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Development of a Laparoscopic Box Trainer Based on Open Source Hardware and Artificial Intelligence for Objective Assessment of Surgical Psychomotor Skills

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Abstract

Background. A trainer for online laparoscopic surgical skills assessment based on the performance of experts and nonexperts is presented. The system uses computer vision, augmented reality, and artificial intelligence algorithms, implemented into a Raspberry Pi board with Python programming language. *Methods.* Two training tasks were evaluated by the laparoscopic system: transferring and pattern cutting. Computer vision libraries were used to obtain the number of transferred points and simulated pattern cutting trace by means of tracking of the laparoscopic instrument. An artificial neural network (ANN) was trained to learn from experts and nonexperts' behavior for pattern cutting task, whereas the assessment of transferring task was performed using a preestablished threshold. Four expert surgeons in laparoscopic surgery, from hospital "Raymundo Abarca Alarcón," constituted the experienced class for the ANN. Sixteen trainees (10 medical students and 6 residents) without laparoscopic surgical skills and limited experience in minimal invasive techniques from School of Medicine at Universidad Autónoma de Guerrero constituted the nonexperienced class. Data from participants performing 5 daily repetitions for each task during 5 days were used to build the ANN. *Results.* The participants tend to improve their learning curve and dexterity with this laparoscopic training system. The classifier shows mean accuracy and receiver operating characteristic curve of 90.98% and 0.93, respectively. Moreover, the ANN was able to evaluate the psychomotor skills of users into 2 classes: experienced or nonexperienced. *Conclusion*. We constructed and evaluated an affordable laparoscopic trainer system using computer vision, augmented reality, and an artificial intelligence algorithm. The proposed trainer has the potential to increase the self-confidence of trainees and to be applied to programs with limited resources.

Keywords

classification of MIS skills, laparoscopy box simulator, augmented reality, objective assessment

Introduction

It has been several decades since the first publication of the modern laparoscopy procedure. Nowadays, it has become a common intervention technique in operating rooms around the world. The revolutionary change on the benefits that this technique brought about[1,2] is well known, and most hospitals have all necessary equipment as a basic instrumental to perform laparoscopic surgery. Also, medical schools have included in the curricula the preparation of new surgeons on this technique. Old school surgeons learn during training courses and improve their technique in a surgical room with animals like dogs, pigs, and rats.[3] Unlike a conventional open surgery, surgeons must master the handling of the instrumental and coordinate the movements of their hands with the visual feedback of a 2-dimensional image. They must practice constantly to maintain the necessary dexterity and continue to improve their laparoscopic surgical skills. However, there are still hospitals where surgical residents perform laparoscopic surgeries under the

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supervision of an experienced surgeon, and the performance of the trainee is evaluated based on the judgment of an expert surgeon.

Although the laparoscopic performance is supervised, there is an implicit risk when training is made in subjects *in vivo*. Previous training and an objective qualification in this minimally invasive technique is required before practicing with human beings in the operating room. A well-accepted alternative for practice and maintaining laparoscopic psychomotor skills are laparoscopic trainers and simulators.[4-6] These devices consist of simulating equipment where the laparoscopic training can be performed without risk of injury to human beings. These training systems are classified as physical trainers, virtual reality simulators, and, a third class, the hybrid trainers.[7,8]

Virtual reality simulators are generally very expensive. Their sophisticated and complex mechanical design, with haptic feedback and elaborated simulating software, allows the trainee to practice in a completely virtual environment, without the need for an expert surgeon. However, excessive costs and low portability of these devices limits the access of the surgical residents.

Physical trainers or box trainers allow a trainee to practice over a realistic environment due to use of real laparoscopic instruments, interacting with tasks designed specially to assess common laparoscopic skills as handling objects, making knots, or cutting tissues. These physical trainers use time as the common metric for assessing the performance of a task, and then analyze those times using statistical tools. It has been reported that box trainers increase the confidence and dexterity of a trainee.[9,10] Even so, the evaluation of laparoscopic skills must be done by an experimented surgeon, thereby pointing to the lack of objective evaluation as the main drawback of low-cost box trainers.[11-13]

On the other hand, hybrid trainers combine the advantages of virtual reality simulators and physical trainers, providing a sense of real world having professional tooling in a virtual environment[14,15]; besides trainees can be objectively evaluated by an intelligent software.[6,16,17] These characteristics, in particular, limit their use in the universities or in the simulation laboratories of health centers.

However, new open source platforms have emerged as alternative technology in order to develop affordable intelligent applications in the health care field,[18-20] where Raspberry, Android, and Python are among the most used.[21-23]

In this article, we present the implementation of an artificial neural network (ANN) in a box trainer as a tool for basic laparoscopic skills evaluation. The ANN was coded in Python program language and executed in a Raspberry Pi board. The evaluation of performance is carried out by software just after the tasks are completed. The ANN was trained with a data set from 20 participants (4 experts, 6 residents, and 10 medical students) who used our training system for 5 days with 2 basic tasks. This affordable box trainer offers a viable option for learning and training of laparoscopic surgery using open source software and hardware components for objective assessment of psychomotor minimally invasive surgery skills of surgeons and residents.

Materials and Methods

Development of Laparoscopic Box Trainer

The construction of the simulator is based on previous reported works related to laparoscopic box trainers[10,24-27] and based on a commercial plastic mannequin to simulate the human body. The trainer is located at the abdominal area of the model. The lid has 3 entry ports, 2 for the laparoscopic instruments and 1 in the center for the fixed webcam. The webcam, used to track the position of the tool tip (previously marked with a green piece of tape), is located right on top of the working area. The output of the webcam is connected to the Raspberry Pi 2 board. Internally, a white LED stripe lights up the working area and a commercial TV monitor gives the visual feedback. A pair of latex gloves simulates the strength and elasticity of the abdominal wall. The commercial mannequin can be replaced by a plastic storage box with dimensions 45 cm length × 35 cm width × 15 cm in height for housing (Figure 1). The laparoscopic training system works with a homemade software program named *Laparoscopia* in multiplatform Python language and OpenCV library.

The software of laparoscopic simulator has implemented 2 basic tasks, based on the MISTELS (McGill Inanimate System for Training and Evaluation of Laparoscopic Skills) program,[28] which measure technical laparoscopic skills.

- *Transferring*: The task consists of transferring virtual reality points from one side of the screen to another, placed in different heights and orientation. The software counts how many dots from left are transferred to the right side of the screen. A dot is counted as correctly transferred when the red point is placed over blue one; this complete movement of the green marker (tip) is detected by the software. An arbitrary preset cutoff time of 2 minutes terminates this task. This task involves skills at hand-eye coordination and spatial perception.
- *Pattern cutting*: The task consists of following the path of the ideal spiral with the tip of instrument, which simulates the circular cut in a gauze. This path of the spiral is drawn on the monitor using augmented reality with OpenCV library. The task

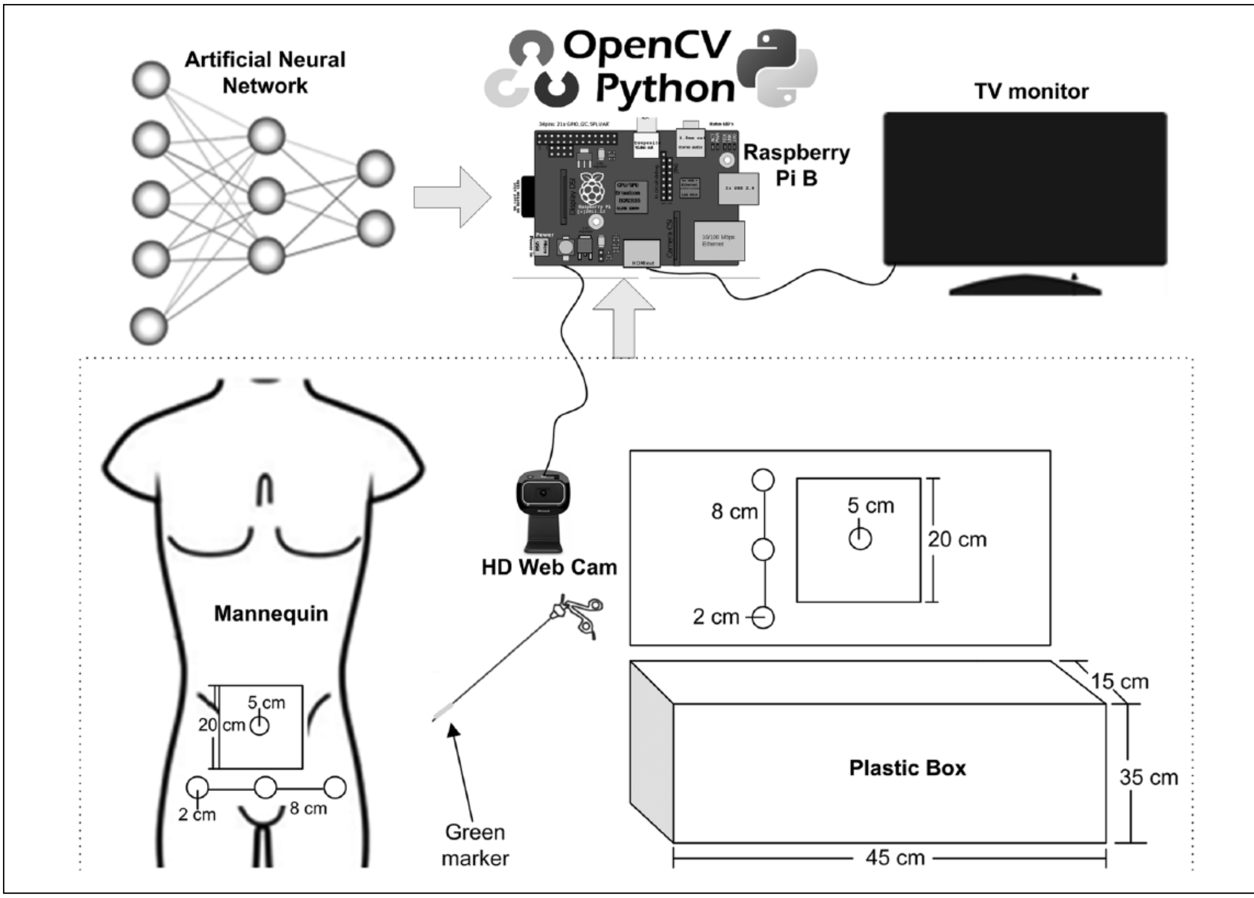

Figure 1. Schematic of the proposed trainer setup.

initiates when the tip is placed at the beginning of the spiral (over blue point) and finishes when it reaches the end of spiral (over red point).

The software Laparoscopia was first applied in Bruno-Sanchez et al[29] as dexterity test, where the dot's transferring time and the mean-squared error between an ideal spiral and a user's trace were the metrics used to evaluate the transferring and pattern cutting tasks, respectively. Experiments in that study proved that it is not possible to discern between experts and nonexperienced by only using the time and the mean-squared error as metrics. Moreover, the user's learning curve over time was also investigated, thus indicating that this information was not relevant to distinguish between the 2 groups.

Participants

A total of 20 volunteers from the medical school at Universidad Autónoma de Guerrero and from the Hospital General "Raymundo Abarca Alarcón" were invited to perform the 2 basic tasks of the trainer for this study. The volunteers were grouped into 2 classes: experienced and nonexperienced. The nonexperienced class consisted of 10 medical students without previous experience in laparoscopic surgery and 6 surgical residents with limited experience in minimal invasive surgery. The experienced class consisted of 4 expert surgeons with >70 laparoscopic procedures performed such as colorectal surgery and hernia repairs. For this study, each user repeated the tasks 5 times daily during a 5-day period. After repetition the software generates a binary image of the traced spiral, which is then computed by the software.

Questionnaire

All the participants answered a questionnaire of 5 questions at the end of the study. They were asked about the following: (1) if the trainer was comfortable to use, (2) whether the system was useful for training process to achieve more confidence in real practice, (3) whether participants would like assembly or construct their own trainer with a step-by-step manual, (4) if they would recommend the trainer for surgical training, and (5) where is the most convenience place to practice. In each question, the participants have 4 options to answer, from

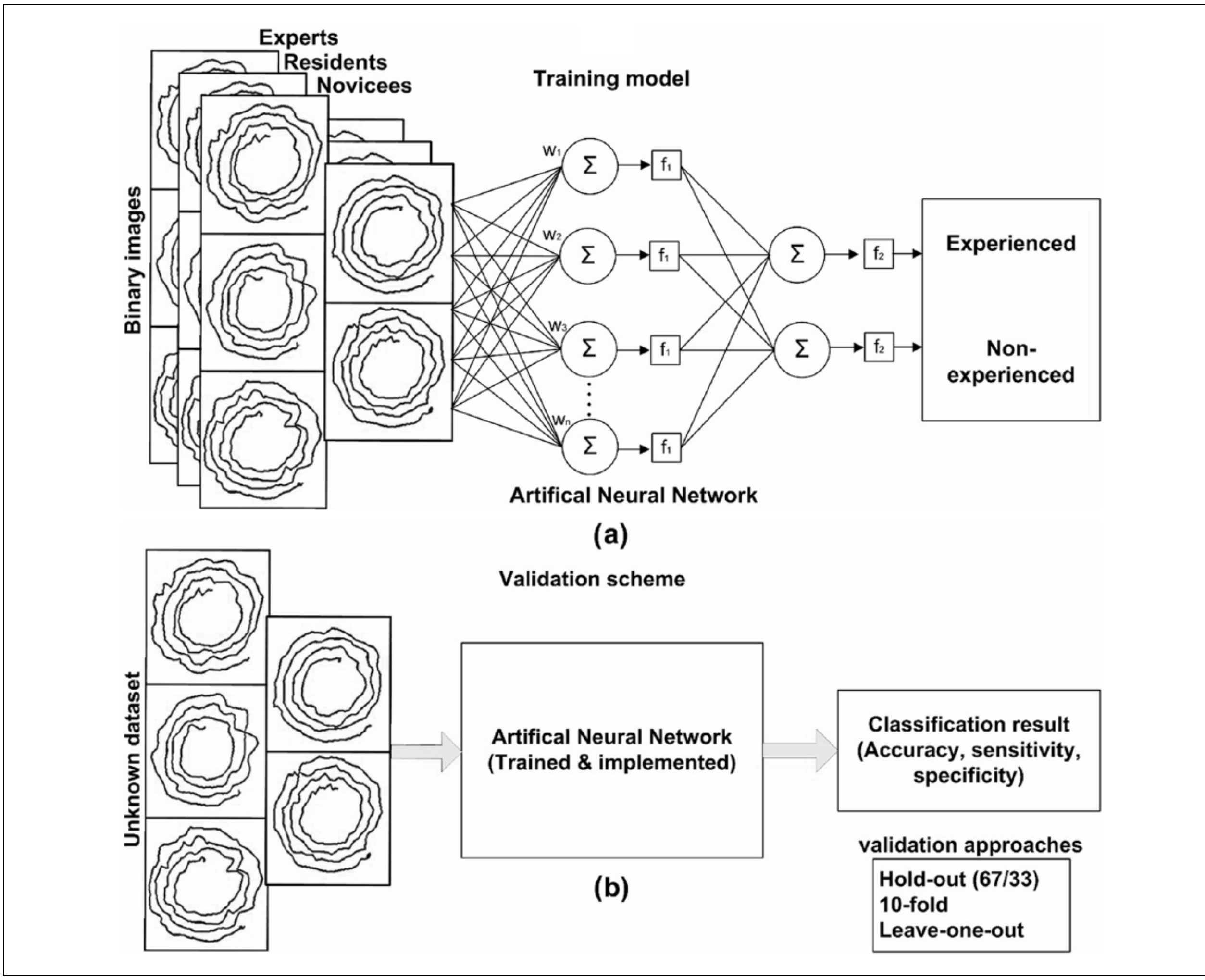

Figure 2. Artificial neural network set up for pattern cutting task. (a) For training input data set was built from images of the trace performed by the users. (b) Validation was performed using 3 schemes.

1 (strongly disagree) to 4 (strongly agree), except for the last question.

Data Collection and Validation

The training data set of the laparoscopic simulator consists of binary images of the traces performed by the different users. The main goal of the ANN setup is to classify the skills and dexterity level, based on the training data of novices, residents, and expert surgeons. The principle of the training model in the ANN is to find the parameters for function evaluation conducting to the lowest error in order to obtain the desired outputs (experienced and nonexperienced). The network is constructed based on a set of data, which is divided into a training set and a test set. In order to validate the training model, the trained network is fed with new set of data.[30] The training model was validated using 3 validations schemes: holdout (67/33), k-fold, and leave one out. The accuracy, sensitivity, specificity, and area under curve (receiver operating characteristic curve) were computed for every validation scheme. Combinations for different training algorithms and a variety of structures having different numbers of neurons, hidden layers, and transfer functions in the ANN were tested. The proposed assessment method for task 2 can be seen in Figure 2. The final selected parameters include an input layer with 2304 neurons (image of 48 × 48 pixels), a hidden layer with 25 neurons, and an output layer with 2 neurons, indicating whether an input corresponds to an experienced or nonexperienced trainee. The proposed ANN uses a backpropagation algorithm, based on the Levenberg-Marquardt optimization, and a logistic transfer function between layers. The time required to train the network was <1 minute.

For the transferring task no ANN is used. Instead, the data obtained by tracking the instrument, using a function in Python, are the following: the coordinates of the marker

Table 1. Classification Results.

Validation Scheme	Accuracy	Sensitivity	Specificity	AUC[a]
Holdout (67/33)	93.94%	0.78	1.00	0.97
10-fold cross-validation	91.00%	0.78	0.96	0.93
Leave-one-out	88.00%	0.74	0.93	0.91

Abbreviation: AUC, area under curve.
[a]Area under receiver operating characteristic curve.

(*x, y*), as well as its area in pixels, such as (*x, y*, area). According to previous studies,[31-33] it is possible to perceive a depth parameter using a single camera, related to the distance from the camera: the more distant the camera is from the marker, its area decreases; the closer it is, then the area increases. In this study for transfer task, the system creates points whose parameters (*x, y*, area) are chosen randomly. The way in which the depth is evaluated in that task is by means of verifying that the area of the marker is in agreement with the area of the point to be transferred. If the area is not consistent in both objects, the software does not allow the point to be manipulated by the instrument. A pre-established threshold for a number of transferred dots corresponding to the 2 levels of expertise was defined.

Statistical Analysis

The Mann-Whitney test was used to identify statistical differences between groups, with 99% confidence, where a value of $P < 0.01$ was considered statistically significant. Besides, the Kruskal-Wallis test was carried out in order to find significant variability of the transferred dots from first day toward the last one. At the same time, a value of $P < 0.01$ was taken as statistically significant. Furthermore, the average transferred points per day were analyzed to establish a proper threshold to discriminate between experienced and nonexperienced users.

Results

Questionnaire

From the questionnaire, 80% (16) rated the trainer as a comfortable instrument for the training process (answering as strongly agree), 90% (18) found our platform useful to achieve more confidence in real practice, 95% (19) said it was important to replicate the anatomy for a better training, 80% (16) would assembly their own trainer (yes for sure), and 10% (2) probably yes and just 5% (1) answered as probably no.

Classification Performance

The classifier performance outcomes for task 2 are shown in Table 1 and Figure 3. In general, the scores of the classifier showed a high capacity to evaluate users as experienced or nonexperienced, with values of area under curve above 0.90. The highest classification rate was in the holdout (67/33) scheme. In this validation, the ANN presented the best results for correct classification, reaching an accuracy of 93.94% with a specificity of 100%. Nevertheless, sensitivity was not greater than 78%. One possible cause of this issue can be the class imbalance where the experienced group constitutes the minority class. Despite the latter, results indicate a high capability of the system to perform a correct classification.

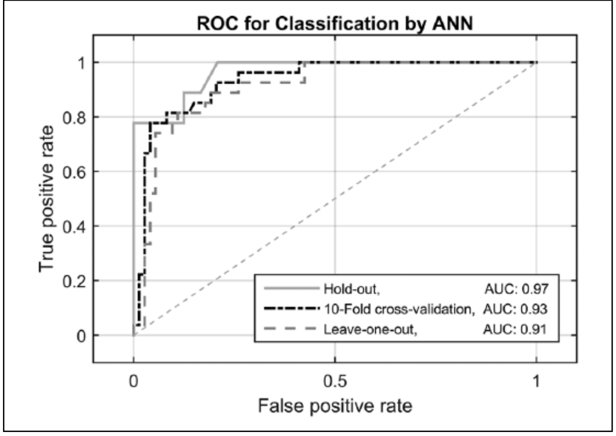

Figure 3. Receiver operating characteristic (ROC) curve for the pattern cutting task.

With the aim to establish a cutoff threshold for identifying whether a user is experienced or not, in task 1, a statistical analysis from results was performed. Here we identify a significant difference, regarding the number of transferred dots, through the 5 training days in the nonexperienced group by means of the Kruskal-Wallis test ($P < 0.0001$). No significant difference ($P = 0.1425$) was found for the experienced ones though, as depicted in Figure 4.

Besides, a Mann-Whitney U test between the 2 groups reported a value of $P < 0.0001$, which is statistically significant with a confidence of 99%. Based on this result, we can say that the number of dots successfully transferred by experienced trainees to those who are not can be used to distinguish their level of expertise. However, still we had to decide a threshold to discriminate an experienced from a nonexperienced user. To this end, we refer

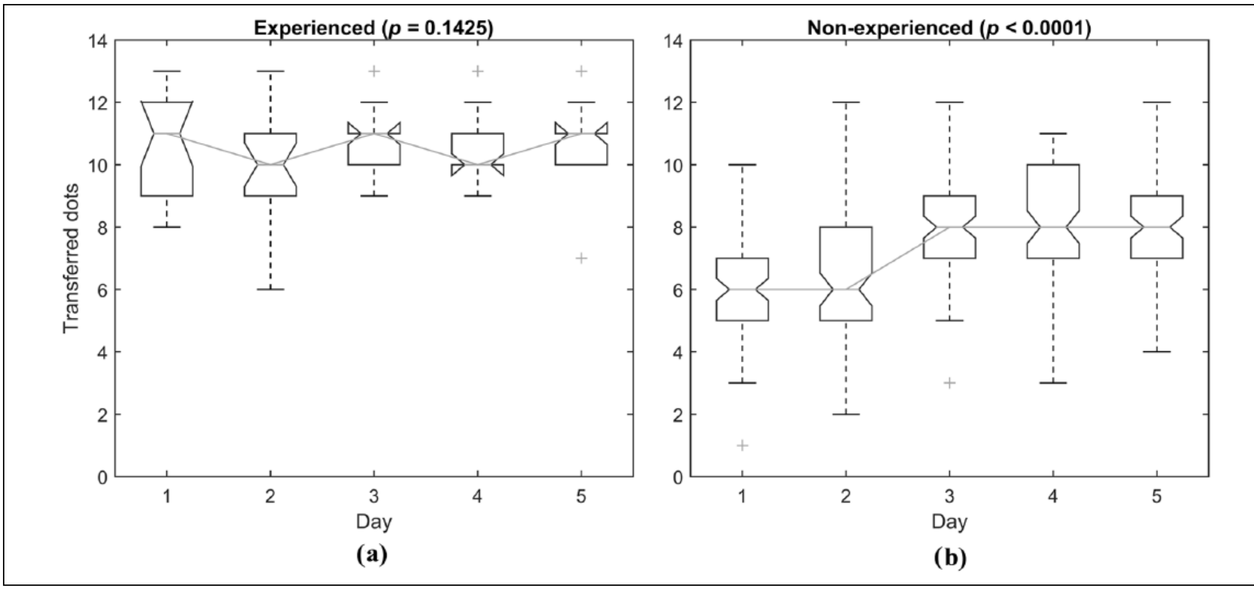

Figure 4. Results of Kruskal-Wallis analysis of variance per group through 5 days training in transfer task for (a) experienced group and (b) nonexperienced group.

Table 2. Average Results for Transferred Dots in Task 2 (5 Repetitions per Day).

Group	Day 1	Day 2	Day 3	Day 4	Day 5	Average
Experienced	10.75 ± 1.52	9.8 ± 1.42	10.55 ± 1.01	10.55 ± 0.89	10.65 ± 1.23	10.46 ± 1.23
Nonexperienced	6.16 ± 1.61	6.64 ± 2.27	7.78 ± 1.91	8.10 ± 1.97	8.1 ± 1.85	7.36 ± 1.92

to the mean (10.46 for experienced and 7.36 for nonexperienced) of transferred dots by each group, as seen in Table 2. Those values suggest that nonexperienced trainees hardly transfer 11 dots in a session, whereas the experienced ones are able to do it successfully. Based on the aforementioned, we established 11 dots as the cutoff threshold to classify users by their level of expertise.

Discussion

The literature shows that there is no gold standard to categorize whether a person is an expert or not. Usually the number of laparoscopic surgeries ensures the expertise level of the surgeons, and also their own natural abilities. So when does a participant become an expert? This is one of the most difficult questions to answer since minimally invasive surgery psychomotor skills improvements depend on several aspects. For novices or residents, to perform many surgeries as possible will be the ideal method to become an expert. This is not possible due to many issues. The laparoscopic box trainers have emerged as an alternative for surgical students who want to become experts. Also, they have been described as simple tools due to the lack of intelligence objective evaluation.

The system presented in this work can be made from a plastic box or from a mannequin. For better results, a mannequin should be used since the human form of the mannequin gives a more realistic effect of the training. Although this will increase the assembly cost, the total cost of the trainer is about US$132 to US$150, having an own monitor or TV for its use. The Raspberry Pi does not need special video device since it has video output by HDMI, VGA, and RCA. The cost of our trainer is similar to others previously reported, which ranged between US$70 and US$488.80.[34-37]

The software with the trained ANN was programmed into a python application, which is a multiplatform programming language; thus, it can be executed in a personal computer or directly into the Raspberry Pi board. The software can be directly downloaded from https://github.com/brunosanz/Tareas-Lapascopia.[38] The final available version of the laparoscopic system can carry out an assessment of 2 basic tasks. The interface of application has a welcome screen with 4 buttons: task 1, task 2, free exercise, and exit. In the interface of each task the user has to name a session and push the start button. When the task has been completed, users can evaluate their performance by the Analysis button. An example of an assessment can be seen in a video (https://goo.gl/RzdhWG).[39]

The purpose of this study is to classify trainees based on the movements and motor skills of actual experienced and nonexperienced users, by a machine learning approach. Although our system was built by 4 experienced and 20 nonexperienced users, they did it during 5 days performing 5 repetitions per day, which means a considerable amount of data. However, there are similar works[40-42] that have been validated by the same number of experts as ours. Due to this, the reported values of sensitivity (0.78) and specificity (1) on the pattern cutting task suggest the ANN has more confidence for discriminating the experienced class. That is, when a trainee outperforms the nonexperienced class but his/her performance is not consistent with the experienced ones, the system labels him/her as nonexperienced. This indicates that when a user is evaluated as experienced, it is because his/her performance noticeably matches with that group of users. On the other hand, the statistical tests provide enough information to support that a threshold of 11 dots is sufficient to determine whether a user is experienced or not in the *transfer* task.

Both tasks were designed in order to simulate pattern cutting task and object transfer using the augmented reality libraries of OpenCV. These 2 tasks are considered as part of fundamental laparoscopic tasks. Most of the trainers perform the evaluation of the user using statistical metrics such as speed, acceleration, and other motion analysis parameters. Although the motion analysis parameters are widely used to perform an objective evaluation, in this work we have presented a novel methodology to capture the movements and psychomotor skills from experienced and nonexperienced users by means of augmented reality and computer vision. This information is then used to evaluate new trainees by using artificial intelligence algorithms. However, further exploration of training tasks, suited for artificial intelligence algorithms, and new validation studies, with the participation of different levels of experience, will be investigated for assessment of performance of both experts and residents with our laparoscopic box trainer.

Conclusions

In the present work, we developed an affordable box trainer, which has an HD webcam, low-cost microprocessor, and intelligent software to perform the assessment immediately after the user has completed each task. Our proposal constitutes the first intelligent laparoscopic box trainer with an objective evaluation based on the performance of 2 types of users. The results indicate that our proposal is highly reliable, as it has been validated by statistical analysis and cross-validation schemes. We believe our trainer can help novices or surgical students to increase their self-confidence and improve their psychomotor skills regarding laparoscopic surgery tasks. Also, the proposed trainer could be considered as a learning and training tool for surgical education programs with limited resources.

Author Contributions

Study concept and design: Gustavo A. Alonso-Silverio, Antonio Alarcón-Paredes, Arturo Minor-Martinez
Acquisition of data: Gustavo A. Alonso-Silverio, Raúl Bruno-Sanchez
Analysis and interpretation: Antonio Alarcón-Paredes, Fernando Pérez-Escamirosa, José L. Ortiz-Simon
Study supervision: Roberto Muñoz-Guerrero, Fernando Pérez-Escamirosa

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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