The Computer Assisted Surgical Trainer: Design, Models, and Implementation

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Abstract

This paper describes a system developed to assist in model-based training of minimally invasive, laparoscopic procedures. The key factor motivating the development of the device called CAST (Computer-Assisted Surgical Trainer) is the need to improve the state-of-the-art in teaching laparoscopy, and ultimately achieve better surgical outcomes. CAST's design concept and architecture is presented with its major elements that facilitate guided (both haptic and visual) execution of tasks, performance assessment, and comparative analysis of results. Both software and hardware models and implementations are given. The system, while currently intended for off-line, laboratory use, has an excellent potential for real-time assistive functions in the operating room.

1. INTRODUCTION AND MOTIVATION

Minimally Invasive Surgery (MIS) is a surgical technique involving small incisions performed by an endoscope and several long, thin instruments. Due to its techniques, the injuries to the tissue are less severe when compared to conventional surgery. Recovery is much quicker and less painful. However, from a surgeon's perspective, MIS presents more challenges than a standard surgery. A surgeon's operating space is limited and the degrees of freedom (DOF) of the instruments are constrained. The use of long and rigid instruments limits tactile feedback that surgeons rely on during open surgery. Since an endoscope is used to observe the operating field, hand-eye coordination becomes an issue as depth perception is significantly impeded.

The limitations of MIS make it a difficult skill to master and perform. Moreover, many issues specific to MIS can result in major morbidity or potential mortality. To minimize the potential risks and to provide improved patients' safety, much research has been done to help surgeons adapt to the MIS environment. The more innate visuospatial, perceptual, and psychomotor ability the surgeon has, the faster he or she will automate the surgical skills. The goal of any surgical training program is to help surgeons automate their basic psychomotor skills before they operate on a patient [19][20]. It has been shown that simulation-based training can enhance surgical MIS performance in both speed and error reduction.

Over the past decade or so, simulation in healthcare has become a burgeoning field. Simulation-based curricula have become an integral part of first responder, nursing, and physician training. In parallel, major equipment manufacturers are developing a range of surgical and other simulators. These simulators are intended to provide a "close-to-reality" experience in the medical training setting. In laparoscopy education, models and simulators range from very simple box-like trainers on which the students carry out vary basic tasks such as grasping or transferring an object from one position to another, to very sophisticated virtual reality-based devices that lead the trainee through a sequence of tasks required to complete a specific procedure (e.g., cholecystectomy) [21][23]

Our work fills the "gap" between the simple and highly expensive devices. In addition, we provide cognitive aids which do not exist in many systems presently marketed. More specifically, we have developed a novel platform called the Computer Assisted Surgical Trainer (CAST) which provides precise assessment, intuitive navigation, and haptic as well as visual assistance in the execution of surgical tasks.

We use a novel adaptive fuzzy inference engine [36] real-time performance assessment. The inference engine models the judgment criteria used by experienced surgeons and provides scalability characteristics in three key aspects: integration of new expert opinions; integration of new evaluation metrics; and integration of new performance data, for the constant improvement of an objective scoring system.

To assist in learning a task, a turn-by-turn augmented reality and haptic-based navigation system has been developed as well. By defining the configuration space of the instrument, a collision-free working space can be established. Students are guided to follow an optimized path (or to avoid "no-fly" areas) and targets by utilizing a multimedia display technique.

A "smart instrument" that embeds a specially designed robot manipulator into the surgical instruments has been designed and implemented as an integral part of the system. In addition to the multimedia navigation information, force and torque can be exerted to the devices through this "smart" manipulator when necessary. When the system detects a mistake made by the user, the instrument leads the trainee back to the optimal task state. This approach not only gives the students an enhanced training ability, but it also provides a new type of safety guarantee capability for future use during the real operating procedure. In summary, CAST is the basis of a new training methodology for surgeons to enhance the situational awareness beyond current approaches.

2. DESIGN CONCEPT AND ARCHITECTURE

Our CAST design concept was driven by the need to simulate surgical procedures in stages, represent anatomical variations and anomalies, permit random introduction of unforeseen crises, and to provide haptic and visual feedback. The system has methods and tools that track and assess trainees' performance.

In [21][22][23][24], we defined three fundamental design layers for CAST. The foundation, called the *Perception Layer* embodies physical sensing devices, tracking (motion, touch accuracy, etc.) and detection algorithms. The key need was to design and implement the ability to precisely track the position of surgical instruments during a training session. This allows us and the trainees to review their performance with respect to a set of metrics such as the *economy of movement, time, accuracy, direction profile, etc.* [21][36]. Thus, the second design layer, the *Comprehension Layer* provides a suite of metrics and algorithms for performance assessment. In the *Comprehension Layer*, we also developed the ability to assess trainees' performance not only quantitatively but also qualitatively. In [36], we presented the knowledge elicitation process to model the performance metrics and the rules involved in the assessment of minimally invasive surgical skills. Our assessment model is based on fuzzy logic, so that it is easier to mimic the judgment that is already performed by experienced surgeons in qualitative terms. An empirical study to validate our approach is described in [36].

The highest, most complex element of our system is the *Projection Layer.* Here we work on implementing knowledge-based reasoning as well as real-time instrument guidance.

Our design features embedded micro-sensors in the instruments employed for simulation training.

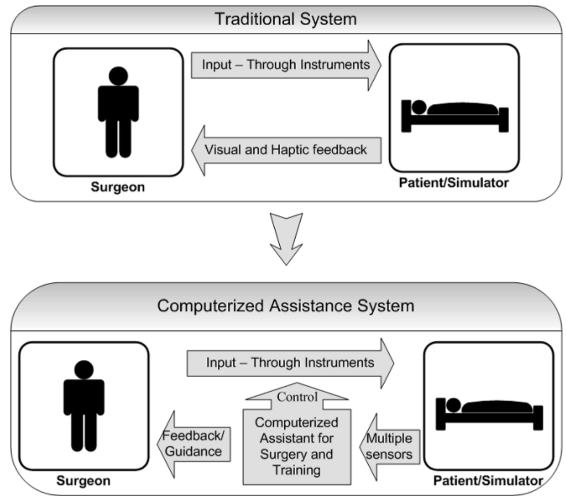

Figure 1. Traditional vs. Computer Assisted System.

The detection and recording of the users' operation permit our system not only to measure a trainee's progress in acquiring psychomotor skills and compare these data to normative databases, but also to evaluate instrument effectiveness in reducing error. Fig. 1 contrasts the CAST System with the traditional approach. In the CAST system, the surgeon acts upon the patient or simulator through instruments and receives visual and force feedback from the CAST both in the operating room and training settings. Our approach implements a "hybrid" system in which joint optimization of actuation, sensing, and computing is performed within a closed loop.

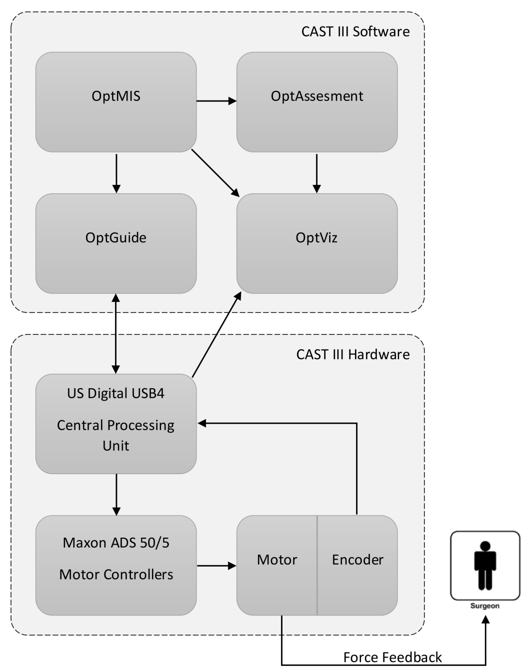

Figure 2. CAST Architecture.

3. MAJOR ELEMENTS

CAST's overall architecture is shown in Figure 2. The two main components are the software and hardware, forming a closed loop which generates force feedback to the user. The interaction between the software and the actual physical system is done through a guidance module (OptGuide) and the US Digital USB4 central processing unit. The overall operation of CASTIII as well as all the building blocks of the two main components are described in the following subsections.

3.1. OptAssessment

We performed a knowledge elicitation process to formulate expert judgment for the assessment of laparoscopic surgical skills. A scoring system based on fuzzy logic capable of distinguishing between four proficiency levels while providing students with a quantitative score was designed. Our design method was composed of the following steps: (1) defining a set of relevant performance metrics in the assessment of laparoscopic surgical skills; (2) eliciting and generating membership functions to model performance metrics; (3) eliciting a set of production rules to model experts' judgment; and (4) defining a set of proficiency levels to categorize subjects. The implemented scoring system named OptAssessment can objectively quantify competency in MIS skills.

3.1.1. Performance Metrics

In [36], we defined five relevant metrics for hand–eye coordination tasks which were validated by an experienced surgeon: time, movement economy ratio, movement direction profile, peak speed width and continuity of movement.

Time: Refers to the total time taken by the trainee to perform the task. *Movement economy ratio:* This metric scales the movement track length. The movement economy ratio is obtained by dividing the optimal path for performing the complete task by the addition of the path drawn by the instrument's tip while passing through the entire task's targets (i.e., all the segments that comprised a task). *Movement direction profile:* quantifies the extent that the instrument deviates in moving from target A to target B.

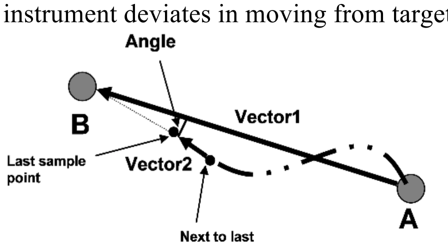

Figure 3. Movement direction profile quantifies the extent that the laparoscopic instrument (dashed line) deviates from an optimal path (solid line) in moving from target A to target B.

Peak speed width: This metric is obtained by dividing the speed wave's peak amplitude by two and calculating the ratio of the resulting areas. The peak speed width parameter depends on the wave's horizontal symmetry; waves closer to a trapezoidal shape reflect better movement control over the instrument than jitter shapes. Therefore, their Peak speed width value approaches one.

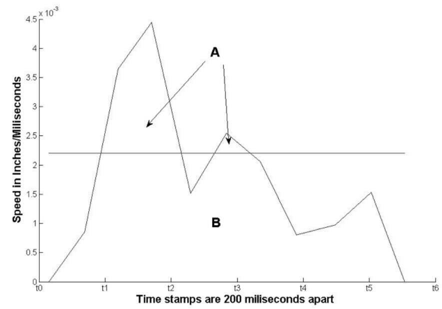

Figure 4. Speed wave described by moving a laparoscopic instrument between two targets. Peak Speed Width is obtained by calculating the ratio between two areas (labeled A and B) that result from dividing the speed wave's peak amplitude by two.

Continuity of movement: This metric is calculated by eliminating recursively the speed's graph troughs to obtain a modified graph and then calculating the ratio of both areas under the curves original speed graph over modified speed graph.

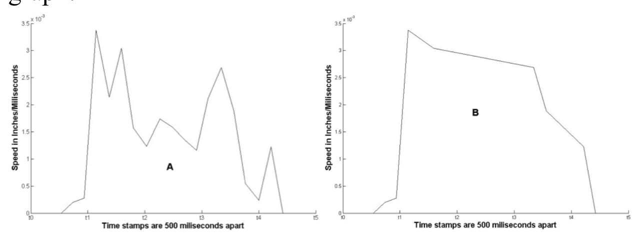

Figure 5. The area under the speed wave described by moving a laparoscopic instrument between two targets is shown on the left side while on the right side a smoother modified speed graphs exhibits a more desirable movement.

3.1.2. Semantic Decomposition and Membership Function Generation

Each metric was decomposed into four fuzzy terms that characterize the performance of the given proficiency level as follows:

-Strong Positive→Expert. -Moderate Positive→Proficient.

-Weak Positive→Beginner. -Negative→Novice.

These fuzzy terms represent the input sets to our inference system. We generated membership functions consisting of straight segments i.e., triangular and trapezoidal, also known as polygonal membership functions. Our elicitation method provided us with the transitional points where two membership functions intersect at the height of 0.5. We used these points to calculate the rest of the critical points needed to construct polygonal membership functions according to the following criteria:

1- We chose a triangular function over a trapezoidal when adequate.

2- We procured vertical symmetry on non-outer membership functions.

3- We satisfied the condition of a partition of unity.

The CAST Scoring System is a five input, one output Mamdani fuzzy model with 20 rules developed with the Matlab Fuzzy Logic Toolbox 2. The inference process is performed automatically by MATLAB.

In [36], we describe an experiment with a total of 38 trainees. Subjects were distributed in five groups according to their expertise in MIS, 17 non-medical students, 11 medical students without previous laparoscopic surgery training, 5 medical students with some laparoscopic surgery training, 4 medical residents and 1 expert surgeon.

A hand-eye coordination task was performed 8 times by each subject. In total 304 samples were used in this study. Subjects were asked to use only their dominant hand (left or right) to perform each of eight trials. For each subject, four trials (odd trials) were used in the system's knowledge base while the other four (even trials) were used for testing purposes.

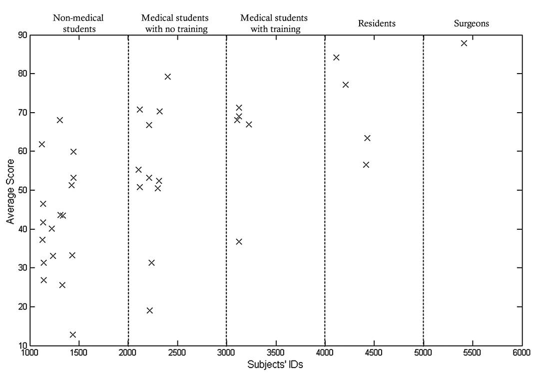

Figure 6. Average score plot. Identification numbers were assigned to subjects according to their MIS experience.

3.2. The Optimal Motion Planning Method: OptMIS

The optimal motion planning method called optMIS generates shortest, collision-free trajectories for laparoscopic instrument movements in the rigid block world used for hand-eye coordination tasks. The method consists of two sequential stages:

1. **Shortest path planning** aimed at generating the path between start and target configurations of a laparoscopic instrument.
2. **Time-optimal trajectory planning** used to specify a time law on shortest paths in order to prevent collisions between instruments.

3.2.1. Shortest Path Planning

At the first stage, the workspace is represented as a mesh of tetrahedrons based on using the proposed Delaunay tetrahedralization algorithm [1]. In particular, the algorithm decomposes the obstacle space (i.e. concave hull) into the union of simplicial complexes (i.e. tetrahedrons). Each simplicial complex is defined as a finite collection of indices and ordered tuples of vertices. Then, a simplicial complex of the free space is obtained by decomposing the overall workspace into a mesh of tetrahedrons and subtracting the obstacle space from it. In contrast to the methods of alpha shapes [2][3], which require defining global or local threshold alpha, the proposed approach provides more flexibility in modeling complex obstacle spaces and is independent of additional parameters.

Once the workspace is decomposed, Dijkstra's algorithm [4] is applied to find the shortest continuous channel of tetrahedrons between start and target configurations. Since Dijkstra's algorithm works on graphs, vertices of a graph are represented as centroids of tetrahedrons that correspond to the free space. At each iteration, Dijkstra's algorithm picks the unvisited vertex (centroid) with the lowest-distance, calculates the distance through it to each unvisited neighbor, and updates the neighbor's distance if smaller. This algorithm always provides the shortest feasible channel without the need to solve more time-consuming k-shortest paths problem [5].

Finally, the shortest curves are constructed through the data points of the shortest continuous channel. An enumerative combinatorics technique is used to evaluate all combinations of the data points and find the one that gives the minimal length of the curve. The cubic spline methodology [6] is utilized to fit third-order polynomials between the data points providing that the curve obtained is continuous and smooth (i.e., zig-zag" movements of laparoscopic instruments are prevented). The obtained curves are then used to interpolate the positions of instruments within the range of targets as represented in Figure 7.

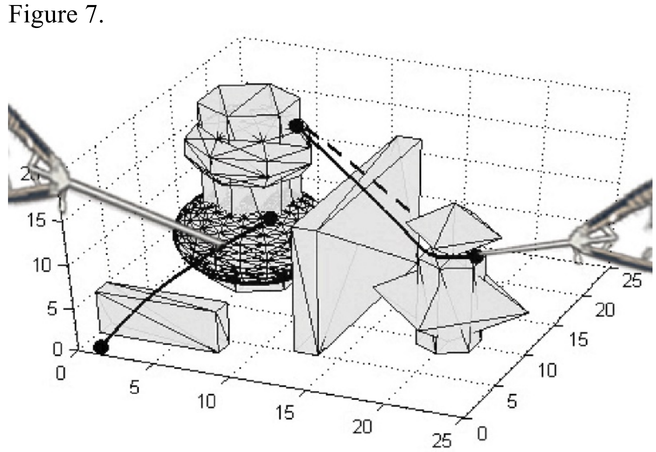

Figure 7. 3D Representation of Planned Path.

3.2.2. Time-Optimal Trajectory Planning

At the second stage of the OptMIS method, an elitist genetic algorithm is applied to find the periods of time when the data points of the shortest curves should be reached in order to avoid collisions between laparoscopic instruments. To achieve this goal, the configurations at which laparoscopic instruments intersect are defined first. Second, a time value is assigned to each intersection configuration in order to prevent collisions between the instruments.

Final optimal trajectories are displayed on a display monitor to provide continuous visual guidance for optimal navigation of laparoscopic instruments.

3.3. OptGuide

The main role of the OptGuide is to provide haptic guidance to a novice trainee [7]. Whenever the instrument tip deviates from the optimal trajectory generated by OptMIS, OptGuide applies force to guide the user in the proper direction. The OptGuide uses the optimal path as a reference input and the actual tip position as a measurement output. Both the reference position and the actual tip position are updated every sampling period. The reference position is calculated by the reference generator module based on the actual tip position and the optimal path. Also, the actual tip position is captured by the encoder unit.

3.3.1. Initial PD Implementation

The initial control scheme for all the motors is a PD controller [7]. This low level controller is encapsulated in the OptGuide class. The controller also ensures that no one axis dominates by using type-2 Axis Synchronization [14]. This technique consists in adding a fed trough term to adjust the gain of each axis based on a coupled-error term described in Equation 1 and Equation 2. The result is a synchronized gain described in Equation 3 that will guide the laparoscopic tool to the desired position in the 3D workspace while following a straight line trajectory.

$$\sigma = \begin{pmatrix} 2 \cdot yawError - (pitchError + insertionError) \\ 2 \cdot pitchError - (yawError + insertionError) \\ 2 \cdot insertionError - (pitchError + yawError) \end{pmatrix}$$

Equation 1. Coupled Error Term.

$$error = \begin{pmatrix} yawError \\ pitchError \\ insertionError \end{pmatrix}$$

Equation 2. Position Error Vector.

$$gain = K_p \cdot error + K_d \cdot error_d + K_{sync} \cdot \sigma$$

Equation 3. Haptic Guidance Control Equation.

As a result, the Computer Assisted Surgical Trainer is able to guide the trainee along a trajectory using haptic feedback with the intention of helping them learn specific surgical tasks and rapidly enhance their laparoscopic skills.

3.3.2. Fuzzy Logic Implementation

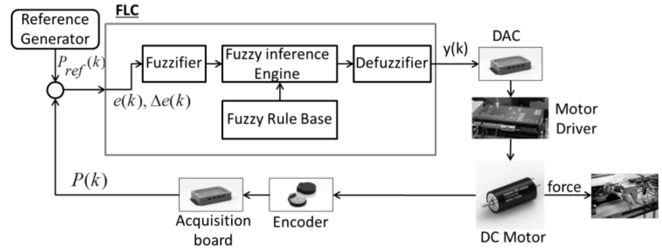

Figure 8. Overall Block Diagram of OptGuide.

OptGuide now uses a Fuzzy Logic Controller (FLC) as a main controller. The overall block diagram of OptGuide is shown in Figure 8. FLC consists of a fuzzifier, a fuzzy rule base, a defuzzifier, and a fuzzy inference engine [8]. The inputs of FLC are position error ($e(k)$) between the reference position and the estimated position and the derivative of the position error ($\Delta e(k)$). The output of FLC is a set value ($y(k)$), used to control a motor [9]. The fuzzifier is implemented by using membership functions.

The triangular and the trapezoid membership functions are used to express the inputs of the system. The singleton membership functions are used to express the output of the system. Figure 9 illustrates the input and the output membership functions. Five fuzzy sets are used for the position error and three fuzzy sets are used for the derivative of error. We determined these sets and their parameters as well as singleton output sets empirically.

Once the inputs are fuzzified, the fuzzy logic rules are designed to represent the control algorithm. IF-THEN statement is used to build the fuzzy rule base. We defined fifteen rules for OptGuide and these are shown in Table 1.

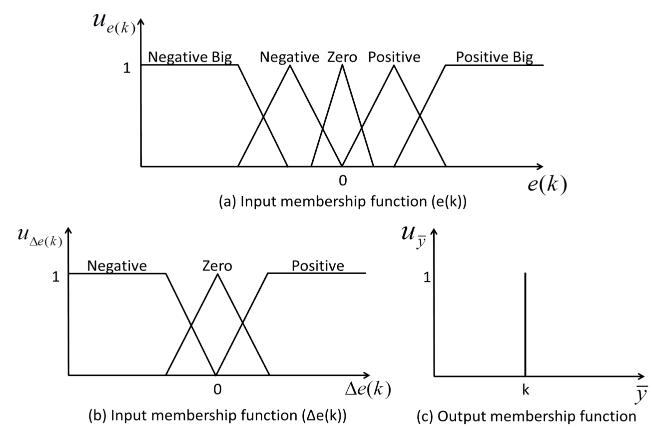

Figure 9. The Membership Functions of FLC.

Table 1. IF-THEN Rules for OptGuide.

e(k) / Δe(k)	NB	N	Z	P	PB
N	$\bar{y}^{(1,1)}$	$\bar{y}^{(2,1)}$	$\bar{y}^{(3,1)}$	$\bar{y}^{(4,1)}$	$\bar{y}^{(5,1)}$
Z	$\bar{y}^{(1,2)}$	$\bar{y}^{(2,2)}$	$\bar{y}^{(3,2)}$	$\bar{y}^{(4,2)}$	$\bar{y}^{(5,2)}$
P	$\bar{y}^{(1,3)}$	$\bar{y}^{(2,3)}$	$\bar{y}^{(3,3)}$	$\bar{y}^{(4,3)}$	$\bar{y}^{(5,3)}$

The product inference engine is used to combine the fuzzy IF-THEN rules.

Finally, the defuzzifier produces a non-fuzzy control output value based on the fuzzy inference engine. The center average method was chosen for the defuzzifier because of computational simplicity. This defuzzifier method is shown in the equation below.

$$y(k) = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} \bar{y}^{(m,n)} \cdot u_{e(k)}^{m} \cdot u_{\Delta e(k)}^{n}}{\sum_{m=1}^{M}\sum_{n=1}^{n} u_{e(k)}^{m} \cdot u_{\Delta e(k)}^{n}}$$

Equation 4. Defuzzifier Equation.

There are three FLCs for yaw, pitch, and insertion axes in OptGuide. Each axis has different physical characteristics. Therefore, we used different parameters of memberships function for each degree of freedom to make the system stable and to consider the different characteristics of each axis.

3.4. OptViz

3.4.1. Motivation:

The OptViz module was developed to provide better hand eye coordination and depth perception. The operating environment is kept similar to standard box trainers, but advanced computer graphics are added to enhance visual user experience.

3.4.2. Overview:

OptViz is responsible for visualizing the surgical training scenario and its optimal path. "Live" data from the camera are merged with virtual objects such as the optimal path and instrument tip location etc., which is rendered on the screen. This module works in two phases:

1. Camera Calibration to generate optimal path file.
2. Rendering and visualization of the optimal path.

The software architecture is illustrated in Figure 10 followed by a description of the steps involved.

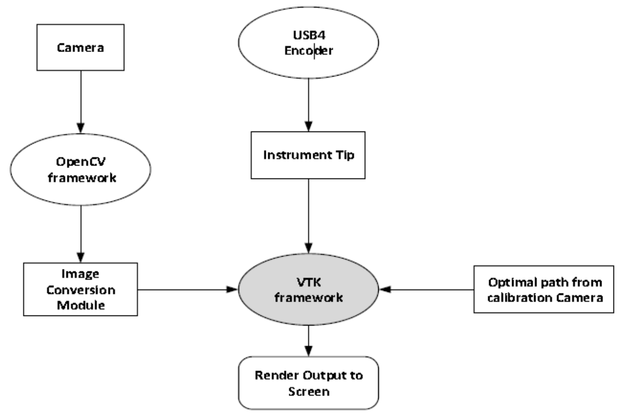

Figure 10. Architechture of OptViz.

3.4.3. Camera Calibration:

Camera calibration is the process of finding intrinsic and extrinsic parameters of a camera, thus enabling one to obtain the camera matrix [10]. The camera matrix denoted by M, finds where a point (x,y,z) in the real world will appear on the image. This matrix is made up of the intrinsic and extrinsic parameters. The extrinsic parameters of a camera include the position and orientation of the camera to a known frame. The intrinsic parameters are more specific to the camera in use and include focal length, ratio of the pixel size, principal point and the angle between axes of the image plane [10]. The assumption is that the camera observes a set of features including points or lines with known positions in a fixed world coordinate system. The CAST workspace is used as the calibration rig.

The steps to calibrate the camera are:

1. View the calibration object
2. Identify points of interests (edges, lines etc.)
3. Obtain camera matrix by minimizing error

The camera matrix computation is performed by considering the eigenvectors corresponding to minimum eigenvalues [10]. When OptViz is fed by the output files generated by OptMIS, it will generate the position of those coordinates in the camera image. This module provides the optimal path file in terms of image world coordinates as the output, which is further used in the visualization/augmented reality overlay stage.

3.4.4. Visualization

1. The optimal path generated using the previous step is visualized in the CASTIII development environment. In order to make the visualization more effective, the following visual cues have been used. Points on the optimal path are rendered as circles, with radii proportional to their normalized Z coordinate values in a range of 2 to 25.
2. A new camera frame is acquired every 50ms. A separate software renderer is used for camera rendering to segregate the CASTIII functionality.

3. Optimal Path is visualized as a function of the percentage of the task completed. This means that as the user progresses, he can visually see the points he has touched as they turn from grey to green.
4. The instrument tip position is represented as a blue circle, which turns green when the trainee navigates on the path. This is an indicator to show that the trainee is moving correctly.
5. Crosshairs on the top corners of the window represent the position of the instrument tip in relation to the closest point on the optimal path. The spheres within the crosshair become smaller if the user moves further along the depth plane, and larger if he moves closer.

These visual cues illustrated in Figure 11 tend to provide assistance to the trainee as he navigates on the optimal path to complete the training task.

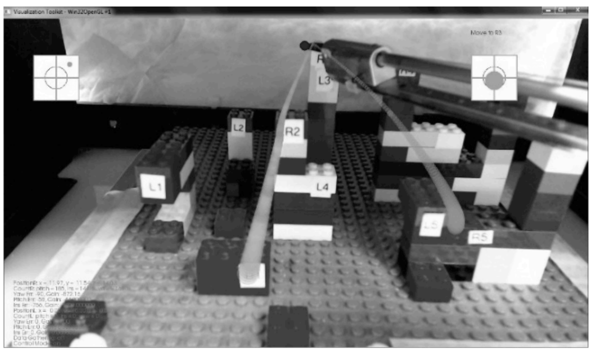

Figure 11. Augmented Reality Using Visual Cues.

4. TECHNICAL REALIZATION

4.1. General Description

The hardware for CAST consists of two fixtures, one for the left hand and one for the right hand, both symmetrically identical and equipped with electronics, sensors and motors for haptic guidance and instrument tip position tracking.

The mechanical platform used in CAST is an aluminum fixture composed of a gimbal with two attachments where standard laparoscopic instruments can be mounted. As in laparoscopic surgery, the gimbal allows four degrees of freedom: yaw, pitch, insertion and roll, all centered around one single entry point which corresponds to the incision. The advantage of this design is that it is polyvalent; installing new laparoscopic tools can easily be done, permitting a vast variety of applications.

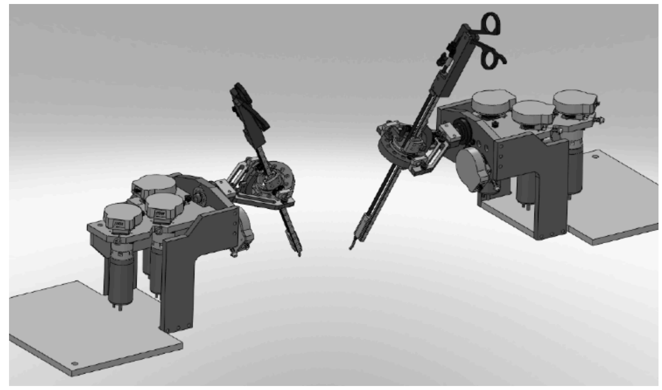
Figure 12. 3D Mechanical Design.

The entire system is cable driven. It provides low backlash, low stretch, high flexibility power transmission, with smooth, no step motion. Each joint controls one cable with pulleys that will drive the corresponding motor and encoder. Figure 12 and Figure 13 illustrate the 3D mechanical design and the physical system respectively.

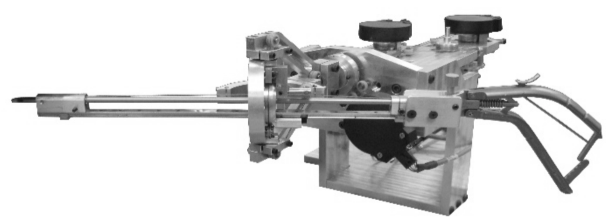
Figure 13. Physical Right Fixture.

4.1.1. Position Determination

Euler angles [11] are a conventional method to determine gimbal position. CAST III uses a similar model by measuring the yaw, pitch, insertion, and roll. Euler angles θ and ϕ describe yaw and pitch, respectively. Insertion determines how deep an instrument moves from the entry point; this is essentially scaling a unit vector where θ and ϕ provide the direction. Roll determines the tip orientation. CAST III uses Cartesian coordinates for its instrument tip position. The tip position is defined by a 3-dimensional vector composed of: the pitch, the yaw and the insertion value. The roll defines the orientation of the tip. The equations to determine the pitch, the yaw and the orientation from the joint position are given in Equation 5, Equation 6 and Equation 7.

$$Pitch = \begin{pmatrix} 1 & 0 & 0 \\ 0 & cos\phi & sin\phi \\ 0 & -sin\phi & cos\phi \end{pmatrix} Yaw = \begin{pmatrix} cos\theta & sin\theta & 0 \\ sin\theta & cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Equation 5 and Equation 6. Pitch and Yaw Position.

$$Orientation = insertion \cdot \begin{pmatrix} cos\theta & sin\theta \cdot cos\phi & sin\theta \cdot sin\phi \\ -sin\theta & cos\theta \cdot cos\phi & sin\phi \cdot cos\theta \\ 0 & -sin\phi & cos\phi \end{pmatrix}$$

Equation 7. Orientation of the Laparoscopic Tool.

Using the center of the gimbal as a local frame of reference, we can then compute the Cartesian coordinates of the tip of the laparoscopic tool using Equation 8.

$$x = -insertion \cdot sin\theta$$

$$y = insertion \cdot cos\phi \cdot cos\theta$$

$$z = insertion \cdot sin\phi \cdot cos\theta$$

Equation 8. Cartesian Coordinates of the End Effector.

Incremental optical encoders measure the four gimbal values. Each optical encoder is attached to a rotating shaft which connects back to its specific gimbal via several pulleys and a cable. These pulleys rotate their specific optical encoders giving a scaled value of the gimbal position.

Each shaft has a mount for motors. These provide haptic guidance to the user. Four motors are necessary to provide haptic guidance for each left and right fixture. These motors are attached to the yaw, pitch, roll and insertion axes.

4.2. Hardware Overview

4.2.1. The Motors

The motors selected for haptic are the Maxon RE35 for the yaw, insertion and orientation and DCX35L for the pitch axis. We use a more powerful motor with a low ratio of 4.3 for the pitch axis as we need more torque to be able to compensate for the gravity and the weight of the laparoscopic tool being used. The use of a high ratio gearbox with the RE35 motor was impractical as it would have increased the friction on the pitch axis, resulting in unsmooth movement from the user perspective.

4.2.2. Data Acquisition

The USB4 [12] module by US Digital, is the central processing unit used to process encoder wheel positions and actuate motors. It connects via USB to a PC, which runs the CAST III software. The encoders used are the E3-2048-188-NDDB from US Digital. Each encoder has 2048 counts per revolution [13]. In the current configuration, we use the 4x quadrature mode resulting in a resolution of 8192counts per revolution.

The servo-amplifier used to control the motors are ADS50/5 and ESCON50/5 from Maxon Motors. They amplify the signal coming from the USB4 module into a power signal (-48V to +48V) to drive the motors.

5. CONCLUSION

This paper has presented an overview of a design and implementation effort to build a low cost, yet sophisticated and "smart" surgical trainer to support laparoscopy education. Key features that distinguish our design are: a) the set of models that are the foundation for sensing and tracking (motion, touch accuracy, etc.) and detection algorithms. b) a set of complex metrics that allow the trainees to review their performance, and c) knowledge-based reasoning as well as real-time instrument guidance techniques. The system prototype is currently in place. In order to verify the utility of our platform, an extensive evaluation experiment must be designed. We will design a series of tests in which we will enroll medical students, residents, surgical fellows, and experienced physicians. In addition to the metrics defined in [36] and section 3.1.1. we will use parameters such as age, visual acuity, years of experience, etc., for in between groups comparisons. These studies will be carried out to assess the efficacy of computer-based vs. conventional training.

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