

Fuzzy Logic-Based Performance Assessment in The Virtual, Assistive Surgical Trainer (VAST)

Chuan Feng, PhD, Jerzy W. Rozenblit, PhD, Allan Hamilton, MD
Electrical and Computer Engineering Department
Arizona Surgical Technology and Education Center, Department of Surgery
The University of Arizona, Tucson, Arizona 85721, USA
jr@ece.arizona.edu

Abstract

The Virtual Assistive Surgical Trainer (VAST) is an approach developed to train surgeons in minimally invasive procedures. It uses surgical instruments augmented with micro-sensors, and knowledge-based inference techniques to provide objective, data-driven feedback and performance assessment for complex exercises. The assessment is typically based on the expertise of senior surgeons and, thus, a single objective standard is difficult to define. To formulate such a standard, and to provide an accurate scoring method, a fuzzy logic method is proposed in this paper. This makes it easier to mimic tasks that are already successfully performed by human experts. A multi-level fuzzy inference engine and new performance metrics are implemented. Experimental results demonstrate the feasibility of this method and the efficacy of the new performance metrics.

1. Introduction

Minimally invasive surgery (MIS) is a modern surgical technique requiring small incisions or no incisions. It is performed with an endoscope and several long, thin instruments through small incisions. Because of its minimally invasive nature, MIS minimizes complications associated with large incisions, operative blood loss and post-operative pain, and speeds up recovery time compared to the traditional open surgery. Unfortunately, from a surgeon's perspective, laparoscopic surgery is more challenging than conventional surgery because of the restricted vision, hand-eye coordination problems, limited working space and lack of tactile sensation. These issues make MIS a difficult skill for medical students and residents to master.

In order to minimize the potential risks inherent in laparoscopic procedures, training must be performed to help the students adapt to the new surgical technique. Because the requirement of basic skill increases rapidly, traditional surgical education methods are not suitable for MIS training. In a similar way, using animals and cadavers have limitations due to ethical issues, animal rights, high cost

and low efficiency. Therefore, effective surgical training and guidance methods are being developed. Surgical simulation is increasingly perceived as a valuable addition to traditional medical training. It has been approved as an effective training method [6] that translates into approximately 30-35% more efficiency as measured by operative time and decreased complication rates compared to a control group not receiving simulation training.

In our work, we propose a design and implementation approach that addresses many of the limitations of the existing systems and advances the state of the art in surgical training, assessment and guidance in laparoscopic surgery [4]. The vision is to bridge the gap between pelvi trainers and virtual reality trainers, combining the advantages of both approaches to design a system that is simple and effective.

Our design features the embedding of micro-sensors [3] into the instruments employed for simulation training. The detection and recording of instrument movement permits our system to not only measure a trainee's progress in acquiring psychomotor skills and compare these data to normative databases, but also to evaluate instrument effectiveness in reducing errors.

From a training perspective, the sensor based system will track and return information on various performance metrics such as position and velocity of instruments, total path length of motion, erratic movements, time taken, number of attempts, dexterity, etc. This is similar to the computer based medical diagnosis system that uses the patient's history, physical examination, and laboratory tests as inputs and gives the possible medical diagnosis result as outputs.

There has been extensive research with regard to computer assistive medical diagnosis systems. Various techniques have been implemented to solve the problems, including symbolic logic, probability and value theory [5], multi-surface pattern separation [12], semantic-based methodology [13], and weight-elimination neural networks [14].

The main issue of the inference systems is that the assessment is typically based on the expertise of senior doctors and, thus, a single objective standard is difficult to de-

fine. The vague definitions are also reasons for the uncertainty. To formulate such a standard, and to provide a more meaningful scoring method, we propose to use fuzzy logic to do the inference. In addition to the fuzzy logic inference engine, some new metrics were also used to improve the efficiency of the performance evaluation.

In the remainder of the paper, we discuss our proposed approach in more detail. In section 2, the fuzzy inference engine is presented. In Section 3, novel performance metrics are introduced to evaluate the training process. In section 4, an experiment is described that proves the feasibility of the proposed method. Section 5 summarizes and concludes the paper.

2. Fuzzy Inference Engine

Fuzzy logic [1] is a technique that mimics how a person would make decisions using a rule-based (“if *condition* then *action*”) approach rather than modeling a system mathematically. However, fuzzy logic is not imprecise. It is an organized mathematical method of handling inherently imprecise concepts.

As we just mentioned above, the performance assessment system is similar to a medical diagnosis system. A typical reasoning process involved in making a medical diagnosis [11] is outlined below:

1. Obtain the case facts.
2. List all the diseases which the specific case can reasonably resemble.
3. Exclude one disease after another until one disease with highest possibility remains.

It frequently occurs that it is not feasible or desirable to make further tests to distinguish among alternative possible diagnoses. Let us think about the following statements, “If the patient has disease A, then there is a certain chance, say approximately 75 out of 100, that he will have symptom B.” As we have mentioned above, the results are often confused with uncertainty.

Usually, probability theory is used to describe the uncertainty. Probability theory uses the concept of Bayesian probability [15], which is the degree to which a person believes a variable is in a set. For the example above, the degree we believe the patient has symptom B is 75%.

In contrast to the techniques introduced before, we use fuzzy set theory to deal with the imprecision inherent in subjective performance expectations derived from expert surgeons [7]. Fuzzy set theory and probability are two different ways of expressing uncertainty. Fuzzy set theory uses the concept of fuzzy set membership to deal with the uncertainty. In classical set theory, an element either belongs or does not belong to a set [16]. On the contrary, fuzzy set theory permits a degree of belonging in the set by the membership function. For the medical diagnosis example above, we can define the fuzzy set {Patient has symp-

tom B}. Therefore, the degree that the patient belongs to the set is 75%.

It seems the distinction between the two methods, probability theory and fuzzy set theory, is mostly linguistic, but in practice, we can use the fuzzy set membership representing membership in vaguely defined sets and avoid talking about randomness. For example, in order to assess the performance of an operation, two fuzzy sets, “good” and “bad” can be defined, and the membership functions will conceal the uncertainty from further inference.

Fuzzy logic is derived from fuzzy set theory dealing with reasoning that is approximate rather than precisely deduced from classical predicate logic. It can be thought of as the application side of fuzzy set theory dealing with well thought out real world expert values for a complex problem [16].

Fuzzy logic usually uses IF/THEN rules to describe the fuzzy relationship. The rules can be expressed in the form:

IF *variable* IS *set* THEN *action*

The advantages of this term is that the solution to the problem can be easily understood by the human operators, so that their experience will be used in the design of the fuzzy relationship. This makes it easier to mimic tasks that are already successfully performed by humans.

In our application, we collect data from sensors (such as the time it takes to move an instrument, its path length etc.), and calculate output in the form of normalized scores. Our method uses inference rules such as “if the instrument speed is very slow, then the score is less than average”, where the word “instrument speed” indicates the input metric and the word “score” is the evaluation output. The first step in developing the fuzzy logic module is knowledge acquisition from experts. This process forms the base of assessment criteria in the form of inference rules. The second step is a survey of senior surgeons to determine the exact membership functions of the input metrics and output scores. For instance, consider an example where the time to clip the cystic artery in laparoscopic cholecystectomy is 20 seconds. Then, according to the membership function we can say that this speed is 90% excellent and 10% good.

2.1. Inference Engine Design

The fuzzy inference engine is shown in the Figure 1. Scilab fuzzy logic toolbox [8] is used to help design this system. Scilab is a comprehensive scientific package freely distributed by INRIA [17]. The fuzzy logic toolbox based on Scilab allows the user to solve his fuzzy problem with little trouble. The toolbox provides complete functions for inference, and an easy to use graphical editor for building complex fuzzy logic system models.

Figure 1 shows the structure of a sample fuzzy inference engine. There are two input parameters: peak and stable, which will be elaborated in the next section, and one

output: score of the performance. The fuzzy logic module implements the inference process by a quantity of fuzzy logic rules set up according to the expertise of senior surgeons.

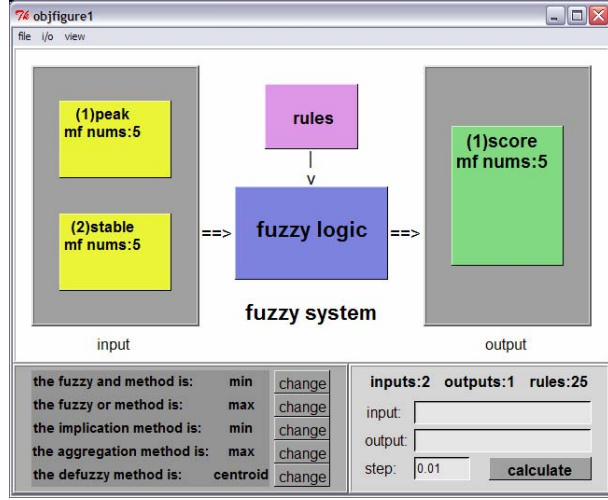


Figure 1: Fuzzy Inference System

The fuzzy inference engine is a static nonlinear mapping between inputs and outputs. The inputs and outputs are “crisp”, that is, they are real numbers, not fuzzy sets. The fuzzification block converts the crisp inputs into fuzzy sets. Fuzzy sets are used to quantify the information in the rule-base. The transformation is produced by the membership functions we introduced above. Membership functions can be expressed as the fuzzification operator F , which is defined by equation 1:

$$F(u_i) = \hat{A}_i^{fuz} \quad (1)$$

Where u_i is an element of the possible input set U_i , and $\hat{A}_i^{fuz}$ denotes the fuzzy set defined on the universe of discourse U_i . There are various transform functions available. In our application, the triangle function was implemented.

Figure 2 indicates the membership functions associated with the input parameter peak. Five fuzzy sets, “Lowest, Lower, Average, Higher, and Highest” are shown in the picture. Triangle function with different parameters are used to describe the fuzzification process.

The inference mechanism uses the fuzzy rules in the rule-base to produce fuzzy conclusions. Figure 3 shows a screen shot of the fuzzy rule editor. Each rule is expressed by the form: If input1 IS set1 AND input2 IS set2, THEN the output IS set0. Where the set1, set2 and set0 are fuzzy sets associated with the input and output crisps.

During the inference process, the inference engine determines which rules are active first; then, it calculates the output by the implied fuzzy sets and overall implied fuzzy set.

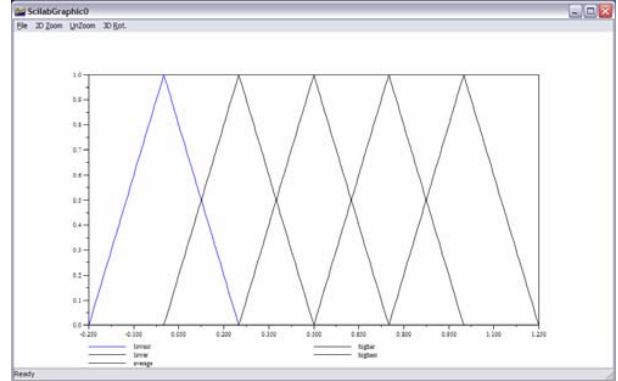


Figure 2: Membership Function Diagram

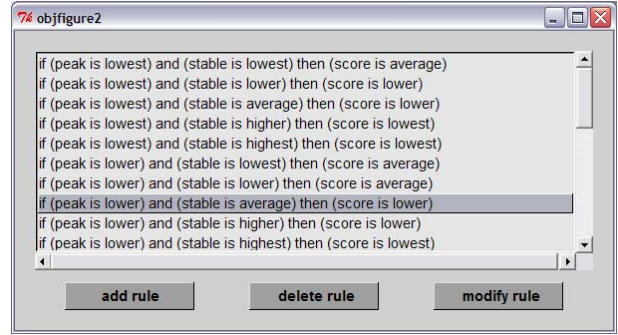


Figure 3: Fuzzy Rules Editor

The implied fuzzy set with membership function can be indicated by equation 2:

$$\mu_{\hat{B}_q^i}(y_q) = \mu_i(u_1, u_2, \dots, u_n) * \mu_{A \rightarrow B_q^i}(x, y_q) \quad (2)$$

Where y_q is the q^{th} crisp output. $\mu_{\hat{B}_q^i}(y_q)$ is the membership function of the implied fuzzy set $\hat{B}_q^i$ and output y_q . $\mu_i(u_1, u_2, \dots, u_n)$ represents the input fuzzy sets which match rule i . $\mu_{A \rightarrow B_q^i}(x, y_q)$ is the rule. We use $\min$ method to do the AND calculation, which intercepts the fuzzy sets.

The overall implied fuzzy set $\hat{B}_q$ with membership function shown in equation 3.

$$\mu_{\hat{B}_q}(y_q) = \mu_{\hat{B}_q^1}(y_q) \oplus \mu_{\hat{B}_q^2}(y_q) \oplus \dots \oplus \mu_{\hat{B}_q^n}(y_q) \quad (3)$$

The equation represents the conclusion reached considering all the rules in the rule-base synchronously. We use the $\sum$ method to achieve the computation.

The inference mechanism operates on the input fuzzy sets to produce output fuzzy sets and the defuzzification block converts these fuzzy conclusions into the crisp outputs. We use the center of gravity method defined in the equation 4.

$$\bar{y} = (\sum_{i=1}^l y_i \mu_{\hat{B}_i}(y_i)) / \sum_{i=1}^l \mu_{\hat{B}_i}(y_i) \quad (4)$$

Where l is the number of rules. y_i is the output for the i^{th} rule. $\mu_{\hat{B}_i}(y_i)$ is the membership function associated with the implied fuzzy set $\hat{B}_i$.

2.2. Multi-Level Inference Engine

Finding associated rules in the inference databases is an important step of the fuzzy inference system. Because the inference rules must cover the entire searching space, the total number of the rules can be expressed in the equation 5.

$$N_{rules} = n^i \quad (5)$$

where N_{rules} is the total number of rules. n is the fuzzy sets' number for each input, and i is the input numbers. From this equation, we know that it will be a disaster setting up all the rules when input number increases. In order to avoid this issue, we implement a multi-level inference engine. The idea of the multi-level inference engine is to divide the inference engine into separately smaller levels. The output crisps of the former level can be used as the input crisps of the later level. Therefore, the total number of the rules can be expressed in the equation 6.

$$N_{rules} = \sum_{j=1}^l n_j^{i_j} \quad (6)$$

Where l is the number of levels. n_j is the fuzzy sets number for each input within level j , and i_j is the input number of level j . If there are 5 parameters needed to be considered, and for each parameter, 5 fuzzy sets are defined, we need to set up 3125 rules for a mono-level inference engine while only 125 rules for a 5-level inference engine.

Another advantage of the multi-level inference is that we can expand an existing inference engine easily by adding a new inference level. An example of the multi-level inference engine is discussed in the section 4.

3. NEW PERFORMANCE METRICS

From the position data obtained from the position sensor (microBIRD [10]), the inference engine calculates key instrument motion metrics. The microBIRD sensors provide 6 degrees of freedom position information (x, y, z, pitch, yaw, and roll) in 3D space. The refresh rate of the sensor is more than 60 Hz. Therefore, we can calculate various motion metrics such as the path length, average speed, and instant speed in real-time. Besides the already validated parameters such as total path length and average speed,

movement economy ratio has been used for performance evaluation in our system.

The movement economy ratio is acquired through equation 7.

$$R_e = \sum_{i=1}^n L_{I_i} / \sum_{i=1}^n L_{R_i} \quad (7)$$

Where R_e is the movement economy ratio; n is the total movement segmentation number; $i=1,2,\dots,n$ is the serial number of each movement segmentation; L_{R_i} is the real path length of movement segment i ; L_{I_i} is the ideal path length of movement segment i .

For a specific training scenario, we select a series of map points on the training space, and the trainee is required to manipulate the instruments touching the map points in sequence. We call the tracking path between two map points a movement segment. The ideal path length is the linear distance between two map points in simple case. In reality, a continuous series of points are observed by the microBIRD sensors. The real path length is the integration of the distance between each two adjacent points.

The movement economy ratio has been used to evaluate the performance of the basic training. It is believed that expert can get higher movement economy ratio than a novice due to hand eye coordination issues. Some latest laparoscopic training simulators have implemented the movement economy ratio to evaluate the basic hand-eye coordination training performance [18].

The issue of the movement economy ratio is that it only scales the movement track length rather than instantaneous speed and moving direction. Due to the incompleteness, a jittering slow movement could be considered as a perfect performance, while a smooth path might be assigned lower score. In order to solve the problem, we implemented speed rate curve and movement direction curve as the additional metrics to enhance the performance of training evaluation.

The speed rate curve showed the speed rate variation during the training. Assume there are n points within one movement segment, and each point has its own time stamp. The instant speed for point i , ($1 \leq i \leq n$) can be calculated through equation 8.

$$S_i = \Delta L_i / \Delta t_i \quad (8)$$

Where ΔL_i is the distance between two points and Δt_i is the time difference of the corresponding time stamps. It was assumed that an expert can maintain a relative steady high speed for a longer time [3]. We used the peak speed rate and steady parameter to transfer the phenomenon into a speed rate profile score.

Figure 4 indicates two example speed rate curve diagrams. The upper diagram in Picture 3 is a "bad" movement because the speed rate changed a lot, which means the performer failed to maintain a steady moving speed.

The lower diagram is a “good” movement because of the smooth transformation and a relative steady high speed.

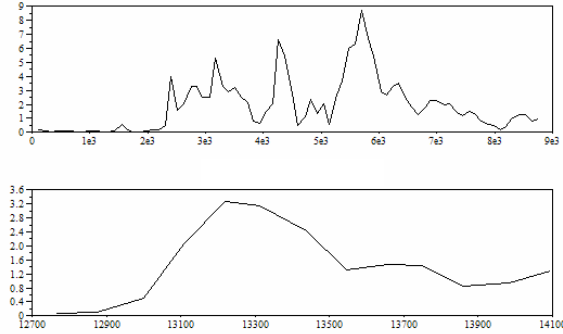


Figure 4: Speed Curve Diagram

The movement direction curve reflected the smoothness of the movement. It can be acquired by the following equation.

$$D_i = \cos \left(\frac{\vec{A}_i \cdot \vec{B}'}{|\vec{A}_i| |\vec{B}'|} \right) \quad (9)$$

Where D_i is the cosine of angle between two vectors: the vector of an instantaneous movement between two sampling points $\vec{A}_i$, and the vector of one movement segment $\vec{B}$. $D_i = 1$ means the direction of the movement is exactly same as the direction of the movement segment. On the other hand, $D_i = -1$ means the direction of the movement is completely opposite to the direction of the movement segment.

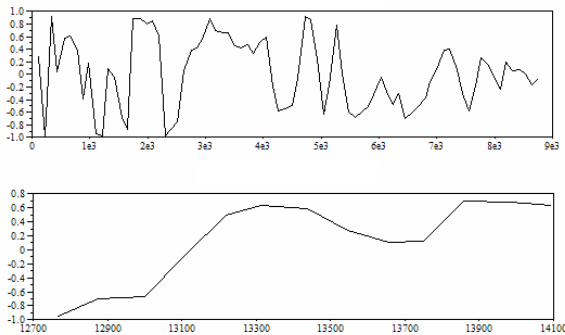


Figure 5: Movement Direction Curve Diagram

During the operation, experts can maintain a relative smooth movement direction curve, while novices try to “search” the target due to a lack of depth perception, which causes their movement to oscillate obviously. This phenomena is similar to what people usually do when they

lose the mouse cursor on a computer screen. In Figure 5, two movement direction curves are shown where the upper one is a “bad” movement with clear direction changes. The curve changes rapidly through 1 to -1 meaning the performer totally lost the track of the instrument and tried to get it back by moving back and forth. The lower one is a “good” movement with smooth direction transition. We used the combination of movement direction profile and speed rate profile to generate the movement profile score of the participant.

4. EXPERIMENT

A hand-eye coordination training experiment was implemented to demonstrate the feasibility of the proposed method. The following picture indicates the experiment scenario. Four targets were labeled as 0, 1, 2, and 3 respectively. The targets were set with various heights within the training box to train basic hand-eye coordination capability of students. The participants were required to move the instrument touching the target in the following sequence: 0 -> 1 -> 0 -> 2 -> 0 -> 3 as fast as they could. We call the movement between two target points a segment, i.e. segment 2 means the movement from 0->2.

The trainee would be required to repeat the procedure until he or she performs adequately. It has been proved that this enforced learning process should help the trainee master the necessary basic skills [19] [20]. Within our experiment, each participant did the exercise five times. Data recorded from eight novices were used to examine the fuzzy logic inference engine.

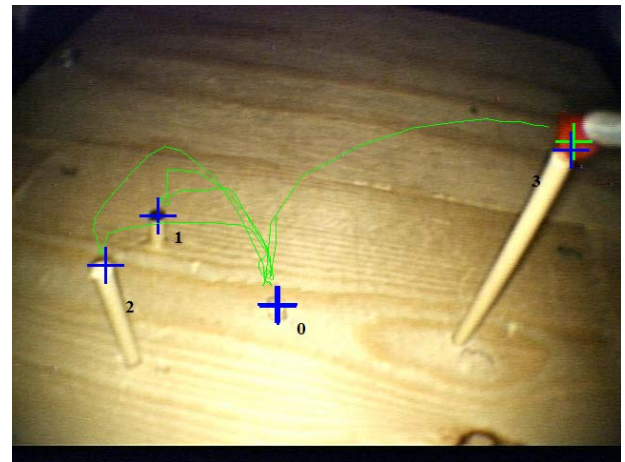


Figure 6: Hand-eye Coordinate Training

Figure 7 indicates the time consumption data of the experiments. From both the time data of the entire performance and time data of segment number 2, we can observe that the time consumption becomes shorter when the trainees repeat the procedure. This “learning curve” indi-

cates that the more experience the trainee gets, the less additional resource he or she requires.

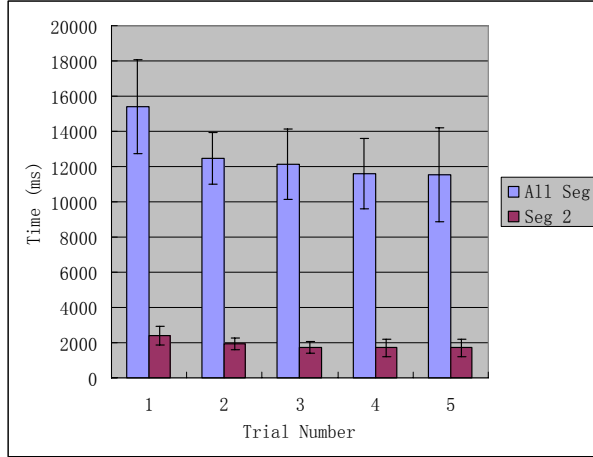


Figure 7: Time Consumption Result from the experiment

The movement economy data shown in the Figure 8 doesn't reflect any obvious learning curve in the first five trials. The reason is that trainees need more trials to improve their movement path for laparoscopic surgery than their speed. Because there is no speed information within the movement economy data, we cannot see a learning curve shown in the figure.

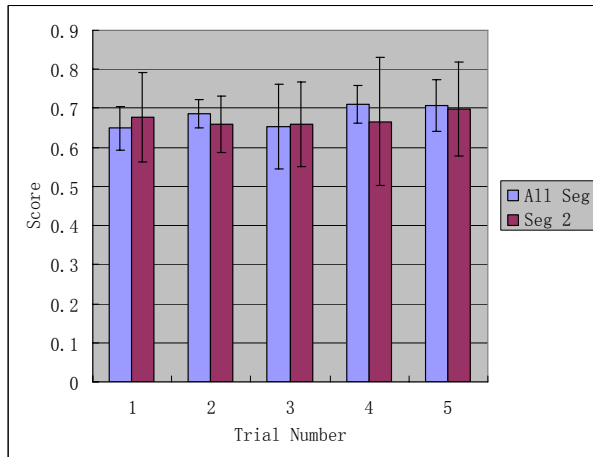


Figure 8: Movement Economy Result from the Experiment

In order to measure both the speed and movement information precisely, the fuzzy inference system is used. Input data of the fuzzy system was speed rate profile and movement direction profile, and output of the fuzzy system was the performance score (0 was the worst, while 1 was the best).

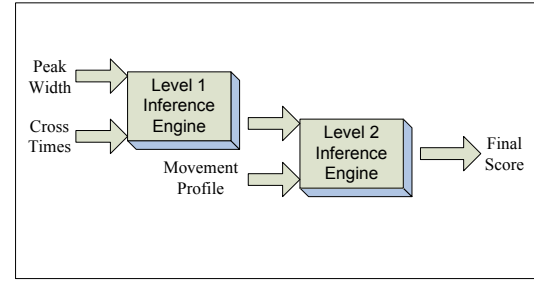


Figure 9: Two Level Inference Engine

The fuzzy inference engine was implemented by the multi-level technique introduced above. Figure 9 shows the structure of the multi-level inference engine. The first level inputs are peak width and cross times. Peak width is used to describe the percentage of relative high speed within the speed rate curve. The high speed region is the part between the first sample point excess 1/2 maximum speed and the last sample point excess 1/2 maximum speed. Cross time is used to describe the speed steady level. It is the time speed curve crossing the 1/2 maximum speed within the peak region.

The output of the first level inference engine is the speed score, which is also one input of the second level inference engine. Another input of the second level inference engine is the movement profile, which is the time movement curve crossing the "0".

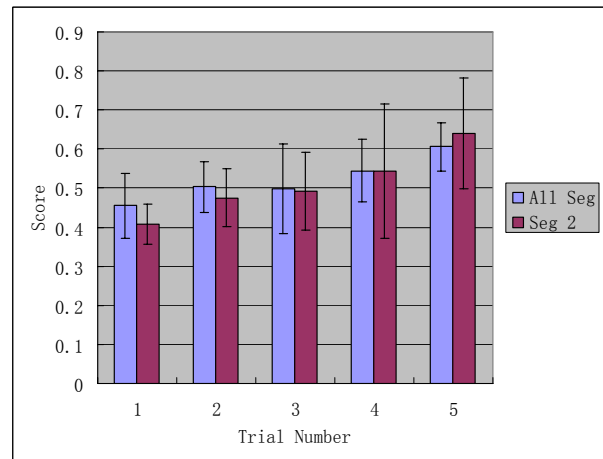


Figure 10: Fuzzy Inference Engine Experiment Result

Figure 10 is the final score chart. The data series "all seg" indicate the overall performance and the data series "seg 2" indicate the movement segmentation from target 1 to target 0. The result shows the performance improvement during training (learning curve), which proves that the fuzzy logic performance assessment method can illustrate the objective performance assessment correctly.

5. CONCLUSION

In this paper, a novel objective performance assessment module for the minimally invasive surgical trainer has been proposed. Given the vague definitions of evaluation metrics, the proposed fuzzy logic inference method can provide normalized scores. New metrics were used to improve the efficiency of the performance evaluation. Experiment results have been presented that validates this argument based on a set of empirical data collected from a laparoscopic trainer.

One advantage of this method is that solutions can easily be understood by human operators, so their experience can be used in the design of the fuzzy relationship. This makes it easier to mimic tasks already successfully performed by humans. Another advantage is that the fuzzy logic method enables quantitative performance assessments, which are superior to the conventional subjective evaluation methods for surgical training.

The initial concept was presented as a poster at the symposium on Computer Simulation in Medicine (Comp-Med) on May 16-18, 2007 at Montreal, Canada.

REFERENCES

- [1] L.A. Zadeh, "Fuzzy Sets", *Information and Control*, 1965, 8, pp. 338-353.
- [2] K. M. Passino, S. Turkovich, *Fuzzy Control*, Addison Wesley Longman, Inc., 1998
- [3] N. Stylopoulos, S. Cotin, and et al, "Computer-enhanced laparoscopic training system (CELTS)", *Surgical Endoscopy*, 2004, 18, pp. 782-789.
- [4] C. Feng, H. Haniffa and et al., "Surgical training and performance assessment using a motion tracking system", *Proc. of the 2nd European Modeling and Simulation Symposium. EMSS 2006*, pp. 647-652. October 4-6, Piera: LogiSim, Barcelona, Spain.
- [5] R.S. Ledley, "Practical Problems in the Use of Computers in Medical Diagnosis", *Proceedings of the IEEE*, Vol. 57, No. 11, 1969, pp. 1900-1918
- [6] J.R. Korndorffer Jr, J.B. Dunne and R. Sierra et al., "Simulator training for laparoscopic suturing using performance goals translates to the operating room", *J Am Coll Surg*. 201 (2005), pp. 23-29
- [7] E.H. Shortliffe, *Computer-Based Medical Consultations: MYCIN*, American Elsevier Publishing Co., Inc., 1976.
- [8] C. Feng, Z. Sun, and L. Su, "Design and implementation of Scilab fuzzy logic toolbox", *IEEE International Symposium on Computer Aided Control Systems Design*. Sept. 2004, Taipei, China. pp. 147-151.
- [9] J. Dankelman, "Surgical robots and other training tools in minimally invasive surgery", *2004 IEEE International Conference on Systems, Man and Cybernetics*. pp. 2459-2464.
- [10] Ascension Technology Co. *microBIRD Technical Reference Guide*. <http://www.ascension-tech.com/>, 2005
- [11] R. Ledley and L. Lusted, "Reasoning Foundations of Medical Diagnosis", *Science, New Series*, Vol. 130, No. 3366. Jul 1959, pp. 9-21
- [12] W. Wolberg and O. Mangasarian, "Multisurface method of pattern separation for medical diagnosis applied to breast cytology", *Proceedings of the National Academy of Sciences*, Vol 87, 1990, pp. 9193-9196
- [13] V. Moret-Bonillo, A. Alonso-Betanzos, and et al. "The PATRICIA Project: A Semantic-Based Methodology For Intelligent Monitoring in the ICU", *IEEE Engineering in Medicine and Biology*, Dec. 1993, pp. 59-68
- [14] C. Ennett and M. Frize, "Weight-Elimination Neural Networks Applied to Coronary Surgery Mortality Prediction", *IEEE Transactions on Information Technology in Biomedicine*, Vol. 7, No. 2, June 2003, pp. 86-92
- [15] Devender Sivia, *Data Analysis: A Bayesian Tutorial*, Oxford: Clarendon Press 1996, pp. 7-8
- [16] G. Klir and Bo Yuan, *Fuzzy Sets and Fuzzy Logic*, Prentice Hall PTR, 1995
- [17] INRIA Meta2 Project/ENPC Cergrene, *Scilab Reference Manual*, INRIA.
- [18] Simbionix Co. 2007. <http://www.simbionix.com>
- [19] B. Law, M.S Atkins and et al, "Eye gaze patterns differentiate novice and experts in a virtual laparoscopic surgery training environment", *Proceedings of the 2004 symposium on Eye tracking research & applications*, 2004, pp. 41-48
- [20] H.M. Hasson, N. V. Kumari and J. Eekhout, "Training simulator for developing laparoscopic skills", *Journal of the Society of Laparoendoscopic Surgeons*, 2001 Jul-Sep;5(3):255-65