NAIST-IS-DD0861210

Doctoral Dissertation

Two Case Studies of Using Fuzzy Modeling for a Classification System in Medical Applications

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September 5, 2011

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A Doctoral Dissertation
submitted to Graduate School of Information Science,
Nara Institute of Science and Technology
in partial fulfillment of the requirements for the degree of
Doctor of ENGINEERING

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Abstract

Fuzzy logic approaches have been widely used and demonstrated successfully in medical fields as well as in other areas since they were introduced by Zadeh. The fuzzy classifier is an algorithm using fuzzy logic that assigns a class label to an object based on the object description. A fuzzy classifier applies all possible input combinations through its membership function to make final output determination which represents the degree of belonging to the output class.

We demonstrate such a classification process using fuzzy classifier in medical applications. Fuzzy logic is suitable in modeling systems which rely on subjective and intuitive decisions from the experts or physicians. In this thesis, two medical applications are demonstrated, first, fatigue classification based on parameters of eye movement, and second, cardiac rest period determination for magnetic resonance coronary angiography. Both applications utilized the same concept of modeling the particular system. To determine the parameter for a membership function threshold, we utilize data-driven from obtained dataset in first application, and use expert-knowledge in second application. The results from both applications show the effectiveness of the fuzzy logic approach in classifying the input variable into certain output category.

In the first application, we explored how eye movement data responded to a fatigue condition due to a nine-hour learning task. We collected eye movement data while observing student participants watching visual stimuli. We classified

*Doctoral Dissertation, Department of Bioinformatics and Genomics, Graduate School of Information Science, Nara Institute of Science and Technology, NAIST-IS-DD0861210, September 5, 2011.

the fatigue condition of the students based on their eye movement parameters. We also investigated the relationship between fatigue and the saccadic eye movement parameters. The results showed that the fuzzy classifier can discriminate the fatigue with an accuracy of 86.54%.

In the second application, we investigated how well the fuzzy classifier determined the cardiac rest period using magnetic resonance coronary angiography based on the normalized cross-correlation value and the normalized frame number of the 4-chamber consecutive frame images of the subject. Furthermore, as the experimental results show, the fuzzy classifier can model the physician-specific decision in determining the rest period.

The results from these two applications showed that fuzzy logic provides a means for encapsulating subjective and intuitive decision process in an algorithm, and have an advantage for modeling uncertain environments.

Keywords:

fuzzy modeling, classification, eye movement, fatigue, cardiac rest period

ファジー分類器の医療応用に関する研究*

Zainal Arief

論文内容の要旨

ファジーロジックは、1965 年に Zadeh によって提案されて以来、正確な数理・確率モデルが立てにくい複雑な実システムのモデリングに広く用いられてきた。しかし、医療分野については他の産業分野に比べてファジーロジックを利用したシステムはまだ少ない状態にある。本論文では医療応用に関するファジー分類器の枠組みを提案し、2 種類のケーススタディによってその有用性を示す。

最初の例は、9 時間に及ぶ授業の前と後に測定した眼球運動のデータから、受講による疲れを同定するためのファジー分類器である。眼球運動の Latency、Duration、Velocity、および Deviation の４変数に対する８個の Gaussian 型ファジーメンバーシップ関数と２つのルールおよび MIN-MAX 法による脱ファジー処理によって 86.54 ％の正確度を示すファジー分類器を構成した。

次の例は、心臓冠動脈ＭＲＩ検査の前準備に必要な拍動静止期間の検出に対する応用である。心臓の動きの静止期間は一般に拡張期の中期から終期にかけて存在するが、具体的にどの期間を静止とするかは、検査機器の性能や対象疾患あるいは医師の好みによって微妙に異なる。この医師による判断の相違をファジー分類器によってモデル化することを目標とした。心臓横断面動画における冠動脈部分の逐次差分と、心拍周期によって正規化した各医師による静止期間のデータに関する台形状のファジーメンバーシップ関数と９種類のルールを構成して、個々の医師の判断を近似する個人別ファジー分類器を作成した。これによって、個人差の生じる理由をモデル上で理解することが可能になった。

以上、医療応用を目指したファジー分類器の構成方法をのべ、その有用性を２種類の医療応用によって示した。

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キーワード
ファジー分類器，疲れ，眼球運動，心臓の動きの静止期間

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Chapter 1

Introduction

This dissertation summarizes the author's research experience and results achieved in fuzzy modeling. The capability of the fuzzy logic with its linguistic terms to model the systems behavior attracted and encouraged this research. This chapter describes the general background, the research problem and explains what is to be expected from the rest of the dissertation.

1.1. Background

Fuzzy logic, as one of the artificial intelligent technique, models with reasoning of inherently vague or uncertain concepts and provides a representation scheme and a function for modeling them. Since the first fuzzy theory paper was published by Zadeh [2], fuzzy logic approaches have been widely used and demonstrated successfully in medical fields [1, 3–7] as well as in other areas.

Fuzzy logic based approach models the system in transparent way than the *black-box* model. We may say that fuzzy modeling is filling the range between the so called *white-box* and *black-box* modeling approaches, which is often denoted as *gray-box* modeling [8]. From the system, the certain parts are modeled with physical knowledge, while uncertain parts are *black-box* modeled.

Many real-world systems are inherently nonlinear and cannot be represented by linear models used in conventional system identification. The fuzzy logic is one of the most popular model developed recently for the identification of non-linear systems. Compared to other well-known approximation techniques such as artificial neural networks, fuzzy systems provide a more transparent representation of the system under study, which is mainly due to the possible linguistic interpretation as rules. The logical structure of the rules eases the understanding and analysis of the model in a semi-qualitative manner, close to the way humans reason in real world.

The Fuzzy logic is especially useful for the systems that cannot be precisely described by mathematical models; those that have significant uncertainties or contradictory conditions, and linguistically controlled devices or systems. It has an advantage for modeling with the problem of uncertainty and imprecision environments by providing conceptual framework in modeling the systems. Intuitive and subjective judgment from experts may be suitably modeled using fuzzy classifier, especially in the medical field where decisions often rely on the expert opinions.

The fuzzy logic has considerable potential for practical applications because such a design method is closer to human thinking and perception and reduces development time.

In this dissertation, we present the generalized fuzzy classifier system to determine the input system in certain category based on the extracted descriptor. The two applications describes how fuzzy logic works, and shows the effectiveness of fuzzy classifier method.

1.2. Research contribution

Probabilistic and fuzzy logic approaches may characterize the system behaviors for a limited dataset in the complex system. Instead of a probabilistic approach, fuzzy logic was used in this research due to the dependency of the output on the extracted features.

Though any modeling concept may be carried out to mimic the experts behavior, the fuzzy logic approach may models the system in simple way. The faced environment may affect the possible extracted feature from the input. While the if-then rule built in the inference system acts as the main process in the classification system. Finally, a simple min-max height method is applied to the defuzzification process to generate classification output.

Through this research, we want to apply computer aided diagnosis based on fuzzy logic approach to assist medical application in fatigue classification and cardiac rest period determination. Our main idea in this dissertation are how to generate the structure and the parameter in the fuzzy logic model. We also want to emulate the decision of an experts or physician in a fuzzy based model. The model may encapsulate their intuitive decisions. The advantages of the fuzzy classifier are promptly illustrated in the two applications given in chapter 3 and in chapter 4. In this dissertation, the primary contributions are

- Utilization of fuzzy logic in modeling the system, provides a means for encapsulating the subjective and intuitive decision making process in an algorithm in simple way.
- Provide a relationship of fatigue and eye movement parameter in our first application wherein the idea of eye movement parameter is used to classify the fatigue condition, and provide a simple way to model physician decision in determining the cardiac rest period in the second application.
- Performance evaluation is done based on specificity, sensitivity and accuracy to validate our proposed modeling method.
- Although our method is used on a specific application, it can be used in other applications with some parameter adjustment.

We seek for the formalization of methodology that allows us to emulate the subjective determination process of human beings with maximum efficiency. Modifications of original algorithms are suggested or adapted from the works of other authors.

1.3. Dissertation Layout

This dissertation is organized as follows:

- **Chapter One** gives the introduction of the fuzzy classifier and the background of the research. The research contributions and the dissertation layout are also given in this chapter.

- **Chapter Two** gives the overview of fuzzy set theory. The structure of the fuzzy model as a classifier is presented in this chapter, covering the concept, structure and parameter generation based on the *if-then* rule system. Related works of other authors were presented in this chapter. The chapter provides the foundation of fuzzy logic that are necessary for the research.

- **Chapter Three** presents an application of fuzzy classifier in fatigue classification based on eye movement parameters. Some related works and background are also given to briefly explain the investigated field. The classification system consists of three stages: image preprocessing, feature extraction and classification process.

- **Chapter Four** covers an application of fuzzy classifier in determining the cardiac rest period from magnetic resonance coronary angiography. The determination system is referred from physicians decision. In this application, the fuzzy classifier models the specific physician decision in determining the cardiac rest period.

- **Chapter Five** summarizes the work already done in our research, continues with the possible developed issue and plan for further research.

Chapter 2

Fuzzy logic for classification system

Ideally, a system S has the model M(S) if M(S) makes it possible to predict the response of S for any given input. Using restricted sets of inputs, the model usually approximates the system response. In traditional approaches, the model is usually represented as collection of differential or difference equation.

In Fuzzy logic based approaches, the model is represented by the set of fuzzy if-then rules. Through the use of this fuzzy if-then rule collection, the model can possibly predict the response of the system [9]. The encapsulated if-then rule which is essential in the design of rule-based systems may be assumed as a processing module. A static or dynamic system which makes use of fuzzy sets or fuzzy logic and of the corresponding mathematical framework is called a fuzzy system. There are a number of ways fuzzy sets can be involved in a system such as a collection of if-then rules with fuzzy predicates, or as a fuzzy relation, and a specification of the systems parameters.

The model developments are important in many disciplines of science and engineering. The model is useful for the system behavior analysis to give insight and better understanding of the mechanism of the system. The design of new processes or controllers needs the model to simulate its characteristics. The usefulness of the model encouraged the models development of the real systems.

Modeling problems are usually solved in the context of mathematical modeling using algebraic, differential or difference equations. Such (white-box) modeling, requires quite understanding on the process that may not possible. Another way is to model the system using input-output data (black-box modeling). The structure of black-box models usually is not related to the structure of the real system and model parameters have no physical meaning. Sometimes a combined approach is used where physics is used for general differential equations and certain model parameters or functions are identified from data using a black-box technique (gray-box modeling) [10]. In the computational part of this hybrid model and application environment, fuzzy sets are instrumental in the formation of an interface. The operation of the fuzzy model is greatly affected by the way the input elements are encapsulated into the fuzzy sets.

This chapter started with the explanation of fuzzy system. Section 2.1 provides a concise introduction and summary of the basic concepts of fuzzy logic i.e: fuzzy sets, fuzzy rules, fuzzy reasoning and fuzzy models which covered the fuzzy classifier, and the previous conducted research in medical application.

2.1. Fuzzy System

The system which make use of fuzzy sets or fuzzy logic and of the corresponding mathematical framework is called a fuzzy system. The ways of the fuzzy sets or fuzzy logic involved to the system may be in the form of:

- System description. A System may be defined as collection of fuzzy relation or fuzzy rules.
- Systems parameters specification. The used parameters in the systems are fuzzy numbers which commonly express the uncertainty.
- Input-output of the systems. Uncertainty input such as noisy data, human perception, etc., can be processed in the fuzzy systems.

The fuzzy systems can be implemented for modeling, data analysis, classification, prediction and control. Commonly, fuzzy system is defined by means of if-then rules, or rule based fuzzy systems. In this dissertation, which focuses on the classification system, for simplification purpose, we call the fuzzy rule based classification as fuzzy classifier.

This section provides an explanation about the basic concepts of fuzzy systems covering fuzzy sets, fuzzy rules, fuzzy reasoning and fuzzy model. More details about fuzzy classifier will be discussed in the following section.

2.1.1 Fuzzy Sets

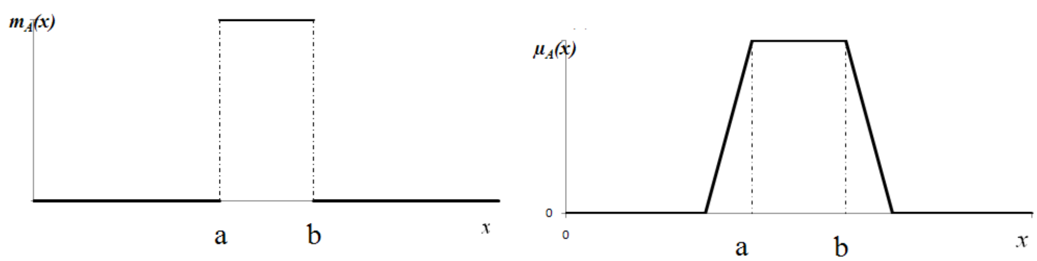
The illustration of classical and fuzzy sets in Fig. 2.1 emphasize the difference of the sets behavior. Given the classical set:

$$A = \{x|a \leq x \leq b\} \tag{2.1}$$

As described in Fig. 2.1(a) there is a clear boundary point a and b such that if x is greater than or equal to a, or if x is less than or equal to b then x is belong to the set A, otherwise x does not belong to this set. This behavior is described in the characteristic function:

$$m_A(x) = \begin{cases} 1 & , x \in A \\ 0 & , x \notin A \end{cases} \tag{2.2}$$

which can be denoted as $m_A(x) \in \{0, 1\}$. The characteristic function of element x to set A is either zero or one. The characteristic function will show whether the element x belongs to or does not belong to the set A.



(a) Crisp set

(b) Fuzzy set

Figure 2.1: Difference of characteristics function of Crisp and Fuzzy set

In Fig. 2.1(b), the numbers located way below a or way above b absolutely does not belong to the set A. The numbers laid between a and b strongly belong to the set A, while the numbers located in the slope area have a certain degree of belonging to the set A, which is represented by membership function $\mu_A(x)$.

In fuzzy sets, as the name implies, there is no clear or crisp boundary on the represented domain. The belongingness of the element to the set is gradually change, and the transition is characterized by the membership function, which is represents the degree of belonging of one element to the set.

If X is a collection of objects denoted generically by x, the fuzzy set A in X is defined as a set of ordered pairs:

$$A = \{(x, \mu_A(x))|x \in X\} \tag{2.3}$$

where X is referred to as the universe of discourse or simply the universe, and it may contain either discrete objects or continuous values. $\mu_A(x)$ is the membership function of element x in set A, and can be denoted as:

$$\mu_A(x) : X \longrightarrow [0, 1] \tag{2.4}$$

which states that the membership function values or degree of belonging are in the interval of 0 to 1.

Clearly, the fuzzy set is the classical set with the characteristic function values between 0 and 1. If the fuzzy set is only limited to have the membership function values $\mu_A(x)$ to either 0 or 1, the A becomes a classical set and $\mu_A(x)$ is the characteristic function of A.

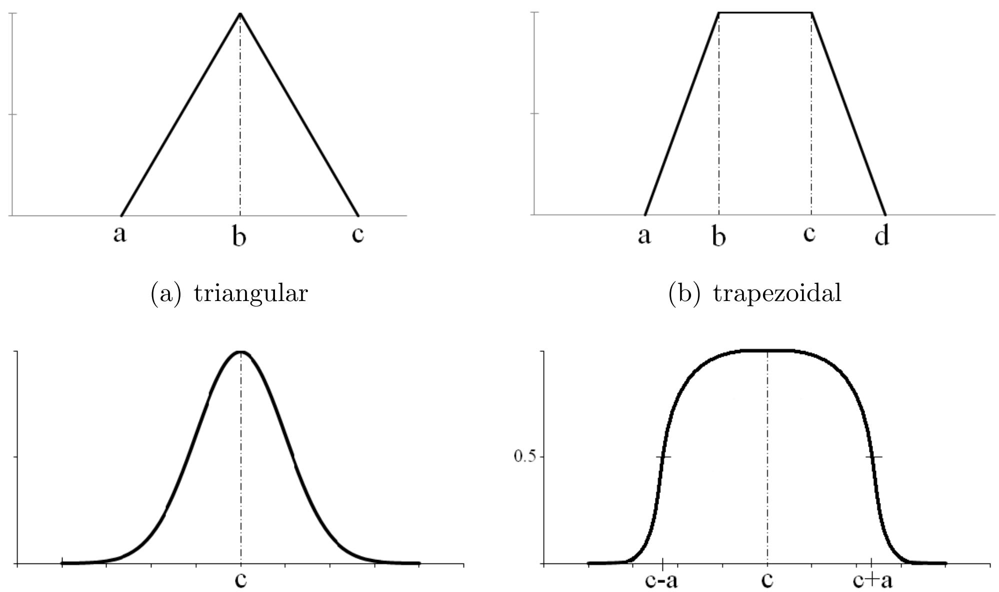
The construction of fuzzy sets depends on the identification of a suitable universe or domain, and the specification of an appropriate membership function. For example, in the universe of discourse of *height*, the membership function specification for the same set (say "tall") may vary considerably between one person to another, hence it is inherently context dependent.

Several commonly used shapes to define membership functions are triangular, trapezoidal, gaussian and bell. The parametric formula for various membership

Table 2.1: Parametric formulas of Common Continuous Membership Functions

Function	Formula
triangular	$\mu_A(x) = max[min(x - a)/(b - a); (c - x)/(c - b); 0]$
trapezoidal	$\mu_A(x) = max[min(x - a)/(b - a); 1; (d - x)/(d - c); 0]$
gaussian	$\mu_A(x) = \exp[-\frac{1}{2}(\frac{x-c}{\sigma})^2]$
bell	$\mu_A(x) = (1 + \|(x - c)/a\|^{2b})^{-1}$

function are summarized in table 2.1 [11, 12] and the graphs are given in the Fig. 2.2.



(a) triangular (b) trapezoidal

(c) gaussian (d) bell

Figure 2.2: Several Common Continuous Membership Function

2.1.2 Fuzzy Rules

A Fuzzy rule is an implication between fuzzy propositions. The simplified fuzzy rule is represented by means of general forms of the fuzzy if-then rules as follows:

if {*antecedent proposition*} **then** {*consequent proposition*}

The antecedent and the consequent can be both fuzzy proposition as in linguistic fuzzy model [13, 14], or the antecedent is a fuzzy proposition and the consequent is crisp function as in *Takagi-Sugeno* fuzzy model [15]. The fuzzy proposition is the linguistic proposition of the type "$\tilde{x}$ is A" where $\tilde{x}$ is a linguistic variable and A is a linguistic constant (term). The degree of belonging of the element x to set A will define the propositions truth value.

The linguistic fuzzy model forms if-then rules for single input single output as a qualitative knowledge :

$$\mathcal{R}_i : \textbf{if } \tilde{x} \text{ is } A_i \textbf{ then } \tilde{y} \text{ is } B_i \tag{2.5}$$

where i (1,2,...,K) are rule numbers. Here $\tilde{x}$ is the antecedent linguistic variable, and A_i are antecedent linguistic term. Similarly, $\tilde{y}$ is the consequent linguistic variable and B_i are consequent linguistic terms. The linguistic terms A_i and B_i are usually selected from sets of predefined terms. With fuzzy sets A and B denoted as $\mathcal{A}$ and $\mathcal{B}$ respectively, we have $A_i \in \mathcal{A}$ and $B_i \in \mathcal{B}$. The membership functions of antecedent and consequent are the mapping of equation 2.4, and it defines the meaning of the linguistic terms.

2.1.3 Fuzzy Reasoning

To derive conclusion from a set of if-then rules, linguistic model need fuzzy inference algorithm or sometimes called fuzzy reasoning (also known as approximate reasoning).

The term fuzzy relation in each rule (in regard of the values $\mathbf{x}$ and $\mathbf{y}$) can be denoted as: $R_i = (X \times Y) \to [0, 1]$. Using relational calculus, from the equation 2.5, the relation of R is computed by the minimum ($\wedge$) operator:

$$R_i = A_i \times B_i, \text{ that is, } \mu_{R_i}(\mathbf{x},\mathbf{y}) = \mu_{A_i}(\mathbf{x}) \wedge \mu_{B_i}(\mathbf{y}) \tag{2.6}$$

For the entire model, fuzzy relation R is given by the disjunction (union) of the K individual rules relation R_i:

$$R = \bigcup_{i=1}^{K} R_i, \text{ that is, } \mu_R(\mathbf{x},\mathbf{y}) = \max_{1 \leq i \leq K}[\mu_{A_i}(\mathbf{x}) \wedge \mu_{B_i}(\mathbf{y})] \tag{2.7}$$

The output of the linguistic model can now be calculated using max-min composition ($\circ$):

$$\tilde{y} = \tilde{x} \circ R \tag{2.8}$$

In Mamdani inference, relational calculus stored in R can be bypassed, and output fuzzy set B_i' calculation rely on the *degree of fulfillment* β_i of the ith rule's antecedent.

$$\mu_{B'}(\mathbf{y}) = \max_{1 \leq i \leq K}[\beta_i \wedge \mu_{B_i}(\mathbf{y})], \ \mathbf{y} \in Y \tag{2.9}$$

where $\beta_i = \max_X[\mu_{A'}(\mathbf{x}) \wedge \mu_{A_i}(\mathbf{x})]$.

In multiple input single output system (MISO), the conjunctive form of the antecedent is given by:

$$\mathcal{R}_i : \textbf{if } x_1 \text{ is } A_{i1} \text{ and ... and } x_K \text{ is } A_{iK} \textbf{ then } y \text{ is } B_i \tag{2.10}$$

where i (1,2,...,K) are rule numbers, x_1,...,x_K are input variables to the fuzzy reasoning, y is the output, A_{i1},...,A_{iM} are fuzzy labels corresponding to the input variables or antecedent, and B_i is a real number of the consequent part of the fuzzy rule. The degree of fulfillment β_i is given by:

$$\beta_i = \mu_{A_{i1}}(x_1) \wedge \mu_{A_{i2}}(x_2) \wedge ... \wedge \mu_{A_{iM}}(x_M),\ 1 \leq i \leq K \tag{2.11}$$

2.1.4 Fuzzy Model

The fuzzy model, also known as fuzzy inference system, is a computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning [11]. The name of fuzzy model is used in Takagi-Sugeno's work [15,17]. Number of names are also given to the fuzzy model since its widely used in multi discipline field such us fuzzy-rule-based system, fuzzy expert system, fuzzy logic controller, or just fuzzy system. The two basic categories of fuzzy model are (1) the Linguistic Model as used in Mamdani type fuzzy model and (2) the Takagi-Sugeno-Kang (TSK) Fuzzy models [16].

The framework of fuzzy model consists of the concept of a rule base, which covers the constructions of fuzzy rules and the usage of the membership function, and an inference mechanism to derive a conclusion from a set of fuzzy if-then rules.

The fuzzy classifier defines a fuzzy model that assigns a class label to an object based on its description and implemented fuzzy if-then inference system [18]. The fuzzy classifier can process crisp or fuzzy input, and from the implemented inference system the conclusion can be derived with appropriate defuzzification strategy.

Despite many types of fuzzy inference system implemented in various applications, this dissertation is focused on the usage of the Mamdani type inference system with its application conducted in some research presented in section 2.2.

Design of fuzzy systems may be seen as a general algorithm consisting of structure and parameter identification phase; structure identification consisting of input and output selection, reasoning selections, the universe of discourse determination, and linguistic labels determination, while parameter identification is needed to obtain optimal value of the membership functions. Applying data-driven techniques are common when the system is supplied with input-output data that reflects the optimal behavior [16].

2.2. Related Works

The related works on fuzzy based classification system are given in this section.

Tsai et al. in [1] presents a model based on fuzzy logic approach [19]. Fuzzy for classification system employ an extracted input features shows good classification performance. The compositional min-max algorithm for inference mechanism and modified height method for defuzzification are implemented suitably in their applications e.g. discrimination of myocardial heart disease from echocardiographic images as shown in Fig.2.3, and classification of clustered microcalcification from mammograms as described in Fig.2.4.

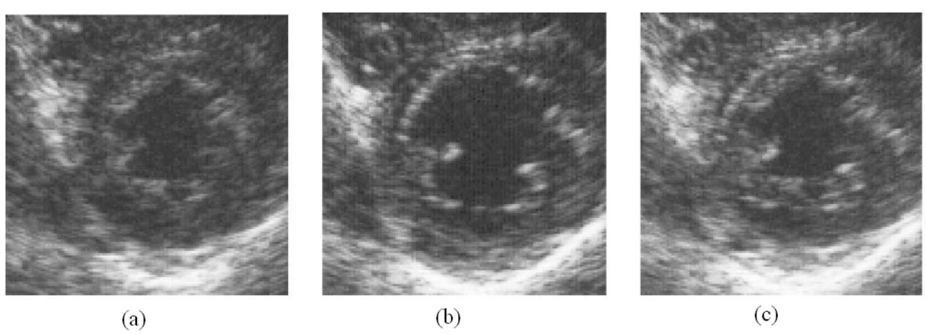


Figure 2.3: Examples of echocardiograms: (a)end-systole, (b)end-diatole, and (c)composite images. (Reprinted with permission from Ref. [1])

The min-max compositional algorithm uses the derived conclusion from MISO system as in equation 2.10. The Gaussian-distributed membership functions (GDMFs) are used in the system. The GDMFs are initially generated using various features obtained from image data sets. Subsequently, the shapes of the

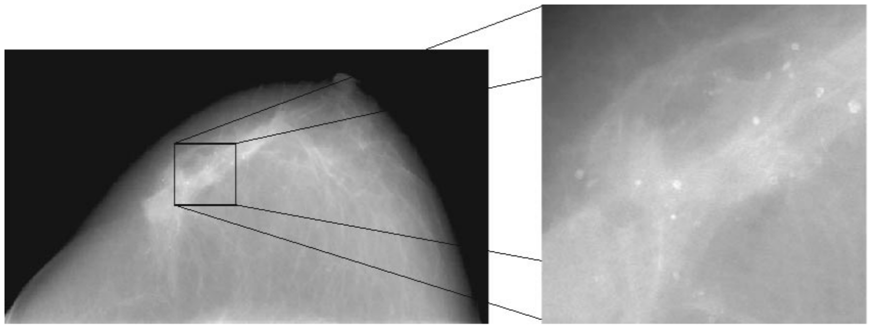


Figure 2.4: An example of mammograms with microcalcifications.(Reprinted with permission from Ref. [1])

GDMFs are optimized using a genetic-algorithm (GA) learning process.

Using the normalized membership function for gaussian shape as formulated in table 2.1 the degree of belonging to certain sets are calculated. Consider x as a specific feature value that can be measured from an image: let the mean value of x from a set of images belonging to the same category be μ, replacing the c variable, and the standard deviation of the feature values be σ, the equation can now be written as:

$$\mu_A(x) = \exp[-\frac{1}{2}(\frac{x-\mu}{\sigma})^2] \tag{2.12}$$

when the value of x for an image is μ, the membership value should be one. When x is gradually set apart from the value of μ, the membership value should become smaller. To determine the optimum membership function, genetic algorithm must be applied at training phase. By varying the value of standard deviation σ with a coefficient c, the shape of the GDMF can be optimized using GA-based learning as:

$$\mu_A(x) = \exp[-\frac{1}{2}(\frac{x-\mu}{c\sigma})^2] \tag{2.13}$$

The proposed computer aided diagnosis scheme, containing four stages: image preprocessing, feature extraction, classifier training, and classification. Fig.2.5 illustrates the min-max compositional inference and defuzzification.

Assume that there are 4 inputs GDMF used for antecedent part i.e. X_1, X_2, X_3, and X_4; for the R_1 category, the respective GDMF values are expected to be $\mu_{R_1}(X_1)$, $\mu_{R_1}(X_2)$, $\mu_{R_1}(X_3)$, and $\mu_{R_1}(X_4)$, and for the R_2 category, the respective GDMF values are assumed as $\mu_{R_2}(X_1)$, $\mu_{R_2}(X_2)$, $\mu_{R_2}(X_3)$, and $\mu_{R_2}(X_4)$. The

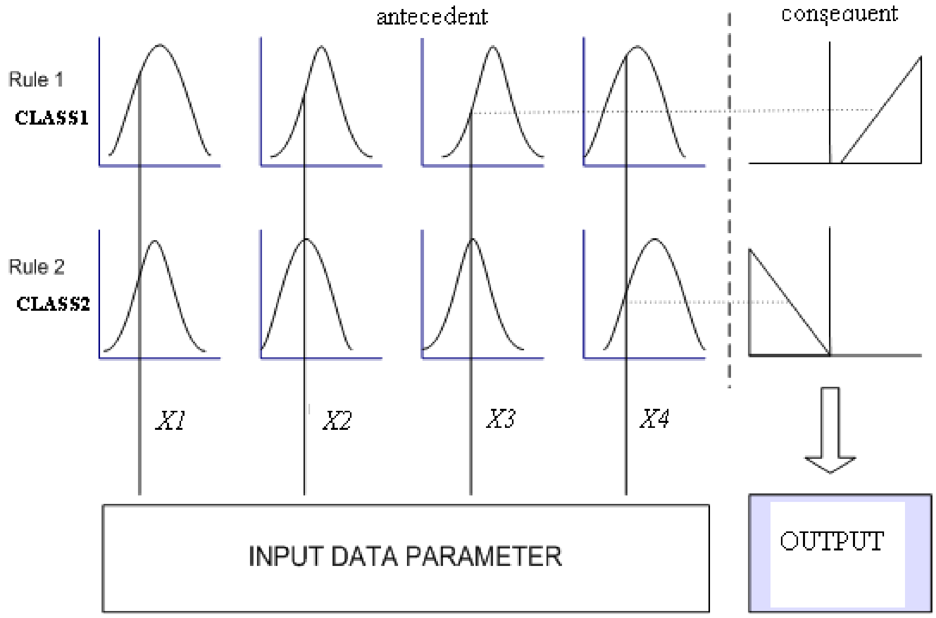


Figure 2.5: Illustration of the MIN-MAX compositional rule of fuzzy inference using eight Gaussian-distributed membership functions.

optimum values of μ and σ are applied for R_1 and R_2. The MIN (minimum) operation is applied to find the minimum value from the membership function for each rule. Then, the minimum values of $\mu_{R_1}(X_1)$, $\mu_{R_1}(X_2)$, $\mu_{R_1}(X_3)$, and $\mu_{R_1}(X_4)$, and those of $\mu_{R_2}(X_1)$, $\mu_{R_2}(X_2)$, $\mu_{R_2}(X_3)$, and $\mu_{R_2}(X_4)$ are given by:

$$\mu_{R_1} = \text{MIN}[\mu_{R_1}(X_1), \mu_{R_1}(X_2), \mu_{R_1}(X_3), \mu_{R_1}(X_4)] \tag{2.14}$$

and

$$\mu_{R_2} = \text{MIN}[\mu_{R_2}(X_1), \mu_{R_2}(X_2), \mu_{R_2}(X_3), \mu_{R_2}(X_4)] \tag{2.15}$$

The MAX (maximum) operation is then applied to find the maximum value from the two minimum values, and is given by:

$$\mu_{R_1 \bigcup R_2} = \text{MAX}[\mu_{R_1}, \mu_{R_2}] \tag{2.16}$$

The modified height method for defuzzification scheme is

$$\text{if } \ \text{MAX}[\mu_{R_1}, \mu_{R_2}] = \mu_{R_1}, \ \text{ then } R_1 \text{ category} \tag{2.17}$$

and

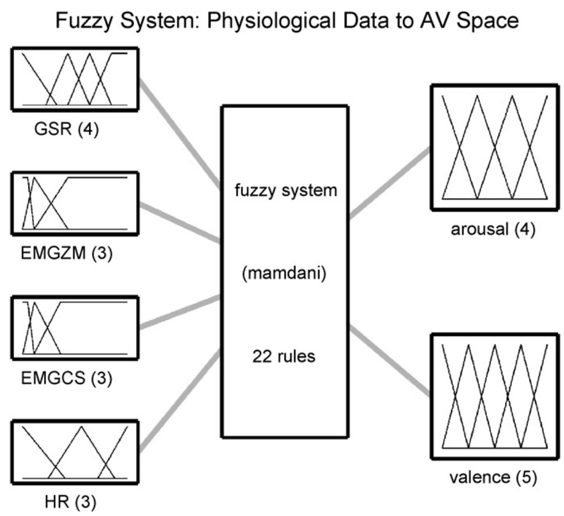
$$\text{if } \mathrm{MAX}[\mu_{R_1}, \mu_{R_2}] = \mu_{R_2}, \text{ then } R_2 \text{ category} \tag{2.18}$$

If $\mu_{R_1} = \mu_{R_2}$, then regarded as misclassification, since it gives uncertain classification output.

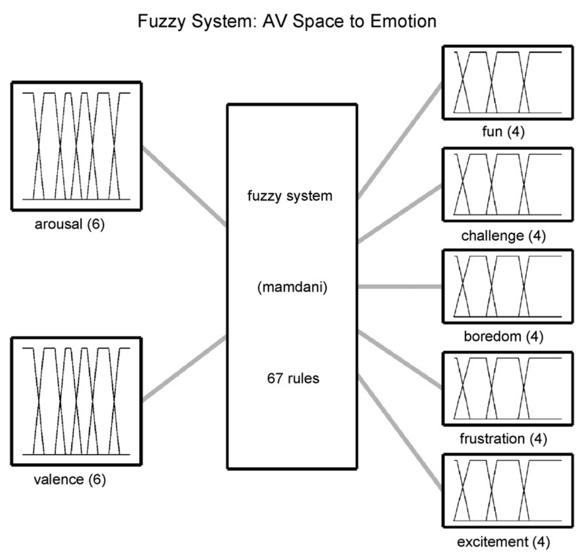
Two other common defuzzification methods are center-of-gravity (CoG) and mean-of-maxima (MoM). The CoG (often referred to as center-of-area defuzzification in the case of one dimensional sets) is actually the same method employed to calculate the center of gravity of a mass. The difference is that the point masses are replaced by the membership values. Mean-of-maxima defuzzification belongs to the class of indexed (or threshold) defuzzification methods that discriminate part of a fuzzy output where membership values are below a certain threshold level. MoM defuzzification takes the mean of those points of fuzzy output that yields maximum membership. However, since the crisp output value is not adopted at this stage, the modified height method [1] is implemented for the defuzzification in our two applications.

Mandryk et al. in [4] implements fuzzy logic to quantify emotional experience when engaged with interactive entertainment technologies. The physiological metrics such as galvanic skin response (GSR), electromyography (EMG) and heart rate (HR) are used to quantitatively and continuously measure emotional state. Two parts of fuzzy logic approach models the data to generate user emotion values. The arousal and valence are computed at first from the normalized physiological signals of GSR, HR, $\mathrm{EMG}_{smiling}$ and $\mathrm{EMG}_{frowning}$, to be carried out in the second stage to generate emotion values for boredom, challenge, excitement, frustration, and fun. The first fuzzy model consist of four inputs (GSR,HR, $\mathrm{EMG}_{smiling}$ and $\mathrm{EMG}_{frowning}$) with two outputs (arousal and valence) as described in Fig. 2.6a. The second fuzzy model consists of two inputs provided by the the first model, and five outputs of emotional states (fun, challenge, boredom, frustration, excitement) as described in Fig. 2.6b.

In the first part, the rules are generated to fulfill the necessity condition to generate the desired output following the theory of how the physiological signals relate to the psychological concepts. On the second part, the rules are generated simply to map the level of arousal and valence in Fig. 2.7 to the levels of fun, challenge, boredom, frustration and excitement. The results from fuzzy



(a)

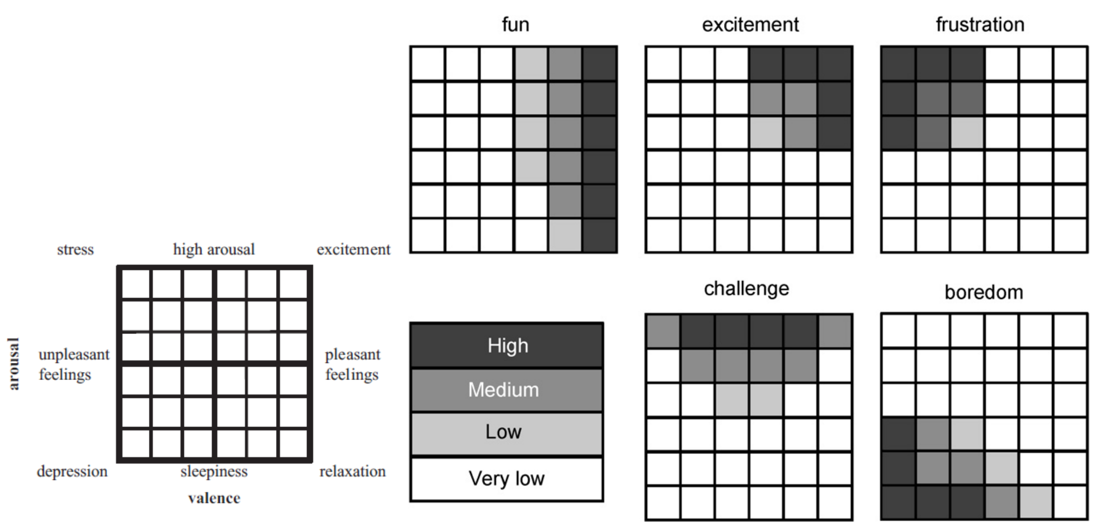


(b)

Figure 2.6: (a)Modeling arousal and valence from physiological data. The system uses 22 rules to transform the 4 inputs into the 2 outputs.(b)Modeling emotion from arousal and valence. The system uses 67 rules to transform the 2 inputs into the 5 outputs.

logic approach are consistent with predictions based on the results from prior experiments.

Anuradha et al. [3] implement the fuzzy classifier to discriminate ECG signals using non-linear dynamic parameters for cardiac arrhythmia classification. The four non-linear parameters considered for cardiac arrhythmia classification of the ECG signals are spectral entropy, poincaré plot geometry, largest lyapunov exponent and detrended fluctuation analysis which are extracted from heart rate signals. The system is described in Fig. 2.8. Linguistic variables (fuzzy sets) describes the ECG features, and fuzzy conditional statements represents the reasoning knowledge and rules. Fuzzy logic if-then rules are formed by applying fuzzy operations to these membership functions for given inputs. The Gaussian distribution membership function is used for input parameters, while trapezoidal membership function is used for output of fuzzy classifier. Good results have been achieved with this method and an overall accuracy of 93.13%



(a) (b)

Figure 2.7: (a)Six level of arousal-valence space.(b)Representation of level of emotion in arousal-valence space.

Silipo et al. [20] introduces two fuzzy models to solve a classification problem of three-class arrhythmia on the basis of electrocardiographic measures. The first fuzzy model is directly derived from a set of medical rules taken from clin-

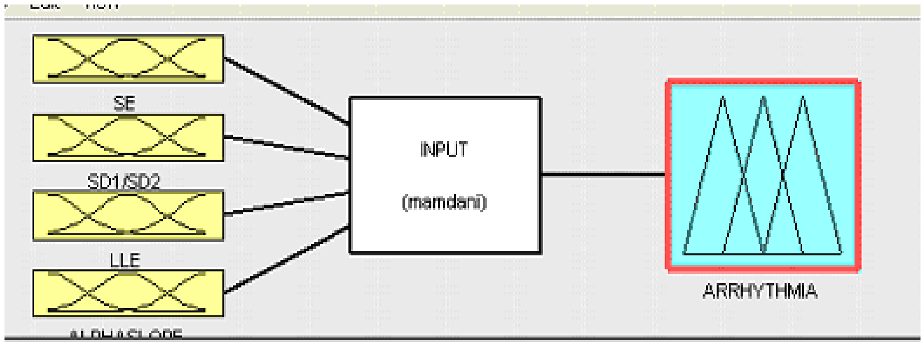


Figure 2.8: Fuzzy based Cardiac Arrhythmia Classifier.

ical practice. The second fuzzy model is automatically constructed on a set of training data extracted from twenty-six records of the Massachusetts Institute of Technology - Beth Israeli Hospital (MIT-BIH) database. The MIT-BIH database is a set of standard test material for evaluation of arrhythmia detectors. Their study focuses on a performance comparison of a knowledge-based and a data-driven based model. They also analyze how much the information contained in the fuzzy model is exploited by input feature for classification purpose.

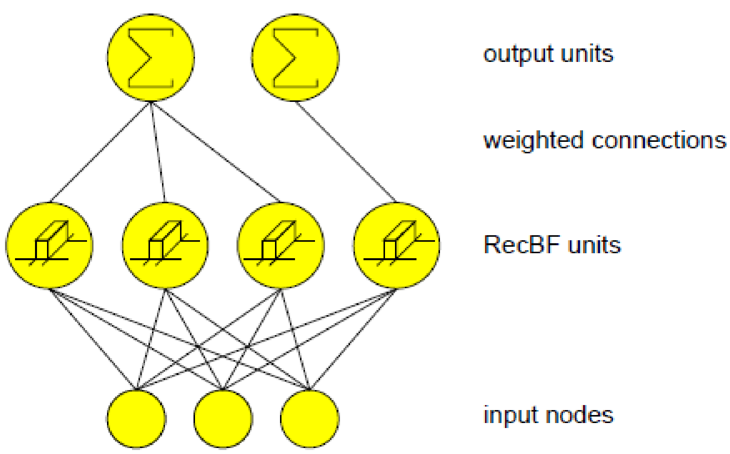


Figure 2.9: The structure of a Rectangular Basis Function Network.

We may say that the first fuzzy model is a similar model in term of its simple generation, with other works mentioned before in this chapter [1, 3], while the second fuzzy model is automatically generated using author's prior work utilizing Rectangular Basis Function Network (RecBFN) [21, 22]. This second model may be seen as a feed-forward networks consisting of an input, one hidden layer and an output layer. An example of a full RecBFN is shown in Fig. 2.9. Each of RecBF in the hidden layer represents one rule.

The performances of the two classifiers on the other thirteen records taken from the MIT-BIH database are comparable and somewhat complementary, since the first fails to recognize ventricular arrhythmia, and the second recognizes supraventricular arrhythmia. The two fuzzy models are then analyzed using the concept of information gain to estimate the impact of each ECG measure on the final decision process. The performances of the data-driven fuzzy systems with respect to the normal beat and ventricular premature beat is superior than the knowledge based fuzzy system. On the other hand, the knowledge-based is superior than data-driven fuzzy system with respect to supra-ventricular premature beat.

2.3. Summary

In this chapter the basics of fuzzy set theory and fuzzy logic are addressed, together with the previous fuzzy related works from other authors in sections 2.1 to 2.2 that appear as extensions to crisp set theory, and serve as the basis for building fuzzy systems.

Fuzzy systems allow the processing of information in linguistic terms that is expressed in the form of if-then rules and is built on the analogy with human reasoning. The presented material in this chapter only covers a small part of the widely developed fuzzy set theory and fuzzy logic. However, the covered material in this chapter is enough to understand the concept of implemented Fuzzy logic in this dissertation.

Other related material that should be addressed regarding the implemented application will be given in the corresponding section. The fatigue condition and eye movement observation and measurement will be presented in chapter 3, and the cardiac rest period and two extracted feature from the magnetic resonance coronary angiography data are given in the chapter 4.

Chapter 3

Application One: Fuzzy Logic Approach on Fatigue Classification due to Learning Task

3.1. Introduction

The brain and body are accustomed to the normal body cycle that they resist such changes causes by work-schedules [23]. According to Holding, a fatigue is a particular kind of change in the performance pattern. Those changes are expressed as a decrement in performance or an increase in error rate with increasing time at task [24]. Fatigue has subjective, objective (performance) and physiological components which may occur in the short term or as a chronic state, but is not the fatigue itself that can be measured. From this definition, in this research we may measure the fatigue through its occurred effects.

Capable to be observed, a fatigue refers to a phenomenon and an effects rather than a cause. Fatigue is associated with physiological changes in brain wave activity, eye movement, head movement, muscle tone and heart rate [25], its effect may be measured and analyzed. Since the human eye movements are controlled by the ocular muscle, which is controlled by brain through a motor nerve, they may be affected. In agreement with this definition, the physiological changes i.e. the changes of eye movements patterns may represent the fatigue. Thus, eye behavior may provide insight to the human behavior corresponding to the cognitive workload [26].

The purpose of this application is to describe and examine the eye movement pattern as metric measurement to the fatigue condition, by implementing a fuzzy logic. In this application, the eye movement parameters were used as an input of a fuzzy based fatigue classification system due to nine hours learning task. These parameters, i.e., saccadic latency, saccadic duration, saccadic peak velocity [27], and movement deviation have been used already to find the relationship between Alzheimer's disease and eye movement parameters [28].

3.2. Method

With the method explained in detail in section 2.2, Tsai et al. [1] employ fuzzy logic for classification. They propose a Computer Aided Diagnosis (CAD) scheme containing four stages: image preprocessing, feature extraction, classifier training, and classification, and apply them to detect myocardial heart disease from echocardiograph images. A fuzzy physiological approach provides a method for quantifying emotional states continuously during a play experience using physiological data. A fuzzy logic model transformed four physiological signals into arousal and valence. A second fuzzy logic model transformed arousal and valence into five emotional states relevant to computer game play: boredom, challenge, excitement, frustration, and fun [4]. Both related works mentioned above, together with other related works [3, 5–7] emphasize the usefulness of fuzzy classifier.

Since fatigue maybe reflected through the change of eye movements, in this research, the stimulated eye movements are measured in two different times which represent two different physical condition. We investigate whether the eye movements will suffer from a nine-hour learning task and experience a particular change due to a fatigue. The investigated eye movements in this research are saccadic and fixation. The saccadic movement is a jerk or sudden eye movement, and fixation is an eye movement control to fixate on one object in the visual field. To classify the fatigue condition, we used the fuzzy classifier with Gaussian distributed membership function.

The classification system consists of three stages: image preprocessing for eye-center coordinates determination, feature extraction to extract the parameter from eye movement, and identification process to classify the extracted parameters into particular class. Fig. 3.1 illustrated the classification system comprising input, main process and output.

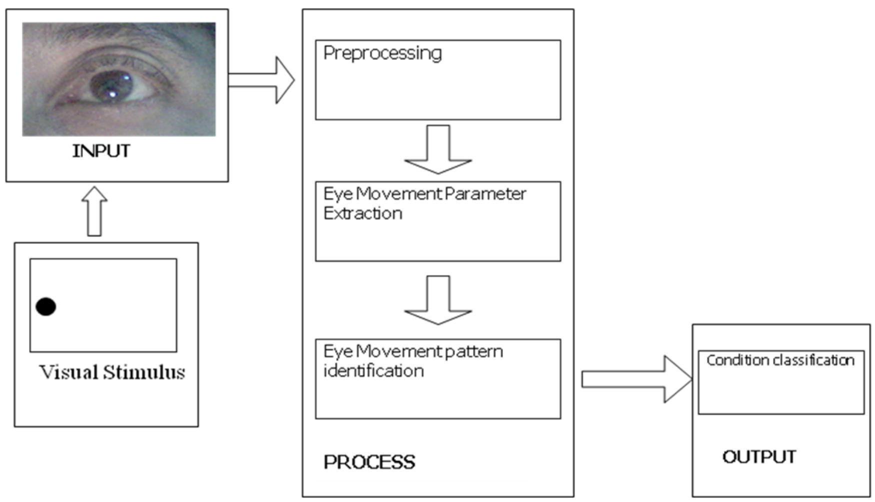


Figure 3.1: Classification System with the main process consists of preprocessing, eye movement parameter extraction, and eye movement pattern identification.

Oohira et al. [29] reported that the saccadic eye velocities between right and left eye has no significant difference when the subjects are examined monocularly with covered the other eye. In agreement with that statement, in this research the eye movement data were captured from the left eye pupil coordinates using web camera.

In another study, smooth pursuit eye movement to a dynamic index is measured, and comparison between Alzheimer-type dementia patients and healthy elderly control as well as healthy young control is performed. Eye movement was triggered by horizontally moving index at three different speed. Consequently, among the 3 groups, significant difference was acquired according to the latency, the pursuit speed, the number of saccadic eye movement and the pursuit movement distance at each speed level [30].

Ettinger et al. [31] investigates the reliability and susceptibility of practiced effects of oculomotor tasks i.e. smooth pursuit, fixation, anti-saccade, and pro-saccade tasks. There are a magnitude of improvement on this measure, which indicates that the poor performers benefits from repeated measurement. In agreement with those investigation, it is also reported that there are no significant difference between male and female [32]. To the knowledge of the authors, there will be some degradation when the performers experience a task in a certain period of time.

In this research, saccadic parameters e.g. latency, duration, and velocity and deviation as fixation parameter are extracted from eye center coordinates when subject is stimulated using 6-second visual stimuli.

To represent non fatigue condition, the stimulated eye movement is measured in the morning with assumption that the participants are in non fatigue condition, on the other hand, fatigue condition was represented with measured stimulated eye movement in the afternoon after experienced nine hours learning task. Bailey et al. [33] demonstrates that an interruption has a disruptive effect on both a user's task performance and emotional state, and that the degree of disruption depends on the user's mental load at the point of interruption. Logically, when the participants are experience a learning task for period of time, they should be some degradation in their physical condition i.e. fatigue, and that fatigue is expected to be shown through their eye movements.

It may not represent the fatigue condition in general, since each participant will have different perception and different scales of fatigue. Although the participants are reported to be in fatigue condition, this fatigue will be relatively low when compared to the fatigue experienced by getting a physical work e.g. long driving task, construction work etc. By the same logic, the non fatigue condition might be expressed differently among participants. To expect the same scale with all participants, we asked them to agree with the non fatigue and fatigue condition assumed in this research. The point in this research is to investigate whether the eye movement will deteriorate with learning task period and provide insight to the student condition corresponding to the learning task. To validate the experienced condition, the participants are asked to fill out a questionnaire as in appendix A.2.

3.2.1 Preprocessing

Preprocessing is conducted to capture participants eye movement for eye center coordinates determination. We used assisted lamp attached on the web camera to gives a light reflex in pupil area. This light reflex determines the eye area and act as a start point to search the eye center coordinate. Moreover, the light illumination from the lamp also maintains the light environment surrounding the left eye. Fig. 3.2 illustrates the boundary search region and eye center coordinate searching method.

To calculate the eye-center coordinates, the searched area was simply limited using the assisted light reflex, to guide the determination of boundaries of eye pupil area. If the assisted light reflex point is (x, y) then the searching area are limited to $x \pm 40$ and $y - 60$ to $y + 30$. Heuristically, this area is used to the eye area for all subjects. The x axis of the eye center coordinate is the mean value from the left and right of pupil edges. While y axis is the mean value of the top and bottom of pupil edges. Eye center coordinate is calculated by averaging eye center calculation from $(y - 20)^{th}$ row to y^{th} row. The left and right edges are calculated by subtracting the gray level value from two adjacent group of pixels (p), and expressed in equation 3.1. If p is greater than or equal to 120, then p is regarded as edge point.

$$Edge = \{p | p \geq 120\} \tag{3.1}$$

where $p = P - P_1$. The P and P_1 are two adjacent groups of pixels and described as

$$P = (F(x, y) + F(x - 1, y)$$
$$P_1 = (F(x - 1, y) + F(x - 2, y)$$

where $F(x, y)$ denotes the gray level value at (x, y). From the experiments, the gray level for pupil area vary from 40 to 75. The threshold is set at 120 to ensure edge point detection. The edge searching process are illustrated in Fig. 3.3. The gray level threshold of 120 is taken to make sure the detected point is the edge point.

Equation 3.2 and 3.3 show the x coordinate of eye center calculation.

$$ctrpoint(i) = \frac{leftedge + rightedge}{2} \tag{3.2}$$

$$ctrpoint = \frac{\sum_{i=1}^{n} ctrpoint(i)}{n} \tag{3.3}$$

where i is the number of calculated eye center and n is the total number of calculated eye centers.

Eye center coordinate data from each participant are recorded for six-second period, and since the visual stimuli tends to stimulate the eye movement horizontally, the x coordinate data from eye movement will be extracted further to obtain its saccadic and fixation parameters.

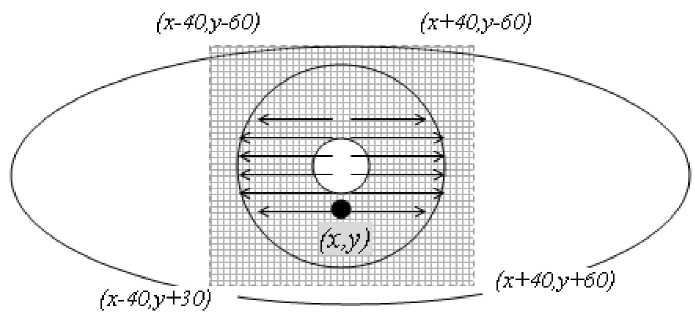


Figure 3.2: Eye center coordinate searching using assisted lamp light reflex in pupil area (x, y).

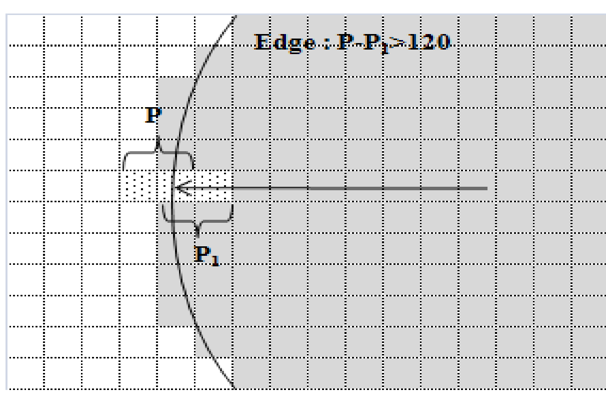


Figure 3.3: The Illustration of the left edge of pupil area searching.

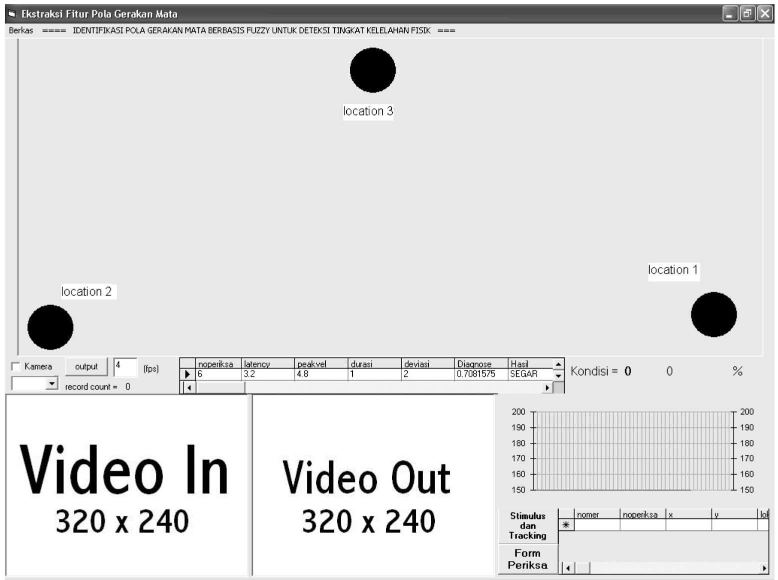


Figure 3.4: Stimulus appearance in three different locations. The object in each location appear twice during six seconds stimulation period

3.2.2 Saccadic and Fixation Eye Movement Parameter

To acquire the eye movement pattern, visual stimuli is used to stimulate the participants to perform the saccadic and fixation eye movement. The stimulus object is visualized at 15” LCD monitor and appear periodically in three different locations. During a six-second period, the participant must stare and follow the stimulus object which occur one at a time in different locations. The stimulus object appear twice every three seconds. Location 1 is at the bottom-right, location 2 is at the bottom-left, and the location 3 is at the up-center of the form as described in Fig. 3.4.

From the recorded eye coordinates in the database, the parameters are extracted. The extracted parameters are saccadic latency, saccadic duration, peak velocity, and deviation. Fig. 3.5 shows a flowchart for an eye movement parameter extraction. The extraction processes are explained as follows:

1. Saccadic latency. To extract saccadic latency parameter, stimulus moving time and eye response starting time must be known. From the recorded data, we marked stimulus moving time with (t_1), and marked eye response

starting time by (t_2). Then we can calculate the saccadic latency by ($t_2 - t_1$).

2. Saccadic duration. The eye movement data with the velocity between 3 (pixel/sampling time) and below 10 (pixel/sampling time) will be considered as a saccadic movement, as thus be recorded. There are 5 saccadic duration from 5 saccadic movement for 6 seconds recorded data. Saccadic duration parameter is obtained from the average of 5 saccadic duration values.

3. Peak velocity. Peak velocity is the highest saccadic movement velocity. The value can be obtained by calculating the coordinate difference between one sampling time to another, and then choose the highest one. Saccadic velocity ranges from 3-15 (pixel/sampling time). The velocity above 15 (pixel/sampling time) will be considered as a noise, or eye blinks.

4. Deviation. Deviation parameter is obtained on eye fixation data. Participants must fixate their eye gaze on the stable object. The capability to maintain fixed stare is different between one participant to another. The unstable fixation will cause an oscillation in the plotted graph. The amplitude of the oscillation can be considered as a deviation. The deviation value is derived from the absolute difference between highest and lowest deviation values.

3.3. Fuzzy Classification

3.3.1 Fuzzification

The Gaussian distributed membership function of fuzzy logic are composed on the number of classified categories. Since there are fatigue and non fatigue categories, every extracted parameter have two membership functions. For each category, if the value of the specific parameter that can be measured from the data is x, and the mean value of x from the datasets be μ and the standard deviation of the feature values be σ, we can determine the normalized Gaussian-Distribution membership function. For every incoming input (extracted parameter), we calculate the membership function for both non fatigue and fatigue conditions, and

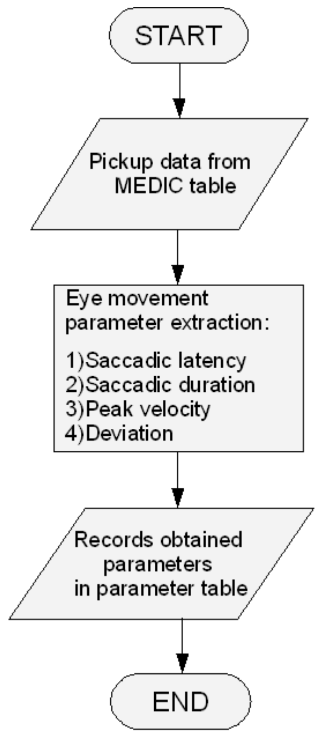


Figure 3.5: parameter extraction

each of the category consists of four parameters: saccadic latency, saccadic duration, velocity and deviation. The normalized membership function is expressed in equation 3.4.

$$f(x) = \exp[-\frac{1}{2}(\frac{x-\mu}{\sigma})^2] \tag{3.4}$$

If the value of x from the image or pattern is μ, the value of the membership function must be one. If the value of x is gradually set apart from the value of μ, the value of the membership will be reduced. If the amount of the dataset is small or limited, the possibility of σ value is less accurate to represent all the characteristics of the images in the same category.

Gaussian shape is used in this application due to the dataset tendency to make a normal distribution. In addition, we may change the stiffness of Gaussian shape easily by inserting a variable in its standard deviation. Before implementing the program, there is a learning step to calculate the μ and σ value from half of the obtained parameter and will be used as learning data.

3.3.2 Defuzzification

The MIN-MAX compositional rule of fuzzy inference method is employed [1]. From the obtained parameter, the mean values and standard deviations for each parameter can be calculated. For the non fatigue category (subscripts with am), the respective GDMF values are assumed to be $\mu_{am}(Q_1)$, $\mu_{am}(Q_2)$, $\mu_{am}(Q_3)$, and $\mu_{am}(Q_4)$, and for the fatigue category (subscripts with pm), the respective GDMF values are assumed to be $\mu_{pm}(Q_1)$, $\mu_{pm}(Q_2)$, $\mu_{pm}(Q_3)$, and $\mu_{pm}(Q_4)$. Q_1, Q_2, Q_3 and Q_4 represent saccadic latency, saccadic duration, peak velocity, and deviation parameters respectively. Besides the mean value, each parameter also has the standard deviation value. From the above values, the MIN (minimum) operation is applied to find the minimum value of all membership functions from each category. Then, the minimum value of $\mu_{am}(Q_1)$, $\mu_{am}(Q_2)$, $\mu_{am}(Q_3)$, and $\mu_{am}(Q_4)$, and that of $\mu_{pm}(Q_1)$, $\mu_{pm}(Q_2)$, $\mu_{pm}(Q_3)$, and $\mu_{pm}(Q_4)$ are given by:

$$\mu_{am} = \mathrm{MIN}[\mu_{am}(Q_1), \mu_{am}(Q_2), \mu_{am}(Q_3), \mu_{am}(Q_4)] \tag{3.5}$$

and

$$\mu_{pm} = \mathrm{MIN}[\mu_{pm}(Q_1), \mu_{pm}(Q_2), \mu_{pm}(Q_3), \mu_{pm}(Q_4)] \tag{3.6}$$

The MAX (maximum) operation is then applied to find the maximum value from the two minimum values, and is given by:

$$\mu_{am \bigcup pm} = \mathrm{MAX}[\mu_{am}, \mu_{pm}] \tag{3.7}$$

The classification scheme is

$$\text{if} \quad \mathrm{MAX}[\mu_{am}, \mu_{pm}] = \mu_{am}, \ \text{then} \ \ am \text{ category} \tag{3.8}$$

and

$$\text{if} \quad \mathrm{MAX}[\mu_{am}, \mu_{pm}] = \mu_{pm}, \ \text{then} \ \ pm \text{ category} \tag{3.9}$$

If $\mu_{am} = \mu_{pm}$, then the classification becomes uncertain and will be regarded as misclassification.

3.3.3 Experiment Settings

1. Participants: Twenty-six visually normal college students ages 18 to 22 participate in this research. No gender difference was examined. The eye

movement data from the participants are measured twice: in the morning, before class, which is assumed to be the non fatigue condition, and in the afternoon, after nine hours of class, which represent the fatigue condition. Thirteen participants are randomly selected and used as learning data to obtain their mean and standard deviation of their eye movement parameters. These mean and standard deviation value are used as parameter of Gaussian distribution membership function. We use all 26 participants as test data for classification.

2. Equipment setting: Eye movement data is taken using a head-mounted camera. Logitech QuickCam Messenger WebCam is used as the image capture device. A 5V lamp mounted on camera is used to assist eye pupil area searching and to maintain light environment surrounding pupil area. The distance between eye position and camera is 10 cm, and 30° below the horizontal line. A 15" monitor is placed in reading distance 40 cm in front of the subject. The experimental environment is shown in Fig. 3.6.

3. Experiment data: To get the desired data, the operator gives a brief explanation about the given stimulus to the participants. The procedure is as follows: Participants are instructed to sit down, relax, and put on the head-mounted camera while staring and following the stimulus movements. The determined pupil coordinates are then recorded in the database. The process is then continued to parameter extraction, followed by classification process to determine the participant's condition.

3.3.4 Statistical Analysis

The eye movement parameters are presented as mean and standard deviation. The fatigue and non fatigue classification as categorical data are presented as counts and percentages. The differences in eye movement parameters between two output categories are assessed using simple model, normal distribution, two samples within Instat+ for Windows (v.3.036, University of Reading, United Kingdom). A p-value of 0.05 is considered statistically significant. Sensitivity, specificity, and accuracy are used to assess the test performance for the fuzzy identification system

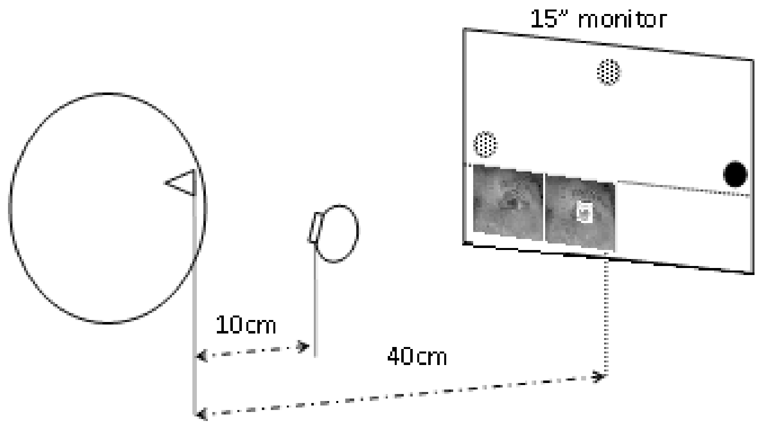


Figure 3.6: Experiment environment showing the distance between subject, web-camera and 15" monitor

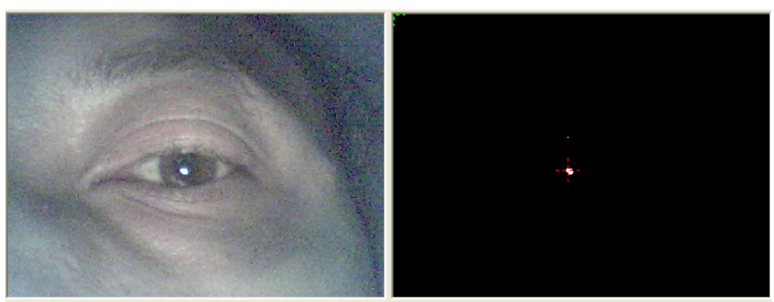


Figure 3.7: Thresholding pupil area from the light reflex point

3.4. Results

With assistance from the light reflex on the pupil area, the boundary of the searching area can be simply determined. Using the threshold algorithm process, the light reflex on eye pupil areas will have a white color distribution, while other areas are become black. With the scanning process to find the biggest pixel value, the light reflex coordinate can be found as described in Fig. 3.7. The light reflex coordinate will be used to determine the boundary of an eye coordinate searching ares as described in section 3.2.1 and illustrated in Fig. 3.2. Fig. 3.8 shows the results of the searching process of the pupil area.

After the boundary of searching area is obtained, the next process is to obtain

Figure 3.8: Searching area of eye pupil center

the eye center coordinates by finding the left and the right pupil edge, then continue with the determination of the eye center coordinate using Equation 3.2 and 3.3 respectively. To find a precise result, the center point calculation is repeated for another y-position in the pupil area as described in Fig. 3.2, and the results are described in Fig. 3.10. However, only x coordinates of eye pupil center are used for further processing, which represent horizontal eye movements, since our stimulus tends to stimulate the eye movements horizontally. From some center point values, average point value will be used and assumed as eye center coordinate.

During the experiment, we have experienced a 10Hz low sampling frequency of an eye movement. Although it may not be considerably suitable for measuring fast eye movement, since we are comparing the eye movement between two conditions for each participant, which had the same sampling frequency, we still can measure the different value between two conditions regarding latency, duration, velocity and deviation. Fig. 3.9 shows the snapshot of the application form appearance.

3.4.1 Parameter extraction

The recorded eye movement data (x coordinate) can be plotted against its sampling time. In order to be processed in the Fuzzy identification system, eye center coordinate must be extracted to obtain its parameter. Using the eye movement parameter extraction algorithm, we can obtain the latency, saccadic duration, peak velocity and deviation. Fig. 3.11 describes x coordinate or horizontal move-

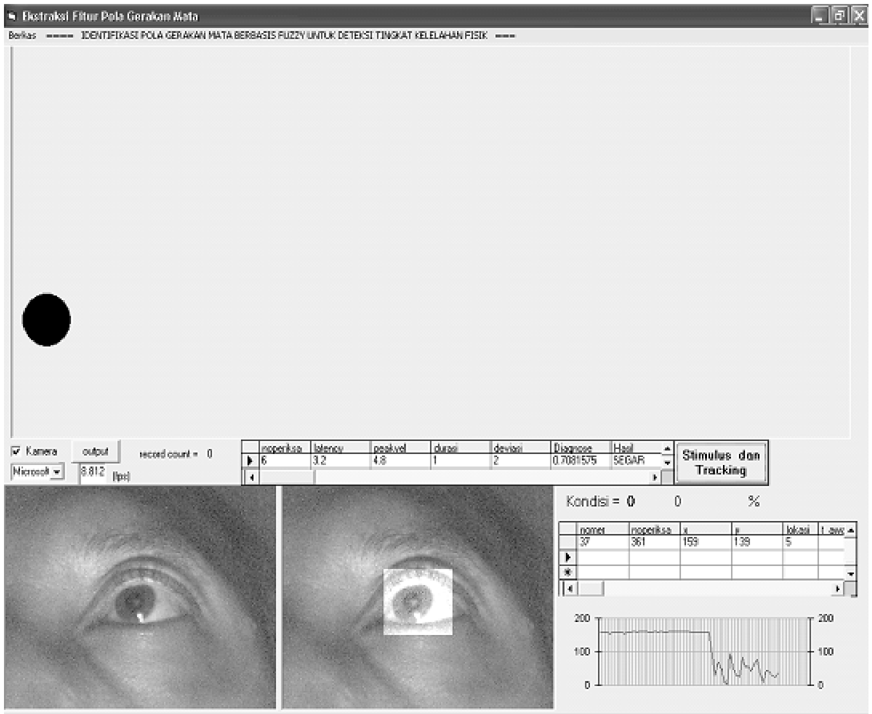


Figure 3.9: Snapshot of Application Form

ment from a particular participant. The figure will be used as a calculation example of eye movement parameters.

Latency

To obtain the latency parameter (l), the time when the stimulus moved from one location to another must be detected, as well as the time when the eye starts to follow the object movement. The time when the stimulus moved from one location to another is marked. For example, using Fig. 3.11, the movement of the stimulus from location 1 to location 2 occurs at the time of sampling 11 (s marked) is recorded as a t_1 variable. Then, we proceed to the next sampling time while checking for an existing eye movement by looking for the x coordinate changes that exceeds 3 pixels per sampling, the minimum eye movement which can be considered as a saccadic movement. When the saccadic movement is found, the sampling time is recorded and regarded as a t_2 variable. From Fig. 3.11, at t_2 equals 14, there is a saccadic movement represented by x coordi-

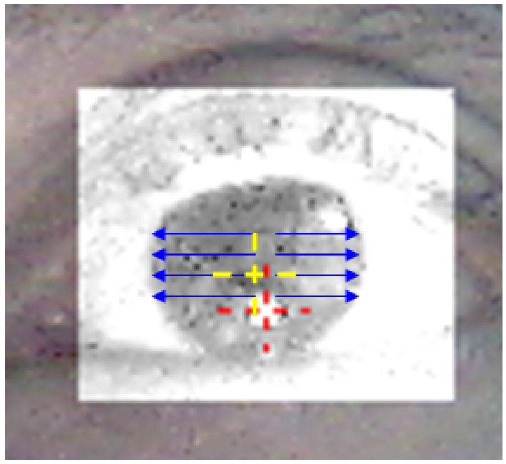


Figure 3.10: Result of eye pupil center coordinate searching

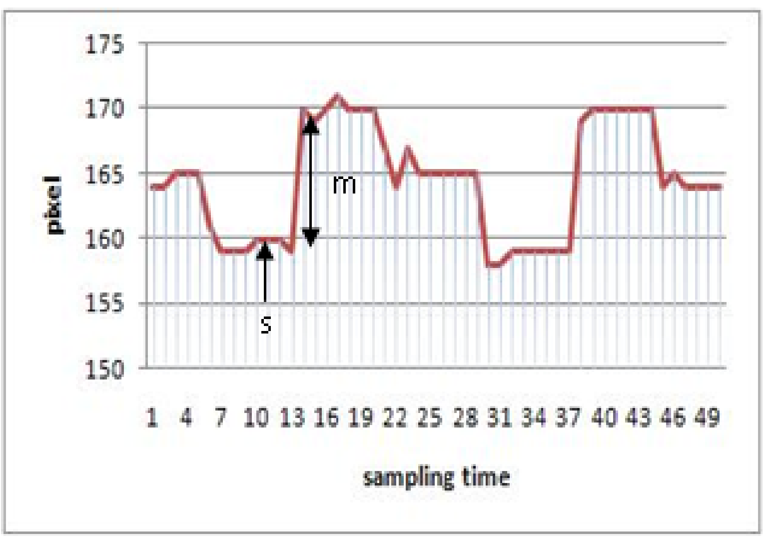


Figure 3.11: The x coordinate of eye pupil center, s: stimulus movement at sampling time=11, m: saccadic movement from 159 to 170 pixel

nate changes from 159 to 170 (m marked), which means the movement velocity is 11 (pixels/sampling). Thus, the value of latency l_1 is:

$$\begin{aligned} l_1 &= t_2 - t_1 \text{ (sampling)} \\ l_1 &= 14 - 11 \text{ (sampling)} \end{aligned} \tag{3.10}$$

the latency unit is a sampling time. But it can also be converted into seconds by multiplied it with the sampling period 0.1 second,

$$\begin{aligned} l &= 1 \text{ (sampling)} \times 0.10 \left(\frac{\text{second}}{\text{sampling}}\right) \\ l &= 0.1 \text{ (second)} \end{aligned}$$

The latency value is also calculated for other location changes. The l_0, l_1, l_2, l_3, l_4 and l_5 are the stimulus movement from location 0 to location 1, location 2 to location 3, location 3 to location 4, location 4 to location 5, and from location 5 to location 6 respectively. The average value of the 6 variables is used for analysis.

Duration

The duration value is determined as a time to perform saccadic movements. The duration for pursuing an object from location 0 to location 1 is marked as variable d_0, from location 1 to location 2 is marked as variable d_1, location 2 to location 3 is marked as variable d_2, location 3 to location 4 is marked as d_3, location 4 to location 5 is marked as d_4, and from location 5 to location 6 is marked as d_5. The average value from the six variables is used for analysis. From Fig. 3.11, we obtained $d_0 = 1$, $d_1 = 1$, $d_2 = 3$, $d_3 = 1$, $d_4 = 1$, dan $d_5 = 1$, thus:

$$d = \frac{1 + 1 + 3 + 1 + 1 + 1}{6} = 1.33 \text{ (sampling)}$$

Velocity

There are six velocities obtained from six saccadic movements. The velocities are calculated by using the absolute difference value of x coordinate from consecutive sampled data. The average velocity is then taken for further analysis. From Fig. 3.11, we calculate the value of $v_1 = 4$, $v_2 = 10$, $v_3 = 3$, $v_4 = 7$, $v_5 = 10$, and

$v_6 = 6$, thus

$$velocity = \frac{4+10+3+7+10+6}{6} \; (\frac{\text{pixel}}{\text{sampling}})$$
$$velocity = 6.67 \; (\frac{\text{pixel}}{\text{sampling}})$$

Deviation

The deviation value (dv) is taken at the time when the eye fixates on a stable object. The eye should not make any movement or no eye coordinate changes should occur at the fixation time. In the non fatigue case, the ability to maintain fixation is greater than that in the fatigue case. The coordinate oscillation below 5 pixels per sampling are then recorded. The values above 5 pixels per sampling are considered as a noise. The absolute value is then taken.

$$dv_i = \text{abs}(x_{max} - x_{min}) \text{ (pixel)} \tag{3.11}$$

where i is an occurred period number
Since there are five period of stable object, the average value is taken as a result, and saved in the parameter database.

Table 3.1 shows the eye movement parameter data from 26 participants, both for non-fatigue and fatigue condition.

3.4.2 Classification

Fuzzification

From the eye movement parameter dataset in table 3.1, we randomly selects 13 datasets as learning data to calculate its mean (μ) and the standard deviation (σ) value. The obtained results are used to determine the function of the Gaussian membership values ranging from 0 to 1 or normalized. The Normalized Membership function is expressed in equation 3.4. The mean (μ) and standard deviation (σ) value for 13 randomly selected participants are shown in table 3.2, both for non fatigue μ_{am} and fatigue μ_{pm} conditions. The next step is to generate the rules and membership function using equation 3.4 with μ value taken from table 3.2. The implemented fuzzy rules are as follow:

Table 3.1: Eye Movement Parameters for non fatigue (am) and fatigue (pm) category from 26 participants

number	latency(sampling)		duration(sampling)		velocity($\frac{\text{pixel}}{\text{sampling}}$)		deviation(pixel)	
	am	pm	am	pm	am	pm	am	pm
1	2.33	2.60	0.80	1.00	4.67	4.20	1.00	1.60
2	2.67	2.75	1.40	1.00	6.50	5.25	1.20	1.67
3	2.20	2.67	2.20	0.60	5.60	4.67	1.80	3.00
4	2.50	2.80	1.20	1.20	5.17	4.20	1.50	1.33
5	2.40	2.75	1.40	0.80	5.80	3.75	1.83	1.33
6	2.00	2.67	1.20	0.80	4.50	6.33	2.00	1.00
7	2.50	2.50	0.80	1.00	6.25	4.75	1.67	2.67
8	2.40	2.75	1.20	1.00	6.40	4.75	1.33	1.67
9	5.00	2.00	0.40	0.80	4.50	4.00	1.00	1.67
10	2.50	3.00	0.80	0.60	5.75	6.00	2.00	2.00
11	1.80	3.00	1.20	1.00	5.00	5.60	2.00	1.00
12	2.60	2.60	1.60	1.00	4.20	5.60	1.57	1.33
13	2.50	3.00	0.80	1.00	6.25	5.25	1.67	2.60
14	2.33	2.50	2.00	1.20	5.67	5.50	1.75	1.80
15	2.00	2.40	2.00	1.00	4.00	4.80	1.57	1.33
16	2.50	2.50	1.60	1.20	6.17	5.83	2.25	1.40
17	2.75	3.00	0.80	1.00	6.25	4.00	2.00	1.50
18	2.33	2.60	0.60	1.20	5.00	5.60	1.00	1.50
19	5.33	2.60	1.20	1.00	6.00	5.60	2.33	2.00
20	2.60	2.67	1.80	1.20	5.20	5.00	1.50	1.20
21	2.50	3.00	0.80	0.60	5.50	4.00	1.50	2.50
22	3.20	3.25	1.00	1.20	5.60	3.75	2.00	2.00
23	2.00	2.83	2.00	1.20	4.33	4.17	2.00	1.33
24	2.00	2.00	0.20	0.60	7.00	5.67	1.00	2.50
25	3.40	2.80	1.00	1.00	6.60	5.40	1.50	1.00
26	3.40	3.00	1.40	1.00	4.60	5.20	1.50	1.25

Table 3.2: μ and σ value for non fatigue and fatigue condition from learning set (13 of 26 participants)

Parameter	Condition	μ	σ	min	max
Latency	am	2.74	0.35	2.50	3.40
	pm	2.70	0.32	2.00	3.25
Duration	am	1.15	0.37	4.20	6.60
	pm	1.03	0.21	3.75	5.83
Velocity	am	5.70	0.74	0.80	1.80
	pm	4.96	0.74	0.60	1.20
Deviation	am	1.68	0.29	1.20	2.25
	pm	1.64	0.48	1.00	2.50

Rule 1 **If** *latency* is *slow* and *duration* is *long* and *velocity* is *high* and *deviation* is *small*, **then** the *condition* is *non fatigue*.

Rule 2 **If** *latency* is *fast* and *duration* is *short* and *velocity* is *low* and *deviation* is *big*, **then** the *condition* is *fatigue*.

Defuzzification

The MIN-MAX method is used for defuzzification process. After building the membership function for each parameter and generating the rules for the non fatigue and fatigue conditions, the system is ready to be implemented.

For example, if one participant has eye movement parameter as follows: latency = 2.67, duration = 2.2, velocity = 6.67, and deviation = 1.6, these parameter values are used as an input x from the generated rule using Gaussian membership function in equation 3.4. The results are μ value of each parameter for non fatigue and fatigue condition. For the non fatigue condition we get:

$$
\begin{aligned}
\mu_{am}(latency) &= \exp[-\tfrac{1}{2}(\tfrac{2.67-2.74}{0.35})^2] &= 0.980 \\
\mu_{am}(duration) &= \exp[-\tfrac{1}{2}(\tfrac{2.20-1.15}{0.37})^2] &= 0.017 \\
\mu_{am}(velocity) &= \exp[-\tfrac{1}{2}(\tfrac{6.67-5.70}{0.74})^2] &= 0.423 \\
\mu_{am}(deviation) &= \exp[-\tfrac{1}{2}(\tfrac{1.60-1.68}{0.29})^2] &= 0.962
\end{aligned}
$$

The MIN operation is then applied to four values of μ_{am}, to find the least value.

$$\mu_{am} = \text{MIN}[0.980, 0.017, 0.423, 0.962] = 0.017$$

For the fatigue condition we get:

$$\begin{aligned}
\mu_{pm}(latency) = &\quad \exp[-\tfrac{1}{2}(\tfrac{2.67-2.70}{0.32})^2] &= 0.994 \\
\mu_{pm}(duration) = &\quad \exp[-\tfrac{1}{2}(\tfrac{2.20-1.03}{0.21})^2] &= 3.13 \times 10^{-7} \\
\mu_{pm}(velocity) = &\quad \exp[-\tfrac{1}{2}(\tfrac{6.67-4.96}{0.74})^2] &= 0.070 \\
\mu_{pm}(deviation) = &\quad \exp[-\tfrac{1}{2}(\tfrac{1.60-1.64}{0.48})^2] &= 0.997
\end{aligned}$$

from the four values of μ_{pm}, and the MIN operation is then applied.

$$\mu_{am} = \text{MIN}[0.994, 3.13 \times 10^{-7}, 0.070, 0.997] = 3.13 \times 10^{-7}$$

Finally, the MAX operation is applied to both MIN values.

$$\mu_{am \bigcup pm} = \text{MAX}[0.017, 3.13 \times 10^{-7}] = 0.017$$

since 0.017 is greater than 3.13×10^{-7}, then the output of the fuzzy system is non fatigue. The classification example is illustrated in Fig. 3.12.

System Performance

System performance is evaluated in case of sensitivity, specificity, and accuracy. Sensitivity or true positive fraction is the probability for positive test result. Specificity or true negative fraction is the probability for negative test result, and accuracy is the probability for correct test result. Equations 3.12, 3.13 and 3.14 calculate the sensitivity, specificity and accuracy.

$$\text{sensitivity} = \frac{TP}{TP + FN} \tag{3.12}$$

$$\text{specificity} = \frac{TN}{TN + FP} \tag{3.13}$$

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.14}$$

where TP, TN, FP and FN are true positive, true negative, false positive, and false negative respectively. In this research, the positive term is denoted for fatigue condition and negative term is denoted for non fatigue condition. The performance results are shown in Table 3.3.

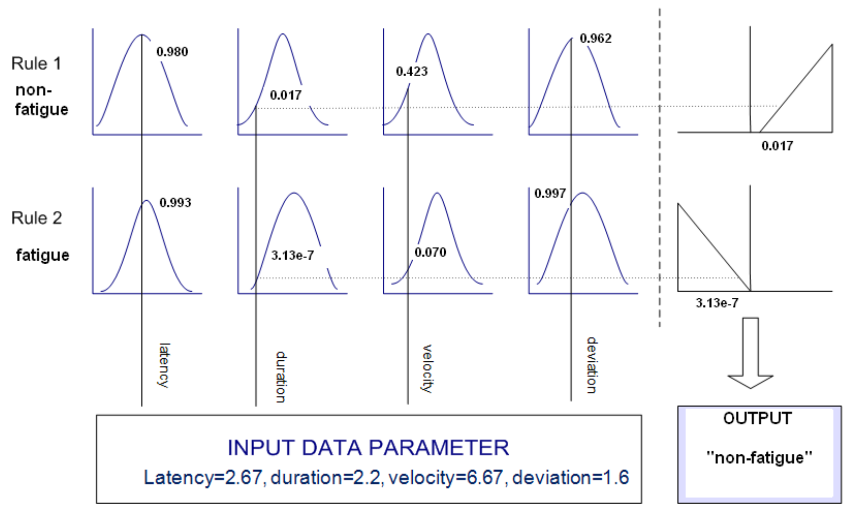


Figure 3.12: Inference mechanism for certain extracted parameter input. Gaussian Distributed Membership Function is used to calculate the degree of belonging to non fatigue and fatigue category. The MIN-MAX method is used for the process.

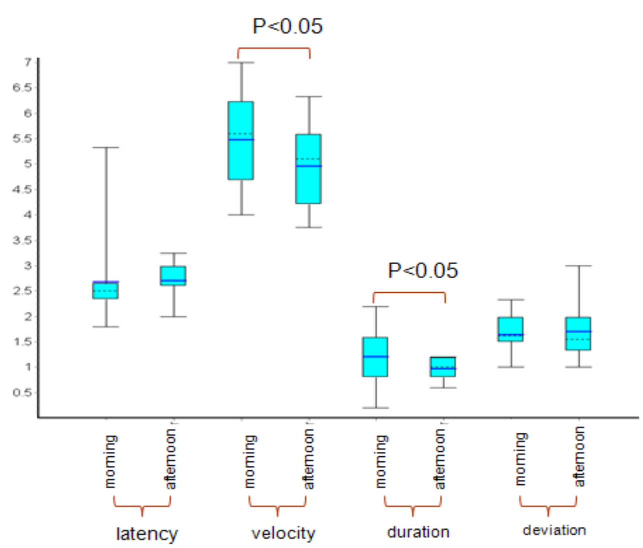


Figure 3.13: Condition classification in various parameter measured from 26 student participants. Velocity and duration are significantly different in non fatigue and fatigue condition ($p < 0.05$).

Table 3.3: System Performance

Method	Sensitivity	Specificity	Accuracy
MIN-MAX	84.62 %	88.46 %	86.54 %

3.5. Summary

This paper has emphasized the usefulness of studying eye movement parameters for physiological approach applications.

The condition classification is approached using Fuzzy-based classification utilizing the Gaussian Distributed membership function, and we reach the classification result as 86.54 %. Through this research, we have confirmed the effectiveness of the usage of the eye movement parameter as an input for distinguishing the condition. This result explains that there is a performance decrement in voluntary eye movement.

The Box-plot for mean comparison between parameter for each condition is shown in Fig. 3.13. The figure shows significant difference in velocity and duration parameters. On the other hand, there is no significant difference in latency and deviation for fatigue and non fatigue condition. Velocity and duration parameters are contribute and validate the different between non fatigue and fatigue measurement ($p < 0.05$). However, all parameters are contribute in determining the physical condition, since it reveal less accurate classification result as 73.08 % when the latency and deviation parameters are omitted from fuzzy classification system. Moreover, the eye movement parameter can not be used separately to determine the condition classification since it reveal even lower classification result.

Combining conventional techniques and artificial neural networks with fuzzy logic, may offers more powerful solutions and higher classification result may be achieved. In addition, applying an optimization algorithm for fuzzy set parameter may improve the classification result as well.

To further improve the detection system performance in general, more heterogeneous participants should be invited in the experiment, such as factory workers, company employees, and drivers. The state of fatigue may be varied as we take the cause of fatigue into account, since the affected participant may feel differently based on their daily activity. In the preprocessing stage, the eye center coordinate estimation method still needs to be enhanced. A higher sampling frequency of captured image may improve the process of input feature extraction.

Chapter 4

Application Two: A Physician-specific model for cardiac rest period determination of MR Coronary Angiography based on Fuzzy Classifier

4.1. Introduction

Coronary artery disease (CAD) is one of the most common cause of human mortality in many countries. Currently, the standard assessment for coronary artery disease diagnosis is coronary angiography (CA). The invasive procedure of conventional CA has lead to recently used of non invasive cardiac imaging devices.

Together with electron beam computed tomography and spiral computed tomography, Magnetic Resonance Coronary Angiography (MRCA) have been introduced over the last few years for cardiac imaging. Although, several problems still remain in MRCA techniques since coronary arteries are moving target due to cardiac contraction and respiration.

Suppression of coronary motion due to respiration and cardiac contraction becomes a challenge in MRCA. In order to minimize blurring of coronary vessels, data acquisition is carried out during cardiac minimum movement.

By adopting some image processing and artificial intelligent algorithms, we develop the algorithm to model the physician's decision in determining the cardiac rest period.

Computerized methods for cardiac rest period determination commonly use an image-based cross-correlation algorithm to find the similarity between template and target image because it provides a good measure for cardiac movement, and has been proven as a robust method [34]. Cross-correlation between images of consecutive heart phases may be used to characterize the cardiac motion, and an optimal acquisition window can be automatically identified. The automatic approach facilitate a rapid and user independent assessment of the optimal cardiac acquisition window for magnetic resonance coronary angiography (MRCA) [35]. However, its use will results a shorter acquisition window when separate volume imaging is preferred, since the rest period is significantly shorter than each of the coronary rest period alone. With no gold standard available for rest period determination, it is still necessary to understand the way of physician to determine the rest period.

The visual assessment by the physician to determine the rest period relies on their experience and intuitive decision, so there is variation of rest period determination among them. Moreover, there are no specific rule that justify the decision of one physician over another. To compare each physician decision, their decision should be modeled, and the fuzzy logic is suitable to model this imprecise knowledge of the physicians. The fuzzy model encapsulate the physician knowledge in a linguistic term, therefore it mirror non-explicit nature of the physician cardiac rest period determination.

Instead of referring to one physician's decision, we want to model different physician's decision in a simple way. The model is expected to be able to characterize the physician-specific decision, since they have their own consideration based on their knowledge or experience. In some cases, a certain physician may suit the requirement needed while other condition may be suited to other physician. The user of this interface application may benefit from the provided alternative of rest period determination modeled from some experienced physicians.

4.2. Cardiac Rest Period

The cardiac rest period (referred to hereafter as rest period) is the period when the cardiac in its minimum or stable movement from the whole period. The diastolic rest period is commonly used for further processing and will be referred as rest period. The rest period is important because image data for the coronary arteries are generally acquired during this period, to minimize blurring due to cardiac movement.

MRI has been used to visualize the coronary arteries recently since its introduced noninvasive technique not associated with radiation. However, when performing MR coronary imaging, we are expected to face some challenges pertaining to coronary imaging. The motion of the vessels during cardiac contraction and the motion of the heart due to respiration may cause a blurring of the images. Also, the complexity of anatomy issue challenges to be overcome.

In their review, Scott, AD et al. [36] describes the type and extent of the motion of the heart due to cardiac and respiratory cycles, which create the image artifacts. Some methods to eliminate the cardiac cycle problem such as ECG gating, subject-specific acquisition window, and section tracking are discussed. With subject-specific acquisition windows and motion-adapted respiratory gating the scanning times can be reduced while maintaining image quality [37].

Laurent et al. [38] presents the methods for ECG-triggered data acquisition and reconstruction. Only those projections for which motion of the heart is expected to be minimal are used for the reconstruction. The minimal movement occurs in the end diastolic phase which can be detected in the ECG in a relative time window of usually 60% to 100% between subsequent R peaks. For coronary artery screening, the optimal ECG trigger time should be determined according to the patient's heart rate, thus greatly reducing motion and motion artifacts during 100-ms acquisitions. [39]. Electrocardiogram (ECG) triggering with data collection during mid to late diastole minimizes blur from coronary artery motion during cardiac contraction. Breath holding or respiratory gated imaging techniques may reduce respiratory motion. The complex coronary anatomy can be studied with two-dimensional (2D) or three-dimensional (3D) acquisition techniques [40].

Wang Y. et al. develops an electrocardiography-triggered M-mode navigator-echo technique to identify the period of minimal cardiac motion in the cardiac cycle. Trigger delays are estimated with the navigator echo-technique and two empirical formula. The quality of image is best with the delay calculated with the navigator-echo technique [41]. Other research shows that during breath hold MR imaging, breath hold pattern is unsuitable. RCA rest period shows large variability in starting point and duration, with no correlation to heart rate [42]. The conducted research from Kim W.Y. et al. [43] demonstrates the dependence of coronary MRA and coronary MR vessel wall imaging on acquisition during periods of reduced bulk cardiac motion. Shechter et al. quantifies the rest period of the CA during the cardiac and respiratory cycle. The dataset is obtained during spontaneous free breathing. The MR motion correction methods are studied to increase the rest period duration. The successful results from the motion correction method depends on the existence of accurate model of the motion, and the ability to estimate the state of the heart at any given time [44].

Various fast scanning techniques are also developed to reduce magnetic resonance imaging artifact, namely, the fast spin echo (FSE) technique, gradient-recalled echo (GRE) techniques and the echo planar imaging (EPI) technique. These techniques provide fast speed imaging which lead to high resolution imaging [45, 46]. All conducted research shows the importance of the rest period as proper acquisition time for image reconstruction.

Based on the cardiac motion, the rest period can be determined using computerized methods which will be subjected to visual assessment by a physician as the standard. The rest periods occur at two cardiac phases at both end-systolic and mid-diastolic phases. To suppress blurring due to cardiac movement, image data acquisition for the coronary arteries is generally implemented during the diastole rest period.

As illustrated in Fig. 4.1, the rest period is expected to occur at the diastolic phase when the ventricles are relaxing. The ventricles volume rises because the blood flows directly from the atrium to the ventricle due to the pressure difference.

This research intends to emulate the decision of a specific physician in a fuzzy-based model for rest period determination. The model may encapsulate their intuitive decision. Probabilistic and fuzzy logic approaches may characterize the system behaviors for a limited dataset in this complex system [47]. Instead of a

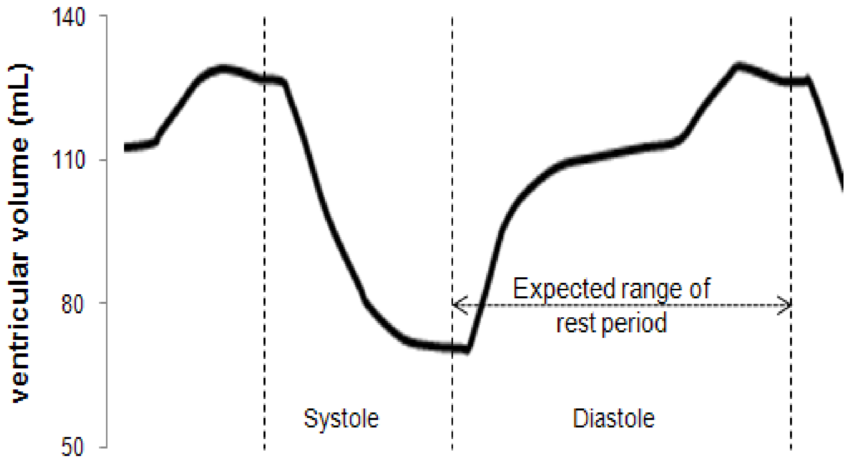


Figure 4.1: The rest period range laid within diastolic phase, when the ventricles are relaxing. The ventricular volume rises due to blood flow from the atrium. Cardiac minimal movement occurs at this phase.

probabilistic approach, fuzzy logic is used in this research due to limited data and the dependency of the output on the extracted features. The proposed system, applied to MR coronary angiography contains two stages: image preprocessing, to extract the input feature, and classification, to classify the input to the rest period or non-rest period condition.

4.3. Method

In the proposed system, the rest period determination uses extracted features from acquired image data. The dataset is derived from retrospectively gated frame images from 20 healthy participants. Their image data are acquired using a 1.5 Tesla Excelart VantageTM MRI scanner (Toshiba Medical Systems, Tochigi, Japan). The 2D Steady State Free Precession (SSFP) images in 4-chamber orientation (horizontal long-axis view) are acquired with FOV of 350mm and a slice thickness of 10mm.

SSFP is first reported by Carr et al. [48] in 1958, and is recently utilized extensively in MR imaging. SSFP imaging is a magnetic resonance imaging (MRI) technique with gradient-echo imaging, which uses steady states of magnetizations.

It offers significant improvements in spatial and temporal resolution with high tissue contrast, decreased magnetic susceptibility and chemical shift artifacts [46]. Among the advantages of SSFP cine imaging are the relative independence of contrast from blood flow, the speed of acquisition, and the high contrast-to noise ratio per unit time [49]. Dharmakumar et al. [50] develops an analysis of the behavior of magnetization in phase space, which demonstrates the essential features of SSFP signals from geometric description.

The four chamber view is a plane through all four chambers including the mitral and tricuspid valves. In many subjects, the 4 chamber view and horizontal long axis (HLA) are similar [51]. In actuality, it differs from the HLA view in that it is planned using both ventricles whereas the HLA is planned off the left ventricle only. The horizontal long axis four-chamber view is one of standard views in cardiovascular imaging. The orientation of a heart is described relative to an imaginary line drawn from the base of the heart (valve plane) to the apex. This image plane is determined by the line that runs from the LV apex of the heart to a midpoint at the base of the heart, often taken to be the midway between the mitral ring [52].

Four physicians determine the rest period area for 20 participants. The physician decision are modeled using fuzzy classifier. The model intend to mimic the behavior of the modeled physician. We modeled two physician decision at first, then used other two additional physicians for further analyses of the system performance.

The proposed method is comprised of two major stages: an image preprocessing stage for extracting the image features, which provides the inputs for the classification system, and a classification stage to classify the input through the fuzzification, reasoning or rule implementation and defuzzification.

4.3.1 Preprocessing

Image preprocessing is performed using a semi-automated approach of manual selection of the ROI (50×50 pixel) placed at the RCA. The RCA is chosen to be the ROI due to its clear movements compared to other cardiac parts. In this preprocessing stage, two features are generated as descriptors for the classification stage, the normalized cross-correlation (NCC) and normalized frame number (fr_{nor}). The NCC is useful in showing similarity between the template image with the observed frame as a target image. Through this information, the ROI movement can be monitored, and the high value of NCC shows its minimum movement towards the template image. The normalized frame number as another input feature plays an important role in the classification system, since its values shows similarity from consecutive frame images towards the template image. Through this similarity measurement we can predict the rest period area. As a result, we used NCC to modulate the presumed determination of the rest period, and manifest it in generated fuzzy if-then rule.

Since our goal is to find the movement of the ROI which is manually placed by the operator, we do not intend to find the matching location of a reference template within one frame. We simply calculate the similarity of the chosen ROI from the consecutive frame with the template image. The ROI similarity in consecutive frame images with the template image may be represented using this simple and effective NCC, calculated using equation 4.1.

$$NCC = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \frac{(f(x,y) - \overline{f})(g(x,y) - \overline{g})}{\sigma_f \sigma_g} \tag{4.1}$$

where $f(x, y)$ and $g(x, y)$ are the gray level of the target and template image, $\overline{f}$ and $\overline{g}$ are the gray level average of the target and template image, σ_f and σ_g are the standard deviation of the target and template image, and M and N are the number of pixels in x and y directions of the ROI respectively.

The NCC values vary from one to minus one, which indicate the similarity index from identical to reversed. We limit this index from one to represent identical, to zero to represent non-similar. For simplicity, values below zero were converted to zero since reversely identical will be categorized as a non-similar.

Within one period of R-R cycle, cardiac minimal movement occurs at 60%-100% [38] or within the diastolic phase when the ventricles are relaxing. The ventricles volume rises because the blood flows directly from the atrium to the ventricle due to the pressure difference. As illustrated in Fig. 4.1, the rest period is expected to occur at this period. Even though any frame from the diastolic phase may be utilized as the template image, in this research, the three-fourth frame is used. Fig. 4.2 illustrates the NCC calculation step.

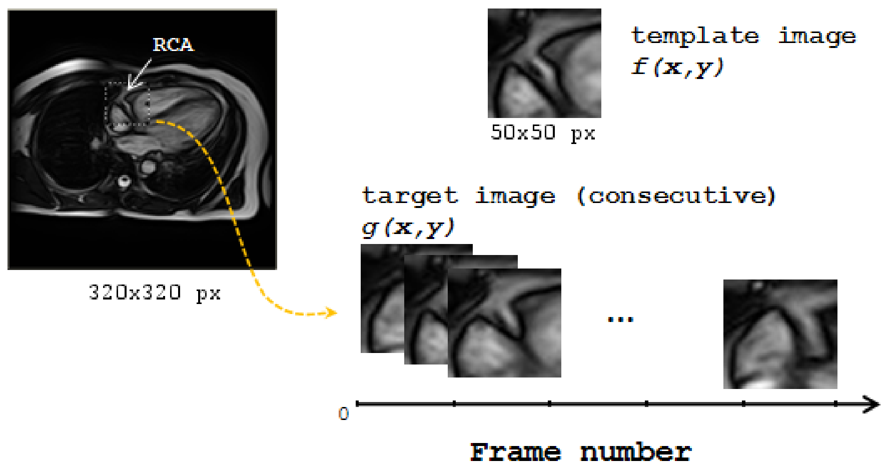


Figure 4.2: Normalized cross correlation (NCC) calculation step between the template image and a consecutive image as the target. RCA was used as the ROI.

As another input for rest-period determination, the normalized frame numbers fr_{nor} are used. Because the rest period duration varies from patient to patient [53], and the total number of frames from each participant in the dataset vary from 49 to 68 frames, we normalize the value of number of frames to 100 to apply the same scale for each participant. The Equation 4.2 shows the fr_{nor} calculation,

$$fr_{nor} = \frac{fr}{fr_{tot}} \times 100\% \tag{4.2}$$

where fr_{nor}, fr, and fr_{tot} are normalized frame number, frame number, and the total number of frame respectively.

Both inputs are used as measured variables to determine whether the cardiac period can be classified as a rest period or a non rest period.

4.3.2 Classification

The fuzzy classifier algorithm consist of three steps: fuzzification, reasoning and defuzzification.

Fuzzification

The first step is to fuzzify the NCC and fr_{nor} as measured variables. Considering the NCC first, depending on the degree of similarity of consecutive frame images with the template image, we can determine how different the current state of the heart with respect to the template state. We use the lowest and highest NCC value that are derived from the physician's decision as an identification parameters for the NCC fuzzy set which are denoted with a and b respectively, as illustrated in Fig. 4.3(a). The fuzzy set labeled *low* is created and ascending membership levels from zero to one are assigned following the linear function described in equation 4.3 for NCC values less than b. The fuzzy set labeled *high* is also created and assigned membership levels ascending from zero to one following the linear function in equation 4.6 for NCC value larger than b. An overlapped area is provided by *modest1* and *modest2* fuzzy sets with membership levels as given in equation 4.4 and 4.5. This NCC threshold quotation captures the decision from the current modeled physician, as other physicians may produce different thresholds. However, the difference among them is not significant.

$$\mu_{low} = \begin{cases} 1 & , x = 0 \\ \frac{b-x}{b-0} & , 0 < x < b \\ 0 & , \text{otherwise} \end{cases} \tag{4.3}$$

$$\mu_{modest1} = \begin{cases} 1 & , x = b \\ \frac{x-a}{b-a} & , a < x < b \\ 0 & , \text{otherwise} \end{cases} \tag{4.4}$$

$$\mu_{modest2} = \begin{cases} 1 & , x = b \\ \frac{1-x}{1-b} & , b < x < 1 \\ 0 & , \text{otherwise} \end{cases} \tag{4.5}$$

$$\mu_{high} = \begin{cases} 1 & , x = 1 \\ \frac{x-b}{1-b} & , b < x < 1 \\ 0 & , \text{otherwise} \end{cases} \tag{4.6}$$

The fuzzification is also applied to the fr_{nor} using three overlapped fuzzy sets labeled *early*, *middle* and *late*, with a trapezoid shape for the *early* set and triangle shapes for the *middle* and *late* set. The middle set represents the rest period area. To assign different rules for the start and end frame of the rest period the *middle* set is divided further into *middle1* and *middle2*. The degree of membership for each fr_{nor} fuzzy set is shown in Fig. 4.3(b) and is calculated using equations 4.7 to 4.10.

$$\mu_{early} = \begin{cases} 1 & ,0 < x \leq c \\ \frac{d-x}{d-c} & ,c < x \leq d \\ 0 & ,\text{otherwise} \end{cases} \tag{4.7}$$

$$\mu_{middle1} = \begin{cases} 1 & ,x = d \\ \frac{x-c}{d-c} & ,c < x \leq d \\ 0 & ,\text{otherwise} \end{cases} \tag{4.8}$$

$$\mu_{middle2} = \begin{cases} 1 & ,x = d \\ \frac{f-x}{f-d} & ,d < x \leq f \\ 0 & ,\text{otherwise} \end{cases} \tag{4.9}$$

$$\mu_{late} = \begin{cases} 1 & ,x = 100 \\ \frac{x-e}{100-e} & ,e < x \leq 100 \\ 0 & ,\text{otherwise} \end{cases} \tag{4.10}$$

In this research, we use the rest period decision from two physicians. Among 20 healthy participants, we selected ten participants as "*dataset1*" and the remaining (10 participants) as "*dataset2*". To optimize the data selection, least square regression analysis is applied. We compare the slope of linear reression function from initial *dataset1* and *dataset2*. From the differences of the slope value, we rearrange the member of the dataset. The optimum dataset combination is obtained by minimizing the slope difference between *dataset1* and *dataset2*, since ideally no difference in decisions from one physician, and maximizing the slope difference between two physicians to emphasize the differences between them. The optimum dataset are illustrated in Fig. 4.4. We use *dataset1* as learning data and *dataset2* as test data for classification, and vice versa.

From the learning dataset of the modeled physician's decision for the RCA case, we used a linear function to find the relationships between the total number of frames and the beginning and end of the rest period as shown in Fig. 4.4. Despite the small correlation value for the total number of frames and the start and end frame of the rest period, this function can distinguish one physician's decision from another.

Using this linear function, the normalized frame fuzzy set threshold can be initiated according to the total number of frames for each subject which is varies within one R-R cycle. We thus create the fuzzy set thresholds c and d with reference to the start frame function and the fuzzy set thresholds e and f with reference to the end frame function. We assign values of c as (least start frame$-SD_{start}$), d as (predicted start frame$+2SD_{start}$), e as (most end frame) and f as (maximum scale of the frame). Thus, the fuzzy set threshold reflects the decision of one specific physician as derived from the learning data. The sets shown in Fig. 4.3 are sufficient for this research. The sets enable us to assign multiple classes for middle set, since we divide it as middle1 and middle2 sets. We can generate the rules that assign different start frame for the same NCC value. For the same normalized frame number, the rest period classification will be defined by its NCC value.

Reasoning

Next, we have to determine whether the cardiac period for each arriving pair or combination of NCC and fr_{nor} will be classified as a rest period or a non-rest period. Expressed with its membership degree value, each arriving pair of measurements will lead to one conditional output following the generated if-then rule.

The generated fuzzy rules are grounded in the concept of how NCC and fr_{nor} relate to rest period condition, that is described briefly in section 4.3.1. The rules also refer to the implemented fuzzy sets that are described in section 4.3.2. The rules are as follows:

- rule 1 : **if** NCC is *low* **then** period is *nonrestp*
- rule 2 : **if** fr_{nor} is *early* **then** period is *nonrestp*
- rule 3 : **if** NCC is *modest1* and fr_{nor} is *middle1* **then** period is *nonrestp*
- rule 4 : **if** NCC is *modest1* and fr_{nor} is *middle2* **then** period is *restp*
- rule 5 : **if** NCC is *modest2* and fr_{nor} is *middle1* **then** period is *restp*

- rule 6 : **if** NCC is *modest2* and fr_{nor} is *middle2* **then** period is *restp*
- rule 7 : **if** NCC is *high* and fr_{nor} is *middle1* **then** period is *restp*
- rule 8 : **if** NCC is *high* and fr_{nor} is *middle2* **then** period is *restp*
- rule 9 : **if** fr_{nor} is *late* **then** period is *nonrestp*

where period is the output in the consequent part with *restp* and *nonrestp* as its sets. All measured variables and output are expressed in its membership degree value. The MIN operation is applied to each rule for their minimum value as in equation 4.11.

$$\mu_i = \text{MIN}[\mu_i(NCC), \mu_i(fr_{nor})] \tag{4.11}$$

where i (1,2, $\cdots$,9) are rule numbers.

Fig. 4.5 shows a representative example of implemented rule for observed image frame from one subject with 0.870 and 62.319 for NCC and fr_{nor} respectively. Using equation 4.3 to 4.10, certain membership levels of each fuzzy set for rule 1 to 9 are calculated. The MIN operation is applied to each rule to reveal their minimum value as in equation 4.11.

Defuzzification

For the defuzzification process, we employ the MIN-MAX compositional height method [1] rather than other techniques e.g. Mean of Maxima and Center of Gravity, since we are dealing with classification process regardless the crisp final result. The MIN values derived from the reasoning stages are processed further using a MAX (maximum) operation to take the largest value as shown in equation 4.12. The consequent part with the maximum membership level will be regarded as an output.

$$\bigcup_{i=1}^{9} \mu_i = \text{MAX}[\mu_1, \mu_2, ..., \mu_9] \tag{4.12}$$

As shown in 4.5, the collected MIN value from fuzzification process for rule 2, 5 and 7 are 0.171, 0.351 and 0.649 respectively, while other rules have zero membership value. The MAX operation will reveal the value from rule 7 as an output, since it has the maximum μ as 0.649. The processed frame will be classified as a rest period frame following designated decision from rule 7. Fig. 4.7 shows representative example of defuzzification process.

The classification process are implemented to all test dataset1 and dataset2 with total of 20 participants. Variety in the number of frames from each participant can be handled with its normalized values. As shown in Fig. 4.6, the generated nine rules are assign an appropriate period for each incoming input combination.

4.4. System Performance

We evaluate the performance of the proposed method in term of method distance to show how close the model can mimic and characterize the modeled physician. The averaged Euclidean distance from 20 participants is analyzed here. The distance is derived from the scatterplot of the start frame versus end frame of the rest period for each method. The Euclidean distance among each method within each subject is calculated first, then the average distance from 20 subjects is calculated as a result. Physician A and physician B are modeled, and the models are evaluated to find how close they approach the modeled physician's decisions. The results are shown in table 4.1. The rest period determination behavior of the physician and the model are plotted in Fig. 4.8 and Fig. 4.9.

On average, the duration of the rest period from physician B is significantly longer and starts significantly earlier in comparison with physician A with $p < 0.05$ (Fig. 4.8a, Fig. 4.9a). Similarly, the rest period determination from model B is significantly longer and starts significantly earlier in comparison with model A with $p < 0.05$ (Fig. 4.8b, Fig. 4.9b). The results show that the determination characteristic can be duplicated by our models.

The scatterplot data for the duration of the rest period between model A, B and modeled physician A and B respectively, show identical tendencies since the data are distributed around identical line as illustrated in Fig. 4.8c and Fig. 4.8d. Similarly, scatterplot of the start frame of the rest period between model A, B and modeled physician A and B respectively, show identical tendencies as illustrated in Fig. 4.9c and Fig. 4.9d.

The model performance is also analyzed using Euclidean distance from the

Table 4.1: Distance among models and modeled physicians

data	model	distance(frames)[1] physician A	physician B
dataset1	model A	2.77±1.34	3.77±2.45
	model B	4.45±1.66	3.03±1.89
dataset2	model A	2.40±1.07	3.93±1.80
	model B	4.19±1.21	2.57±1.10
average	model A	2.59±1.19	3.85±2.10
	model B	4.32±1.41	2.80±1.52

[1] physician A and physician B distance is 4.40±2.26 frames.

modeled physician. Table 4.1 summarize the results for the distance calculation between the model and the modeled physician. For dataset1, only model B have approach significantly closer towards physician B as compared to physician A. For dataset2, both model A and B can approach significantly closer to the modeled physician. On average, the distance between the model and the modeled physician is significantly closer compared with the distance to other physicians as graphed in Fig. 4.10. For model A to physician A and model A to physician B group, a preliminary test for the equality of variances indicates that the variances of the two groups are significantly different with $p = 0.009$, therefore, a two-sample t-test is performed assume unequal variances. The results reveal that the mean score for Model A to physician A (M= 2.59 SD= 1.19, N= 20) is significantly smaller than the scores for Model A to physician B (M= 3.85, SD= 2.10, N= 20.) , $p <= 0.05$. For model B to physician B and model B to physician A group, a preliminary test for the equality of variances indicates that the variances of the two groups are not insignificantly difference $p = 0.38$, therefore, a two-sample t-test is performed that assume equal variances. The results show a mean score for Model B to physician B (M= 2.80 SD= 1.52, N= 20) is significantly smaller than the scores for Model B to physician A (M= 4.32, SD= 1.41, N= 20.) , $p <= 0.05$.

The setting of the fuzzy set thresholds using a linear function for the start and end frame vs total number of frames shows effectiveness in modeling physician-specific decision. In this research, learning and test dataset from healthy participants are used. If arrhythmia dataset are used, insufficient classification result may be obtained, since it will influence the cross-correlation pattern within the R-R cycle.

The implemented fuzzy logic algorithm provides a means for modeling the subjective decisions of a physician in a simple way through its fuzzy set. In detail, the shapes and the thresholds of the fuzzy sets reflect the current modeled physician. Other physicians decisions may produce different fuzzy sets according to their own definitions, which may affect the shapes and thresholds. The normalized cross correlation and normalized frame number which are transformed to the fuzzy set represents the physician's decisions suitably. It is still undetermined whether these two features can completely describe the rest period condition. However, in terms of cardiac movement and rest period area, these two features represent the physician's decisions. The results can be improved by tuning the system. The measured variables for fuzzy set construction may also be explored to find the best determination of the rest period. The algorithm can be extended further to accommodate additional variables.

4.4.1 Validation with additional data

For further validation of the model, we use the rest period decision from additional two physicians (physician C and physician D). We calculate the distance of rest period decision among physicians before further analysis, and the result is shown in Fig. 4.11. Using the same clustering as used for physician A and physician B, we have obtained the linear function to determine the fuzzy set threshold as illustrated in Fig. 4.12.

We analyze the behavior from four physicians in term of start frame and duration of the rest period as illustrated in Fig. 4.13. Box and whisker plots show relationships among four physician decision for 20 participants. Physician A decision for start frame of rest period is significantly later compared to decision of physician B, C and D with $p < 0.05$. Physician A decision for duration of rest period is significantly shorter compared to physician B, C, and D with $p < 0.05$.

We also analyze the model behavior in determining the start frame and duration of rest period. The results illustrated in Fig. 4.14 show that the model can duplicate the modeled physician behavior. Box and whisker plots show relationships among four models decision for 20 participants. The start frame decision of model A is significantly later compared to decision of model B, C and D with $p < 0.05$, and model A decision for duration rest period is significantly shorter compared to model B, C, and D with $p < 0.05$.

In terms of the averaged distance among the model and physician, we plot a histogram to illustrate the distance comparison among them. As illustrated in Fig. 4.15, based on the calculated mean score of the distance, model A to physician A is significantly smaller than model A to physician B, and model A to physician C. The distance of model B to physician B is significantly smaller than the distance of model B to physician A. The distance of model C to physician C is significantly smaller than the distance of model C to physician A. The distance of model D to physician D is significantly smaller than the distance of model D to physician A. Statistically, the results from the models are approach significantly closer to the modeled physician comparing to other physicians. However, in this research, when the distance between two physicians is less than 3.17 frames, the model does not approach significantly closer to the modeled physician.

Table 4.2 show the averaged distance of the models toward physicians. The diagonal area in the table are the distance of the model toward modeled physician, which show closer distance compared to other physicians. However, model C distance toward physician C is further than model C distance toward physician B, due to the high similarity between physician B and physician C as shown in Fig. 4.13.

Table 4.2: Averaged Distance of the Models towards Physicians (in frames)

	model A	model B	model C	model D
Physician A	2.59	2.99	5.06	3.99
Physician B	3.85	2.80	3.09	3.01
Physician C	4.24	3.06	3.28	3.61
Physician D	2.90	2.90	3.45	2.69

We also evaluate the performance of the fuzzy classifier in term of overall accuracy. Overall accuracy is the probability that a classification test from the model is correctly performed with respect to modeled physician and is defined as follows:

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.13}$$

where TP,TN, FP and FN are true positive, true negative, false positive, and false negative respectively.

These value are calculated by comparing the rest period determination from physician with classification results from the model, as illustrated in Fig. 4.16. In this research, the positive term is denoted for rest period condition and the negative term is denoted for non rest period condition.

Table 4.3 show the classification accuracy of the models toward physicians. The diagonal area in the table are the accuracy of the model toward modeled physician, which show higher classification accuracy compared to other physicians. However, model C accuracy toward physician C is less than model C accuracy toward physician B, due to the high similarity between physician B and physician C as shown in Fig. 4.13. The model can not distinguish the difference between those two physicians.

Table 4.3: Classification Accuracy of the Models toward Physicians

	model A	model B	model C	model D
Physician A	94.71 %	91.35 %	89.63 %	91.77 %
Physician B	92.55 %	94.50 %	93.78 %	93.83 %
Physician C	91.29 %	93.68 %	93.10 %	92.44 %
Physician D	94.10 %	93.90 %	92.89 %	94.21 %

4.5. Summary

We have proposed a fuzzy classifier method for modeling physician-specific decisions in determining the cardiac rest period for MR coronary angiography. The proposed method offers a simple way to build a model which can mimic physician-specific decisions from limited dataset. A trapezoid and triangle shape of the membership function are employed. In terms of the method distance, the results demonstrate the effectiveness of the normalized cross-correlation and normalized frame number as a fuzzy set. For modeling the physician decisions, the fuzzy logic algorithm is relatively easy to implement in a software. Modeling the decisions from different physicians can be accommodated by modifying the shape and thresholds of the fuzzy sets. In term of measured variables, the algorithm can be extended easily by incorporating other necessary variables. To more accurately characterize the rest period, other features can be extracted as measured variables and be investigated further.

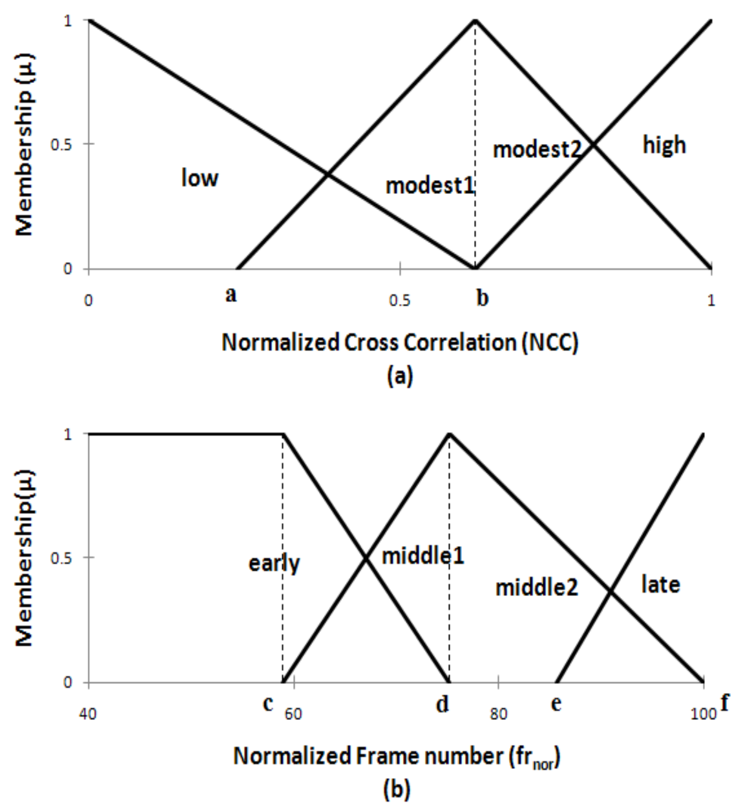


Figure 4.3: (a) Membership function for normalized cross-correlation (NCC) is used with $a = 0.24$ and $b = 0.62$ for low and high thresholds respectively. (b) For normalized frame number fr_{nor}, fuzzy triangle membership functions of *early*, and *late* are used to represent non rest period condition, *middle1* and *middle2* is used to represent rest period condition. Fuzzy set threshold c, d, e and f are determined from the learning dataset.

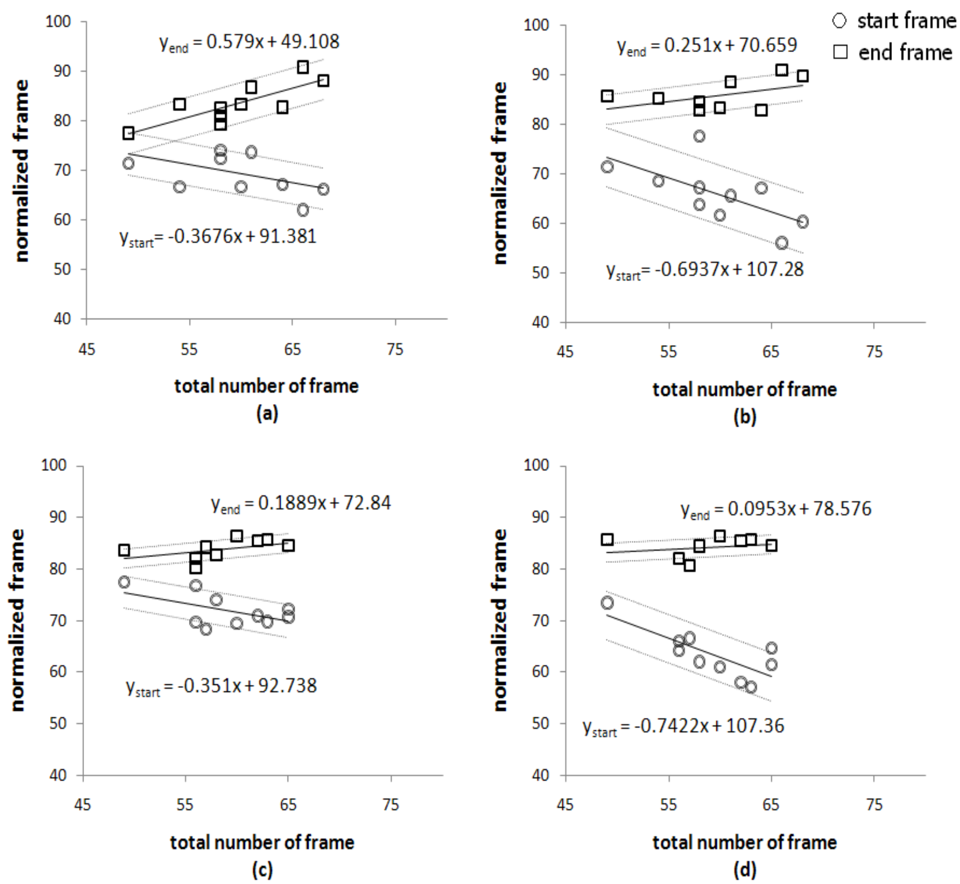


Figure 4.4: Scatterplot showing the relationships between the start frame and end frame of the rest period with the total number of frames for each participant. A linear function is used to define the normalized frame number fuzzy set threshold. (a)(c) physician A decision using dataset1 and dataset2 respectively (b)(d) physician B decision using dataset1 and dataset2 respectively.

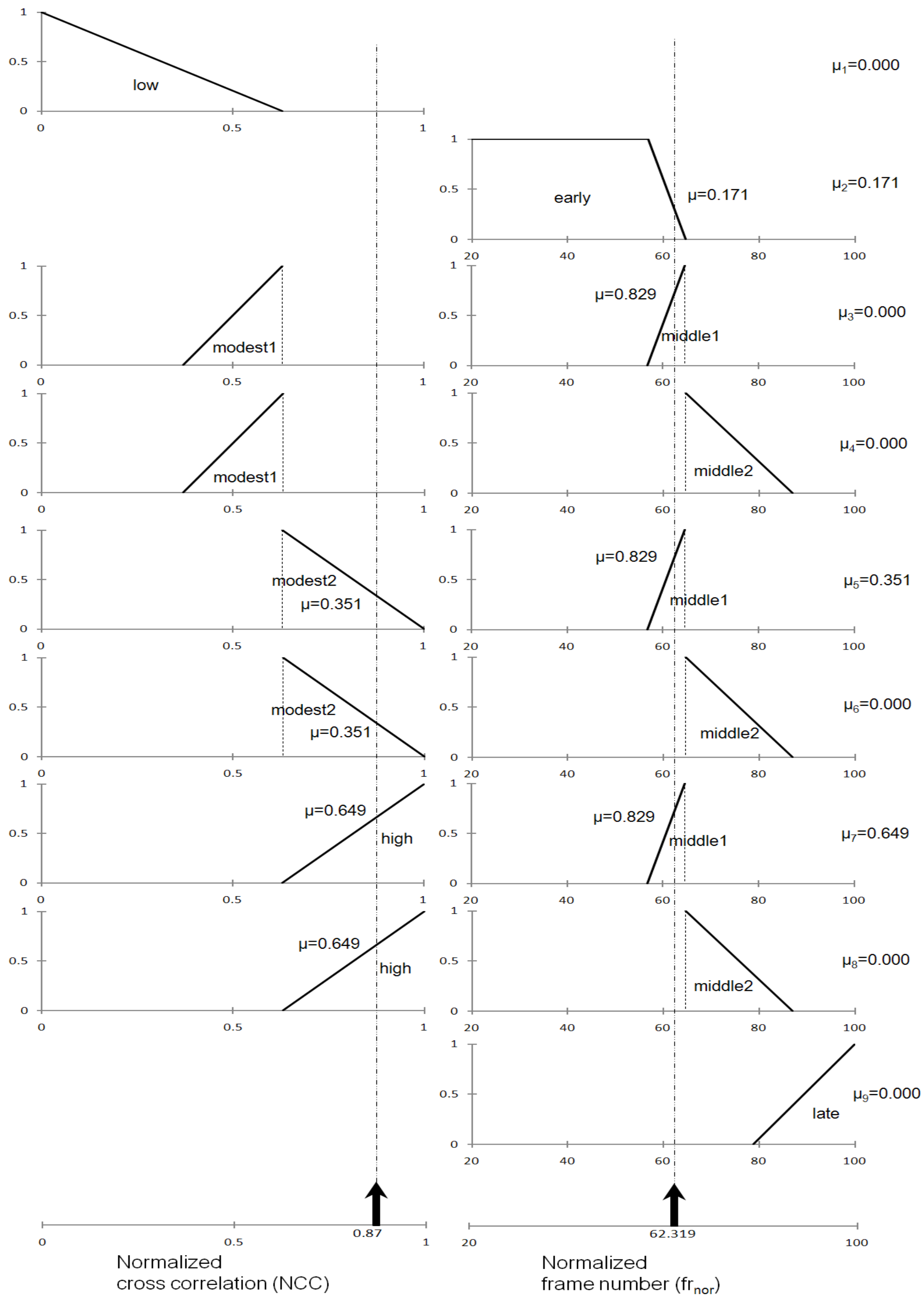


Figure 4.5: Representative example of implemented rule for observed image frame from one subject with NCC=0.87 and fr_{nor}=62.319

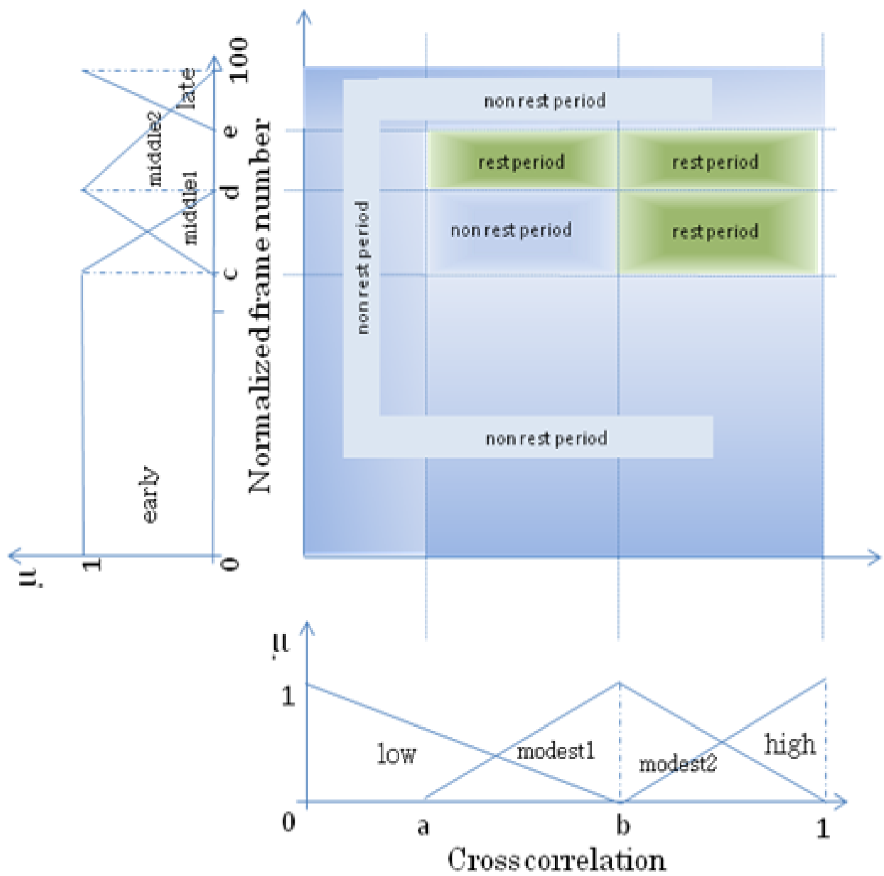


Figure 4.6: The generated rules are assign appropriate period for ech incoming input combination

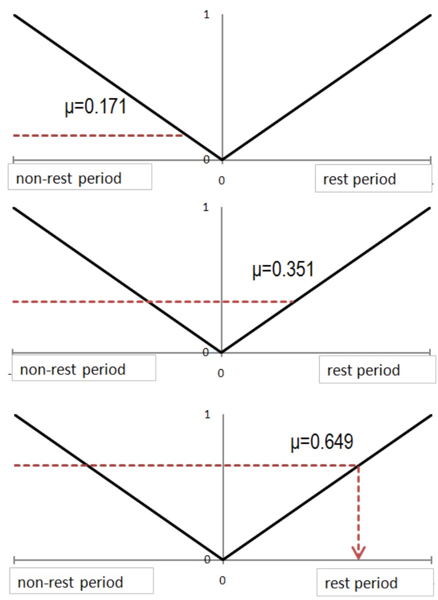


Figure 4.7: Defuzzification Process collect the MIN value from fuzzification stage and appoint the MAX value as classification output.

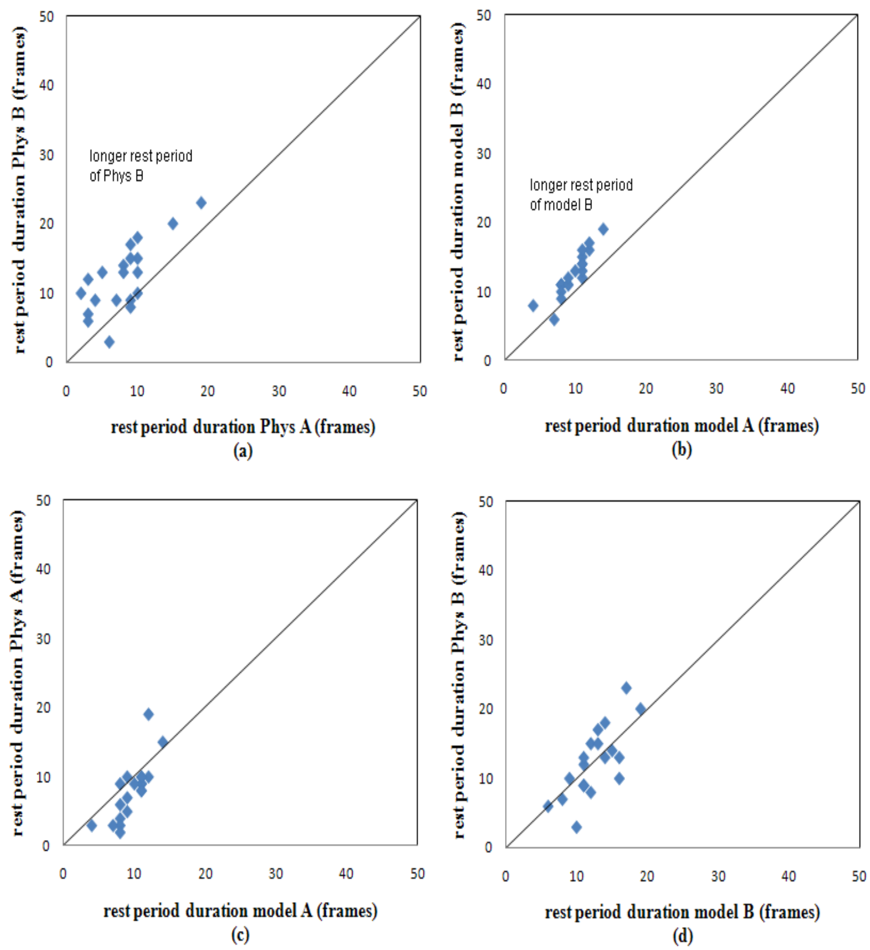


Figure 4.8: Scatter plots of rest period duration in 20 participants of (a) Physician A and Physician B (b) model A and model B (c) model A and Physician A (d) model B and Physician B. From (a) and (b) model A can mimic the characteristic of Physician A, as well as model B mimic Physician B.

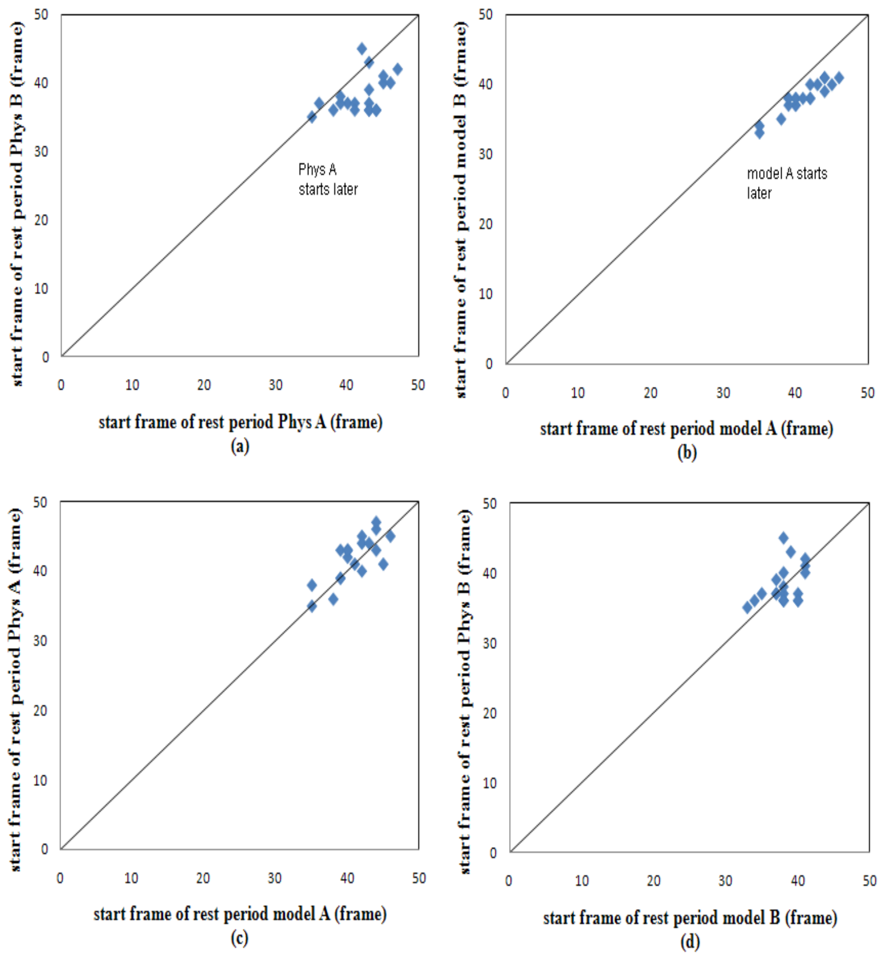


Figure 4.9: Scatter plots of the start frame of the rest period in 20 participants of (a) Physician A and Physician B (b) model A and model B (c) model A and Physician A (d) model B and Physician B. From (a) and (b) model A can mimic the characteristic of Physician A, as well as model B mimic Physician B.

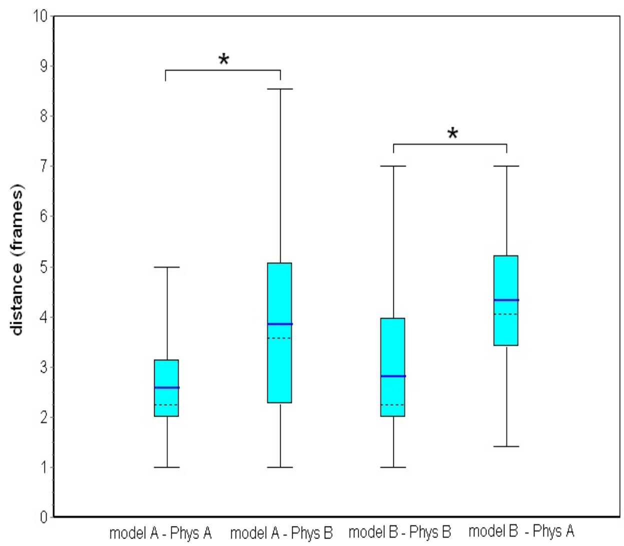


Figure 4.10: Box and whisker plots show relationships between distance of model and modeled physician from 20 participants. Model A is significantly closer to Physician A than to Physician B, and model B is significantly closer to Physician B than to Physician A with $p < 0.05$ (*)

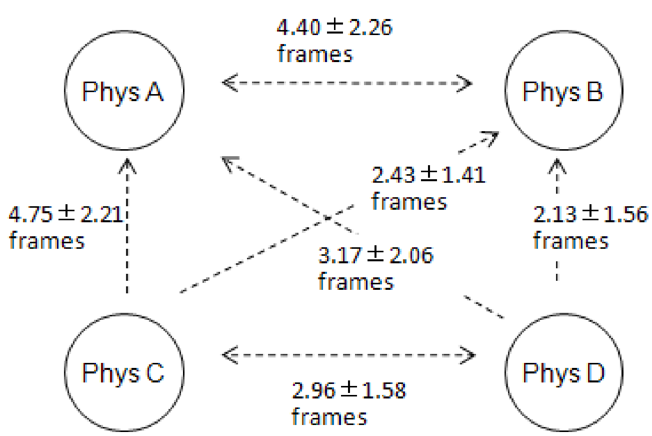


Figure 4.11: The distance among four physicians

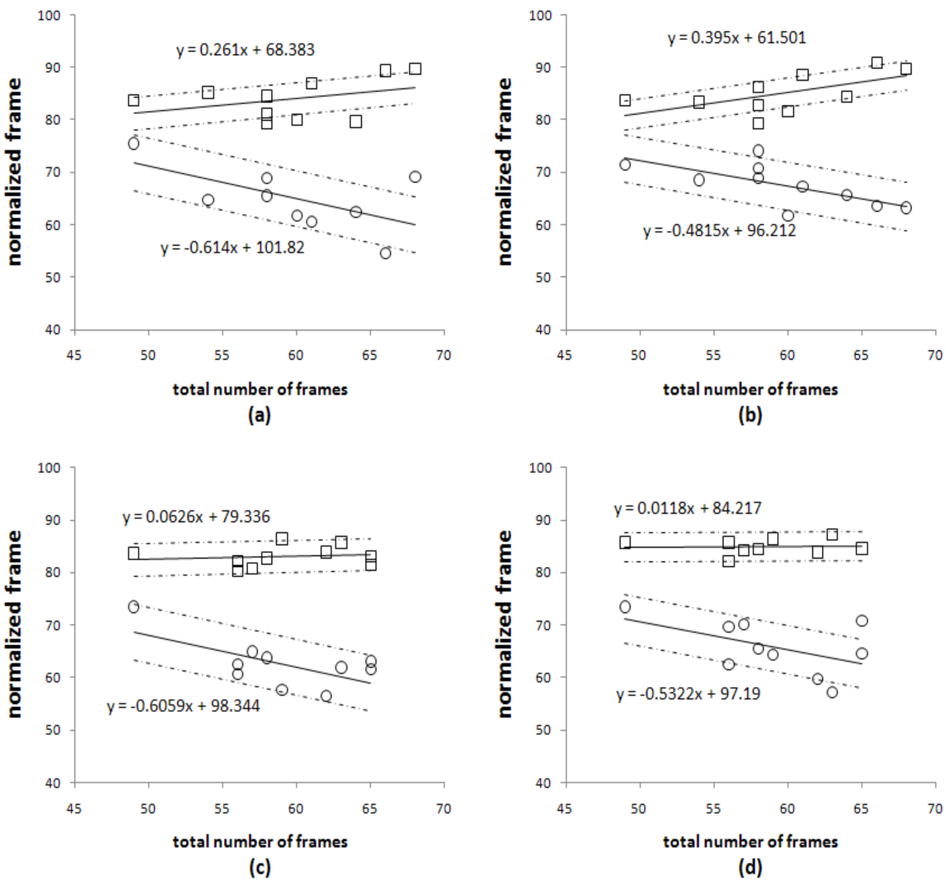
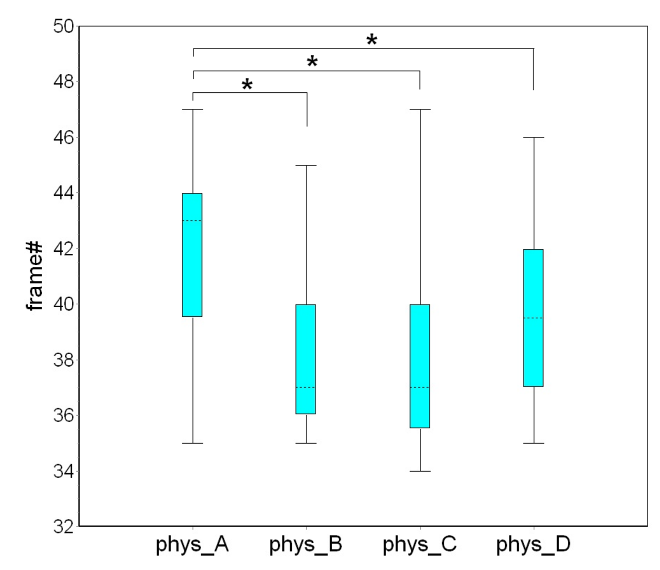
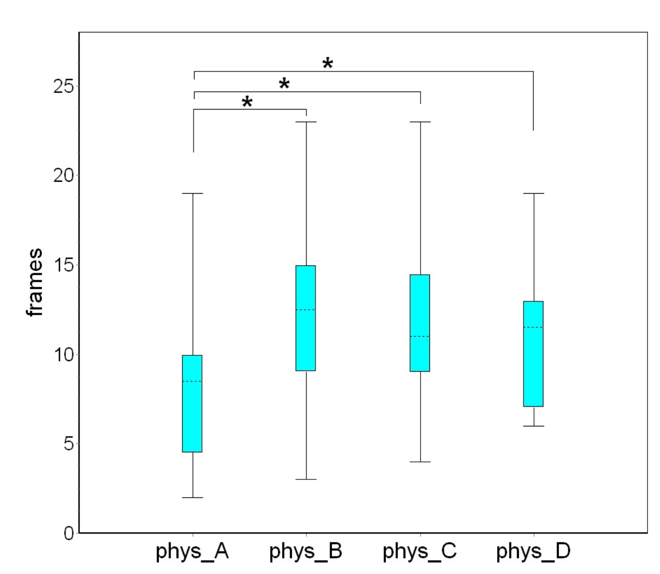


Figure 4.12: Scatterplot showing the relationships between the start frame and end frame of the rest period with the total number of frames for each participant. A linear function is used to define the normalized frame number fuzzy set threshold. (a)(c) physician C decision using dataset1 and dataset2 respectively (b)(d) physician D decision using dataset1 and dataset2 respectively.

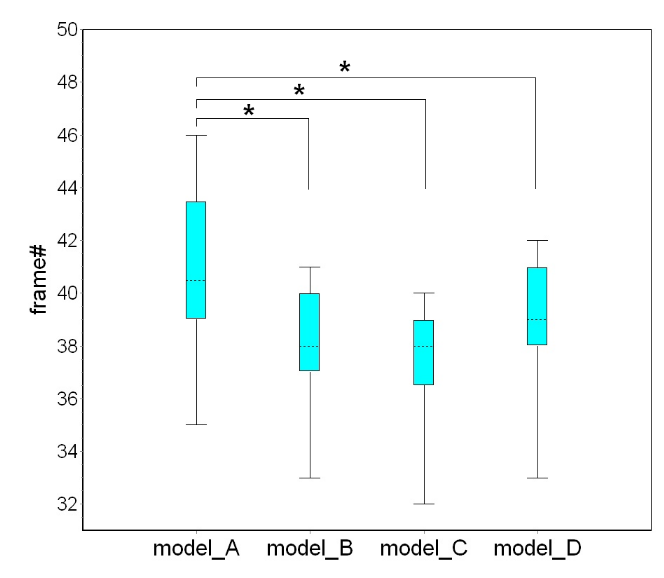


(a)

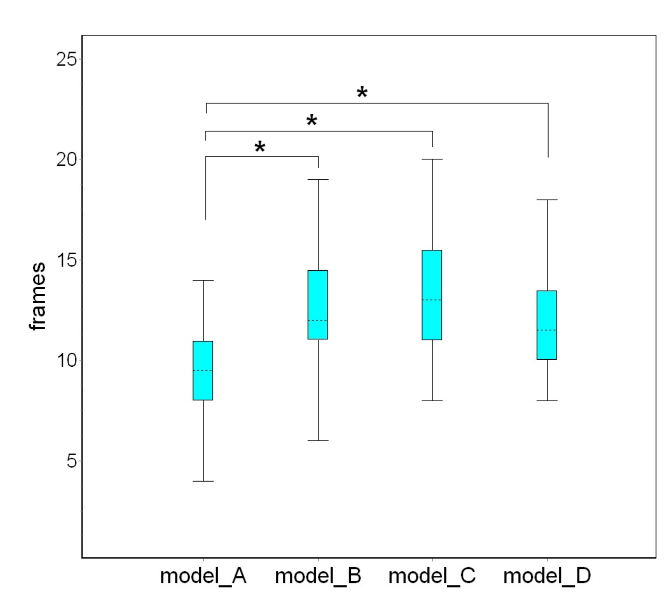


(b)

Figure 4.13: Box and whisker plots (a)start frame relationship among four physicians (b)duration relationship among four physicians.



(a)



(b)

Figure 4.14: Box and whisker plots (a)start frame relationship among four models (b)duration relationship among four models.

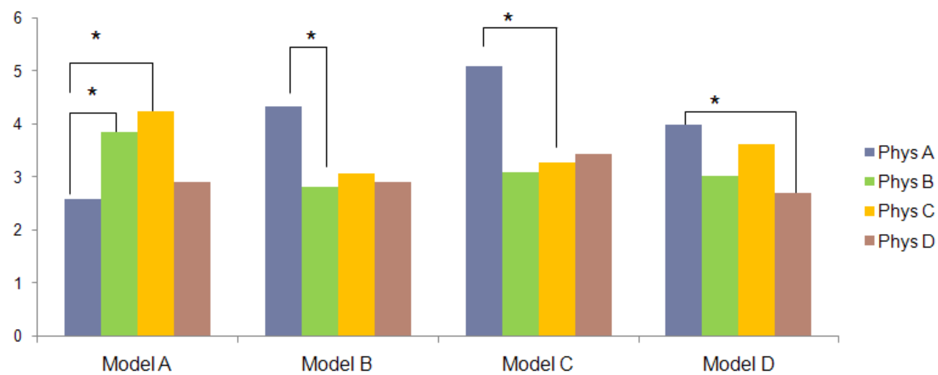


Figure 4.15: Histogram showing the distance among the models and physicians. The model approach significantly closer to the modeled physician compared to other physician.

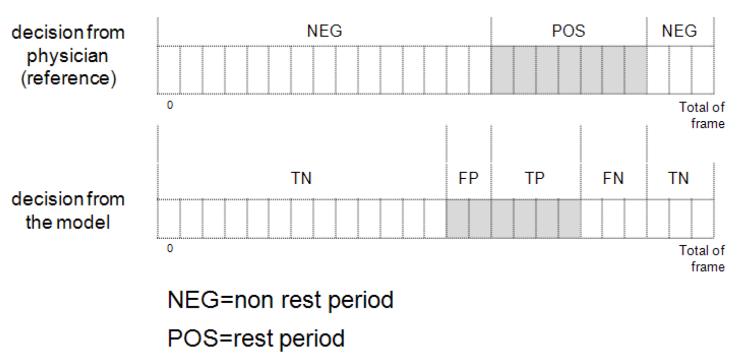


Figure 4.16: The accuracy of classification results is calculated by comparing the decision of the model with the modeled physician

Chapter 5

Conclusion

5.1. Conclusion

The main theme of this dissertation is how to implement fuzzy classifier in medical field, especially in the fatigue classification due to nine-hour learning task on the first application and cardiac rest period determination from MR coronary angiography to mimic physician-specific decision on the second application.

In the first application, we present a method for classifying fatigue condition due to learning task. Our developed fuzzy logic model transform four eye movement parameters into fatigue condition. In the experiment regarding the accuracy of the detection system, we have confirmed the effectiveness of the usage of the eye movement parameter as an input for distinguishing the condition. The output from the classification system shows acceptable result in term of accuracy as 86.54%. This results suggest that the method of fuzzy classifier has the potential to become clinically useful for early diagnosis of fatigue condition. We also demonstrate that certain eye movement parameters are affected by the physical condition change due to learning task. The classification system performance can still be improved by implementing the proper eye center coordinate estimation method in preprocessing stage. A higher sampling frequency of captured image may improve the process of input feature extraction. Such support system of eye movement pattern extraction [54] may be suitably applicable to our classification system. In the classification stage, we may implement the optimization algorithm to find the optimum parameter for the fuzzy set. To further validate the classification system, more heterogeneous subjects should be invited as participants in the experiment, such as factory workers, company employees, and drivers.

In the second application, we present a method for modeling physician decision in determining the rest period using normalized cross correlation and normalized frame number fr_{nor}. We develop a fuzzy logic model that transformed two input features into rest period condition. The output from the model has conformed to expected values for each physician. In addition, we provide a model which can mimic specific physician, thus the operator or user can choose the appropriate model for the particular circumstances. For this application, such similarity measurement method may have significant effect on the classification results. Normalized cross correlation may be implemented suitably if the values can show proper movement of the observed region of interest. Other parts of cardiac such as left coronary artery and cardiac apex may be used as ROI instead of right coronary artery. Certain parameter may be adjusted to trade off among three ROI, for showing the smooth and properly movement of the heart.

In general, design of fuzzy systems may be seen as a selection of the input and output variables, selection of the appropriate reasoning mechanism of the fuzzy model, the universe of discourse determination, and linguistic labels determination. Parameter identification is needed to obtain optimal value of the membership functions. Applying data-driven techniques is common when the system is supplied with input-output data that reflects the optimal behavior of the system. Parameter identification using learning data provide suitable threshold for the generated membership function in both first and second applications.

Fuzzy logic model can be built on top of the experience of experts and learning data, in contrast with neural networks, which take learning data to create a models. The benefit of fuzzy logic is that we can describe the system behavior in simple `if-then´ relations, and directly use the revealed expert knowledge to optimize the system performance, while neural networks need to learn using learning data to reveal the knowledge.

5.2. Future Work

In this dissertation, we have implemented a parameter identification of fuzzy membership function from learning data. We may implement other features which may considerably determine the final result. In designing and generating the implemented rules, expert knowledge may also be embedded with the generated rule from learning dataset. In terms of implementation in the real world, several issues should be considered such as further improvement of modeling algorithms to optimize the accuracy of fuzzy systems, and also the investigation of linguistic term usability. The concept of linguistic usability of fuzzy systems must be investigated in order to find out if it has any significant use for classification systems.

Combining conventional techniques and artificial neural networks with fuzzy logic, more powerful solutions may be offered.

Further heuristics and empirical studies in these two applications will give useful insights to medical field, as well as demonstrate fuzzy effectiveness in classifying task.

Acknowledgements

First of all, I would like to thank my supervisor, Professor Kotaro Minato, who gave me the opportunity to study in his laboratory. I greatly appreciate all his assistance and support during my doctoral course period in his laboratory. His warmth and kind attention has made me feel very welcome.

I would like to thank my thesis committee, Professor Kenji Sugimoto and Associate Professor Tadao Sugiura for their valuable comments and supervision of my work. Their valuable comments and suggestions and also critical questions, improved the achievement of this dissertation.

Also my deep appreciation to Assistant Professor Tetsuo Sato for his supervision and assistance throughout my research during my three years course in NAIST. His valuable contributions improved my overall work.

Thank you to Dr. Shigehide Kuhara from Toshiba and Dr. Tomohisa Okada from Kyoto University hospital for their supervision and comments for the improvement of the research in cardiac rest period determination. This work is a part of cooperation project from our laboratory with Toshiba Co.

Thank you to all members and staff of Biomedical Imaging and Informatics Laboratory for their friendly support and hospitality. Their cheerfulness and support during my stay in Japan and during my work in the laboratory keep the warm horizon among us.

I gratefully appreciate to the Ministry of National Education, Government of Republic of Indonesia for granting the scholarship for my doctoral course in Japan. The scholarship has offered me a wide and useful knowledge and new experience.

I would also like to thank to the Director of Electronic Engineering Polytechnic Institutes of Surabaya for his support by encouraging me to take the opportunity to study in Japan.

To all my friends here in Japan, especially from Indonesian community friends and international friends, I thank you for all the enjoyable activities and warm moments during my study. Our friendship undoubtedly decorated my years of study in NAIST.

Thanks to my mother and my father for their priceless support, encouragement and motivation, also always pray for my success. Their prayers, wishes and support are behind my achievements.

Last but not least, I wish to thank my lovely family: my wife Nur Qoniah, my daughter Ema Machfudhah, my two sons Muhamad Muamar and Muhammad Rafi. Their meaningful support and encouragement boost me to achieve my doctoral degree. They always pray for my success in pursuing my goal in studying here, my goal is their goal. I have no doubt they will achieve a better goal in the future.

Publication List

Journal

1. Zainal Arief, Djoko Purwanto, Dadet Pramadihanto, Tetsuo Sato, Kotaro Minato, Fuzzy Logic Approach on Fatigue Classification due to Nine Hours Learning Task Based on Eye Movement Parameter, *Journal of eHealth Technology and Application*, 8(2):127-134, September 2010.

2. Zainal Arief, Tetsuo Sato, Tomohisa Okada, Shigehide Kuhara, Shotaro Kanao, Kaori Togashi, Kotaro Minato. Physician-specific Model for Cardiac Rest Period Determination for MR Coronary Angiography using Fuzzy Classifier. In *Transaction of Japan Society of Medical and Biological Engineering*. vol.49 no.5 (To appear).

International Conferences

1. Zainal Arief, Djoko Purwanto, Dadet Pramadihanto, Tetsuo Sato, Kotaro Minato. Relation between Eye movement and fatigue: Classification of morning and afternonn measurement. In *Proceeding of International Conference on Instrumentation, Communication, Information Technology and Biomedical Engineering (ICICI-BME)*. pages 345-350. Bandung, November 2009.

2. Zainal Arief, Tetsuo Sato, Tomohisa Okada, Shigehide Kuhara, Shotaro Kanao, Kaori Togashi, Kotaro Minato. Development of Automated and Semi-automated Analysis Software for Coronary Rest-period. In *Journal of Cardiovascular Magnetic Resonance* 12(I): Abstract of 13th Annual SCMR

Scientific Sessions - 2010, Poster Presentation P48. Phoenix AZ, January 2010.

3. Zainal Arief, Tetsuo Sato, Tomohisa Okada, Shigehide Kuhara, Shotaro Kanao, Kaori Togashi, Kotaro Minato. Radiologist Model for Cardiac Rest Period Determination based on Fuzzy Rule. In *Proceeding of 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society.* pages 4092-4095. Buenos Aires, Argentina. September 2010.

Domestic Conferences

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Appendix

A. First Application

A.1 Manual Instruction

- Main menu of the application is described in Fig. A.1. From this menu we can edit or enter the participants data by choosing **Edit Data Master Pasien**. The fill in form is illustrated in Fig. A.3.

Figure A.1: Application Main Menu

- To proceed to the eye movement pattern recognition, choose the **Perekaman Pola** menu to display the diagnose number as described in Fig. A.3 of the participants before the recording process begin.

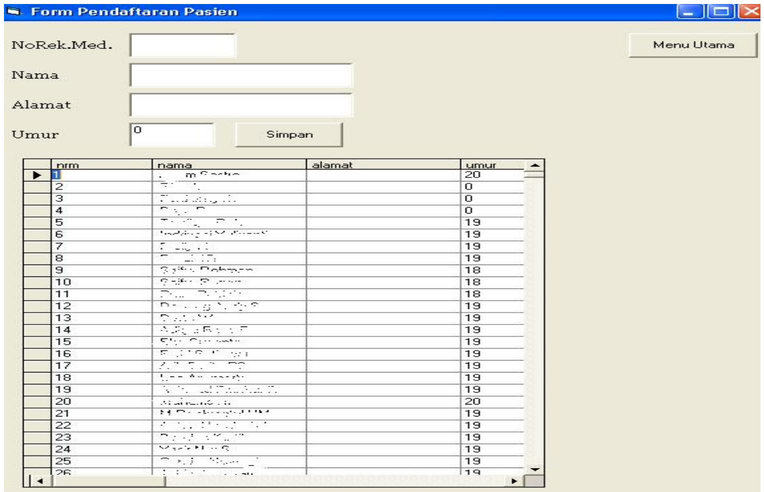


Figure A.2: Entri data form

- After filling in the data form, the recognition process can begin. The recognition form is described in Fig. A.5.
- Put the head mounted camera to the participant.
- Choose camera driver detected on the system and check in camera box.
- Choose Output menu to display image processing result.
- Choose **Stimulus dan Tracking** menu to start the stimulus movement and tracking of eye pupil center.
- The results are displayed in the graph and recorded in the database as described in Fig. A.4
- Stimulus will appear for 6 seconds, continued with parameter extraction process and finally physical condition identification.
- Parameter value and identification results are recorded in the database.
- To repeat the process, return to the **Perekaman Pola** menu.

A.2 Questionnaire

Questioner for Physical condition confirmation
(for ”non fatigue” condition)

1. Your bed time is:
    - above midnight
    - before midnight
2. Your activity before sleeping:
    - no strenuous physical activity (relax)
    - strenuous physical activity
3. Your wake up time:
    - before 4 am
    - after 4 am

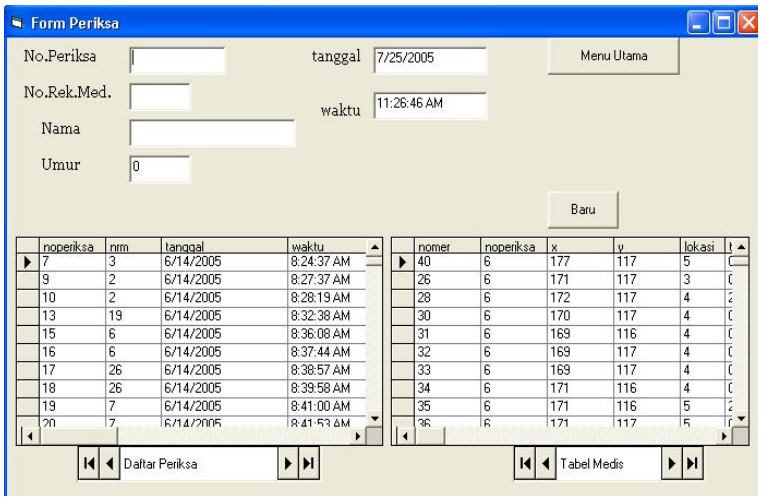
Questioner for Physical condition confirmation
(for ”fatigue” condition)

1. Before measurement, you have been awake for:
    - more than 9 hours
    - less than 9 hours
2. Your activity before measurement:
    - minimum 2 hours sleep
    - ordinary/learning activity
3. Your wake up time:
    - before 4 am
    - after 4 am

B. Second Application

B.1 Manual instruction for rest period determination

- MRCA data reading and visualize selected frame (described in Fig. B.1).
- Region of interest manual selection as the template image for similarity calculation (described in Fig. B.2).
- Continue with cross correlation calculation for similarity measure and frame number detection as input feature for fuzzy classification.
- The rest period determination results from two modeled physicians are shown in the application form (described in Fig. B.3).



noperiksa	nrm	tanggal	waktu
7	3	6/14/2005	8:24:37 AM
9	2	6/14/2005	8:27:37 AM
10	2	6/14/2005	8:28:19 AM
13	19	6/14/2005	8:32:38 AM
15	6	6/14/2005	8:36:08 AM
16	6	6/14/2005	8:37:44 AM
17	26	6/14/2005	8:38:57 AM
18	26	6/14/2005	8:39:58 AM
19	7	6/14/2005	8:41:00 AM

nomer	noperiksa	x	y	lokasi
40	6	177	117	5
26	6	171	117	3
28	6	172	117	4
30	6	170	117	4
31	6	169	116	4
32	6	169	117	4
33	6	169	117	4
34	6	171	116	4
35	6	171	116	5

Figure A.3: Diagnose number form

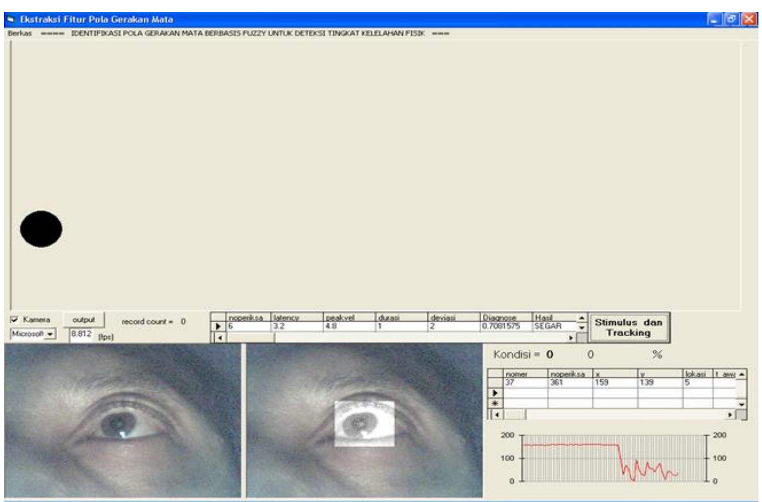


Figure A.4: Stimulus appearance

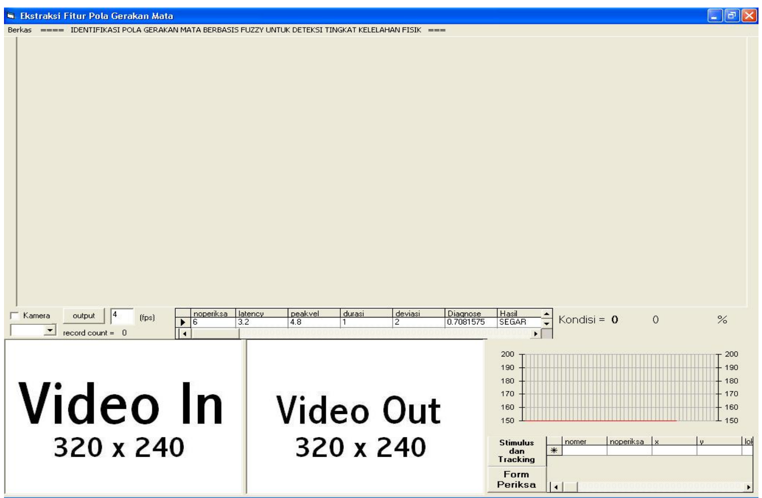


Figure A.5: Recognition form

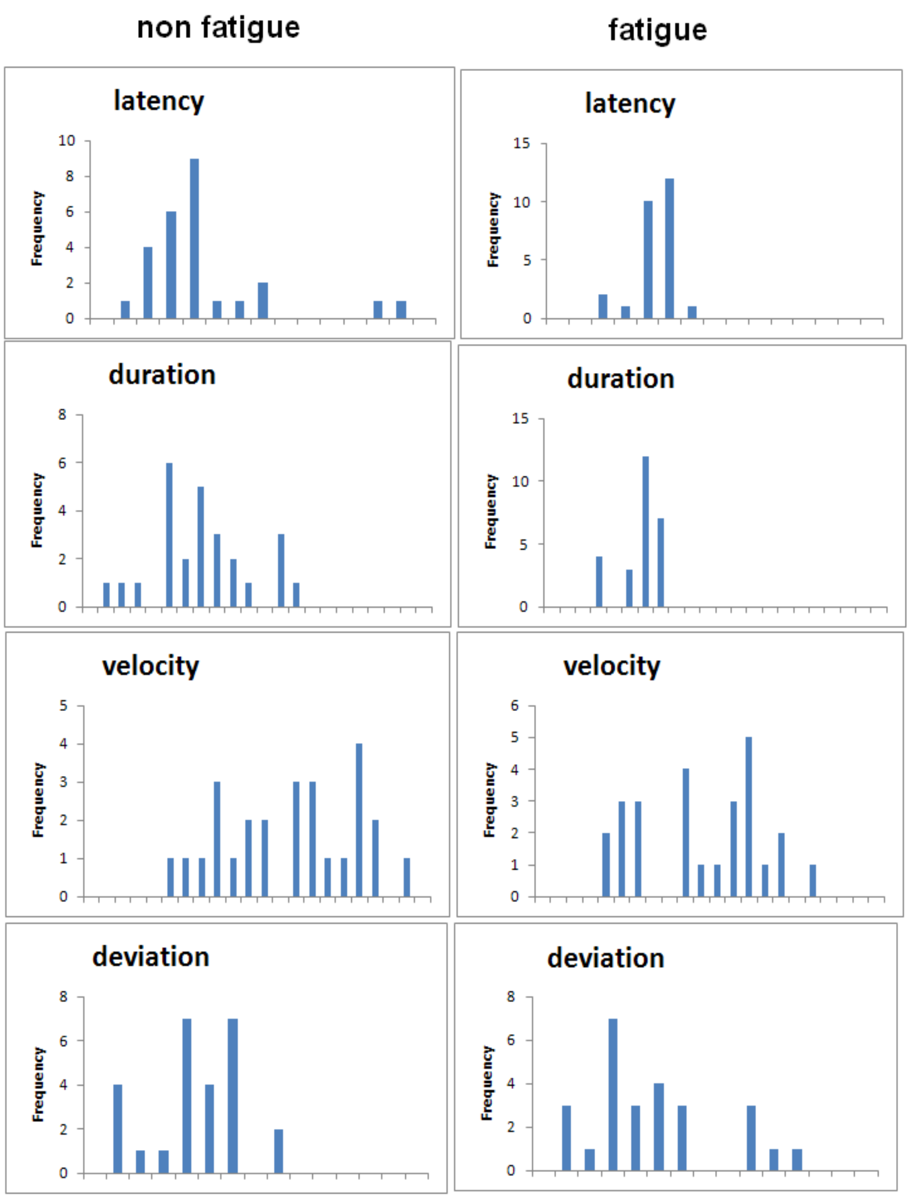


Figure A.6: Distribution of eye movement parameter from 26 participants tent to make normal distribution

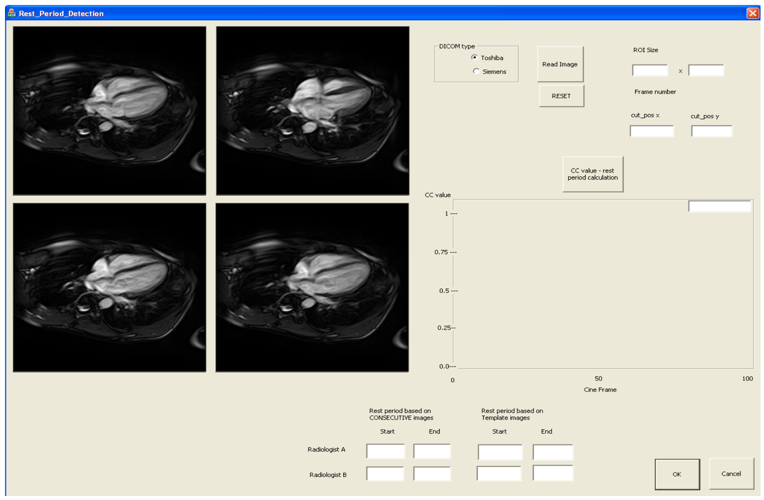


Figure B.1: Displaying image frame data

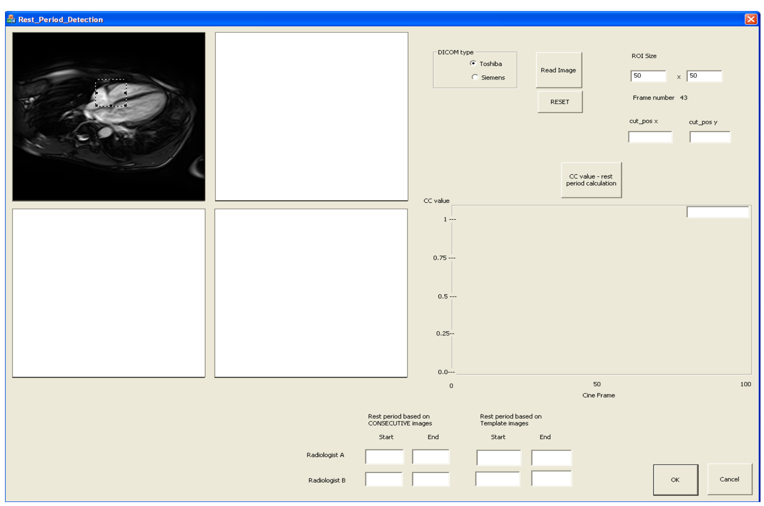


Figure B.2: Region of interest selection as a template image

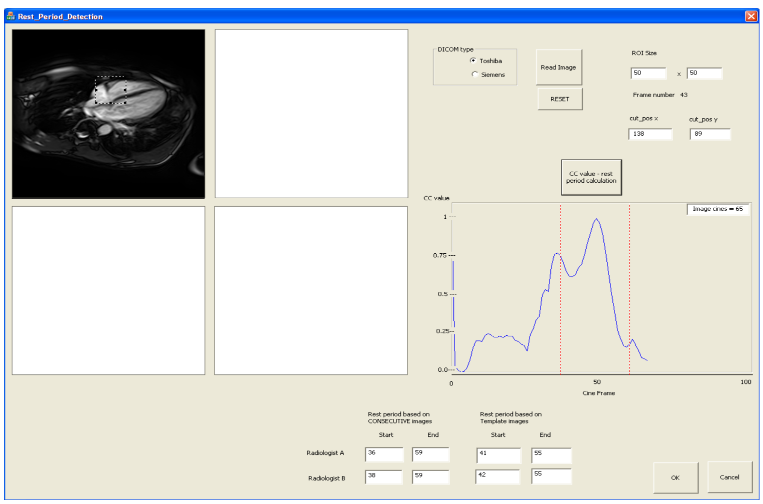


Figure B.3: Determination results