A Fuzzy Forecasting Logic for Glove Protein Sample Retrieving System

Jin-Long Tan, Kok-Swee Sim, and Boon-Chin Yeo

Abstract—**This research paper discusses the design of a fuzzy logic controller to control the cutting efficiency of the latex glove sample retrieving system. The protein level estimation system used in glove manufacturer as quality assurance requires tedious procedures to retrieve samples from latex glove for sample preparation. Total of eight pieces of sample are cut from a latex glove with 20 mm by 20 mm dimension per piece. However, the protein sample extraction process usually is time-consuming and causing in the dropping of production efficiency rate. The fuzzy logic controller is a method that can make the decision with rule-based that is based on human knowledge. The fuzzy logic is developed for the latex glove sample retrieving system with glove weight and cutting deepness diagnosis. The applied fuzzy logic design can perform the deepness adjustment of cutting edge. The purpose of this research is to improve the efficiency of the cutting process with the implementation of fuzzy logic controller system. First improvement is the deepness control of the cutting actuator, which the performance has been increased from 95.20% to 98.79%. Second improvement is related to the sample size accuracy, which has been increased from 81.87 % to 90.99%.**

Index Terms— **Cutting Efficiency, Fuzzy Logic, Latex Glove, Protein Estimation, Quality Assurance, Sample Retrieving**

I. INTRODUCTION

NATURAL Rubber Latex (NRL) medical glove is made out of natural rubber latex and protects the hand from dermatitis [1], [2]. The natural rubber latex is usually obtained from the rubber tree, which is also known as Hevea brasiliensis. This natural rubber latex medical gloves were developed in 1982 by London Rubber Co [3], [4]. The latex gloves are provided two essential protections, such as to shield the patients from contagion during surgery operation and protect the Health Care Workers (HCWs) from unmasking to bloodborne pathogens [5]. Therefore, latex gloves are playing an essential role in the healthcare sectors [6].

In rubber manufacturer and glove industry, the protein concentration on the products is needed to be detected for quality control [7]. Before the rubber and latex products are sold to the market, Quality Assurance (QA) is undergoing [8], [9]. The QA process involves many procedures, including sample retrieving, samples testing, and samples analysis [10], [11].

The current glove sample retrieving system is unable to cut the sample sides completely. Certain sections of the sample are uncut, which need additional action to cut the remained section [12], [13]. This will result in slower the QA process and reduce the productivity of the glove manufacturer [14]. Thus, this project aims to design and implement the fuzzy logic into the glove sample retrieving system. In order to analyze the performance of the cutting process, there are different factors are related. These factors are the weight of the glove and the deepness of the cutting actuator. The weight of the glove is used to predict the thickness. At the same time, the actuator deepness represents the distance between the actuator edge and the latex glove surface. Suitable deepness is needed to cut through latex glove. The glove surface is placed perpendicular to the blade of the cutting actuator. It forms a 90-degree cutting angle, which has the highest cutting efficiency on cutting angle degree [15], [16].

The fuzzy logic input involves the weight of the latex glove used for the cutting process, and the output involves the deepness of the actuator cut through the latex glove surface. As a fuzzy logic requirement, the factors are linked together to form a Fuzzy Inference System (FIS) [17] for the glove sample retrieving system.

II. FUZZY LOGIC OVERVIEW

In 1965, Lotfi Zadeh published a mathematical theory of fuzzy sets, a logic-based computerize model algorithm. The fuzzy set can simulate the problem solving with nature and logical method [17]. This system defines "degree of truth" rather than "true" or "false" [18], [19]. Fuzzy logic formalizes human reasoning with a set of IF-THEN rules base. With the definition of membership functions and the combination of the fuzzy interference engine that is able to perform fuzzification and defuzzification functions, the fuzzy logic system is developed [20], [21].

A fuzzy logic set, $A \subseteq X$ represents the collection of components with $x \notin X$. Each X can either belong to or not belong to the fuzzy logic set A. Membership function of the fuzzy logic maps the components of X to the membership variables. The variables are either $x \notin A$ or $x \in A$. The fuzzy logic enables the notion of degree on the components to a fuzzy set. The fuzzy set allows the value to be defined between Boolean value 1 and 0 or True and False as compared to the conventional controller [22], [23]. It provides the notion of degree for membership functions (MF)s. $\mu_A(x)$ is the MF of x in set A. If X is the condition meet for component x, then the fuzzy set A in x is defined as $A = \{(x, \mu_A(x)) \mid x \in X\}$.

There are three types of mathematical formulas used for MF to fuzzifier the elements: Gaussian MF, Trapezoidal MF, and Triangular MF.

Manuscript received March 29, 2020; revised April 09, 2020. This work was supported in part by the Multimedia University Malaysia.

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A. Gaussian Membership Function

Gaussian MF is plotted base on two parameters, *m*, and *k*, as where *m* represents the centre, and *k* represents the width of the fuzzy set.

$$\mu_A(x) = e^{-\frac{(x-m)^2}{2k^2}} \tag{1}$$

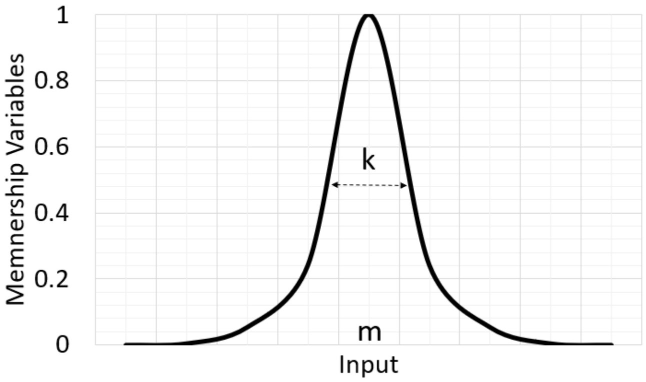


Fig. 1. Gaussian Membership Function

B. Trapezoidal Membership Function

The trapezoidal shape MF is plotted base on four parameters. These parameters are *a*, *b*, *c*, and *d* that represent the coordinate value of x. Those coordinates indicate the four corners of the trapezoid with a sequence of $a < b < c < d$.

$$\mu_A(x) = \begin{cases} 0, & (x<a) or (x>d) \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \end{cases} \tag{2}$$

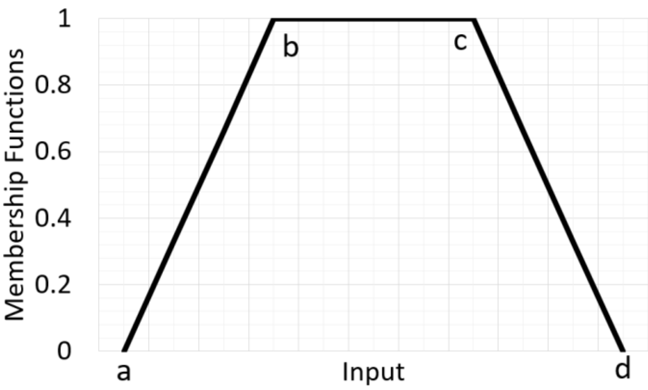


Fig. 2. Trapezoidal Membership Function

C. Triangular Membership Function

The triangular shape MFF is plotted base on three parameters $\{a, b, c\}$. These parameters are *a*, *b*, and *c* that represent the coordinates value of *x*. Those coordinates indicate the three corners of triangular with a sequence of $a < b < c$ [24], [25].

$$\mu_A(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x \le b \\ \dfrac{c-x}{c-b}, & b < x < c \\ 0, & x \ge c \end{cases} \tag{3}$$

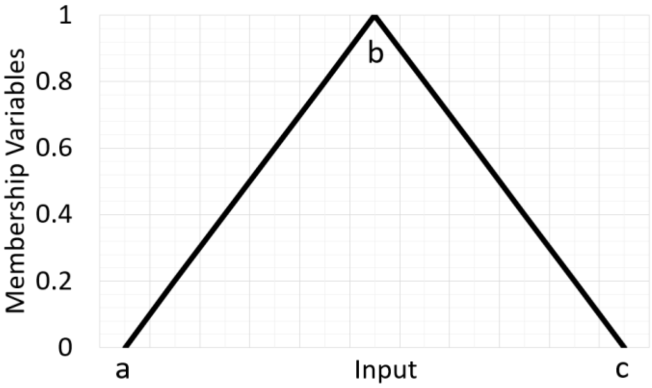


Fig. 3. Triangular Membership Function

In the fuzzy logic system, the input and output parameters are represented in linguistic variable form. The concept of this linguistic variable is to provide a basis for approximate reasoning for the crisp values. The linguistic variable declares the value in the form of words, sentences rather than numerical digit [26], [27]. The input variable is received in a noun when in linguistic forms, such as speed, temperature, pressure, distance. The fuzzy set can convert Boolean variables from just 0 and 1 to the linguistic variable with a range of 0 to 1, such as 0.1, 0.5, and 0.96.

FIS is a rule-based system that evaluates all the fuzzy rules and determines truth values from the IF-THEN rules base. FIS can be implemented and used as the controller that is formed with four operation components. These four components are shown as follow:

1) A set of *rule base* that formed from several of fuzzy IF-THEN rules.
2) A *fuzzy inference engine* unit that performs the inference operation based on the rules base.
3) A *fuzzifier* that performs fuzzification which converts the crisp inputs into linguistic variables fuzzy set.
4) A *defuzzifier* that perform the defuzzification which converts the fuzzy set results of the fuzzy inference engine into a crisp output [28].

The IF-THEN rules base with conditional statements is defined as If *x* is *A*, then *y* is *B*. This rule base is formed with an antecedent and a consequent. The antecedent form as "*x* is *A*" where *x* is the input element of the fuzzy set. The consequent form as "*y* is *B*" where *y* is the output element of the fuzzy set [29], [30]. The flow chart of the FIS of the glove sample retrieving system is shown in Fig. 4.

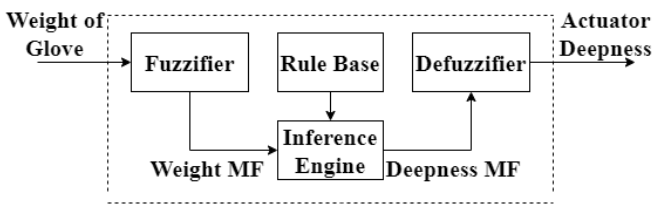


Fig. 4. Fuzzy Inference System of Latex Glove Sample Retrieving System

The FIS computes the output of the fuzzy set based on the fuzzification input MF. Then, the fuzzified inputs are processed according to the fuzzy rules to establish the rule base. Thus, several fuzzy IF-THEN rules must be set. The example rule with fuzzy conditional statement is represented as:

IF X_i is A_i, THEN Y_i is B_i

Where X_i represents the ascendant of the rule, and A_i is the linguistic input variable of the ascendant. While Y_i represents the consequent of the rule and B_i is the linguistic output variable of the consequent.

Defuzzification is a conversion technique that converts the fuzzy set into crisp values. Several methods can be used for the defuzzification process, such as the Lambda-cut method, Maxima methods, Centroid method, and Weighted average method [31]. These methods are discussed below.

D. Lambda-Cut Method

The Lambda-cut method also called the Alpha-cut method. It can convert the crisp value of a fuzzy set or relation. The Lambda-cut set, A_λ, is x, where the MF value is corresponding to x when it is equal or greater than the λ. The given value of λ in the transformation is ($0 \le \lambda \le 1$). The equation for the transformation of the crisp set to a given value is shown as (4).

$$A_\lambda = \{x \mid \mu_A(x) \ge \lambda\} \tag{4}$$

E. Maxima Method

The Maxima method is defuzzification of the fuzzy set values based on the max-membership principle. This technique is applied when the height of output membership is unique. From the principle, three maximum points are stated as First of Maxima, Last of Maxima, and Mean of Maxima. The First of Maxima is defined as (5), the Last Maxima is defined as (6), and the Mean of Maxima is defined as (7).

$$X^* = \min\{x|C(x)| = \max_w C\{w\}\} \tag{5}$$

$$X^* = \max\{x|C(x)| = \max_w C\{w\}\} \tag{6}$$

$$X^* = \frac{\sum X_i \in M^{(X^i)}}{|M|} \tag{7}$$

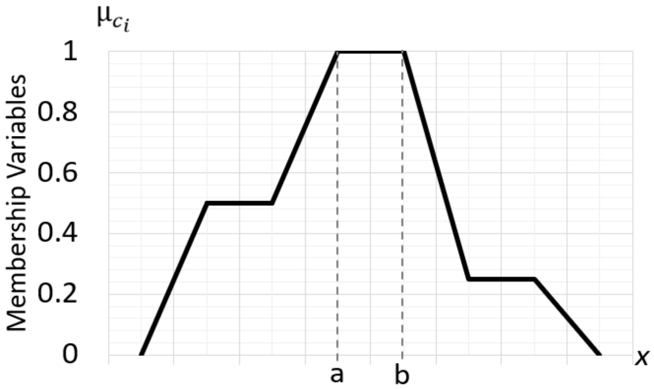


Fig. 5. Maxima Method Membership Principle

$$X^* = \frac{a+b}{2} \tag{8}$$

a represents the First of Maxima input value, and b represents the Last of Maxima input value. By using equation (8), the X^*, the crisp output can be calculated.

F. Weighted Average Method

The weighted average method, also known as the Sugeno method is suitable to be used when the output MF is in the symmetrical output. The crisp value is calculated from the fuzzy set MF. C_1, C_2, C_3… C_n are the outputs MF of the fuzzy set, and xi is the middle-value C_i MF of the fuzzy set. The formula and graphical example of the weighted average method with triangular MF are shown as (9) [32].

$$X^* = \frac{\sum_{i=1}^{n} \mu c_i(x_i)\cdot(x_i)}{\sum_{i=1}^{n} \mu c_i(x_i)} \tag{9}$$

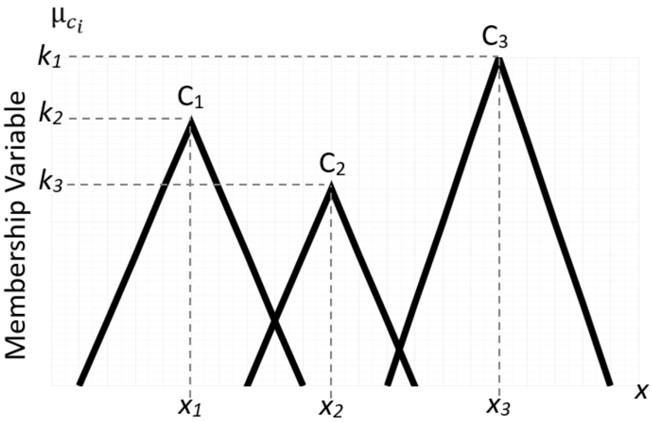


Fig. 6. Sugeno Method Membership Principle

x represents the coordinates of the MF center point according to the x-axis. While μ represents the coordinates of the MF center point according to the y-axis. C_1 is the center of the triangular MF, which is connected with the vertical line of x_1 and the horizontal line of k_2, which is the second-highest point. C_2 is the center of the trapezoidal MF, which is connected with the vertical line of x_2 and the horizontal line of k k_3, which is the lowest point. Similar to C_1, C_3 is the center of the triangular MF, which is connected with the vertical line of x_3 and the horizontal line of k_1, the peak of the defuzzification MF.

The glove sample retrieving system is needed to cut and retrieve eight prices of samples with dimension 20 mm by 20 mm from a single latex glove. The square size sample required four sides are cut completely in order to retrieve a sample. The glove sample retrieving system cut a sample from the glove with two sides by two sides. The cutting performance is measured with a percentage of completion, assume that is 25% completion for each side of samples, a total of 100% if four sides are cut completely. The cutting completion of sample calculation method is as shown in Fig. 7.

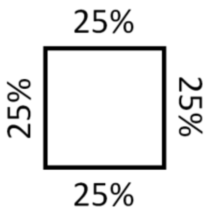


Fig. 7. Cutting Performance Calculation

However, the existing control system uses fixed deepness for the actuator. Consequently, certain sections of the samples may be remained uncut after the glove cutting process. Fig. 8 shows an example glove sample, in which the circle regions are the uncut sections.

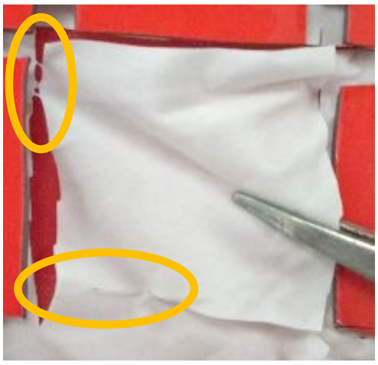


Fig. 8: Glove Samples with Uncut Section

The fuzzy logic controller is implemented and replaced the current controller to improve the cutting efficiency and completion of the samples. The input of the fuzzy logic controller for the glove sample retrieving system is the weight of the glove. Based on the weight of the latex glove, the thickness can be predicted. The measured weight will be the crisp input. Then, the crisp input is fuzzifier and converts into input MF. The fuzzy IF-THEN rules base is applied to the fuzzy inference engine, and MF is obtained. The fuzzy set output is processed by using defuzzification and converted the fuzzy set into crisp output, the actuator deepness. The illustrated diagram of the actuator is cut into the latex glove is shown in Fig. 9.

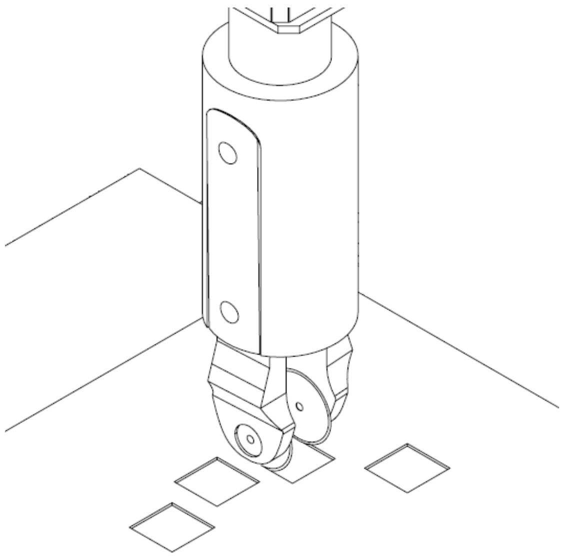


Fig. 9. Illustrated Diagram of Actuator Cutting Process

III. Methodology

A. Fuzzification of Input: Weight of Glove

The input of the fuzzy logic controller for the glove sample retrieving system is the weight of the glove. Based on the weight of the latex glove, the thickness can be measured. The fuzzy logic inference system is shown in Fig. 8. The crisp or linguistics input is the weight of the glove. The crisp input is fuzzified and converted into a fuzzy set input MF. Then, the fuzzy IF-THEN rules base is applied to the fuzzy inference engine, and fuzzy set output MF is obtained. The fuzzy set output process with defuzzification and converts the fuzzy set into crisp output, the depth of the actuator. The fuzzy logic controller for the glove sample retrieving system is designed and performs the operations by following the architecture shown as Fig. 6.

There are different linguistic variables or parameters for the linguistic input, weight: low, medium, and high. The fuzzy logic inference system processes and converts the crisp input, the weight of glove into crisp output, the depth of the actuator. The weight is measured by using a laboratory weighing scale device, which allows the four decimal digits of the unit. To ensure the fuzzy system accuracy, the thickness of the glove also is measured as the reference of the result. The thickness is measured by using a digital Vernier caliper. A gradient slope formula is used to calculate the ratio of thickness and weight of the glove, and the ratio slope formula is defined as (10).

$$y = mx + c \tag{10}$$

where m is defined as (11).

$$m = \frac{y_2 - y_1}{x_2 - x_1} \tag{11}$$

where y is the thickness of the glove, and x is the weight of the latex glove. m represents the gradient or angle of the line to the x-axis, and c represents the intercept point on the y-axis. A set of weight-to-thickness ratio data is plotted and shown as Fig. 10.

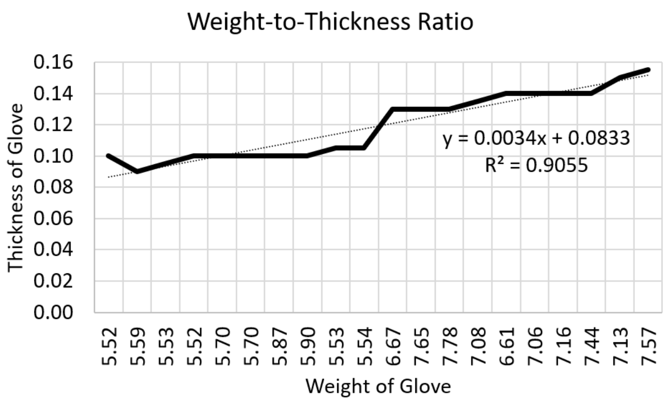


Fig. 10. Weight-to-Thickness Gradient Linear Graph

m is 0.0034, and c is 0.0833, with the R^2 value of 0.9055. From the data chart, the maximum measurement of the weight is 8.0 g, and the minimum is 5.0 g. While the maximum measurement of the thickness is 0.18 mm, and the minimum is 0.05 mm. The gradient line equation is shown in (12).

$$thickness = 0.0022(weight) + 0.0846 \tag{12}$$

A triangular MF is plotted based on the linguistic input of the glove sample retrieving system. The MF is shown in Fig. 11.

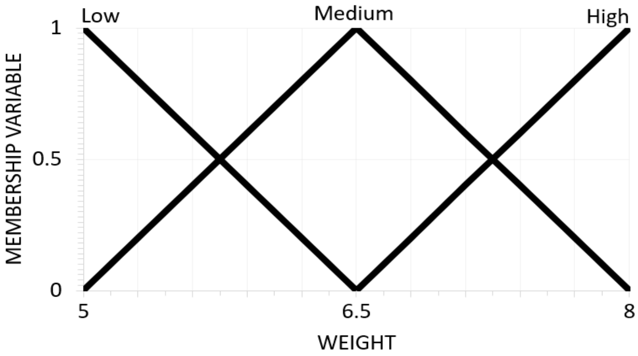


Fig. 11. Membership Function of Linguistic Input: Weight

B. Defuzzification of Output: Actuator Deepness

There are different linguistic variables or parameters for the linguistic output for deepness: shallow, average, and deep. The deepness of the actuator cut into the glove is measured in millimeters. A triangular MF is plotted based on the linguistic output of the glove sample retrieving system. The MF is shown in Fig. 12.

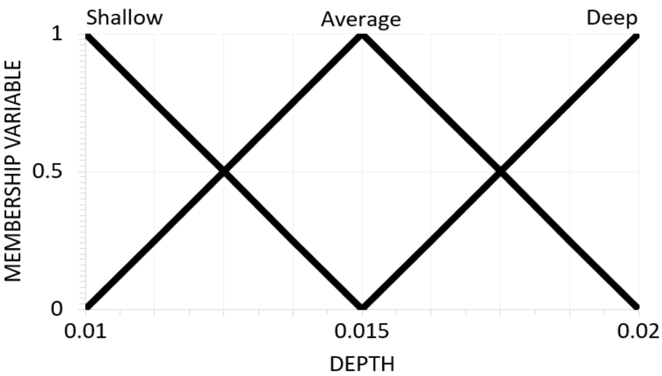


Fig. 12. Membership Function of Linguistic Output: Deepness

After MF processing with a fuzzy inference engine, the result is obtained. The defuzzification technique used for the actuator deepness is the Sugeno method and it is also known as the Weighted Average method. The defuzzification process converts the membership value into the crisp value. The example of calculation for the defuzzification technique is shown in Fig. 13.

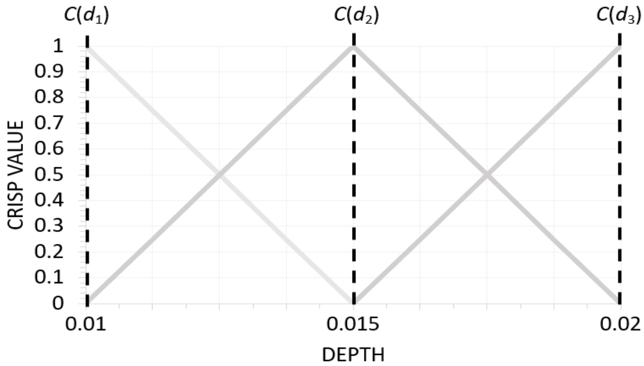


Fig. 13. Example Defuzzified Crisp Output

The Sugeno equation is expressed as (13).

$$C_{out} = \frac{C(d_1)\cdot x_1 + C(d_2)\cdot x_2 + C(d_3)\cdot x_3}{C(d_1)+C(d_2)+C(d_3)} \tag{13}$$

C_{out} is the predicted distance for the actuator to travel downward deep into the glove surface. $C(d_1)$ represents the center point for shallow membership function. $C(d_2)$ represents the center point for average membership function and $C(d_3)$ represents the center point for deep membership function. The x_1, x_2, and x_3 represent the crisp value coordinate aligned with center point $C(d_1)$, $C(d_2)$, and $C(d_3)$, respectively. The linguistic input and output have a range base on the parameter of the weight of glove and depth of cutting actuator. The classification of the parameter and linguistic variable is shown in Table I.

TABLE I
CLASSIFICATION OF INPUT AND OUTPUT VARIABLE RANGE

Linguistic Input		Linguistic Output	
Label	Range	Label	Range
Low	[5, 5, 6.5]	Shallow	[0.01, 0.01, 0.015]
Medium	[5, 6.5, 8]	Average	[0.01, 0.015, 0.02]
High	[6.5, 8, 8]	Deep	[0.015, 0.02, 0.02]

$C(d_1)$, $C(d_2)$, and $C(d_3)$ are calculated and based on the parameter as shown in Table I and obtained by using equation shown as shown in (14), (15), and (16), respectively.

$$C(d_1) = \begin{cases} 1, & d_1 \le 0.01 \\ \dfrac{0.015 - d_1}{0.005}, & 0.01 < d_1 < 0.015 \\ 0, & d_1 \ge 0.015 \end{cases} \tag{14}$$

$$C(d_2) = \begin{cases} 0, & d_2 \le 0.01 \\ \dfrac{d_2 - 0.01}{0.005}, & 0.01 < d_2 < 0.015 \\ 1, & d_2 = 0.015 \\ \dfrac{0.02 - d_2}{0.005}, & 0.015 < d_2 < 0.02 \\ 0, & d_2 \ge 0.02 \end{cases} \tag{15}$$

$$C(d_3) = \begin{cases} 0, & d_3 \le 0.015 \\ \dfrac{d_3 - 0.015}{0.005}, & 0.015 < d_3 < 0.02 \\ 1, & d_3 \ge 0.02 \end{cases} \tag{16}$$

C. Fuzzy Inference Engine

Fuzzy Inference Engine is the controller for FIS that derived the known rules base to the fuzzy sets. The fuzzy rules are formed with the sets of IF-THEN statements. The rule usually is set based on linguistic variable and simple English language. Two sets of rules are listed and tested. The rule base set A and set B for fuzzy set on glove sample retrieving machine are shown in Table II and Table III, respectively.

TABLE II
RULES SET A ON GLOVE SAMPLE RETRIEVING FUZZY SYSTEM

Rule No.	Linguistic Input	Linguistic Output
	Weight of Glove	Actuator Deepness
1	Low	Shallow
2	Medium	Average
3	High	Deep

The rule set A statements are listed as following:

1) IF weight of glove is low, THEN actuator deepness is shallow.
2) IF weight of glove is medium, THEN actuator deepness is average.
3) IF weight of glove is high, THEN actuator deepness is deep.

TABLE III
RULES SET B ON GLOVE SAMPLES FUZZY SYSTEM

Rule No.	Linguistic Input	Linguistic Output
	Weight of Glove	Actuator Deepness
1	Low	Shallow
2	Medium	Shallow
3	Medium	Average
4	Medium	Deep
5	High	Deep

The rule set B statements are listed as following:

1) IF weight of glove is low, THEN actuator deepness is shallow.
2) IF weight of glove is medium, THEN actuator deepness is shallow.
3) IF weight of glove is medium, THEN actuator deepness is average.
4) IF weight of glove is medium, THEN actuator deepness is deep.
5) IF weight of glove is high, THEN actuator deepness is deep.

The simulation results of the fuzzy rule set A and ruleset B are shown in Fig. 14, and Fig. 15, respectively.

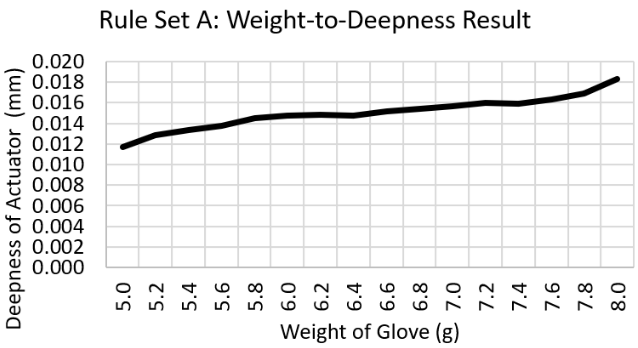


Fig. 14. Result of Rule Set A: Defuzzified Weight-to-Deepness Output

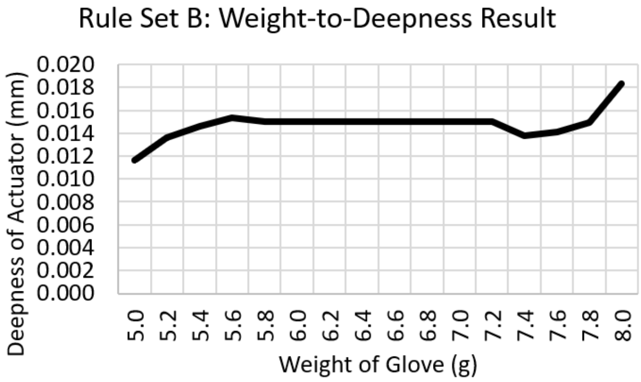


Fig. 15. Result of Rule Set B: Defuzzified Weight-to-Deepness Output

The fuzzy inference system further tested by using the thickness of the glove as the input of the fuzzy set. Direct using the weight of glove as an input method is compared with the converted thickness of glove as an input method. The simulation output of the fuzzy set with convert thickness as input is shown in Fig. 16, and Fig. 17, respectively.

Fig. 16. Result of Rule Set A: Defuzzified Thickness-to-Deepness Output

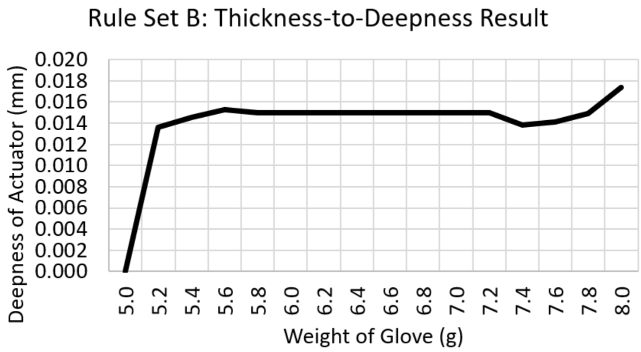


Fig. 17. Result of Rule Set B: Defuzzified Thickness-to-Deepness Output

As shown in Fig. 14, and Fig. 15, the fuzzy rule set A has a smooth and reasonable result that approach logical output compared to the fuzzy rule set B. Moreover, as shown in Fig. 14, and Fig. 16; Fig. 15, and Fig. 17, the fuzzy set input weight of glove has a smooth result as compared with the thickness of glove as input. Thus, the fuzzy rule set A is applied to the fuzzy inference controller system of the glove sample retrieving system.

IV. RESULT AND DISCUSSION

The glove sample retrieving system can cut and retrieve eight pieces of samples from a single latex glove. The square size sample required four sides to be able to cut a sample completely with 20 mm by 20 mm dimension. The glove sample retrieving system cut a sample from the glove with two sides by two sides. The cutting performance is measured with a percentage of completion, assume that 25% completion for each side of samples, a total of 100% if four sides are cut completely and system accuracy that measured base on the length of sample side along to the x-axis and y-axis.

A. System Performance Testing Schedule

The fuzzy logic system is tested on 10 brands, each brand three gloves, and a total of 30 gloves are tested. These brands are labeled with samples A, B, C, D, E, F, G, H, I, and J. From these 30 glove samples. Each glove is cut into 8 pieces of samples for quality assurance. A total of 240 test data for the system. The schedule for the glove sample retrieving system is shown in Table IV.

TABLE IV
GLOVE BRAND AND SAMPLES TEST LIST

Brand	No. of Glove Tested	Glove Samples (Pieces)
A	3	8
B	3	8
C	3	8
D	3	8
E	3	8
F	3	8
G	3	8
H	3	8
I	3	8
J	3	8
	Total	240 test data

B. System Performance Based on Sample Cutting Completion

The cutting performance of two types of glove sample retrieving system is measured and compared. They are the glove sample retrieving system without the implementation of fuzzy logic and with the fuzzy logic controller. The sample retrieving system without is tested with a fixed depth of 81.50 mm, 81.51 mm, and 81.52 mm. While the system with fuzzy logic allows the deepness adjustment for cutting actuator. The average percentage of samples cutting performance of the system without applied fuzzy logic is compared. The glove sample retrieving system is tested and shown in Fig 18 and Table V.

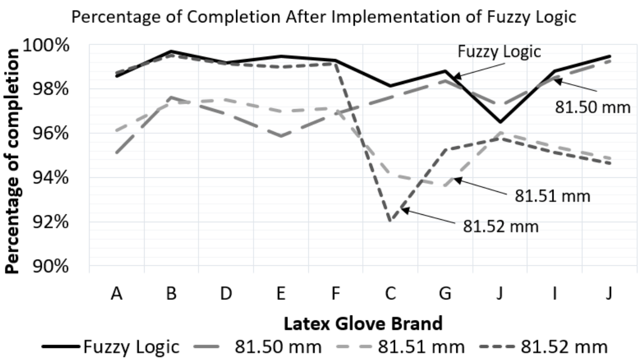


Fig. 18. Percentage of Completion of System with and without Fuzzy Logic System

TABLE V
IMPROVEMENT ON PERCENTAGE OF COMPLETION

System Type	Deepness (mm)	Average
With Fuzzy Logic	Adjustable Range: 81.50-81.52	98.79%
Without Fuzzy Logic	Fixed: 81.50	97.34%
	Fixed: 81.51	95.91%
	Fixed: 81.52	96.83%

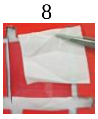
The cutting performance is measured and obtained after tested on 30 gloves sample. The glove sample retrieving system with fuzzy logic has achieved a 98.79% cutting performance, which is a better result compare to fixed actuator depth.

By controlling the deepness of the actuator with the fuzzy logic controller, the performance of the glove sample retrieving system has been increased. The comparison of the system before and after the implementation of fuzzy logic is shown in images. The images of the cut brand A glove samples 1 result are shown in Table VI and Table VII, respectively.

TABLE VI
PERCENTAGE OF COMPLETION OF GLOVE SAMPLE RETRIEVING SYSTEM WITHOUT FUZZY LOGIC CONTROLLER

Sample No.	1	2	3	4
Sample Image				
Completion %	98	98	95	91
Sample No.	5	6	7	8
Sample Image				
Completion %	94	93	97	96

TABLE VII
PERCENTAGE OF COMPLETION OF GLOVE SAMPLE RETRIEVING SYSTEM WITH FUZZY LOGIC CONTROLLER

Sample No.	1	2	3	4
Sample Image				
Completion %	99	99	100	99
Sample No.	5	6	7	8
Sample Image				
Completion %	100	100	100	100

As shown in Table VI and Table VII, the average cutting completion percentage with the implementation of fuzzy logic for sample A is 99.57%. Which has increase of 4.43% compared to the glove sample retrieving system without the implementation of fuzzy deepness prediction. Therefore, the fuzzy prediction of cutting deepness can improve the cutting efficiency of the glove sample retrieving system.

C. System Performance Based on Sample Size Accuracy

To ensure the size of the cut samples to has square size with at least 20 mm by 20 mm, the distance between the edge of the rotary cutter must be 20 mm or more. 20 mm is set as the standard for the length measurement for each side. Therefore, the area for the samples is calculated to ease the accuracy measurement standard of 400 mm^2 for each sample. The cut samples are measured with Vernier caliper. The result for the sample retrieving system with or without the fuzzy logic controller is recorded. Several formulas are used to calculate the accuracy of the sample size based on the horizontal and vertical length of the square size sample. The equation for absolute error for the sample area is shown as (17).

$$\Delta A = x_m \cdot \Delta y_m + y_m \cdot \Delta x_m \tag{17}$$

ΔA represents the absolute error of the sample area; Δx_m represents the absolute error of measured sample side length along the x-axis, and Δy_m represents the absolute error of measured sample side length along the y-axis. While x_m represents the measured sample side length along the x-axis, and y_m represents the measured sample side length along the y-axis. From calculated absolute error with (17), the percentage of the accuracy can be obtained. The accuracy of the sample retrieving system is calculated by using (18).

$$Accuracy = 100\% - \left[\frac{\Delta A}{A} \times 100\% \right] \tag{18}$$

A represents the expected area of the sample, which is 400 mm^2. The accuracy of the system with and without the fuzzy logic controller is shown as Table VIII.

TABLE VIII
IMPROVEMENT ON SAMPLES SIZE ACCURACY

Brand of Glove	Samples Size Accuracy	
	Without Fuzzy Logic Controller	With Fuzzy Logic Controller
A	60.06%	92.66%
B	90.36%	91.60%
C	85.97%	88.85%
D	96.47%	91.18%
E	95.41%	93.44%
F	88.76%	93.31%
G	88.31%	89.44%
H	66.80%	88.94%
I	87.56%	87.15%
J	59.05%	93.32%
Average Accuracy	81.87%	90.99%

As shown in Table VIII, the sample retrieving system with the fuzzy logic controller has higher accuracy, which has 90.99% compared to the system without the fuzzy logic controller that achieved 81.87%. The sample size accuracy of the sample retrieving system has greatly improved with the implementation of the fuzzy logic controller.

V. CONCLUSION

Based on the result of 30 gloves from 10 brands, the glove sample retrieving system result is compared between before and after the implementation of the fuzzy logic controller. The system performance based on sample cutting completion has been increased from 96.69% to 98.79%. Meanwhile, the sample size accuracy has been increased from 81.87% to 90.99%. Overall, the performance of the glove sample retrieving system has been greatly improved with the implementation of fuzzy prediction logic. Based on the fuzzy logic set, the weight of the glove as input and forecasted deepness of the cutting actuator as output have highly increased the cutting efficiency of the sample retrieving process for quality assurance in glove manufacturer.

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