Attention-Aware Robotic Laparoscope Based on Fuzzy Interpretation of Eye-Gaze Patterns

6 authors, including:

Songpo Li
Colorado School of Mines

14 PUBLICATIONS   21 CITATIONS

Fernando J Kim
Denver Health Medical Center/University of C…

238 PUBLICATIONS   2,911 CITATIONS

Diedra Gustafson
Denver Health and Hospital Authority

29 PUBLICATIONS   47 CITATIONS

Wilson R Molina
University of Colorado

77 PUBLICATIONS   740 CITATIONS

Songpo Li
Department of Mechanical Engineering,
Colorado School of Mines,
Golden, CO 80401
e-mail: soli@mines.edu

Xiaoli Zhang[1]
Mem. ASME
Department of Mechanical Engineering,
Colorado School of Mines,
Golden, CO 80401
e-mail: xlzhang@mines.edu

Fernando J. Kim
Department of Urology,
Denver Health Medical Center,
Denver, CO 80204
e-mail: Fernando.Kim@dhha.org

Rodrigo Donalisio da Silva
Department of Urology,
Denver Health Medical Center,
Denver, CO 80204
e-mail: Rodrigo.DonalisiodaSilva@dhha.og

Diedra Gustafson
Department of Urology,
Denver Health Medical Center,
Denver, CO 80204
e-mail: Diedra.Gustafson@dhha.org

Wilson R. Molina
Department of Urology,
Denver Health Medical Center,
Denver, CO 80204
e-mail: Wilson.Molina@dhha.org

Attention-Aware Robotic Laparoscope Based on Fuzzy Interpretation of Eye-Gaze Patterns

Laparoscopic robots have been widely adopted in modern medical practice. However, explicitly interacting with these robots may increase the physical and cognitive load on the surgeon. An attention-aware robotic laparoscope system has been developed to free the surgeon from the technical limitations of visualization through the laparoscope. This system can implicitly recognize the surgeon's visual attention by interpreting the surgeon's natural eye movements using fuzzy logic and then automatically steer the laparoscope to focus on that viewing target. Experimental results show that this system can make the surgeon–robot interaction more effective, intuitive, and has the potential to make the execution of the surgery smoother and faster. [DOI: 10.1115/1.4030608]

1 Introduction

1.1 Laparoscopic Surgery. Laparoscopic surgery has been widely adopted in modern medical practice. For example, over 96% of the approximate 1×10^6 cholecystectomies are performed each year in the U.S. using laparoscopic surgical techniques [1]. The great distinction is drawn at the employment of slender surgical instruments and laparoscopes compared with traditional surgeries. Instruments and laparoscopes are inserted into the patient's body through small incisions (typically 5–10 mm wide). During the surgery, they are manipulated and positioned separately by the primary surgeon and/or a human assistant to carry out appropriate operations on and/or visualization of the surgical site. Performing the surgery laparoscopically can significantly reduce the trauma to patients' tissue and consequently reduce blood-loss, postoperative pain, hospitalization, and recovery time. As a result, laparoscopic surgery has achieved great popularity among surgeons and patients.

Visualization and focus of the surgical site can be challenging, however, which may increase the operating time and frustration, especially when re-adjusting of the laparoscope is required during a critical part of surgery. The laparoscope must be frequently re-adjusted and is usually done by the surgeon's assistant via oral communication to choose the correct operating site [2,3]. In light of the fact that the surgical field is being projected remotely from the patient's body on a monitor and the assistant is watching the monitor from a different angle relative to the surgeon, it can be difficult for the assistant to fully understand which area of the surgical field the surgeon would like to view through oral communication. Some other common issues with using a human assistant to position the laparoscope include hand tremor, fatigue, and a fulcrum effect at the trocar insertion point [3].

1.2 Robotic Laparoscope Systems. To overcome the problems caused by manually positioning the laparoscope, robotic laparoscope systems have been developed to substitute human assistants. Such robotic systems have fine manipulation capabilities including scalable, steady, tremor-free motion, and enhanced dexterity. By 2009, at least 27 kinds of robotic laparoscopes have been commercialized or published in referred articles [4] and this number has been growing rapidly in recent years. These robotic systems include AESOP made in the U.S. by Computer Motion, Inc. [5], EndoAssist made in the UK by Armstrong Healthcare Ltd. [6] which is now known as Freehand system from Prosurgics, Inc. [7], LapMan made in Belgium by Medsys s.a. [8], and Naviot made in Japan by Hitachi Co., Ltd. [9].

Although these systems remove the need for human assistants, interacting with these robots may increase physical and cognitive load on the surgeon. Explicit control of these robots through a control interface, such as joystick, foot pedal, voice command

---

controller, or head/face motion-activated system, could be an additional task that distracts the surgeon's attention from the surgical site and may result in frustration and prolonged surgical time. For example, in joystick/button control, the surgeon needs to remove his/her hand from the manipulation of the surgical instruments to re-adjust the laparoscope [10]. Voice-recognition software may accept wrong commands and may limit what the surgeon can say to others in the operating room (OR) [11]. Using head movement to control the robotic laparoscope requires the surgeon to move his/her head an additional amount while performing a surgery, which may complicate the surgery [12] and tire the surgeon, especially during long procedures. Therefore, reducing the surgeon's control burden by increasing the level of the autonomy in robotic laparoscopic systems is a necessity to simplify their use for surgeons and ensure their smooth and fast operation.

1.3 Automatic Laparoscopy

1.3.1 Automatic Instrument Following. To free the surgeon from explicitly steering the laparoscope, the development of several automatic laparoscope adjustment systems has been attempted [13–16]. In those systems, the laparoscope is automatically adjusted to focus on the primary surgical instrument. The hypothesis of this strategy is that the position of the instrument's tip represents the surgeon's region of interest in the laparoscopic images. Several techniques have been adopted to track the position of the instrument's tip, including pattern recognition [17], color identification [13,14], and opto-electronic barcode identification [18]. However, none of these has really gained broad clinical acceptance because the position of the instrument's tip cannot always stand for the surgeon's visual need [19]; there are cases that the surgeon needs to observe a specific location without manipulating it.

1.3.2 Gaze-Controlled Laparoscopes. Gaze tracking is a technique that continuously estimates where the user is looking by monitoring his/her eye movements. Nowadays, optical eye tracking devices have gained wide acceptation and usage [20–23] due to their noninvasiveness and inexpensiveness. Eye-gaze tracking has been widely used as a tool to study cognitive science, psychology, neurology, and visual behaviors. Recently, using gaze as a novel modality to explicitly control or implicitly interact with a computer [24,25] or robot [26,27] has drawn much attention due to its unique characteristics including affordability, ease of usage, unobtrusiveness, etc. [28,29]. In particular, gaze has been used as a unique communication means to assist people who have motor impairment or need an extra hand in human–machine interaction. For example, disabled people can use gaze for typing through an onscreen keyboard [30], triggering buttons on a monitor [31], and controlling a wheelchair [32] and even a robotic arm [33].

In 2010, Yang and coworkers attempted to use the surgeon's gaze to steer a robotic laparoscope system by gazing at a button or a particular screen portion which represented a motion command for a robot joint or a certain step movement toward one direction [34]. Staub et al. [35] established another gaze-controlled method in ARAMIS surgical robotic system. In their system, gaze was used to define the laparoscope's moving direction, and a foot pedal was needed to activate the robot as well as to stop the robot's motion along that direction.

In our previous work, we proposed a direct gaze-guided robotic laparoscope system [36,37] in which the surgeon could directly indicate the visual target using his/her gaze. The rational of our research is "what you are looking at indicates your viewing attention." The surgeon just needs to naturally look at the site that he/she is interested in and the robot automatically follows the surgeon's viewing attention. Compared with the indirect, incremental control strategies in previous robotic laparoscope systems using eye gaze, the direct control in our system effectively reduced the surgeon's direct interaction with the robotic laparoscope.

The learning curve for the surgeon to become familiar with the robot operation was significantly shortened, as there was no need for the surgeon to know the control techniques behind the laparoscopic image. Therefore, by using this gaze-guided laparoscope system, the surgeon can focus more on the exploration and manipulation at the surgical site, instead of dealing with operating the robot.

1.4 Challenges in Gazed-Based Interaction. The common issue with gaze-based interaction, not only existing in gaze-based laparoscope control but also in general computer/robot interaction, is the lack of an effective interpretation method to recognize the user's point of attention from his/her natural eye-gaze data. As eye movements can never be "off" [38], wherever a person looks a command may get activated without the user's intention to do so, which is widely known as the "Midas touch" problem [39,40]. The most common solution to overcome this problem is to add an extra confirmation produced by the user. Some popular confirmations include a prolonged fixation (dwell-time method), intentional blink, and additional physical confirmation (such as a button or a foot pedal). However, those factitious and imposed rules may bring extra mental and physical burdens upon the user.

To identify the surgeon's visual attention to steer the laparoscope from the gaze data is even more challenging because of the uncertainty caused by the complex surgical environment. Unexpected situations like bleeding or failure in one specific operation may occur during a procedure. In addition, the surgeon may look at objects or areas unrelated to the needs of surgical operation. These challenges make the common confirmation strategies inappropriate for the OR. Because of those effects, an appropriate value of the dwell-time can hardly be defined for an entire surgery procedure. When the dwell-time is not long enough to distinguish the normal eye movements, the laparoscope's motion errors will increase due to the misinterpretation which will require more time to correct. At the same time, the errors will increase mental burden on the surgeon as he/she may be always worrying about accidently triggering the robotic motion. If the dwell-time is too long, the surgeon has to unnaturally maintain his/her gaze at the target for an additional amount of time, which may limit the surgeon's natural viewing behaviors and easily result in fatigue. Correct recognition of surgeon's visual attention becomes more critical in the OR due to safety consideration, as any unauthorized movement of the laparoscope caused by the incorrect interpretation of the surgeon's gaze can lead to serious consequences for the patient. Therefore, a more natural and intuitive but also effective, methodology is urgently needed to recognize the correct visual attention from the surgeon's natural eye-gaze data. This would allow the surgeon to use his/her gaze to communicate and interact with the computer or machine without extra tedious eye gestures.

To address the problems mentioned above, we presented a novel attention recognition method by analyzing the surgeon's natural eye-gaze movement patterns. Compared with the traditional dwell-time method, we investigated the gaze-based robot control by interpreting the eye-gaze movements at the pattern level, which considered the surgeon's current and historic visual behaviors, to better understand the surgeon's viewing attention. A fuzzy logic inference engine was developed to infer the surgeon's visual attention using the extracted eye-gaze movement patterns. Using the presented attention recognition method, the robotic laparoscope system has the potential to shift from the automatic level to the autonomous level, as shown in Fig. 1.

2 Methods: Visual Attention Inference Using Fuzzy Logic Interpretation of Visual Behaviors for Robotic Laparoscope

2.1 Gaze-Guided Laparoscopic View Interaction. Our gaze-guided robotic laparoscope system, shown as Fig. 2, allows the surgeon to directly control the laparoscopic view using eye gaze [36,37]. When a new visual attention of the surgeon is
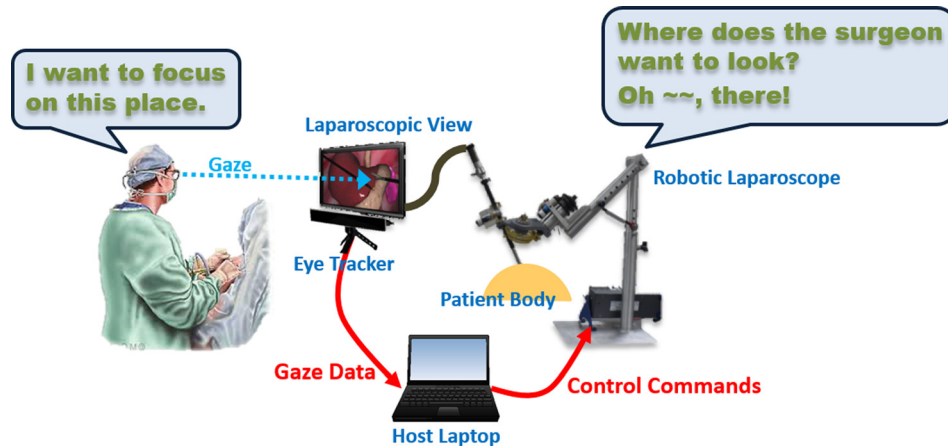
Fig. 1 The flowchart of the attention-aware gaze-guided robotic laparoscope system
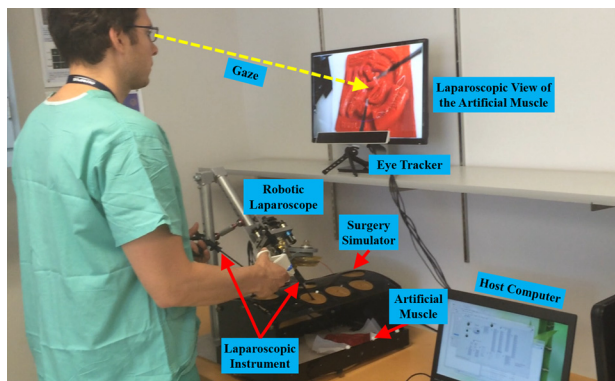

Fig. 2 The setup of the gaze-guided automated robotic laparoscope system. The image of the artificial muscle in the surgery simulator is projected on a monitor through the robotic laparoscope.

recognized, the system can automatically steer the robotic laparoscope to focus on the region of interest. The advantage of this system is to introduce a direct control approach in which the visual attention on the image in two-dimensional pixel coordinates is directly mapped to the robot's three-dimensional motion in Cartesian space into gaze-based robotic laparoscope systems. The kinematics transformation can be expressed as Eq. (1), where p^{atten} is the position of the surgeon's visual attention on the laparoscopic image in pixel; $[m]$ is a mapping relationship from the laparoscopic image in pixel to the Cartesian position in terms of the laparoscope frame; $[T]$ is a coordinate transformation matrix from the laparoscope frame to the robot base frame; and P^c is the target position of the laparoscope so that it can focus on the surgeon's new visual attention.

$$P^c = [T][m] \cdot p^{atten} \qquad (1)$$

The gaze-guided laparoscope system comprises a robotic laparoscope system and one eye tracking system. Compact bevel-geared robot for advanced surgery (CoBRASurge), which was built in our previous research [41], is used as the robotic laparoscope holder. Its capability as a robotic laparoscope holder has been validated in animal tests [42,43]. CoBRASurge is based on a spherical bevel-geared mechanism consisting of three gear pairs and six turning pairs. It creates a mechanically constrained remote center of motion (RCM), which contains three rotational degrees of freedom (DOFs) and one translational DOF passing through it. During surgery, the RCM is aligned with the surgical entry port which guarantees that movements of the instrument or the laparoscope will not tear the incisions.

The eye tracking system, GP3 Eye Tracker from Gazepoint, is used to track where the surgeon is looking on the monitor. GP3 is a video-based remote eye tracking system which allows a certain amount of head movement, 25×11 cm (horizontal $\times$ vertical) and ± 15 cm in depth. It can report the gaze at $60\,Hz$ with an accuracy of 0.5–1 deg and draft <0.3 deg. A per-user calibration is needed before it can be used for eye tracking.

This system is hosted on a laptop running LABVIEW software (National Instruments, Austin, TX). In our previous work, the gaze control adopted a traditional dwell-time method. A sliding window filter is first used to remove involuntary eye movements as well as saccades from raw gaze data. From the refined gaze data, the surgeon's visual attention is recognized by using the dwell-time method which is derived from the ground truth that a human's eye-gaze focuses on an object when he/she is interested in it. A dwell-time threshold is defined, and when the surgeon's gaze focuses on a small area longer than this threshold, visual attention is recognized. The visual attention, represented as a point or an area on the screen, is converted into a series of motion commands to drive the robot toward the visual attention. Although this dwell-time method was adopted in this previous study, it could undermine the usability of the whole system in practical applications as it forces the surgeon to stare at the visual targets for a long time to distinguish the attention from normal visual behaviors. It could affect the efficiency of the system and lead to extra fatigue for the surgeons.

2.2 Eye-Gaze Behavior Studies

2.2.1 Superimposed Eye Movements. Human eyes make many different movements, including the convergence for visual focusing, pursuit motion for visual tracking, saccades for attention shifting, etc. It is more important to note that some movements are involuntary, for example, rolling, nystagmus, drift, and micro-saccades along with physiological nystagmus. Also, visual distractions, blank stares, and blinks may occur. Due to these superimposed eye movements, the gaze data estimated from human eye movements will consist of "noise," and must therefore be "filtered." After being filtered, the eye-gaze data representing the surgeon's attention processes can be recognized.

2.2.2 Vision Center and Visual Acuity. In general, a human tends to put visual targets at his/her vision center. This is related to a term called visual acuity, which describes the extent to which a human can clearly see a target within the visual field. Visual acuity exponentially decreases as the object shift farther from the vision center [44]. This means that for clear perception, it is better to directly look at it than looking askance at it. Additionally, looking askance at an object for a long time will lead to incredible fatigue and stress on human eyes. Another very important aspect is that when a target is viewed directly, its surroundings are also

visible within human split vision, in other words, even if the human is concentrating on the visual target, he/she can also stay aware of the surroundings, which can eliminate the emergencies and incidents caused by blind vision. In the human–monitor scenario, the visual target or manipulation target is usually located at the center of the monitor for clear, comfortable visualization, and awareness of the surroundings. In cases like this, we say the display is focusing on the manipulation or visualization target.

Based on these components of vision characteristics, an elliptical central is defined at the center of the monitor displaying live video (shown in Fig. 3) and is called the focusing area. It is assumed that during stable manipulation and/or visualization, the manipulation target and visual target should be within this elliptical central area and the surgeon's gaze should be within it as well. In this condition, the robotic laparoscope will stand still to provide stable view to the surgeon. When the surgeon's gaze falls out of this focusing area, it may indicate that the surgeon has lost interest (manipulation or visualization interest) to the current focus area, and the laparoscope should be adjusted to focus on surgeon's new attention area. The size of this elliptical central area is adjustable based on the surgeon's preference. In default, its major axis is half long as the screen's width and its minor axis is three fifths of the screen's height, which covers about 23% of the entire screen.

2.2.3 Eye-Gaze Movement Patterns. As mentioned previously, the acquired gaze data are superimposed with noise and it is very difficult to recognize the surgeon's visual attention from eye movement data. Currently, most of the attention recognition methods are still at the fixation level, such as the dwell-time method which only considers how long a human's gaze has been maintained on an object or area. In this method, the historical eye movements before gaze starts settling are discarded. Further exploration of the historical eye movement data at the pattern level should provide more clues about how human attention is shifted from one location and generated at another.

By observing the surgeon's eye-gaze behaviors, two common eye-gaze patterns are identified in our study as shown in Fig. 3. The dots are clusters of gaze points and the arrows show the path of these gaze clusters. In pattern A, the gaze cluster starts from the inside of the focus area and returns back after moving out once. In this instance, the gaze cluster 2 may be caused by a visual distraction or a quick glance. It suggests that when the gaze cluster first moves out of the focus area after staying in it for a long time, there is a possibility that the new gaze cluster is caused by some visual distractions and the surgeon will look back in the focus area shortly. Therefore, the robot needs to be aware of this situation and be conservative in its activation to reduce the chance of misinterpretation. In contrast, pattern B shows that the gaze cluster is shifting outside of the focus area, which means there is a high possibility that the surgeon has lost his/her interest in the current vision center and is searching for the next visual target. Given this situation, the robot should be more sensitive to the duration of gaze maintaining on an object or a small area and responsively adjust the laparoscope to focus on surgeon's new visual attention.

2.3 Noise Filter. An adaptive sliding window filter is developed for filtering the raw gaze data, illustrated in Eqs. (2) and (3). N is the size of the sliding window. $\boldsymbol{P}_i$ and $\tilde{\boldsymbol{P}}_i$ are the position of
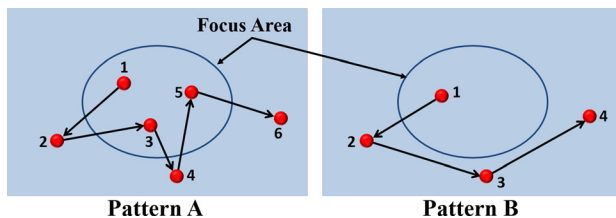
the ith raw gaze point and the gaze point after being processed by the filter, respectively. E_i is an influence coefficient derived by Eq. (3), which indicates whether this new received gaze point affects the output or not. This filter first assigns the influence coefficient, either 0 or 1, to each received gaze point, based on the relative distance from the gaze point to the centers of the points in the current sliding window. The output of the filter is the mean position of all the gaze points, whose influence coefficients are 1, in the sliding window. This filter is developed to remove the noisy eye movements caused by blinks, attention shifts, and tracking failure. Additionally, it can remove involuntary eye movements such as rolling, nystagmus, drift, and microsaccades to smooth the gaze points.

$$\tilde{\boldsymbol{P}}_i = \frac{1}{\sum_{k=1}^{N} E_{i-k+1}} \left\{ \sum_{j=1}^{N-1} \tilde{\boldsymbol{P}}_{i-j} * E_{i-j} + \boldsymbol{P}_i * E_i \right\} \qquad (2)$$

$$E_i = \begin{cases} 1, & \left\| \boldsymbol{P}_i - \dfrac{1}{\sum_{k=1}^{N} E_{i-k}} \sum_{j=1}^{N} \tilde{\boldsymbol{P}}_{i-j} * E_{i-j} \right\| \leq \text{threshold} \\[4ex] 0, & \left\| \boldsymbol{P}_i - \dfrac{1}{\sum_{k=1}^{N} E_{i-k}} \sum_{j=1}^{N} \tilde{\boldsymbol{P}}_{i-j} * E_{i-j} \right\| > \text{threshold} \end{cases} \qquad (3)$$

2.4 Fuzzy Logic Interpretation of Eye-Gaze Data. In 1965, Zadeh published the fuzzy set theory to better model the uncertainty in the real world [45]. It has the potential to be a suitable tool for surgical applications to better handle uncertainties during a surgical operation caused by the complexity of the surgery and the surgeon's eye movement behavior. Some successful instances of using the fuzzy logic theory in machine control include the Sendai railway (1987) in Japan, the Mitsubishi air conditioner [46], research trials such as intelligent behaviors of humanoid robots [47] and mobile robot navigation [48,49].

A fuzzy logic inference engine is developed to infer the surgeon's visual attention by interpreting his/her eye-gaze behavior data. It measures the likelihood of the current gaze cluster being a new visual attention rather than other visual behaviors like searching, glancing, etc. The inference output will be control strategy, "standstill" or "activation" which the laparoscope robot should adopt in order to keep the current focusing area or move to surgeon's new visual attention.

The elliptical focus area is defined at the screen center as the boundary to differentiate between "the current view is good" and "the current view has expired." As mentioned earlier, normally the surgical target being manipulated as well as the surgeon's visual attention would be inside the focus area where it indicates that the current view is good, therefore, the laparoscope should stand still and focus on this area. When the surgeon's visual attention falls out of the focus area, it means the current view has expired.

The fuzzy inference engine, illustrated in Fig. 4, consists of three components: membership functions, IF-THEN inference rules, and inference conclusion. There are two membership functions which model how the current gaze points focus on one location and how the historical gaze behaved before focusing on that location. The membership functions convert the measurement of gaze behaviors into three fuzzy descriptions, with degrees of truth, indicating how likely the situation is fitted. The IF-THEN rules tell, at different situations, what control strategy (standstill or activation) should be adopted. All the likelihoods of these control strategies can then be fused and the one with the higher likelihood will be the inference output.

2.4.1 Membership Functions. The surgeon's historical eye-gaze behaviors are modeled by two fuzzy logic membership
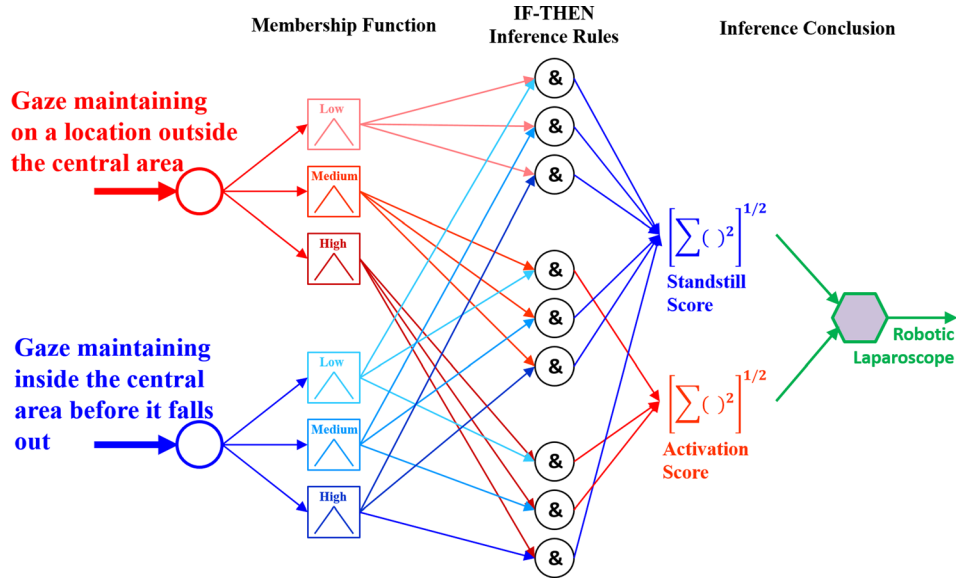

Fig. 3 Two kinds of historical eye-gaze behaviors in a surgical operation

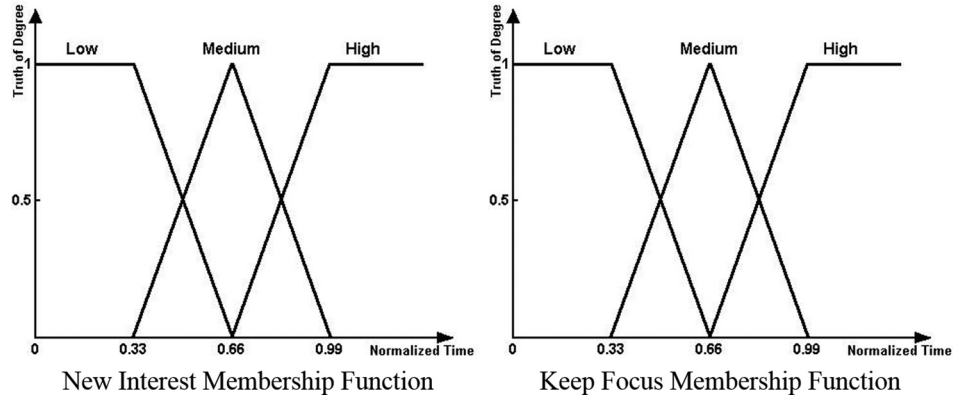**Fig. 4 The overall procedure of the fuzzy inference engine**

Fig. 5 Fuzzy logic membership functions

functions, new interest (NI) and keep focus (KF), respectively. NI function measures how likely a small area outside of the focus area, concentrated on by the current gaze points, is the surgeon's new visual interest based on the duration the gaze points have been maintained in that area. It is described as possibility level low, medium, and high with degrees of truth, which are calculated, respectively, using the duration of gaze points. KF function is the measurement of the surgeon's interest in the current focus view. The input for KF is the period that gaze stays within the focus area before falling outside of it, and the outputs are the degrees of truth for each possibility level (low, medium, and high). The duration inputs are first normalized by T, which is an empirically determined duration of a human's attention on a visual target. In both membership functions, 0.33, 0.66, and 0.99 are selected as the cutoff values for the possibility low, medium, and high levels. Two membership functions are illustrated in Fig. 5. The degree of truth for each level is calculated using Eqs. (4)–(6).

$$S_{\text{low}} = \begin{cases} 1 & t \in [0, 0.33) \\ (0.66 - t)/0.33 & t \in [0.33, 0.66) \\ 0 & t \in [0.66, 0.99) \\ 0 & t \in [0.99, \infty) \end{cases} \quad (4)$$

$$S_{\text{medium}} = \begin{cases} 0 & t \in [0, 0.33) \\ (t - 0.33)/0.33 & t \in [0.33, 0.66) \\ (0.99 - t)/0.33 & t \in [0.66, 0.99) \\ 0 & t \in [0.99, \infty) \end{cases} \quad (5)$$

$$S_{\text{high}} = \begin{cases} 0 & t \in [0, 0.33) \\ 0 & t \in [0.33, 0.66) \\ (t - 0.66)/0.33 & t \in [0.66, 0.99) \\ 1 & t \in [0.99, \infty) \end{cases} \quad (6)$$

2.4.2 IF-THEN Inference Rules. Two control strategies are considered in the fuzzy inference engine to activate the laparoscope or to make it stand still. The IF-THEN inference rules formulate which control strategy is appropriate based on the situation described by the NI and KF possibility levels. Nine inference rules are designed to determine how the laparoscope should be steered, activated, or fixed. The nine rules are listed as follows and also summarized in Table 1. In each inference rule, a logic AND operation is used to deduce the conclusion, as shown in Eq. (7), where O_i is the output of ith inference rule, and L_{NI} and L_{KF} are the degrees of truth for the corresponding membership levels.

Table 1 IF-THEN fuzzy inference rules

	KF$_{low}$	KF$_{medium}$	KF$_{high}$
NI$_{low}$	Standstill	Standstill	Standstill
NI$_{medium}$	Activation	Standstill	Standstill
NI$_{high}$	Activation	Activation	Standstill

Rule 1: **IF** *NI is low* **AND** *KF is low*, **THEN** *laparoscope stand still*.

Rule 2: **IF** *NI is low* **AND** *KF is medium*, **THEN** *laparoscope stand still*.

Rule 3: **IF** *NI is low* **AND** *KF is high*, **THEN** *laparoscope stand still*.

Rule 4: **IF** *NI is medium* **AND** *KF is low*, **THEN** *activate the laparoscope*.

Rule 5: **IF** *NI is medium* **AND** *KF is medium*, **THEN** *laparoscope stand still*.

Rule 6: **IF** *NI is medium* **AND** *KF is high*, **THEN** *laparoscope stand still*.

Rule 7: **IF** *NI is high* **AND** *KF is low*, **THEN** *activate the laparoscope*.

Rule 8: **IF** *NI is high* **AND** *KF is medium*, **THEN** *activate the laparoscope*.

Rule 9: **IF** *NI is high* **AND** *KF is high*, **THEN** *laparoscope stand still*.

$$O_i = \min(L_{NI}, L_{KF}) \tag{7}$$

2.4.3 Inference Output. Among the nine IF-THEN rules, those inference results with the same control strategy are fused using a square accumulation method, as shown in Eqs. (8) and (9), and the square root of the resultant is considered to be the likelihood score of that control strategy, which are the activation score (AScore) and standstill score (SScore), respectively. AScore measures how likely it is that the current gaze position is the surgeon's visual attention and whether the laparoscope needs to be activated to focus on this new area. In contrast, SScore measures how likely it is that the laparoscope should stand still. AScore and SScore from the fuzzy engine across the entire input domain are shown in Fig. 6. When AScore is greater than SScore and also greater than 0.8 (a threshold value of attention confirmation), the system considers that visual attention of the surgeon outside the focus area has been recognized and then the robot is activated to follow the surgeon's visual attention. The threshold value 0.8 is selected based on the analysis of the AScore and SScore plot in Fig. 6.

$$AScore = \sqrt{O_4^2 + O_7^2 + O_8^2} \tag{8}$$

$$SScore = \sqrt{O_1^2 + O_2^2 + O_3^2 + O_5^2 + O_6^2 + O_9^2} \tag{9}$$
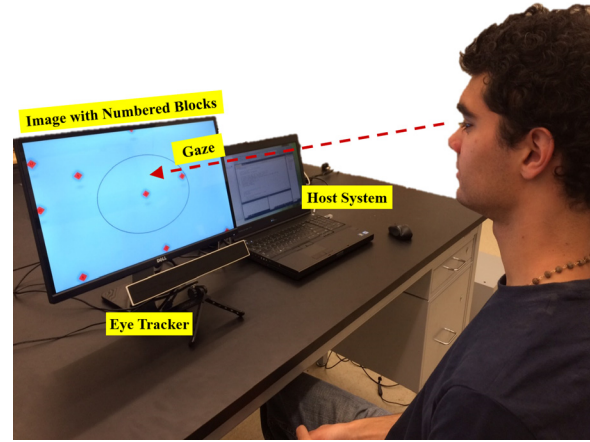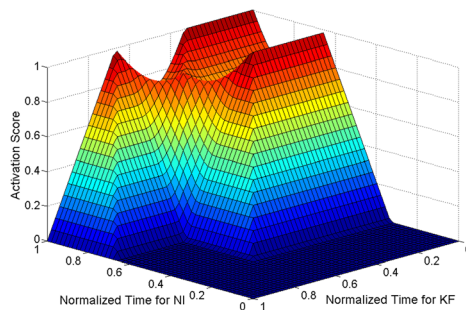
Fig. 7 The experiment setup with a virtual simulator

3 Experiments

Both simulations and benchtop experiments were performed to evaluate the fuzzy inference system. Simulation results were to evaluate the accuracy and time response of the fuzzy gaze interpretation method as the simulation environment eliminated the potential disturbances introduced by other components of the physical system. In the benchtop experiments with clinical participants, we focused on evaluation of the user experience of the overall system.

3.1 Visual Exploration Simulation. A visual exploration simulator was created which included an image with numbered blocks on it. A part of the image was displayed to the participants, and the participants were asked to explore the rest of the image using his/her gaze. When participants' visual attention fell out of the focus area, the display was updated and the new display was the image centered at the attended block. Different attention recognition methods, the fuzzy logic inference method and the dwell-time method were tested using this simulator. The setup is shown in Fig. 7.

3.2 Experiment Trials. Benchtop experiments were performed at the Department of Urology, Denver Health Medical Center, Denver, CO. Five subjects (two were experienced surgeons and the other three were clinical/surgical researchers) participated in the experiments. They were asked to perform target exploration tasks laparoscopically in the virtual simulator first and then in a surgical training box with numbered blocks inside. A short introduction and demonstration were given first, and then they started to use the system directly without practice.
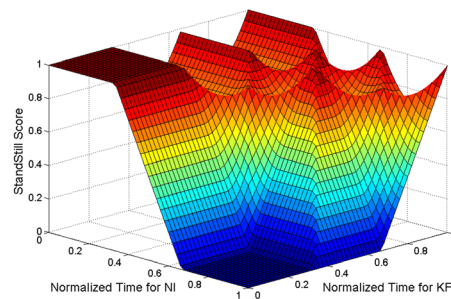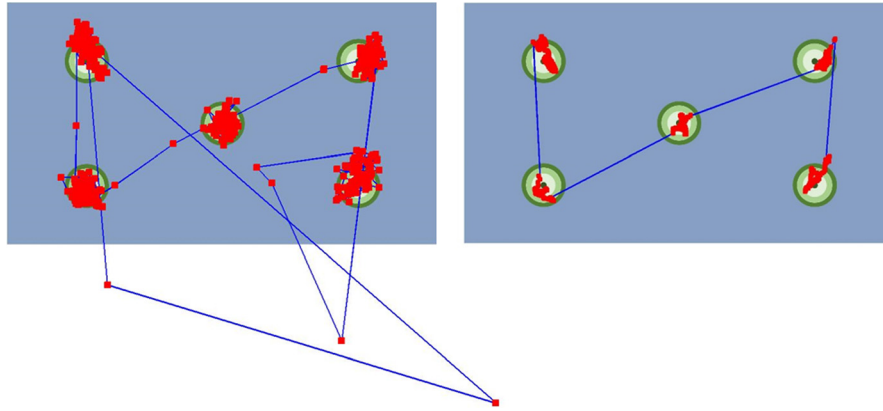
Fig. 6 AScore and SScore

Fig. 8 Comparison between the raw gaze data (left) with refined gaze data (right). The small squares are the gaze points. The big circles are the targets that the subject gazed upon on the monitor. The lines are the trajectory of the eye movements.

In the simulation tests, subjects were asked to change the field-of-view at least ten times using the fuzzy inference method and another at least ten times with the dwell-time method. Therefore, at least 50 view change samples for each method were collected. In the benchtop tests, the experiments were separated into two trials to avoid fatigue and other side effects caused by continuous and intensive view changing. Subjects were asked to focus on different areas in the surgical training box by steering the presented laparoscope system using their eyes. Both the fuzzy inference method and the dwell-time method were integrated into the system and subjects were asked to use both methods, respectively, in two trails to finish the exploration. During the trials, eye movement data and the system response time were recorded.

A threshold of 2.0 s was used for the dwell-time method based on our previous studies [36,37]. Threshold values shorter than 2.0 s could easily cause faulty recognition of the surgeon's visual attentions and led to incorrect movements of the laparoscope. The T value for normalization in fuzzy membership functions was taken as 1.5 s.

After each view update, the subject was asked to verbally report all the numbered blocks in the focus area to force the subjects to perform a certain observation of the central area. After that, the subject was asked to change the view to focus on another numbered block outside of the focus area by looking at that block. This block could be one that the subject had seen earlier or had not previously seen. This simulated both conditions in which the surgeon knows the position of the target object before gazing upon it and in which the surgeon is unaware of the object's location and must search for it.

In the interaction with the robot, the subjects were asked to explore in the surgery simulator by steering the camera to focus on different areas using the presented system. Fuzzy inference method and dwell-time method were both integrated and the subjects needed to use both methods separately in two trails to finish the exploration.

3.3 Questionnaires. After the experiments, a questionnaire was given to the subjects. The questionnaire was customized based on system usability scale (SUS), a widely used global assessment of system usability [50], and new items specific for gaze studies were added in. SUS is a ten-item Likert scale which ranges from 0 to 100. Twelve new evaluation criteria specific for gaze studies were added and they were designed following the same scaling rule of SUS. Twenty-two criteria were scored separately as three subsections. Section 4.3.1 includes the original ten items and three new ones for evaluating the overall system usability. Section 4.3.2 constitutes five items for evaluating the user

experience over repetitive tests, and Sec. 4.3.3 is for a comparison of user experience between the two attention recognition methods.

4 Results

4.1 Gaze Data Filter. The raw gaze data and refined gaze data using the adaptive sliding window filter are shown in Fig. 8 (the raw gaze data plot on the left and the refined gaze data on the right). The gaze data were collected when the subject looked at five visual targets on the screen and small red squares were the gaze points. It shows that even when a human tries to focus on a visual target, gaze data can still be quite noisy due to the involuntary rolling, nystagmus, drift, blink, and microsaccades. Gaze points are scattered around a visual target instead of concentrated on it, and there are gaze points that are shifted a great amount from the visual targets, which may be caused by blinks or eye tracking failure. For the refined gaze data, the noises are eliminated and the data concentrated on the visual targets, which is very helpful for the visual attention recognition.

4.2 Experiment Results. All the subjects successfully accomplished the exploration tasks using both attention recognition methods, which confirmed that the gaze-based interaction for laparoscopic view change is easy to use and participants can manage it effectively.

The response time (how long the subject needed to maintain his/her gaze on a visual target before his/her visual attention was recognized) was summarized. Using the dwell-time method, the five subjects made 57 view changes and the average response time was 2.063 s, with the maximum of 2.283 s and the minimum of 2.0 s. This result is consistent with the dwell-time threshold of 2.0 s. The slight variation is because the participants needed a little time to stabilize their eyes in order to focus on one target. In the fuzzy inference method, 58 view changes were generated by the participants and the average response time was 1.456 s, with the maximum of 2.517 s and the minimum of 0.833 s. The average response time is very close to the cutoff value of NIs high level ($1.5 s \times 0.99 = 1.485 s$). The summarized response time is illustrated as a boxplot in Fig. 9. The red crosses were outliers whose values were relatively far from the medium. The median for the dwell-time method was 2.05 s, and the median was 1.367 s for the fuzzy inference method.

4.3 Questionnaire Evaluation

4.3.1 Subsection 1 (Overall System Usability). The extended SUS with three added evaluation questions has a score that ranges from 0 to 130 (a higher score means the system has a better
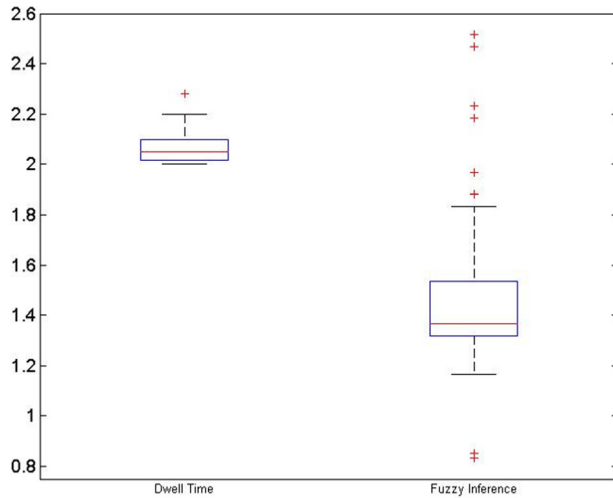
Fig. 9 Comparison of the response time in the dwell-time method and the fuzzy inference method

Fig. 11 The summary of user experience over repetitive tests for each method. The average score of the dwell-time method is 38.5, which is comparable to 38 for the fuzzy.

usability). The three new questions focus on the system's efficiency and accuracy. Each participant's scores in two control methods are shown in Fig. 10. The average score of the dwell-time method is 88.5 and the fuzzy inference method is 100.

4.3.2 Subsection 2 (User Experience Over Repetitive Tests). This section was to see if the user experience varies much after familiarization. It is composed of five questions. The total score is 50, and the results are shown in Fig. 11. The average score of the dwell-time method is 38.5, which is comparable to 38 for the fuzzy inference method.

4.3.3 Subsection 3 (Comparison of User Experience Between Two Methods). This section is for the comparison of user experience on the fuzzy inference method over that in the dwell-time method. It mainly focused on user experience on the response time, comfort level, and intensity level of each method. The total score ranges between 0 and 40 (The value closer to 0 means that the dwell-time method is superior to the fuzzy inference method and the value closer to 40 means that the fuzzy inference method is better than the dwell-time method). In the results, the average is 28, with the maximum of 30 and the minimum of 22.5. The results are summarized in Fig. 12.
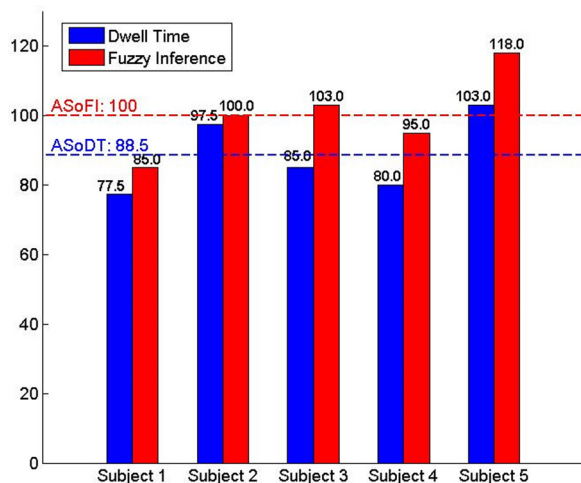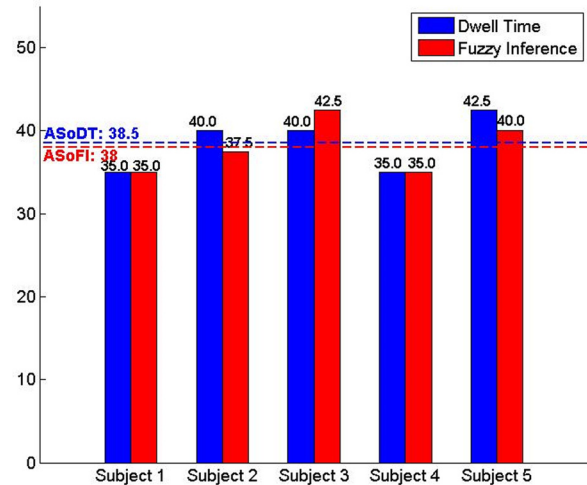

Fig. 10 The summary of system usability score in two different methods. The higher score means that the system has a better usability. ASoFI: average score of the fuzzy inference method. ASoDT: average score of the dwell-time method.
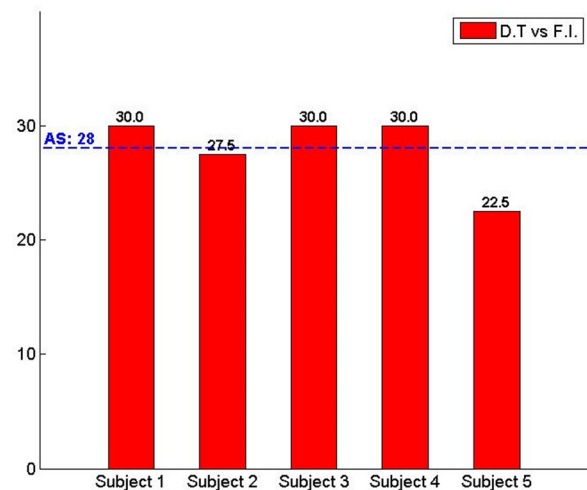

Fig. 12 User experience comparison of the fuzzy inference method over the dwell-time method. The total score ranges between 0 and 40 (the value closer to 0 means that the dwell-time method is superior to the fuzzy inference method and the value closer to 40 means that the fuzzy inference method is better than the dwell-time method).

5 Discussion

In the experiments, the response time using the fuzzy inference method varied widely from 0.833 s to 2.517 s, based on the subjects' historic visual behaviors in the last 3 s. The majority of the response times in the fuzzy inference method were less than those of the dwell-time method (1.367 s versus 2.05 s). The system using the fuzzy inference method was more responsive and activated more quickly when it could clearly tell that the current location gazed upon was the subject's visual attention based on his/her historic visual behaviors. Otherwise, it was more conservative and waited to collect more data to confirm a new visual attention. In this way, the robot can respond efficiently without undermining its accuracy. These results show that the fuzzy inference method has advantages over the traditional dwell-time method in terms of efficiency. While both methods have good accuracy, the minimal threshold for the dwell-time method was 2.0 s and the fuzzy inference method had an average response time of 1.456 s.

From the results of questionnaire Sec. 4.3.1, it primarily shows that gaze is a promising interaction modality to allow the surgeons to naturally and effectively interact with the laparoscopic view because both methods have relatively high scores. The results also show that the fuzzy inference method has a better usability than the traditional dwell-time method. Specifically in both methods, the participants highly agree that the gaze-guided robotic laparoscope system is simple, straightforward, and easy to use (average score is 3.1 out of 4); people can learn to use it very quickly (average score is 2.8 out of 4) and they need to learn little before using it (average score is 3.4 out of 4). In the mental aspect, the subjects felt confident using this system (average score 2.9 out of 4).

In questionnaire Sec. 4.3.2, fuzzy inference method earned comparable score as dwell-time method. This shows that each method is consistent and repeatable. The participants started to use the system without practice and his/her user experience did not deteriorate as they became more familiar with the system in the second trial. This means that the empirical dwell-time threshold, the fuzzy inference's cutoff value, and the minimization combination operation are reasonable to provide a good user experience to the surgeons. And from the results in questionnaire Sec. 4.2.3, it concludes that the participants preferred the fuzzy inference method over the dwell-time method, as it can better understand users' intent and correctly and efficiently recognize users' visual attention.

Form our experiments, 57 samples for the dwell-time method and 58 samples for the fuzzy inference method from five clinical participants were collected. These participants had professional or closely related experience on the laparoscopic surgery and understood the need of view change during the surgery. Analysis of these results clearly showed the advantages of the fuzzy inference method in response time and user experience. Further tests are needed to evaluate effectiveness of the presented system in animal operations or with a bigger population of clinical participants.

6 Conclusion

In this paper, a novel visual attention recognition method is introduced which is based on fuzzy logic interpretation of eye-gaze movements at the pattern level. It is the first time fuzzy logic has been used to recognize the surgeon's visual attention based on eye-gaze patterns. It can effectively and efficiently recognize the surgeon's visual attention from his/her natural eye-gaze behaviors. Integrating this fuzzy logic interpretation method into the laparoscopic view interaction will constructively enhance the surgeon's performance during the operation. The entire system can effectively and correctly recognize the surgeon's attention on the surgical site and then automatically steer the robotic laparoscope to focus on it. Therefore, intervention of the laparoscope can be eliminated from the surgeon's to do list. It can completely free the surgeon's hands to manipulate the surgical instruments while naturally adjusting the laparoscopic view using his/her eyes at the same time. Using this system, the surgeon will be able to accomplish the operation more smoothly, as it can eliminate switching back and forth between different control modes of the surgical instrument and laparoscope. Consequently, the operation time can be reduced as well as the cost and risk related to it.

Nomenclature

AS = average score
$AScore$ = activation score
$ASoDT$ = average score of dwell-time
$ASoFI$ = average score of fuzzy inference
E_i = influence coefficient of ith gaze point
KF = keep focus
L_{KF} = the truth of degree of one certain possibility level of KF membership function
L_{NI} = the truth of degree of one certain possibility level of NI membership function

m = a mapping relationship from the laparoscopic image in pixel to the Cartesian position in terms of the laparoscope frame
N = sliding window size
NI = new interest
O_i = the inference result using ith IF-THEN rule
P_i = the position of the ith raw gaze point
$\bar{P}_i$ = the position of the ith gaze point after being processed
p^{atten} = the position of the surgeon's visual attention on the laparoscopic image in pixel
P^c = the target position of the laparoscope so that it can focus on the surgeon's new visual attention
S_{high} = the truth of degree for level high in fuzzy membership function
S_{low} = the truth of degree for level low in fuzzy membership function
S_{medium} = the truth of degree for level medium in fuzzy membership function
$SScore$ = standstill score
SUS = system usability scale
T = a coordinate transformation matrix from the laparoscope frame to the robot base frame
$threshold$ = a predefined distance threshold for adaptive rolling window filter
$2D$ = two-dimensional
$3D$ = three-dimensional

References

[1] Wikipedia, 2014, "Laparoscopic Surgery," accessed Sept. 29, 2014, http://en.wikipedia.org/wiki/Laparoscopic_surgery

[2] Martins Rus, J. R., Jatene, F. B., de Campos, J. R., Monteiro, R., Tedde, M. L., Samano, M. N., Bernardo, W. M., and Das-Neves-Perira, J. C., 2009, "Robotic Versus Human Camera Holding in Video-Assisted Thoracic Sympathectomy: A Single Blind Randomized Trial of Efficacy and Safety," Interact. Cardiovasc. Thorac. Surg., **8**(2), pp. 195–199.

[3] Stolzenburg, J. U., Franz, T., Kallidonis, P., Minh, D., Dietel, A., Hicks, J., Nicolaus, M., Al-Aown, A., and Liatsikos, E., 2010, "Comparison of the Free-Hand® Robotic Camera Holder With Human Assistants During Endoscopic Extraperitoneal Radical Prostatectomy," BJU Int., **107**(6), pp. 970–974.

[4] Taniguchi, K., Nishikawa, A., Sekimoto, M., Kobayashi, T., Kazuhara, K., Ichihara, T., Kurashita, N., Takiguchi, S., Doki, Y., Mori, M., and Miyazaki, F., 2010, "Classification, Design and Evaluation of Endoscope Robots," *Robot Surgery*, Seung Kyuk Baik, ed., InTech, Rijeka, Croatia, pp. 1–24.

[5] Sackier, J. M., and Wang, Y., 1994, "Robotically Assisted Laparoscopic Surgery: From Concept to Development," Surg. Endoscopy, **8**(1), pp. 63–66.

[6] Aiono, S., Gilbert, J. M., Soin, B., Finlay, P. A., and Gordan, A., 2002, "Controlled Trial of the Introduction of a Robotic Camera Assistant for Laparoscopic Cholecystectomy," Surg. Endoscopy, **16**(9), pp. 1267–1270.

[7] Prosurgics, "FreeHand," Prosurgics Inc., San Jose, CA, accessed Nov. 13, 2014, http://www.freehandsurgeon.com

[8] Polet, R., and Donnez, J., 2004, "Gynecologic Laparoscopic Surgery With a Palm-Controlled Laparoscope Holder," J. Am. Assoc. Gynecol. Laparoscopists, **11**(1), pp. 73–78.

[9] Tanoue, K., Yasunaga, T., Kobayashi, E., Miyamoto, S., Sakuma, I., Dohi, T., Konishi, K., Yamaguchi, S., Kinjo, N., Takenaka, K., Maehara, Y., and Hashizume, M., 2006, "Laparoscopic Cholecystectomy Using a Newly Developed Laparoscope Manipulator for 10 Patients With Cholelithiasis," Surg. Endoscopy, **20**(5), pp. 753–756.

[10] Guthart, G. S., and Salisbury, J. K., Jr., 2000, "The Intuitive™ Telesurgery System: Overview and Application," IEEE International Conference on Robotics and Automation (ICRA '00), San Francisco, CA, Apr. 24–28, pp. 618–621.

[11] Kraft, B. M., Jager, C., Kraft, K., Leibl, B. J., and Bittner, R., 2004, "The AESOP Robot System in Laparoscopic Surgery: Increased Risk or Advantage for Surgeon and Patient?" Surg. Laparoscope, **18**(8), pp. 1216–1223.

[12] Gilbert, J. M., 2009, "The EndoAssist Robotic Camera Holder as an Aid to the Introduction of Laparoscopic Colorectal Surgery," Ann. R. Coll. Surg. Engl., **91**(5), pp. 389–393.

[13] Wei, G., Arbter, K., and Hirzinger, G., 1997, "Real-Time Visual Servoing for Laparoscopic Surgery. Controlling Robot Motion With Color Image Segmentation," IEEE Eng. Med. Biol. Mag., **16**(1), pp. 40–45.

[14] Wang, Y. F., Uecker, D. R., and Wang, Y., 1998, "A New Framework for Vision-Enabled and Robotically Assisted Minimally Invasive Surgery," Comput. Med. Imaging Graphics, **22**(6), pp. 429–437.

[15] Nishikawa, A., Asano, S., Fujita, R., Yohda, T., Miyazaki, F., Sekimoto, M., Yasui, M., Takiguchi, S., and Monden, M., 2003, "Robust Visual Tracking of Multiple Surgical Instruments for Laparoscopic Surgery," Computer Assisted Radiology and Surgery 17th International Congress and Exhibition (CARS 2003), London, June 25–28, p. 1372.

[16] Ko, S. Y., and Kwon, D. S., 2004, "A Surgical Knowledge Based Interaction Method for a Laparoscopic Assistant Robot," 13th IEEE International Workshop on Robot and Human Interactive Communication (ROMAN 2004), Kurashiki, Japan, Sept. 20–22, pp. 313–318.

[17] Lee, C., Wang, Y.-F., Uecker, D. R., and Wang, Y., 1994, "Image Analysis for Automated Tracking in Robot-Assisted Endoscopic Surgery," 12th IAPR International Conference on Pattern Recognition (ICPR), Conference A: Computer Vision and Image Processing, Jerusalem, Oct. 9–13, pp. 88–92.

[18] Kranzfelder, M., Schneider, A., Blahusch, G., Schaaf, H., and Feussner, H., 2009, "Feasibility of Opto-Electronic Surgical Instrument Identification," Minimally Invasive Ther. Allied Technol., 18(5), pp. 253–258.

[19] Nishikawa, A., Asano, S., fujita, R., Yamaguchi, S., Yohda, T., Miyazaki, F., Sekimoto, M., Yasui, M., Miyake, Y., Takiguchi, S., and Monden, M., 2003, "Selective Use of Face Gesture Interface and Instrument Tracking System for Control of a Robotic laproscope Positioner," 6th International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI 2003), Montréal, Canada, Nov. 15–18, pp. 973–974.

[20] Merchant, J., Morrissette, R., and Porterfield, J., 1974, "Remote Measurement of Eye Direction Allowing Subject Motion Over One Cubic Foot of Space," IEEE Trans. Biomed. Eng., 21(4), pp. 309–317.

[21] Morimoto, C. H., and Mimica, M. R. M., 2000, "Eye Gaze Tracking Techniques for Interactive Applications," Comput. Vision Image Understanding, 18(4), pp. 331–335.

[22] Stampe Dave, M., 1993, "Heuristic Filtering and Reliable Calibration Method for Video-Based Pupil-Tracking Systems," Behav. Res. Methods Instrum. Comput., 25(2), pp. 137–142.

[23] Ji, Q., and Zhu, Z., 2002, "Eye and Gaze Tracking for Interactive Graphic Display," Machine Vision and Application, Springer, New York, pp. 139–148.

[24] Barea, R., Boquete, L., Ortega, S., Lopez, E., and Rodriguez-Ascariz, J. M., 2012, "EOG-Based Eye Movements Codification for Human Computer Interaction," Expert Syst. Appl., 39(3), pp. 2677–2683.

[25] Krolak, A., and Strumillo, P., 2012, "Eye-Blink Detection System for Human-Computer Interaction," Univers. Access Inf. Soc., 11(4), pp. 409–419.

[26] Liu, C., Ishi, C. T., Ishiguro, H., and Hagita, N., 2012, "Generation of Nodding, Head Tilting and Eye Gazing for Human-Robot Dialogue Interaction," 7th ACM/IEEE International Conference on Human-Robot Interaction (HRI), Boston, Mar. 5–8, pp. 285–292.

[27] Ma, J., Zhang, Y., Cichocki, A., and Matsuno, F., 2015, "A Novel EOG/EEG Hybrid Human-Machine Interface Adopting Eye Movements and ERPs: Application to Robot Control," IEEE Trans. Biomed. Eng., 62(3), pp. 876–889.

[28] Hansen, D. W., and Ji, Q., 2010, "In the Eye of the Beholder: A Survey of Models for Eye and Gaze," IEEE Trans. Pattern Anal. Mach. Intell., 32(3), pp. 478–500.

[29] Wikipedia, 2015, "Eye Tracking," accessed Apr. 30, 2015, http://en.wikipedia.org/wiki/Eye_tracking

[30] COGAIN Communication by Gaze Interaction, 2013, "Gazetalk," COGAIN Association, Frederiksberg, Denmark, accessed Oct. 3, 2014, http://wiki.cogain.org/index.php/Gazetalk

[31] Tobii, 2014, "Computer Access Through Eye Gaze," Tobii AB, Danderyd, Sweden, accessed July 3, 2014, http://www.tobii.com/PCEye2011

[32] Purwanto, D., Mardiyanto, R., and Arai, K., 2009, "Electric Wheelchair Control With Gaze Direction and Eye Blinking," Artif. Life Rob., 14(3), pp. 397–400.

[33] Atienza, R., and Zelinsky, A., 2005, "Intuitive Interface Through Active 3D Gaze Tracking," International Conference on Active Media Technology (AMT 2005), Kagawa, Japan, May 19–21, pp. 16–21.

[34] Noonan, D. P., Mylonas, G. P., Shang, J., Payne, C. J., Darzi, A., and Yang, G.-Z., 2010, "Gaze Contingent Control for an Articulated Mechatronic Laparoscope," 3rd IEEE, RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob), Tokyo, Sept. 26–29.

[35] Staub, C., Can, S., Jensen, B., Knoll, A., and Kohlbecher, S., 2012, "Human-Computer Interfaces for Interaction With Surgical Tools in Robotic Surgery," 4th IEEE, RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob), Rome, June 24–27, pp. 81–86.

[36] Zhang, X., Li, S., Zhang, J., and Williams, H., 2013, "Gaze Contingent Control for a Robotic Laparoscope Holder," ASME J. Med. Devices, 7(2), p. 020915.

[37] Li, S., Zhang, J., Xue, L., Fernando, K., and Zhang, X., 2013, "Attention-Aware Robotic Laparoscope for Human-Robot Cooperative Surgery," IEEE International Conference Robotics and Biomimetics (ROBIO), Shenzhen, China, Dec. 12–14, pp. 792–797.

[38] Jacob, R. J. K., and Karn, K. S., 2003, "Eye Tracking in Human-Computer Interaction and Usability Research: Ready to Deliver the Promises," Mind, 2(3), pp. 577–605.

[39] Glenstrup, A. J., and Engell-Nielsen, T., 1995, "Eye Controlled Media: Present and Future," Bachelor's thesis, Information Psychology, Laboratory of Psychology, University of Copenhagen, Copenhagen, Denmark.

[40] Møllenbach, E., Hansen, J. P., and Lillholm, M., 2013, "Eye Movements in Gaze Interaction," J. Eye Mov. Res., 6(2), pp. 1–15.

[41] Zhang, X., and Nelson, C. A., 2008, "Kinematic Analysis and Optimization of a Novel Robot for Surgical Tool Manipulation," ASME J. Med. Devices, 2(2), p. 021003.

[42] Nelson, C. A., Zhang, X., Shah, B. C., Goede, R. M., and Oleynikov, D., 2009, "Multipurpose Surgical Robot as a Laparoscope Assistant," Surg. Endoscopy, 24(7), pp. 1528–1532.

[43] Nelson, C. A., Zhang, X., and Oleynikov, D., 2009, "Tool Guidance Using a Compact Robotic Assistant," J. Rob. Surg., 3(3), pp. 171–173.

[44] Kim, J., Abdel-Malek, K., Mi, Z., and Nebel, K., 2004, "Layout Design Using an Optimization-Based Human Energy Consumption Formulation," SAE Technical Paper 2004-01-2175.

[45] Zadeh, L. A., 1965, "Fuzzy Sets," Inf. Control, 8(3), pp. 338–383.

[46] Wikipedia, 2014, "Fuzzy Control System," accessed Jan. 20, 2015, http://en.wikipedia.org/wiki/Fuzzy_control_system

[47] Dadios, E. P., Biliran, J. J. C., Garcia, R.-R. G., Johnson, D., and Valencia, A. R. B., 2012, "Humanoid Robot: Design and Fuzzy Logic Control Technique for Its Intelligent Behaviors," Fuzzy Logic: Controls, Concepts, Theories and Applications, InTech, Rijeka, Croatia, pp. 3–20.

[48] Hong, T. S., Nakhaeinia, D., and Karasfi, B., 2012, "Application of Fuzzy Logic in Mobile Robot Navigation," Fuzzy Logic: Controls, Concepts, Theories and Applications, InTech, Rijeka, Croatia, pp. 21–36.

[49] Ahmad, S., Siddique, N. H., and Tokhi, M. O., 2012, "Modular Fuzzy Logic Controller for Motion Control of Two-Wheeled Wheelchair," Fuzzy Logic: Controls, Concepts, Theories and Applications, InTech, Rijeka, Croatia, pp. 37–58.

[50] Brooke, J., 1996, "SUS: A Quick and Dirty Usability Scale," Usability Evaluation in Industry, Taylor & Francis, London, p. 189.