

SURGICAL DEXTERITY INVESTIGATION AND CLASSIFICATION USING  
DEEP LEARNING ON A VIRTUAL REALITY SIMULATOR

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## **DEDICATION**

This thesis is dedicated to my family who gave humongous supports without any hesitations.

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## ABSTRACT

Surgical dexterity is an essential criterion to evaluate candidates for surgical competency. Many factors may affect surgical dexterity but they were not studied in depth in previous works. There was a lack of evidence presented using objective measurements to identify factors that could potentially influence surgical dexterity. Hence, this thesis aims to investigate the correlation between various human factors and the manual dexterity of surgeons, with the aid of a 3D virtual reality simulator and objective measurements. A custom data acquisition module was developed, namely “Green Target Module”, to acquire positional data of hand movements from the subjects when controlling a cursor in a 3D virtual reality (VR) scene. The positional data were recorded and extracted into seven objective parameters, which were endpoint accuracy, endpoint precision, motion path length, economy of movement, motion smoothness, motion path accuracy and motion path precision. Body posture, visual magnification and handedness were investigated to identify the setups that resulted in better performance. In addition, a questionnaire was filled by all subjects to collect their background information and habits, such as specialty, years of experience, sleeping duration, coffee intake and video games ability, in order to investigate how these human factors affect the surgical dexterity. A total of 34 subjects from different surgical backgrounds were recruited for the experiments. All subjects performed better with sitting posture, 10x visual magnification and when using the dominant hand. No significant differences were found across groups with different daily sleeping hours. In terms of specialty, oral and maxillofacial surgeons recorded significantly longer path length and lower economy of movement, motion path accuracy and precision compared to ophthalmology surgeons, obstetrics and gynaecology surgeons, and neurosurgeons. However, they performed smoother motions compared to ophthalmology surgeons, obstetrics and gynaecology surgeons, and general surgeons. In terms of experience, surgeons with 6 to 10 years of experience performed shorter motion path length and better economy of movement than those with less than 6 years and more than 10 years of experience. Interestingly, surgeons who had less than 11 years of experience performed better in motion path accuracy, motion path precision, motion smoothness and endpoint accuracy compared to surgeons who had more or equal to 11 years of experience. For coffee consumption, surgeons with daily coffee intake of less than 1 cup performed significantly smoother path, higher motion path accuracy and precision compared to those who consumed more. Surgeons with exposure to video games recorded shorter path length and better economy of movements, endpoint accuracy and precision compared to those without. Finally, deep learning based on convolutional neural network was used to classify the category of factors related to human dexterity. The highest average accuracy and weighted F1-score for classifying specialty, year of experience, daily sleeping hours, daily coffee consumption, and video game exposure were (97.29%, 94.25%), (90.04%, 85.18%), (90.37%, 90.3%), (90.97%, 84.6%) and (92.9%, 92.65%). In conclusion, surgical dexterity has been investigated and classified using deep learning on a 3D virtual reality simulator.

## ABSTRAK

Ketangkasan pembedahan adalah kriteria penting untuk menilai calon bagi kecekapan pembedahan. Banyak faktor boleh mempengaruhi ketangkasan pembedahan tetapi tidak dikaji secara mendalam dalam kajian sebelum ini. Terdapat kekurangan bukti yang pernah dikemukakan menggunakan pengukuran objektif untuk mengenal pasti faktor yang berpotensi mempengaruhi ketangkasan pembedahan. Oleh itu, tesis ini bertujuan untuk mengkaji hubungan antara pelbagai faktor manusia dan ketangkasan insani pakar bedah, dengan bantuan simulator realiti maya 3D dan pengukuran objektif. Modul perolehan data khusus telah dibina, iaitu "Modul Sasaran Hijau", untuk memperoleh data posisi pergerakan tangan dari subjek ketika mengawal kursor dalam pandangan realiti maya 3D. Data kedudukan direkod dan diekstrak kepada tujuh parameter objektif, iaitu kejituan titik akhir, kepersisan titik akhir, panjang laluan gerakan, ekonomi pergerakan, kelancaran gerakan, kejituan laluan gerakan dan kepersisan laluan gerakan. Postur badan, pembesaran visual dan dominasi tangan disiasat untuk mengenal pasti pengaturan yang berprestasi lebih baik. Sebagai tambahan, borang soal selidik diisi oleh semua subjek untuk mengumpul maklumat latar belakang dan tabiat mereka, seperti bidang kepakaran, tahun pengalaman, tempoh tidur, pengambilan kopi dan kemampuan permainan video, untuk menyiasat faktor manusia yang mempengaruhi ketangkasan pembedahan. Seramai 34 subjek dari latar belakang pembedahan yang berbeza direkrut untuk eksperimen. Semua subjek berprestasi lebih baik dengan postur duduk, pembesaran visual 10x dan penggunaan tangan dominan. Tidak terdapat perbezaan signifikan antara kumpulan dengan tempoh tidur harian yang berbeza. Dari segi bidang kepakaran, pakar bedah mulut dan rahang atas merekodkan secara signifikan laluan gerakan yang lebih panjang dan ekonomi pergerakan, kejituan dan kepersisan laluan gerakan yang lebih rendah berbanding dengan pakar bedah mata, pakar bedah obstetrik dan ginekologi, dan pakar bedah saraf. Walau bagaimanapun, mereka melakukan gerakan yang lebih lancar berbanding dengan pakar bedah oftalmologi, pakar bedah obstetrik dan ginekologi, dan pakar bedah am. Dari segi pengalaman, pakar bedah dengan pengalaman 6 hingga 10 tahun menghasilkan panjang laluan gerakan yang lebih pendek dan ekonomi pergerakan yang lebih baik daripada mereka yang mempunyai pengalaman kurang dari 6 tahun dan lebih dari 10 tahun. Yang menariknya, pakar bedah yang mempunyai pengalaman kurang dari 11 tahun menunjukkan prestasi yang lebih baik dalam kejituan dan kepersisan laluan gerakan, kelancaran pergerakan dan kejituan titik akhir berbanding dengan pakar bedah yang mempunyai pengalaman lebih atau sama dengan 11 tahun. Bagi pengambilan kopi, pakar bedah dengan pengambilan kopi harian kurang dari 1 cawan menghasilkan secara signifikan laluan yang lebih lancar, kejituan dan kepersisan laluan gerakan yang lebih tinggi berbanding dengan mereka yang minum lebih banyak. Pakar bedah yang mempunyai pendedahan kepada permainan video mencatatkan panjang laluan yang lebih pendek dan ekonomi pergerakan, kejituan dan kepersisan titik akhir yang lebih baik berbanding dengan yang tiada. Akhirnya, pembelajaran dalam berasaskan jaringan saraf konvolusional digunakan untuk mengklasifikasikan ketangkasan pembedahan mengikut kategori faktor yang dikaji. Ketepatan purata tertinggi dan skor-F1 berwajaran untuk mengklasifikasikan bidang pengkhususan, tahun pengalaman, tempoh tidur harian, pengambilan kopi harian, dan pendedahan kepada permainan video adalah (97.29%, 94.25%), (90.04%, 85.18%), (90.37%, 90.3%), (90.97%, 84.6%) dan (92.9%, 92.65%). Kesimpulannya, ketangkasan pembedahan telah disiasat dan dikelaskan menggunakan pembelajaran dalam pada simulator realiti maya 3D.

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## LIST OF ABBREVIATIONS

HO	-	House Officer
OR	-	Operating Room
VR	-	Virtual Reality
AI	-	Artificial Intelligence
THA	-	Total Hip Arthroplasty
CABG	-	Coronary Artery Bypass Mammoplasty
GRS	-	Global Rating Scale
ASs	-	Autopsy Scores
LR	-	Logistic Regression
SVM	-	Support Vector Machine
CNN	-	Convolutional Neural Network
LOSO	-	Leave-One-Super-trial-Out
LOUO	-	Leave-One-User-Out
3-D	-	3-Dimension
IR	-	Infra-Red
DOF	-	Degree Of Freedom
Conv-pool	-	Convolution-pooling
ReLU	-	Rectified Linear Unit
TP	-	True Positive
TN	-	True Negative
FP	-	False Positive
FN	-	False Negative
Dom	-	Dominant
Non-Dom	-	Non-Dominant
M.O.	-	Medical Officer
MWSS	-	Moving Windows Step Size
OPH	-	Ophthalmology
O&G	-	Obstetrics and Gynaecology
NEU	-	Neurosurgery
GEN	-	General Surgery

- O&M - Oral and Maxillofacial
- LSTM - Long Short-Term Memory
- SENet - Squeeze-and-Excitation Network

## LIST OF SYMBOLS

$d$	-	Deviation error
$\mu$	-	Mean
$\sigma$	-	Standard deviation



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# CHAPTER 1

## INTRODUCTION

### 1.1 Introduction

Surgery can be defined as a work of art that necessitates the use of one's hands [1]. Indeed, surgeons need to possess good hand eye coordination with excellent visuo-spatial awareness as well as a high degree of fine motor skills in order to ensure that complex surgical operations are performed accurately and safely for preventing or reducing blood loss [2]–[5]. A significant amount of surgical training and repeated practice are needed to improve the surgical performance and competency level of a surgeon [6], [7]. Hence, surgical education plays an crucial role in providing highly efficient training and effective practice platforms to enhance the surgical skills of resident surgeons [8], [9].

To continue with a surgical career path, medical graduates will usually have to become house officers (HO). Then, he or she is led by a surgical expert via mentorship at a designated hospital after graduating from medical school [10]. They have to grab opportunities to learn the craft via direct observation, and try to mimic the motions of an experienced mentor in the operating room (OR) and at the bedside [11]. As reflected in the frequently quoted phrase “See One, Do One, Teach One”, there is no doubt that learning, practicing and teaching through mentorship are becoming an essential legacy for a young surgeon-to-be to inherit the necessary surgical skills [12], [13]. It is not enough for house officers to learn surgical skills through observations as the executions are also crucial for mastering surgical skills by imitating the motions and hands-on practice for multiple times repeatedly [14].

Conventionally, house officers improve their surgical skills by practicing incisions, sutures, knot tying and other basic procedures on animal organs or synthetic models [15]. Although this method could help the house officers to train and improve

their surgical skill competencies, it still increases the risk of difficulties if there are unsuspected conditions in the patients encountered [16]. Since animal organs or artificial cadavers are used for practicing in normal conditions, they do not provide the challenge or special circumstances that are often faced in real patients [17], [18]. In order to mimic the unexpected situations that are rarely found from animal organs and artificial cadavers, virtual reality simulators have been introduced and are widely used to practice as well as assess the surgical skills of house officers [19]–[21].

With the growth of technology, virtual reality simulations have been in great demand for surgical training and assessments [22], [23]. They are usually implemented together with robotic machines and displays to mimic responsive feedback as well as visualise the scenes based on the movements from handling and control [24]. Besides, the usage of the virtual reality simulations is broadening to telemedicine with the aid of 5G [25], and even includes gaming [26]. The implementation of virtual reality simulation has shifted surgeons to the laboratory to learn basic surgical skills, instead of taking higher risks on living patients in the operating room [27]. It shows that many solutions including simulation have been proposed to provide more learning opportunities within current resource constraints [28].

There are various virtual simulators that can be used by house officers. For instance, the LAP Mentor high-fidelity virtual reality simulator (3D Systems, formerly Symbionix USA Corp, Cleveland, OH) can assess endoscopic skills [29], and knee arthroscopy simulator can assess the arthroscopy skills [30], [31]. Several studies have identified the importance of virtual reality to support the surgical skills evaluation using objective measurements and matrices with the simulator supports [32], [33]. Therefore, it is crucial to study the motions of dexterous surgeons in order to achieve an objective assessment of surgical skills using automated technology [34].

However, several arguments have arisen from the use of virtual reality simulations as a surgical evaluation tool. This is because results have found a lack of correlation between participants' scores using the current academic factors and the scores from any of the surgical dexterity tests according to Jardine *et al.* [35]. Current academic factors are usually cognitive attributes, that consist of structured tests of

knowledge. However, the result from Ogunyemi *et al.* showed the mean of overall scores from 20 top-ranked candidates were significantly higher than other candidates [36], given that both authors are using the same LAP Mentor simulator. VR simulation is still recommended to evaluate visual spatial and psychomotor skills as these are surgical skills criteria [35]. With this recommendation, Ahmmad *et al.* proposed the use of objective measurements to evaluate the surgical dexterity performance by using “Green Target Module” with custom hardware setup [37], [38]. However, it was found that there is a lack of discussion about the factors affecting surgical dexterity performance by evaluating objective measurements.



Figure 1.1 LAP Mentor high-fidelity virtual simulator

Therefore, this study proposes further investigation into the factors that affect the performance of surgical skills using objective measurements. Many studies have shown that postures [39]–[41], visual magnifications [42]–[44] and handedness [45]–[47] of surgeons causing fatigue [48] during surgical procedures can result in the performance of overall surgical outcomes being affected. However, some studies were evaluated based on subjective surveys without objective measurements and the experiment settings would be a factor that affect the surgical dexterity assessment. Besides, it has also been found that different surgical backgrounds would affect the psychomotor performance of participants depending on the experimental set up. This is not limited to experience [49], [50] and expertise [51]–[53] of the subject, but also includes specialty [54]–[56], sleep deprivation [57]–[59], coffee consumption [60]–[62], and video game exposure [63]–[66].

The first part in this study investigated controllable settings that can help improve performance outcome of surgeons in a simple hand movement task. In the second part, further analysis was conducted to identify human factors that may affect a surgeon's hand dexterity. With that, the settings and human factors that influences hand dexterity of surgeons can be identified. Finally, the last part of this work used the hand motion data obtained from the surgeons to create a deep learning model that can identify the background of a surgeon based on the input hand motion data. This deep-learning model is envisioned to be relevant in a surgical simulator where users can perform some tasks and the surgical training simulator would be able to gauge the performance level of the user as benchmarked with existing surgeons' skill level.

## **1.2 Problem Statements**

There are numerous studies related to the assessment of surgical skills using commercialised or developed simulators which are available to surgeons nowadays. However, there is still a lack of evidence on the use of objective measurements to identify settings and other human factors that could potentially affect surgical performance. This is due to the different experiment setups implemented and various surgical backgrounds of the participating subjects. Hence, different physical factors and human factors are required for further investigation to identify the reasons behind the discrepancies found in similar research. Before investigating the factors, a module with higher flexibility is required to enable the experiment setups to be altered. Additionally, the module needs task that can assess surgeons with different surgical backgrounds and assess their basic psychomotor skills.

A small study previously conducted by Ahmmad [67] found that some parameters, such as motion smoothness and end-point accuracy, were significantly different between the surgeon and non-surgeon groups. This showed the potential of using objective based measurements to identify skill level of a surgeon. This study will use the module, knowledge and techniques learnt from the earlier research to further the investigation with a larger population of surgeons and surgeons from different surgical backgrounds to obtain a more in-depth understanding of surgical dexterity. The investigation will look at the surgeons' dexterity under different experimental

controlled factors and human factors, and then to use their hand motion data to implement an artificial intelligence (AI) classification algorithm that can categorise recorded hand motion data into different surgical backgrounds.

### **1.3 Research Objectives**

This research aims to first identify settings that can help improve dexterity and then investigate the influence of various human factors towards manual dexterity, using psychomotor measurements. The findings may help the surgical community to identify ways to improve surgical outcome. Additionally, the hand motion data would be useful for the development of a classification algorithm in a surgical trainer to rate a trainee's skill level. Hence, this research emphasises the following objectives:

1. To determine, using objective-based measurements, the controllable settings that allow surgeons to perform better on a 3D virtual reality (VR) simulator.
2. To determine the influence of various human factors towards hand dexterity performance with a 3D virtual reality (VR) simulator.
3. To configure a convolutional neural network (CNN) model that can distinguish the motion data of surgeons into different human factors on a 3D virtual reality (VR) simulator.

### **1.4 Research Scope**

Surgical skills are assessed from several angles. Theoretical knowledge and surgery procedural skills are not assessed but manual dexterity is emphasised in this study. However, manual dexterity can be assessed by using various types of simulators or hardware combinations implemented. Moreover, there are many variables found in controlling the experiment settings and the participants with different surgical backgrounds. Thus, there are some scopes are highlighted to achieve the objectives, such as follows.

- i. The combination hardware and custom build software data acquisition module are used to record and assess the manual dexterity.

- ii. The controllable settings that will be investigated in this study will be posture (sitting versus standing), handedness (dominant versus non-dominant) and viewing magnifications of 1x and 10x.
- iii. The human factors to be studied are specialty, year of experience, sleeping hours per day, coffee consumption per day and video game exposure.
- iv. The deep learning classification algorithm uses convolutional neural network and only classifies the hand motion which was obtained from the best performing experimental controlled settings
- v. The hand motion data would be classified based on the human factor categories.

## **1.5 Thesis Organisation**

The thesis is organised into seven chapters. Chapter 1 briefly explains the general background of the surgical skills assessments, problem statements, research objectives and research scope of this thesis. Next, Chapter 2 provides a literature review of the existing factors analysis such as postures, handedness and visual magnification, and different human factors such as specialty, year of experience, sleeping hour, coffee consumption and video game exposure investigated with different experimental setups. Following that, Chapter 3 explains the methodology of this study detailing the data acquisition tool development, data collection, data pre-processing and data analysis. The study encompasses two main investigations on experimental controlled factors and human factors affecting dexterity, followed by a deep learning configuration that categorises the factors affecting surgical dexterity. Chapter 4 shows the results, analysis, and discussion for the experimental controlled factors whereas Chapter 5 presents the results, analysis, and discussion for human factors. Chapter 6 explains the results, analysis, and discussion about deep learning classification on human factors. Finally, Chapter 7 concludes with the findings and contributions of this study, in addition to a few recommendations for possible future work.

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## LIST OF PUBLICATIONS

1. Cham, Y. K., Su, E. L. M., Yeong, C. F., Siti, N. Z. A. , Suneet, S. and Anil, G.,  
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