.1.3, a case is composed of three main parts: *problem*, *solution* and the *outcome*, but in this CBR system, the case structure has been slightly changed due to insufficient data at this stage of research. However, the attributes that were selected by 'attribute selection' using *WEKA*, constitute the following three parts of case structure for this case base system: *description*, *problem* and *solution*. These three sections in the case structure are explained as follows:

Description: All those selected attributes, which may be relevant but are not predictive, should be assigned to this category of the data. For instance, *subject key* which is not predictive, but without this attribute, identification of one case from the other would not be possible, therefore, it is assigned to the description data. *Solution*: This is another non-predictive category which contains the set of attributes describing the goal, for instance, the *vascular territory* of the stroke patients. It also contains feedback or outcome, like *lesion location*. *Problem*: This is the category that contains the predictive data. Even if the predictivity is in question, the attribute is still included since the retrieval system can be later adjusted (through restriction / relaxation Section 4.2.1.2). Attributes like *affected arm* and *KINARM scores* are the predictive attributes in this category. Figure 5.6 displays the structure of a case in CBR system.

Based on this structure, cases that constitute the case base are referred to as the "*source cases*". A *source case* corresponds to a control subject, or a previous stroke patient who has a confirmed diagnosis as well as prognosis. Therefore, the information in a *source case* may be prolific for a new *target case* and may act as a milestone in terms of treatment and rehabilitation.

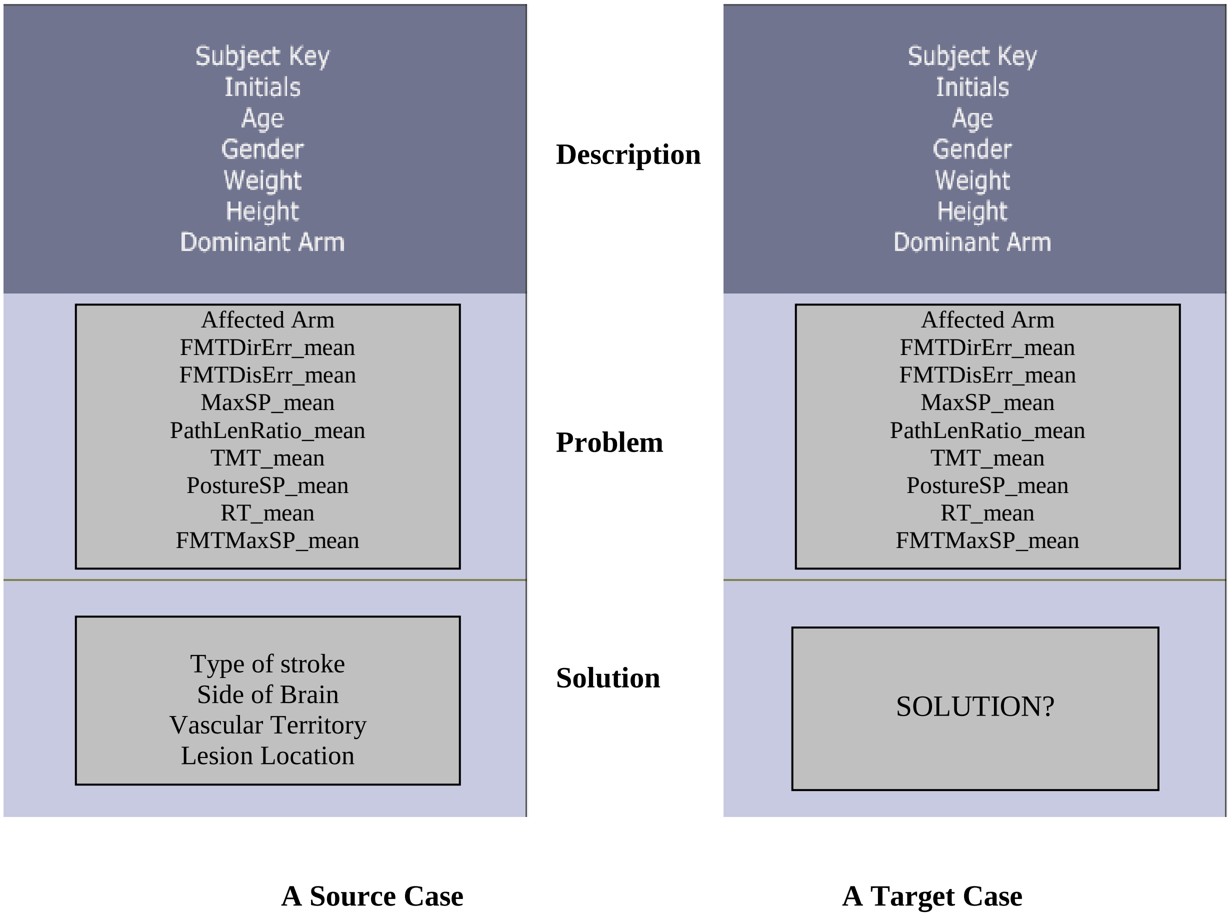


Figure 5.6: Composition of a case structure - the basis of CBR organization.

On the other hand, the "input case" which initially is not a part of the case base is the case that needs to be solved and is denoted as the "target case". It has the description and problem but does not have a solution yet. The goal of CBR is to draw a solution for the target case. The target case here refers to a new stroke patient whose diagnosis is yet to be confirmed and who has an indefinite prognosis. Figure 5.7 further elaborates how cases are represented in *TA-3*.

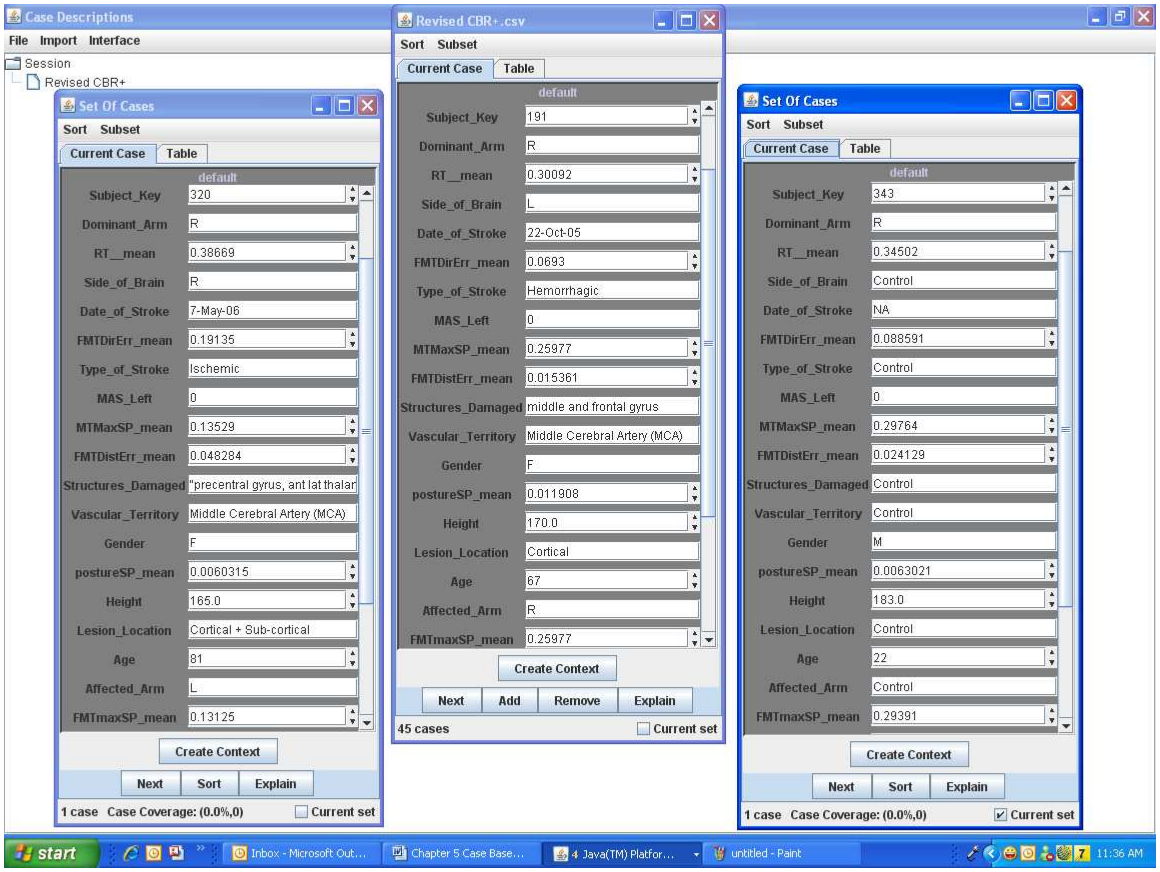


Figure 5.7: View of $\mathcal{TA}$-3 showing three different source cases with corresponding attributes of patients with subject keys 191, 320 and 343.

5.4 Phase II – Retrieval of Cases

Having the case base built, the next step is to proceed towards the third objective of this thesis, which is to finalize a *retrieval criterion* capable of retrieving similar cases, when a target case is provided. *Identification* of *appropriate attributes* to be considered *for matching* is the main step in defining the *retrieval criterion*. This is the point where applying automated machine learning classification was prolific. As mentioned earlier in Section 5.3.2, with the application of classification and attribute selection functions, the *predictor* attributes, that constituted the *problem* part of the case structure, were identified.

As explained in section 4.2.3, the main retrieval criterion is context-based where the *Context* is a view of a case, comprising of a finite set of attributes with associated constraints on the attribute values. *TA-3* provides a flexible approach in making the context an explicit parameter in the similarity function [81]. This means that for a particular retrieval request, the reasoner can specify the context as a subset of useful attributes, and can also apply constraints (automatically or manually) on the attributes within that context.

In order to carry out experiments three contexts, A, B and C, were defined and were based on the automated classification performed by *WEKA*. Results from different contexts and comparing them in terms of maximum true positives and least false positives, is shown in Table 5.6. Each attribute in a context is assigned a priority which is responsible for the transformation that takes place during retrieval. For instance, a *lower priority attribute* is more likely to undergo *transformation*, whereas a *higher priority attribute* will remain unchanged. Therefore, if one attribute has a low priority of 0, and another has a high priority of 3, the constraints on the low priority category will be relaxed three times before any change is made to the high priority category during transformation. In this way even if the relevance of certain attributes is uncertain, they can still be included (with a low priority) and will not negatively affect the system performance. The lower the priority, the higher the chance of transformation and vice versa.

Context A	**Priority**	**Context B**	**Priority**	**Context C**	**Priority**
RT_mean	1	Affected Arm	3	Affected Arm	8
Affected Arm	0	RT_mean	2	FMTDirErr_mean	7
		PathLenRatio_mean	1	FMTDisErr_mean	6
		PostureSp_mean	0	MTMaxSP_mean	5
				PathLenRatio_mean	4
				TMT_mean	3
				PostureSP_mean	2
				RT_mean	1
				FMTMaxSP_mean	0

Table 5.6: Context A, B and C; their constituent features and corresponding priorities.

5.5 Phase III – Experiments and Results

The main objective of this experimentation was to be able to classify a new stroke subject according to the following four perspectives:

- To classify the type of stroke: *hemorrhagic or ischemic.*
- To classify the stroke subject as a *right brain affected* or *left brain affected* stroke.
- To classify the prognosis of stroke patient in terms of *affected vascular territory* and identify the *lesion location.*
- To differentiate a *stroke* subject from a *control*.

Possible results of retrieval could be:

- No cases retrieved – meaning no match found
- All cases retrieved are of the same category, or
- The result is a mixture of cases from different categories.

The first result implies that either there are too few cases in that class, or the range in context is too small, or the similarity function needs to be redefined. The second result is simple and applicable, therefore, the solution of the returned cases could be applied to the target case. However, a third and interesting possibility is a mixture of different categories where some cases satisfy few constraints of the context while some do not. Figure 5.8 displays a snap shot from TA-3 showing the retrieval phenomenon with respect to transformations applied.

Figure 5.8: Different retrieval results inTA-3 reflecting variations in transformations. More cases are retrieved with increasing relaxation (12) and with increase in restriction, the number of cases falls to (5), (1) and no cases.

Trial No.	***Context***	***Target Case***	***Relaxation***	***No. of cases retrieved***	***True Positives***	***False Positives***	***True Negatives***	***False Negatives***
1	A	Control	**0%**	**5**	**4**	**1**	**34**	**6**
			50%	**10**	**9**	**1**	**34**	**0**
2	B	Control	0%	5	5	0	35	5
			50%	10	10	0	35	0
3	C	Control	**0%**	**5**	**5**	**0**	**35**	**5**
			50%	**10**	**10**	**0**	**35**	**0**
4	A	Left Brain Stroke	0%	2	2	0	29	14
			50%	10	8	2	27	8
5	B	Left Brain Stroke	**0%**	**7**	**7**	**0**	**29**	**9**
			50%	**10**	**7**	**3**	**26**	**9**
6	C	Left Brain Stroke	0%	3	3	0	29	13
			50%	12	12	0	29	4
7	A	Right Brain Stroke	**0%**	**8**	**8**	**0**	**28**	**9**
			50%	**11**	**10**	**1**	**27**	**7**
8	B	Right Brain Stroke	0%	4	4	0	28	13
			50%	10	8	2	26	9
9	C	Right Brain Stroke	**0%**	**9**	**9**	**0**	**28**	**8**
			50%	**10**	**10**	**0**	**28**	**7**

Table 5.7: Retrieval results reflecting number of cases retrieved with varying contexts. The experiment was conducted with alternating target cases as control, left brain affected and right brain affected strokes. The 0% and 50% column represents the corresponding change in retrieval results with respective transformation. The change in transformation clearly shows the changed number of retrieved cases. More similar cases are retrieved with the increase in relaxation of the retrieval criterion.

According to the graph in Figure 5.9 on the next page, it is clearly understood that context C has the best retrieval results in terms of highest number of true positives and least number of false positives. Therefore, context C was preferred over the other two contexts and chosen for the experimentation for diagnostic purpose.

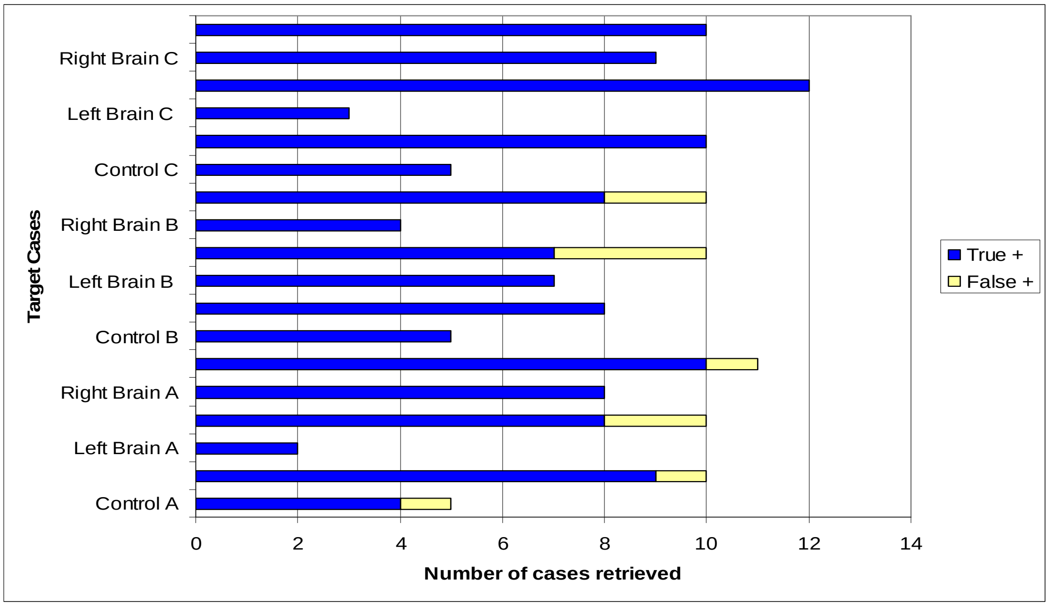


Figure 5.9: Graph showing the retrieved true and false positives with respect to contexts A, B and C. Context C(on top) clearly reveals not only the highest number of true positives but also absence of any false positives, shown as yellow tip.

In order to perform statistical analysis of the results, the sensitivity, specificity and accuracy were calculated in order to quantify the performance of the CBR system. The sensitivity or the recall rate measures the proportion of actual positives which are correctly identified as such (i.e. the percentage of sick people who are identified as having the condition) and the specificity measures the proportion of negatives which are correctly identified (i.e. the percentage of well people who are identified as not having the condition). A sensitivity of 100% means a test recognizes all sick people as such where as a specificity of 100**%** means that the test recognizes all healthy people as healthy. Table 5.8 shows the result of these statistical values.

$$\textbf{\textit{Sensitivity}} = \frac{\sum \text{True Positives}}{\sum \text{True Positives} + \sum \text{False Negatives}} * 100\%$$

$$\textbf{\textit{Specificity}} = \frac{\sum \text{True Negatives}}{\sum \text{True Negatives} + \sum \text{False Positives}} * 100\%$$

$$\textbf{\textit{Accuracy}} = \frac{\sum \text{True Positives} + \sum \text{True Negatives}}{\sum \text{True Positives} + \sum \text{False Negatives} + \sum \text{True Negatives} + \sum \text{False Positives}} * 100\%$$

To explain the designation of true and false positives and negatives, respectively let us take for instance the case of a left brain affected stroke as a target:

- A *True Positive* is a left brain stroke case that was correctly retrieved according to the context.
- *False Negative* is a left brain stroke case that was left during retrieval but should have been retrieved.
- *True Negative* will be all the controls and right brain stroke cases other than the left brain affected cases.
- *False Positive*: A control or a right brain affected case, incorrectly retrieved in a left brain stroke target.

Sensitivity	***Specificity***	***Accuracy***
50.97 %	98.06 %	82.42 %

Table 5.8: Statistical results

5.6 Phase IV - Testing and Evaluation for diagnostic support

A good evaluation not only analyzes how well the system performs, but it may also reflect how the system can be improved. Furthermore, the evaluation may also reveal the various factors influencing the system's performance that can be regulated to achieve optimum results. In order to meet our objective to evaluate the accuracy of the CBR system in classifying cases, cross-validation testing [91], was applied. Cross-validation is the statistical practice of partitioning a sample of data into subsets in a way that the analysis is initially performed on a single subset, whereas the other subset(s) are retained for subsequent use in confirming and validating the initial analysis.

In order to perform *cross validation* for the CBR system, the data set was divided into two subsets. One subset of data is the *training set* with 30 cases and the other is the *validation* or *testing set with 15 cases*. The test set was used to assess the performance of the system by removing each case in the test set from the case base, one after the other, considering it a *target case*. Based on this test case (*target case*) from the system, a context was defined. The system was then directed to retrieve one or more similar case(s) from the case base, based on the current context.

The results of these experiments are elaborated in the following Table 5.9. The target case column displays the information whether it is a right arm affected stroke, a left arm affected stroke or a control. Total cases are the total number of cases retrieved, for instance in trial 1, the target case was a right affected arm stroke. 11 cases were retrieved altogether out of which, 9 strokes were ischemic and 2 were hemorrhagic. The majority refers to ischemic. In vascular territories, there are 9 MCAs (middle cerebral artery), 1 PCA (posterior cerebral artery) and 1 VA (vertebral artery). MCA is the leading one. Out of 11 retrieved cases, 9 are with left side of the brain affected and 2 with the right brain affected so more cases refer to the left brain. For lesion location 5 are SC (sub cortical), 3 are C (cortical), 2 are C+S (Cortical+Subcortical) and 1 is with lesion in the BS (Brain stem). Proposed solution is derived on the basis of majority of retrieved cases. Therefore, for the first trial, the proposed solution is that the target case is a subject with ischemic stroke, left side of the brain affected with an MCA and SC affected by stroke. When the proposed solution was checked if what was predicted about the target case was right or wrong, all four solutions that were proposed were correct, therefore the error percentage was calculated to be 0%, where as when 1of the solution is wrong out of 4, as in trial 3, the error percentage is 25%.

Trial No.	Target Case	Cases Retrieved	Diagnostic Analysis				Proposed Solution	Error % in prediction
		Total Cases	Type of Stroke	Vascular Territory	Affected Side of Brain	Lesion Location		
1	**Affected Right arm**	11	**Isch:9** Hem:2	**MCA:9,** PCA:1, VA:1	**Left:9** Right:2	**SC:5,** C:3, C+SC:2, BS:1	Ischemic, MCA, Left Brain, SC	0%
2	**Affected Right arm**	10	**Isch:8** Hem:2	**MCA:5,** PA:1, PIA:1, VA:2, PCA:1	Left:10	**BS:4**, SC:2, C:3, C+SC:1	Ischemic, MCA, Left Brain, BS	0%
3	**Affected Right arm**	2	**Isch:1** Hem:1	**MCA:2**	Left:2	**C:2**	I/H, MCA, Left Brain, C	Conflict between I/H 25%
4	**Affected Right arm**	10	**Isch:10**	**MCA:6,** PICA:1, PA:1, VA:1, PCA:1	Left:10	C:3, **C+S:4,** SC:2, C:1	Ischemic, MCA, Left Brain, C+S	0%
5	**Affected Right arm**	11	**Isch:11**	**MCA:7**, PA:1, PICA:1, VA:2	**Left:9,** Right:2	**C:4,** C+S:2, BS:3, SC:2	Ischemic, MCA, Left Brain, C	0%
6	**Control**	10	Control	N/A	N/A	N/A	Control	0%
7	**Control**	10	Control	N/A	N/A	N/A	Control	0%
8	**Control**	10	Control	N/A	N/A	N/A	Control	0%
9	**Control**	10	Control	N/A	N/A	N/A	Control	0%
10	**Control**	10	Control	N/A	N/A	N/A	Control	0%
11	**Affected Left arm**	2	**Isch:2**	**MCA:2**	Left:1, Right:1	**SC:2**	Ischemic, MCA, L/R Brain, SC	L/R Brain conflict 25%
12	**Affected Left arm**	11	**Isch:11**	**MCA:8,** PICA:1, , PCA:1, PCA+MCA:1	Left:2, **Right:8,** L+R:1	**C+S:6**, SC:3, C:1, Cereb:1	Ischemic, MCA, Right Brain, C+S	0%
13	**Affected Left arm**	11	**Isch:11**	**MCA:8,** PICA:1, , PCA:1, PCA+MCA:1	Left:2, **Right:8,** L+R:1	C:1, **C+S:6,** Cereb:1, SC:3	Ischemic, MCA, Right Brain, C+S	C instead of C+S 25%
14	**Affected Left arm**	1	**Isch:1**	**MCA:1**	**Right:1**	**C+S:1**	Ischemic, MCA, Right Brain, C+S	0%
15	**Affected Left arm**	11	**Isch:11**	PCA:3, **MCA:6,** PCA+MCA:1, PICA:1	Left:1, Right:9, L+R:1	SC:6, C:1, **C+S:3**, Cereb:1	Ischemic, MCA, Right Brain, SC	PCA instead of MCA 25%

Table 5.9: Results of Cross Validation with 15 cases as targets in the testing set. Please refer to the Appendix for abbreviations of vascular territories and lesion locations.

Experiment	Hypothesis	Methodology	Diagnostic Results	
			True %age	**False %age**
Perspective 1	A stroke subject can be identified as suffering from a *hemorrhagic or ischemic stroke.*	Context C that comprised of 9 parameters was chosen as the most efficient and effective retrieval criterion. The constituent parameters of Context C were: Affected arm, FMTDirErr, FMTDistErr, MaxSP, Path LenRatio, TMT, PostureSP, RT and FMTMaxSP. One of the cases was selected at random by the CBR system as a target case such that the solution was unknown. The proposed solution was derived from retrieval results according to the context. The accuracy of proposed solution was determined by checking the actual solution of the target case.	93.3% 14/ 15	6.6% 1/15
Perspective 2	A stroke subject can be classified as a *right brain affected* or *left brain affected* stroke.		93.3% 14/15	6.6% 1/15
Perspective 3	The prognosis of a stroke subject can be predicted in terms of the potential *vascular territory affected* and the potential lesion *location.*		Vas.Ter 14/15 93.3% Les.loc 14/15 93.3%	Vas.Ter 1/15 6.6% Les.loc 1/15 6.6%
Perspective 4	A target case can be classified as a control or a stroke subject.		100% 15/15	0% 0/15

Table 5.10: Experiments, demonstrating the corresponding hypothesis, methodology and results of the classification.

5.7 Phase V – Scope of Adaptation

There is no specific adaptation module in the *TA-3* system. It is up to the user to re-use the retrieved cases in order to solve the new problem. The main goal is to be able to retrieve the appropriate cases that satisfy the context. According to *null adaptation* [70], once the goal is achieved, the case solutions can be re-used in any workable and practical manner by the domain experts or some other program that can provide decision support. As a reasoner, as far as the scope of this research is concerned, the objective is fulfilled. One of the approaches applied in this research to choose one case from a number of retrieved cases is to classify the retrieved cases in terms of number of transformations; the case with minimum transformations should be given priority over the others.

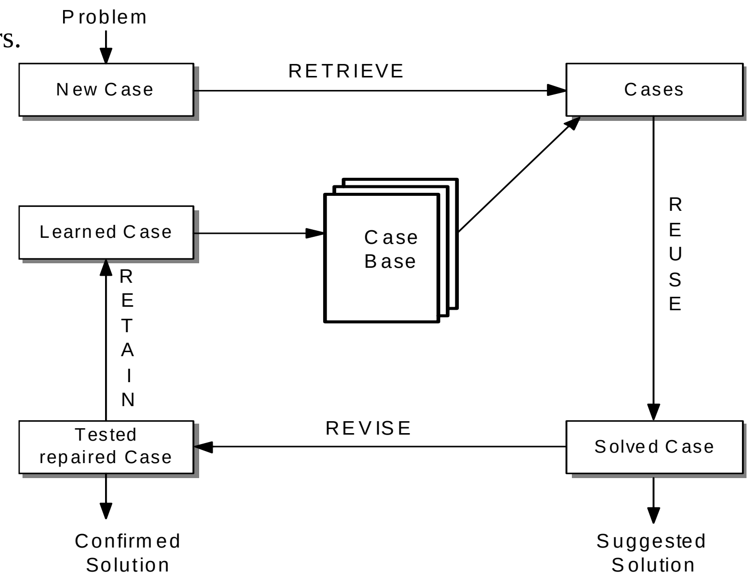


Figure 5.10: CBR Cycle

If we recall the CBR cycle repeated here as figure 5.10, the results refer to the "suggested solution" phase. The results are tested and verified by comparing the solution attained by applying CBR and according to the true and false percentage in Table 5.9, the diagnostic capabilities are significantly good. The results can be further improved with a variety in lesion location and vascular territory values as well as more number of hemorrhagic stroke subjects, which was limited for now.

Chapter 6

Conclusions

"No person was ever honored for what he received.

Honor has been the reward for what he gave."

(Calvin Coolidge)

This chapter concludes the thesis with a discussion of results that were derived from this research. It also outlines the contributions that were made by the application of this computational technique to the knowledge base. In addition, it gives a brief description of the future directions which offer a promising avenue for further research in the broad horizon of AI. This research enabled me to validate the significance of CBR for the stroke domain. The CBR system presented a simple approach towards reasoning in this domain by providing a flexible case representation, an efficient case base organization and an effective retrieval algorithm.

There are multiple features that were discovered by applying *TA-3* as a frame work for this research. Since *TA-3 is* a flexible system, it can be applied to any decision support system where information can be represented as attribute-value pairs, and where problems are solved by iteratively accessing and using previously derived information. *TA-3* is different from other case-based tools because it does not use pre-defined retrieval strategies. Instead, case retrieval is customized and can be dynamically changed for a particular domain and specific application. It provides a meaningful classification system which not only improves access time, but also makes visualization easier to understand. Knowledge-mining with *TA-3* is user-oriented; therefore it enables the user/reasoner to have full control of the precision, recall and coverage.

6.1 Objectives vs. Contributions

The major and most important contribution that this research has made is the opening of a new horizon in the field of stroke assessment and that is with the development of a new diagnostic support tool for the first time by implementing CBR. CBR has been successfully applied and demonstrated to have great results in health informatics and now with the domain of stroke, it adds to its list of diagnostic applications.

I would further like to recall the objectives that were stated in the first chapter in order to evaluate if they were successfully met by conducting this research:

- The first objective was to develop a case structure comprising of relevant attributes of stroke patient data that will have an impact on diagnosis and rehabilitation. This objective was fulfilled by performing "automated attribute selection" that produced a set of significant relevant attributes, and after applying machine learning classification, an appropriate case structure was successfully constituted.
- The second objective led to the construction of a case based system for implementing the CBR model. With this research a case base was built which comprised of forty-five (45) cases. Out of which there were ten (10) controls, seventeen (17) right brain affected strokes, sixteen (16) left brain affected strokes and two (2) with both sides of the brain affected.
- The third objective was to define a retrieval method to conduct CBR. *TA-3* was the tool used for devising a flexible approach for context-based retrieval criterion. Context was

employed as a user-defined, explicit parameter to carry out particular retrieval requests and the most appropriate context was chosen by comparing different context experiments.

- The fourth objective was to determine the diagnostic support measure that can be taken to propose the potential motor and / or sensory deficit based on the previous known impairments (solutions). By analyzing the results of retrieval experiments, four perspectives were defined as a means of diagnostic analysis, namely:1) identifying if it is a control or a stroke subject; 2)if a stroke, which type of stroke; 3) Which side of the brain was affected; 4) Identifying the affected vascular territory and the location of lesion; all based on the similar retrieved cases.
- The last two objectives referred to testing, evaluating and validating the CBR system performance. The sensitivity, specificity and accuracy were calculated for the experiments and the percentage of true and false results verifies the success of this application itself.
- The CBR system for stroke patients can be considered as a novel CBR application for the stroke domain that may facilitate the clinicians in not only their decision-making of the diagnosis and prognosis but also an effective means to validate the imaging test results (CT/MRI).
- KINARM was used for the assessment of stroke patients in this research, which was a more objective means of dysfunction assessment as compared to all the other clinical assessment protocols used till date.

6.2 Shortcomings

Every research has some shortcomings and deficiencies that create room for improvement. For this study I would say that data accuracy and completeness of data is a fundamental factor because no conclusion can be justified unless the authentication and comprehensiveness of input data is guaranteed. Secondly, with the increase in the number of representative cases and recorded tasks, the CBR performance can be further improved and be more prolific in terms of diagnostic accuracy.

6.3 Future Directions

- One of the most important factor that this research leads to is the field of *analysis of stroke rehabilitation outcomes*. CBR may prove to be an effective approach in analyzing outcomes of stroke rehabilitation, because it can be used as a repository of different stroke patients. In normal practice, the estimates and predictions of activity limitations/disability following a stroke are very difficult to obtain, because the patients that are selected for stroke studies are either population based or referral based. Therefore, it influences the severity of limitations measured in a stroke sample. This is one of the reasons why outcome measures may be inconsistent, unreliable or invalid. The times of assessment during recovery period also varies for the same reason.
- Using CBR as a diagnostic facilitator tool may also give the clinician an estimate of the time frame involved in rehabilitation.
- In future, it is very likely that with the availability of more periodic (clinical and KINARM) assessment data, the clinician / therapist would be able to decide what protocols can be prolific and what would not be beneficial for the patient in the light of what previous patients have experienced. As a consequence, it may prove to be an efficient strategy to implement cost analysis on rehabilitation of stroke patients.
- In terms of KINARM future innovations, an eye-tracking system is to be incorporated in the robotic setup, in order to elaborate the assessment of stroke patients by tracking their vision along with their ability to perform movement. This will not only enable the clinicians to quantify eye motor function of the stroke patients but eventually provide interesting outcomes of eye-hand coordination.
- The KINARM set-up is to incorporate a gaming interface, in order to avoid monotony of subjects during the reaching tasks that will not only keep them captivated, but also perform the experiment in a potentially better way.

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APPENDIX A

KINARM Specifications

Human KINARM Lab Specifications

Two motorized KINARM™ robots for simultaneous right and left-handed investigation

- Workstation and visual display for presentation of 2D virtual targets in the actual plane of limb motion
- System-integrated chair with wheelchair-style seating (including removable foot, arm and head rests)
- Data acquisition hardware, including up to 32 channels of analog input
- Dexterit-E™ - data acquisition and experimental control software
- Computer system to run Dexterit-E™ (including a real-time computer for precise and safe action)
- Simlib - a library of Simulink blocks to assist with rapid custom Task Program creation (Simulink and other Mathworks toolboxes must be purchased separately)
- Optional data analysis software (Visual 3D)

System Specifications:

- Real-time control and data acquisition at 1kHz
- Peak torque pulse of 12Nm (~35N at the hand)
- Feedback resolution of 0.0045°, (~30micron at the hand)
- End-point stiffness of ~5 N/mm
- 45" wide usable workspace
- Fits a large range of adult sizes (approximately 4'10" to 6'6")
- System footprint 10‘x10’ (when in use)

Human KINARM Lab Includes:

The human KINARM Lab is a complete research lab based on the KINARM, a robotic exoskeleton for the arm. Currently, the human KINARM Lab is used by basic and clinical researchers studying motor learning, coordination, neural basis of movement, Brain-Machine Interface, haptics, stroke, cerebral palsy, Fetal Alcohol Syndrome, cerebellar dysfunction, dystonia, and spinal cord injury.

Complete Research Lab

The human KINARM Lab lets you start collecting data immediately. Standard system includes two KINARM™ robotic exoskeletons for the upper limbs, 2D virtual reality display, experimental control software and hardware, ready-to-use tasks and optional data analysis software.

Study Both Arms Simultaneously

The use of two KINARM robots permits comparison of inter-arm performance as well as the study bimanual coordination.

Dual Function Robots

Each KINARM robot can be used as an exoskeleton for the shoulder and elbow (leaving the hand free to interact with objects in the environment) or as a hand-based end-point robot.

2D Virtual Reality

Standard system includes 45" wide 2D virtual reality display for natural, intuitive presentation of visual stimuli.

Easy To Use and Powerful

System includes Dexterit-E™, behavioural control and data acquisition software, which combines the power of a real-time operating system with the ease of a WindowsTM-based interface. Standard Task Programs can be used immediately for data collection. Custom Task Programs can be created using high-level graphical programming tools.

(Courtesy of BKIN technologies [115]

List of KINARM Tasks:

A – Unloaded targets in space

B – Sensory matching (human subjects only)

C – Passive movement

D – Postural trials where loads are applied, but no movement occurs

E – Reaching to targets in space with a viscous load applied

F – Reaching to targets in space with an interaction load applied

G – Reaching to targets in space with a bias load applied

H – Not assigned

I – Perturbation from centre target

List of Vascular Territory Abbreviations:

MCA: Middle Cerebral Artery

PCA: Posterior Cerebral Artery

VCA: Vertebral Cerebral Artery

PICA: Posterior Inferior cerebral artery

PA: Pontine Artery

List of Lesion location Abbreviations:

C: Cortical

SC: Sub-cortical

C+SC: Cortical +Sub-Cortical

Cer: Cerebellar

BS: Brain Stem

List of Attributes:

Clinical Data:	**Features Table:**
Affected Side	Trial Key
Initials	Arm
Date of Birth	Features
Age	Method
Gender	Time
Date of Stroke	Feature Value
Height:	Units

Weight

Dominant Hand

CT/MRI performed (Y/N)

Location of Stroke

Days since stroke

Sessions and Subjects Table:

Subject key

Date of birth

Expermentor

Project

Category(Stroke/Control)

Features for set table:

Set key

Condnum

Trial

Number in set

trial Key

Start time

Method

Arm

Feature

Time

Feature Val.

Code comments

Units

Strokes Table:

Stroke key

Stroke Subject visits table:

Date

Subject Key

Stroke Key

Type of Stroke

Side of Brain

Lesion Location

Vascular Territory

Structures Damaged

Assessments Table:

CT/MRI dates

Reflex Biceps (Left+Right)

Reflex Triceps (Left+Right)

Reflex Brachio (Left+Right)

Folstein Score

Ashworth (Left+Right)

ROM (Left+Right)

Dyna Hand (Left+Right)

Dyna Pinch (Left+Right)

Thumb (Left+Right)

Perdue (Left+Right)

Perdue (Assembly)

Perdue (Both)

Chedoke arm (Left+Right)

Chedoke Hand (Left+Right)

Vision (Left+Right)

Hemi Neglect

Type of stroke

Affected arm

Previous Stroke

Vasc Key

Comments

Location Key

Side of brain

Subjects Table:

Category

Gender

KGH ID

Physician Name

Physician Phone

Dominant Hand

Sessions Table:

Session

Day

Project

KIN Version

Soft Version

Hard Version

PLC Version

File Version

Session Key

Ax Key

Site Code

BIT

FIM Score

Aphasia

Proprioception

Sets Table:

Session Key

Set Number

Task Variable Key

Task Code

File name

Rate

Time Stamp

Arm moved by motors

Task description

Task variant

Variant Description

Trial Table:

Condition Key

Trial Key

Start Time

Numbers in set

Error

Comments

List of Selected Attributes:

Attribute Number		Name of Attribute	Sum of Rank -ing	Attribute Ranking according to various WEKA Algorithms: Cfs	Chi squar	Gain Ratio	Info Gain	One R	PCA	Sym. Uncert.	Wrapper
1	15	Affected Arm	47	15	18	15	18	10	1	9	15
2	9	FMTDirErr_mean	62	19	5	9	5	8	2	11	18
3	2	FMTDisErr_mean	68	(n+1)	2	11	2	9	3	24	5
4	11	MaxSP_mean	69	(n+1)	15	18	15	13	4	15	2
5	5	PathLenRatio_mean	75	(n+1)	6	5	6	11	5	19	9
6	18	TMT_mean	83	(n+1)	19	2	9	12	6	14	11
7	19	PostureSP_mean	87	(n+1)	11	6	11	3	7	16	6
8	6	RT_mean	98	(n+1)	9	19	19	1	8	12	19
9	10	FMTMaxSP_mean	99	(n+1)	20	10	20	2	9	17	10
10	8	Dominant Arm	110	(n+1)	10	21	10	7	10	18	20
11	4	Structures Damaged	117	(n+1)	21	8	21	4	11	25	21
12	7	Side of Brain	121	(n+1)	8	20	8	5	12	13	8
13	3	Date of Stroke	123	(n+1)	4	4	4	23	13	2	4
14	12	Vascular Territory	130	(n+1)	1	1	1	24	14	22	3
15	21	Lesion Location	133	(n+1)	7	3	7	21	15	7	7
16	1	Chedoke Arm_R	134	(n+1)	3	7	3	22	16	6	1
17	13	Chedoke Hand_L	141	(n+1)	23	23	23	15	17	2	23
18	20	Chedoke Hand_R	147	(n+1)	22	22	22	14	18	5	22
19	24	Chedoke Arm_L	159	(n+1)	25	25	25	18	(n+1)	23	25
20	23	Weight	156	(n+1)	24	24	24	25	(n+1)	21	24
21	22	Height	158	(n+1)	13	13	13	17	(n+1)	4	13
22	14	MAS_L	162	(n+1)	12	12	12	19	(n+1)	10	12
23	25	MAS_R	163	(n+1)	17	17	17	16	(n+1)	3	17
24	17	Gender	167	(n+1)	14	14	14	6	(n+1)	1	14
25	16	Age	174	(n+1)	16	16	16	20	(n+1)	8	16
26	26	Subject Key	183	(n+1)	20	10	20	2	(n+1)	17	10
27	27	Type of Stroke	224	(n+1)	(n+1)	(n+1)	(n+1)	(n+1)	(n+1)	(n+1)	(n+1)

List of selected attributes and their corresponding ranks according to the scheme for attribute selection (SAS).

APPENDIX B

Scanned Forms

Providence Continuing Care Centre

NATIONAL REHABILITATION REPORTING SYSTEM

Discharge Recording Form

Client Name: ______________________ **Record#** __________

ACTIVITIES AND PARTICIPATION

FIM™ instrument

	Discharge
Self-Care	
41. Eating	
42. Grooming	
43. Bathing	
44. Dressing—Upper Body	
45. Dressing—Lower Body	
46. Toileting	
Sphincter	
47. Bladder Management	
48. Bowel Management	
Transfers	
49. Bed, Chair, Wheelchair	
50. Toilet	
51. Tub, Shower	
Locomotion	
52. Walk/Wheelchair	⬭ Walk ⬭ Wheelchair ⬭ Both
53. Stairs	
Communication	
54. Comprehension	⬭ Auditory ⬭ Visual ⬭ Both
55. Expression	⬭ Vocal ⬭ Non-Vocal ⬭ Both
Social Cognition	
56. Social Interaction	
57. Problem Solving	
58. Memory	

FIM Levels

NO HELPER

7 Complete Independence (Timely, Safely)

6 Modified Independence (Device)

HELPER

Modified Dependence

5 Supervision

4 Minimal Assistance (Subject = 75% +)

3 Moderate Assistance (Subject = 50% +)

Complete Dependence

2 Maximal Assistance (Subject = 25% +)

1 Total Assistance (Subject = 0% +)

(NOTE: Leave no blanks; enter 1 if not testable due to risk)

PROVIDER TYPE

PT Support staff Involved in care Yes ☐ No ☐

OT Support staff Involved in care Yes ☐ No ☐

400233 (05/03) PAGE 6 OF 8 PATIENT RECORD FORM

Information is recorded in this form at the time of patient discharge from the hospital.

Dec. 4, 2006

Stroke Classification System

***indicates primary filing criteria**

Date(s) of Stroke(s):____

Number of Strokes*: One vs. Multiple

Side of Brain affected*: Left vs Right vs. Both

Anatomic Location*:

L/R Cortical
L/R Sub-cortical
L/R Cerebellum
L/R Brainstem

Provide anatomic structures damaged – (eg. caudate):______________________________
____
____
____

Vascular Territory(ies) and side(s) affected (if several strokes indicate date of strokes where possible)*:

L/R Anterior Cerebral Artery
L/R Middle Cerebral Artery
L/R Posterior Cerebral Artery

L/R Anterior Communicating Artery
L/R Posterior Communicating Artery

Basilar Artery
L/R Vertebral Artery

L/R Superior Cerebellar Artery
L/R Anterior Inferior Cerebellar Artery
L/R Posterior Inferior Cerebellar Artery

Form used to collect information for the stroke subjects during their KINARM assessment in order to classify the degree of impairment. (Continued on next page)

Size of each lesion (provide details):______________________________
____
____
____
____
____

Mechanism of Stroke*: Ischemic vs. Hemorrhagic

If ischemic - embolic or thrombotic or unknown?
If embolic - ?cardioembolic source? Oral contraceptive related? Drug related?
Was this a migrainous stroke?
Was this a “lacunar infarct”?

Ischemia Acute Treatment:
TPA/Thrombolytics given: Y or N
Hemorrhage after TPA?
Did the Patient receive Carotid Endarterectomy (Y/N) – indicate date?

If hemorrhagic - subarachnoid or intracerebral?
Was there an aneurysm? Was there trauma? Hematologic Abnormality?

Hemorrhage Acute Treatment:
Was surgery performed? Describe the procedure… (eg. stenting vs. craniotomy and clipping, or craniotomy and removal of dead tissue)

History of Transient Ischemic Attacks (TIAs)?____________________________
____
____

Handedness of patient*: L vs. R vs. Ambi

Affected Arm: L vs. R vs. Both vs. Neither

Perceptual Impairment:

Visual Field Deficit (Y/N):
If yes: L/R Hemianopsia
Other (list type)

Clinical Evidence of L/R Hemineglect (Y/N)

Quantitative Assessment of Arm Movements in Stroke Patients Using KINARM
ANAT-024-05

KINARM Project: Control - CIHR

Date of Clinical Assessment:____________________
Date of Robotic Assessment:____________________
Clinical Examiner:________________________
KINARM Examiner:________________________

Control Biographical Info

Patient Code:____________________

Age:____________________

Sex:____________________

Weight:____________________

Height:____________________

Handedness:____________________

CT/MRI head scan ever performed (Y/N) and Date:__________

History of Previous TIAs (Y/N)? How many and when? __________________
____

History of Previous Stroke (Y/N)? How many, when and where in brain? _______
____

Highest level of education obtained?______________

Medical/Surgical Comorbities:

1.____________________
2.____________________
3.____________________
4.____________________
5.____________________
6.____________________
7.____________________
8.____________________
9.____________________
10.____________________

Form used to collect information for the stroke and control subjects during their KINARM assessment ***Page 1 of 9 (Continued)***

Quantitative Assessment of Arm Movements in Stroke Patients Using KINARM
ANAT-024-05

Current Medications:

1.________________________
2.________________________
3.________________________
4.________________________
5.________________________
6.________________________
7.________________________
8.________________________
9.________________________
10.________________________

Physical Examination

Strength

Shoulder (score 0 to 5)

	Left	Right
Shoulder Flexion	0 1 2 3 4 5	0 1 2 3 4 5
Shoulder Extension	0 1 2 3 4 5	0 1 2 3 4 5
Shoulder Abduction	0 1 2 3 4 5	0 1 2 3 4 5
Shoulder Internal Rotation	0 1 2 3 4 5	0 1 2 3 4 5
Shoulder External Rotation	0 1 2 3 4 5	0 1 2 3 4 5

Elbow (score 0 to 5)

	Left	Right
Elbow Flexion	0 1 2 3 4 5	0 1 2 3 4 5
Elbow Extension	0 1 2 3 4 5	0 1 2 3 4 5
Forearm Supination	0 1 2 3 4 5	0 1 2 3 4 5
Forearm Pronation	0 1 2 3 4 5	0 1 2 3 4 5

Wrist (score 0 to 5)

	Left	Right
Wrist Flexion	0 1 2 3 4 5	0 1 2 3 4 5
Wrist Extension	0 1 2 3 4 5	0 1 2 3 4 5

Fingers (score 0 to 5)

	Left	Right
Finger Flexion	0 1 2 3 4 5	0 1 2 3 4 5
Finger Extension	0 1 2 3 4 5	0 1 2 3 4 5
Finger Abduction	0 1 2 3 4 5	0 1 2 3 4 5

Quantitative Assessment of Arm Movements in Stroke Patients Using KINARM
ANAT-024-05

Reflexes

(score 0 to 4+)

	Left	Right
Biceps	0 1+ 2+ 3+ 4+	0 1+ 2+ 3+ 4+
Triceps	0 1+ 2+ 3+ 4+	0 1+ 2+ 3+ 4+
Brachioradialis	0 1+ 2+ 3+ 4+	0 1+ 2+ 3+ 4+

Tone

Modified Ashworth Score for elbow flexors

Left	Right
0 1 1+ 2 3 4	0 1 1+ 2 3 4

Available Range of Motion(degrees, as measured with Goniometer)

	Left	Right
Elbow		
Shoulder – Int. Rot.		
Shoulder – Ext. Rot.		

Proprioception

Thumb Localizing Task

Left	Right
0 1 2 3	0 1 2 3

After confirming normal proprioception in the unaffected arm, by the patient touching the nose while their eyes closed, the examiner lifts the affected arm to eye level. The patient is then asked to grasp the thumb of the affected hand with the good hand, and this is repeated. The examiner then places a hand over the patient's eyes and raises the patient's affected hand to well above patient's head. The patient is then asked to grasp the thumb as before.

Severe Difficulty (score = 3): The patient is unable to find his thumb and does not climb up the affected arm in order to locate it.

Moderate Difficultly (score = 2): The patient finds the affected arm and then this leads him to find the affected thumb.

Slight Difficulty (score = 1): The patient aims in the right general direction but misses the affected thumb by no more than 3 inches, and is able to locate it within 5 seconds.

No Difficulty (score = 0): The patient is able to locate the affected thumb accurately.

Grip and Pinch Strength by Dynamometer:

Grip Strength Left Hand		Grip Strength Right Hand	
Pinch Strength Left Hand		Pinch Strength Right Hand	

Effective Date –January 24, 2007 3

Quantitative Assessment of Arm Movements in Stroke Patients Using KINARM
ANAT-024-05

Purdue Peg Board:

Scoring

-test to be done in consecutive order, unless the subject is left handed, then test batteries 1) and 2) are reversed

Description	Score
1) Right Hand (30 seconds)	
2) Left Hand (30 seconds)	
3) Both Hands (30 seconds)	
4) Right + Left + Both hand (note: this is not an actual test; it is a mathematical sum calculation)	
5) Assembly (60 seconds)	

Chedoke-McMaster Stroke Assessment Scale for U/E

CONTROLS WILL BE SCREENED TO ENSURE THEY CAN COMPLETE LEVEL 7, IF A CONTROL FAILS LEVEL 7, THEY WILL BE REJECTED FROM THE STUDY

Taken from Chedoke-McMaster Stroke Assessment, Development, Validation and Administration Manual, Table 2.4

Stages of Motor Recovery of the Chedoke Assessment Impairment Inventory

Stage	Description
1	Flaccid Paralysis is present. Phasic stretch reflexes are absent of hypoactive. Active movement cannot be elicited reflexly with a facilitory stimulus, or volitionally.
2	Spasticity is present and is felt as a resistance to passive movement. No Voluntary movement is present but a facilitory stimulus will elicit the limb synergies reflexly. These limb synergies consist of stereotypical flexor and extensor movements.
3	Spasticity is marked. The synergistic movements can be elicited voluntarily, but are obligatory. In most cases, the flexion synergy dominates the arm, the extension synergy the leg. There are strong and weak components within each synergy
4	Spasticity decreases. Synergy patterns can be reversed if movement takes place in the weaker synergy first. Movements combining antagonistic synergies can be performed when the prime movers are the strong components of the synergy.
5	Spasticity wanes, but is evident with rapid movement and at the extremes of range. Synergy patterns can be reversed even if the movement takes place in the strongest synergy first. Movements utilizing the weak components of both synergies acting as prime movers can be performed. Most movements become environmentally specific.
6	Coordination and patterns of movement are near normal. Spasticity as demonstrated by resistance to passive movement is no longer present. A large variety of environmentally specific patterns of movement are now possible. Abnormal patterns of movement with faulty timing emerge when rapid or complex actions are requested.
7	Normal. A "normal" variety of rapid, age appropriate complex movement patterns are possible with normal timing, co-ordination, strength and endurance. There is no evidence of functional impairment compared to the normal side. There is a "normal" sensory-perceptual-motor system.

Quantitative Assessment of Arm Movements in Stroke Patients Using KINARM
ANAT-024-05

RIGHT ARM

(Affected/Unaffected – circle one)

Starting position: *Sitting with forearm in lap in in a neutral position, wrist at 0°, and fingers flexed* unless indicated by elements *in italics* that are different or more specific

	ARM		HAND
1	☐Not yet stage 2	1	☐Not yet stage 2
2	☐Resistance to passive abduction or elbow extension ☐Facilitated elbow extension ☐Facilitated elbow flexion	2	☐Positive Hoffman ☐Resistance to passive wrist or finger extension ☐Facilitated finger flexion
3	☐Touch opposite knee ☐Touch chin ☐Shoulder shrugging > ½ range	3	☐Wrist extension > ½ range ☐Finger/wrist flexion > ½ range ☐*Supination, thumb in extension*: thumb to index finger
4	☐Extension synergy then flexion synergy ☐Shoulder flexion to 90° ☐ *elbow at side, 90° flexion*: supination then pronation	4	☐Finger extension then flexion ☐Thumb extension > ½ range then lateral prehension ☐Finger flexion with lateral prehension
5	☐Flexion synergy then extension synergy ☐Shoulder abduction to 90° with pronation ☐*Shoulder flexion to 90°*: pronation then supination	5	☐Finger flexion then extension ☐*pronation*: finger abduction ☐*Hand Unsupported:* opposition of thumb to little finger
6	☐Hand from knee to forehead 5x/5 seconds ☐*Shoulder flexion to 90°*: trace a figure 8 ☐*Arm resting at side of body:* Raise arm overhead with full supination	6	☐*Pronation*: tap index finger 10x in 5 seconds ☐*Pistol Grip*: pull trigger, then return ☐*Pronation:* wrist and finger extension with finger abduction
7	☐*Sitting:* clap hands over head then clap hands behind back 3x/10 seconds ☐ *shoulder flexion to 90°:* scissor in front 3x in 5 sec ☐ *elbow at side, 90° flexion:* resisted shoulder extension rotation	7	☐thumb to finger tips, then reverse 3X in 12 sec ☐bounce a ball 4 times in succession, then catch ☐pour 250ml from 1 litre pitcher, then reverse

☐Stage of Right Arm ☐Stage of Right Hand

Page 5 of 9

Quantitative Assessment of Arm Movements in Stroke Patients Using KINARM
ANAT-024-05

Left ARM
(Affected/Unaffected – circle one)

Starting position: *Sitting with forearm in lap in in a neutral position, wrist at 0°, and fingers flexed* unless indicated by elements *in italics* that are different or more specific

	ARM		HAND
1	☐Not yet stage 2	1	☐Not yet stage 2
2	☐Resistance to passive abduction or elbow extension ☐Facilitated elbow extension ☐Facilitated elbow flexion	2	☐Positive Hoffman ☐Resistance to passive wrist or finger extension ☐Facilitated finger flexion
3	☐Touch opposite knee ☐Touch chin ☐Shoulder shrugging > ½ range	3	☐Wrist extension > ½ range ☐Finger/wrist flexion > ½ range ☐*Supination, thumb in extension*: thumb to index finger
4	☐Extension synergy then flexion synergy ☐Shoulder flexion to 90° ☐ *elbow at side, 90° flexion*: supination then pronation	4	☐Finger extension then flexion ☐Thumb extension > ½ range then lateral prehension ☐Finger flexion with lateral prehension
5	☐Flexion synergy then extension synergy ☐Shoulder abduction to 90° with pronation ☐*Shoulder flexion to 90°*: pronation then supination	5	☐Finger flexion then extension ☐*pronation*: finger abduction ☐*Hand Unsupported:* opposition of thumb to little finger
6	☐Hand from knee to forehead 5x/5 seconds ☐*Shoulder flexion to 90°*: trace a figure 8 ☐*Arm resting at side of body:* Raise arm overhead with full supination	6	☐*Pronation*: tap index finger 10x in 5 seconds ☐*Pistol Grip*: pull trigger, then return ☐*Pronation:* wrist and finger extension with finger abduction
7	☐*Sitting:* clap hands over head then clap hands behind back 3x/10 seconds ☐ *shoulder flexion to 90°:* scissor in front 3x in 5 sec ☐ *elbow at side, 90° flexion:* resisted shoulder extension rotation	7	☐thumb to finger tips, then reverse 3X in 12 sec ☐bounce a ball 4 times in succession, then catch ☐pour 250ml from 1 litre pitcher, then reverse

☐Stage of Left Arm ☐Stage of Left Hand

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Vision

Acuity:

	Left	Right
Visual Acuity		

Fields:

Normal (circle)

Or

Diagram Field Loss:

Left Eye:

Left hemifield	Right hemifield
Upper Centre	Upper
Lower	Lower

Right Eye:

Left hemifield	Right hemifield
Upper Centre	Upper
Lower	Lower

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FIM Questionaire Score:

Appendix A

Muscle Strength Grading
(taken from *A Guide to Physical Examination and History Taking*, Barbara Bates, 1987)

GRADE	DESCRIPTION
0	No muscular contraction detected
1	A barely detectable flicker or trace of contraction
2	Active movement of the body part with gravity eliminated
3	Active movement against gravity
4	Active movement against gravity and some resistance
5	Active movement against full resistance without evidence of fatigue. This is normal muscle strength.

Reflex Grading
(taken from *A Guide to Physical Examination and History Taking*, Barbara Bates, 1987)

GRADE	DESCRIPTION
0	No Response
1+	Somewhat diminished; low normal
2+	Average; normal
3+	Brisker than average; possibly but not necessarily indicative of disease
4+	Very brisk, hyperactive; often indicative of disease; often associated with clonus

Modified Ashworth
(taken from *Recovery after Stroke*, Ed. Barnes, Dobkin and Bogousslavsky, 2005)

SCORE	DESCRIPTION
0	No increase in tone
1	Slight increase in muscle tone, manifested by a catch and release or by minimal resistance at the end of ROM when the affect part(s) is moved in flexion or extension
1+	Slight increase in muscle tone, manifested by a catch, followed by minimal resistance throughout the remainder (less than half) of the ROM
2	More marked increase in tone through most of the ROM but affected part(s) easily moved
3	Considerable increase in muscle tone, passive movement difficult
4	Affected part(s) rigid in flexion or extension

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Modified Edinburgh Handedness Inventory

Please indicate your preferences in the use of hands in the following activities putting + in the appropriate column. Where the preference is so strong that you would never try to use the other hand unless absolutely forced to, put + +. If in any case you are really indifferent put + in both columns.

Some of the activities require both hands. In these cases the part of the task, or object, for which hand preference is wanted is indicated in brackets.

Please try to answer all the questions, and only leave a blank if YOU have no experience at all of the object or task.

	Task	Left	Right
1	Writing		
2	Drawing		
3	Throwing		
4	Scissors		
5	Toothbrush		
6	Knife (without fork)		
7	Spoon		
8	Broom (upper hand)		
9	Striking a match (match)		
10	Opening a box (lid)		
i	Which foot do you prefer to kick with?		
ii	Which eye do you use when using only one?		