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Computer-Guided Laparoscopic Training with Application of a Fuzzy Expert System

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Abstract. Laparoscopic surgery is a widely accepted operating technique which continues to spread into different areas of medicine. Because of it's differences to open surgery (like limited perception) it demands a different training program than the traditional surgical training programs. Since it's introduction in 1980's several training curriculums for laparoscopic surgeons have been deployed and a set of skills that need to be mastered during the training has been defined. The training system proposed in this paper uses a knowledge base to guide the trainee trough the process of acquiring the necessary skills, based on the trainees measured performance in several areas. The system's guidance allows for better understanding of areas that need additional work and for faster acquisition of those, without the need for extra attention from the tutoring staff.

1 Introduction

Since it's raise in the early 1980's laparoscopic surgery has spread from cholecystectomy and appendectomy into many areas of surgery, including orthopaedic surgery, gynaecological surgery and others. The main reason behind it's growth are the significant benefits it brings into the healing process. Theese include: limited scarring, reduction in pain and recovery time, leading to a smaller risk of complications. Study conducted by Hansen et al. [1] shows that patients who have undergone laparoscopic appendectomy had five times fewer wound infections, two times shorter discharge time and fewer of them required narcotic analgesia.

On the other hand, there is a number of downsides, for instance the surgeon's perception both haptic and visual - is very limited, which extends the procedure time (in the open appendectomy case 40 as opposed to 63 minutes in laparoscopic appendectomy [1]) and the likelihood of human error. Also investment in expensive instruments and a very long training period are required.

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There is a strong need, expressed in [2],[3],[4],[5], for computer assisted laparoscopic surgeon training. Reference [2] more thoroughly describes the motivation behind developing such a system.

The expert system described in this paper is designed to aid in the process of training laparoscopic surgeons within a computer-guided surgical training system and uses a fuzzy-logic reasoning as described in [6,7]. The simulator system used is based on the VAST trainer [8] and extends it as described in [2]. A structure-from-motion algorithm following [9] is used to recover the viewed scene's 3D geometry which then serves for defining no-fly zones within the scene.

The *no-fly zones* are an important concept used in this system. Those are the regions within the operating field where the appearance of an instrument is expected to inflict injury to the patient, i.e. nerves or vessels which shouldn't be irritated nor cut during the procedure. It is one of the goals of the presented system to teach the trainee to avoid such regions.

The simulator itself is a standard laparoscopic setting (camera and instrument) with a position sensor embedded at the tip of the instrument.

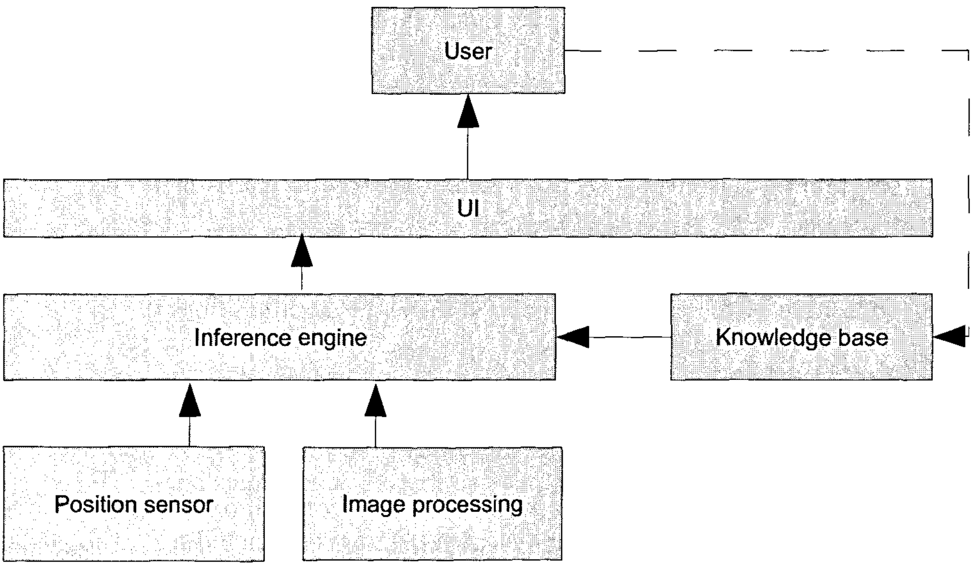

Fig. 1. Diagram of the proposed expert system

The system makes use of the information from a position sensor placed on the tip of the laparoscopic instrument and the 3D geometry of the scene to draw conclusions based on a set of rules from the system's knowledge base, Fig. 1. The image processing component of the system, described in more detail in Section 2, is used to build the 3D model for determining the no-fly zones. The 3D model is not used for visualisation purposes, but serves the inference engine for drawing conclusions about the users behaviour in relation to the no-fly zones. The system can then alert the user about aproaching a no-fly zone in a manner similar to the parking sensor devices installed in modern cars, this and other means of interaction are described in Section 4.

2 Image Processing

The image processing component leads to obtaining a depth-map of the viewed scene from a series of images. Consider a following example of 2 input images of a training model as in Fig. 2. The image pair has been automatically selected from a set of views and next further processing has occured to obtain a depth-map representation of the 3D geometry of the scene, Fig. 3.

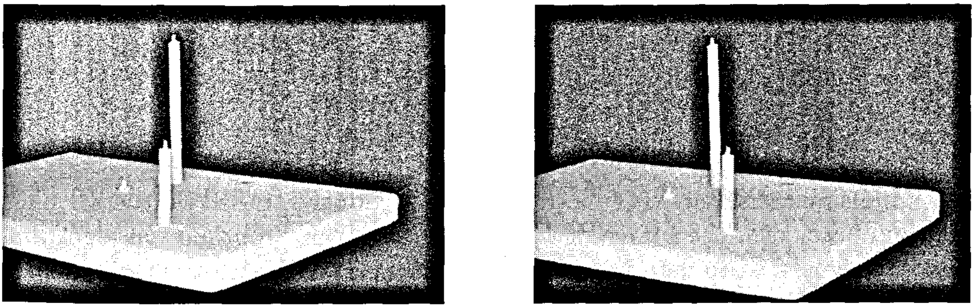

Fig. 2. 2 views of a training model used during exercises

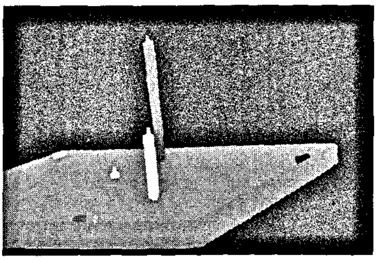

Fig. 3. Depth map image obtained with the structure-from-motion algorithm

The reconstructed approximation of the 3D relations of the scene are not aimed for visualisation, only for the step of defining no-fly zones. It is important to note, that the presented depth map has some flaws which are especially due to the lack of texture on the examined model.

3 Training

The training is based on simple tasks that trainees have to complete within a specified time. Several types of exercises have been proposed by others [10,11], the common goal is to practice dexterity, coordination and depth perception. Example exercies are :

- knot tying,
- cutting and suturing,
- picking up objects,
- touching different points on a model.

Each exercise is associated with a different physical model which is placed in the pelvi-trainer's box. The trainee's score is calculated with respect to :

- elapsed time
- length of the path of the instrument tip
- accuracy

and the score is calculated in a following manner :

$$S = \left(\frac{k_t}{t} + \frac{k_s}{s} + k_A \cdot A\right) \tag{1}$$

where k_i are the weights of i-th metric, t is the time metric, s is the path length metric, A is the accuracy metric (which is less or equal to 1).

As indicated in [2] another metric can be introduced, based on the 3D information obtained in the course of work of the structure-from-motion algorithm. This metric is used to determine the risk factor involved with the trainee's performance and it is related to breaches of the no-fly zones. The concept of this metric is that the score should be significantly decreased upon hitting a hazardous region (no-fly zone), defined for each exercise as a sphere with radius R with the center H_c in a certain point on the model

$$S = \left(\frac{k_t}{t} + \frac{k_s}{s} + k_A \cdot A + k_H \cdot H\right) \tag{2}$$

with

$$H = -\frac{2R_H}{|d(H_c, T)| + R_H} + 1, \tag{3}$$

and $d(H_c, T)$ being the distance between the center of the hazard sphere H_c and the instrument tip T. The H metric defined in such a way yields negative score for any position inside the no-fly zone, zero score for the tip on the sphere of the no-fly zone and positive score for anywhere outside the zone.

4 Inference Engine

The inference engine uses the dynamic data from the position sensor and image processing and the embedded knowledge from the knowledge base to conclude and inform the trainee about the areas where he or she underperforms during the exercise. The UI provides several means of communication with the user, i.e. the information about proximity to a no-fly zone can be presented as an auditory signal of a frequency that is dependent to the membership function defined in formula (5) creating an effect similar to the parking sensors embedded in car bumpers.

4.1 Movement Classification

In general the proposed engine deals with movements and their features, therefore a formalization of the term *movement* is needed. A movement m is defined by a pair of parameters (V, T), where V is the current speed vector and T the current position vector of the instrument's tip. Using such formalism movements can be divided into several classes, with respect to speed (F^+ set for fast movements and F^- for slow movements), path smoothnes (S^+ for smooth and S^- for rough ones), etc.

Arising from the metric introduced in Section 3 is the qualification of the movement as close to a no-fly zone, member of the H^+ set and far from a no-fly zone, member of H^- set. Further risky (belonging to the set R^+) and non-risky (the R^- set) movements can be defined, with regards to the distance from a no-fly zone, but also current speed of the movement.

We propose that the mentioned membership functions are not crisp, but fuzzy [12] - as it is hard to define i.e. a particular distance and speed at which a no-fly zone is safe from being breached. Let's consider the sets of risky and non-risky movements (R^+, R^-). The relation of a movement belonging to either R^+ or R^- shouldn't in fact be binary and can be expressed as a following fuzzy relation

$$m \in R^+ \iff (m \in H^+ \cap m \in F^+) \tag{4}$$

where H^+ and F^+ are fuzzy sets containing movements that are respectively, close to no-fly zones and fast. The membership functions for the H^+ and F^+ sets are as follows :

$$\mu_{H^+}(m) = \begin{cases} 0 & \text{for} \quad d(H_c, T) > R_H + 1 \\ R_H - d(H_c, T) + 1 & \text{for} \; R_H < d(H_c, T) < R_H + 1 \\ 1 & \text{for} \quad d(H_c, T) \leq R_H \end{cases} \tag{5}$$

$$\mu_{F^+}(m) = \begin{cases} 0 & \text{for} \quad v < 0.1 \\ \frac{0.1 - V}{10} + 1 & \text{for} \; 0.1 < v < 10 \\ 1 & \text{for} \quad v > 10 \end{cases} \tag{6}$$

where the parameter 1 in formula (5) and parameters 0.1, 10 in (6) are measured in cm and $\frac{cm}{s}$ respectively. In a similar manner we define the membership functions of the remainding movement classes.

4.2 Reasoning

Based on the classification of movements and the rules encoded in the knowledge base the system can evaluate the weaknesses of the trainee and provide simple advice on how to improve performance. The advice offered by the system is of the form

- your movements are too fast,
- your movements are too inprecise,
- your moving too close to a no-fly zone,

also the system can advise the user to go to a certain exercise which is designed to emphasise the particular skill the system considers to be weak. For instance the system can evaluate the movements as inprecise and can suggest the user to move to a training drill designed to practice the precision of movements.

5 Knowledge Base

The knowledge base of the expert system contains rules which are related to the movement classification, for example :

1. **If** the path between two points is not a straight line **then** the movement is not optimal.
2. **If** the instrument is in proximity to a no-fly zone **then** the movement is risky.
3. **If** the instrument moves very slow **then** the movement not optimal.
4. **If** the instrument moves very fast **then** the movement is risky.
5. **If** the instrument doesn't touch the specified points **then** the movement is inaccurate.
6. **If** the trainee's score is far lower than the average score **the** the overall performance was poor.

In addition a set of rules containing expert advice is available and presented to the user accordingly.

5.1 Feedback

The feedback mechanism of the presented system is such that the trainees' scores are recorded into the knowledge base. One of the consequences is that the trainee can be informed by the inference engine about how his performance stands among his peers. The recorded data also plays an important role in the development of the system as it indicates the weak points of the trainees and informs the developers about areas that need additional attention, i.e. during designing new exercises. After collecting a number of results from several trainees it is possible to see what are the common weaknesses and address them.

6 Preliminary Results

Brief analysis of the performance of the system's 3D recovery part shows that the accuracy of the Z-coordinate's reconstruction of the model pictured in Fig. 2 is far from perfect. After applying proper scale to the reconstructed model the maximum error of the depth estimation was in the range of $\pm 6mm$, which for the discussed model is 5% of it's total depth. The influence of the error on the system's performance can be partially minimized by enlarging the no-fly zones however it is clearly a significant flaw in the current version of the system.

The essence of the problem seems to lay in the last step of the 3D reconstruction process, which is stereo matching. During that step a pair of images, which has been earlier matched and transformed, is examined to find pixel disparities for every pixel in an image. Several methods are known and a thorough analysis along with a testing method is given in [13]. Authors of the method selected for use in the presented system present promising results [14], even for poorly-textured models, however similar results couldn't be achieved for the model from Fig. 2.

7 Conclusions

The presented expert system based on fuzzy reasoning is a good solution for laparoscopic training programs based on computer-assisted simulators and application of the 3D reconstruction pipeline is a promising tool for more elaborate inference methods. A mathematical formalism for describing and classifying motion of the instrument's tip, which is strictly related to the trainee's skills, as well as a classification of movements has been given. The rules used by the inference engine to classify the movements and offer advice have been presented.

The image processing part of the system needs further attention, but already shows promising results. Especially models that are poorly textured produce 3D representations biased with a significant error, as it is the case with the model presented in this paper. Stereo matching algorithms that deal with such textureless objects are available and they will be examined for application in future versions of the proposed system.

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