HAND GESTURE RECOGNITION WITH BODY SENSOR NETWORKS

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ABSTRACT

With the steady advances in surgical technology, quantitative assessment of surgical skills is increasingly being used for surgical training. Traditional approaches mainly rely on the use of wired sensors attached to surgical instruments or the surgeon's hand. This limits the free movement of the operator and can potentially alter the normal behaviour of the surgeon. The purpose of this paper is to provide a pervasive skills assessment tool based on the Body Sensor Network (BSN). By integrating a novel optical sensor with the BSN node, it provides an accurate wireless gesture sensing platform for assessing basic laparoscopic skills.

Key words: body sensor networks, minimal invasive surgery, skills assessment, gesture recognition

1. INTRODUCTION / BACKGROUND

Advances in surgical technique are inseparably linked to advances in surgical technology and the pace of this change is constantly accelerating. Most aspects of medicine have historically been learnt in an apprenticeship model by means of observation, imitation, and instruction. In such a setting, much of the expertise transferred from mentor to trainee is implicit, and cannot be transferred easily to a didactic setting. Minimal Invasive Surgery (MIS) has been an important technical development in surgery in recent years. It achieves its clinical goals with reduced patient trauma, shortened hospitalisation and improved diagnostic accuracy and therapeutic outcome. Laparoscopic surgery is a subset of the general field of MIS and relates to most procedures performed in the abdomen in which the surgeon is required to operate by remote manipulation using specially designed, elongated instruments inserted into port sites that are located through small incisions at specific points in the abdominal wall. The operative field is viewed by means of a laparoscope in which a small camera relays a video signal to a 2D monitor. During laparoscopic surgery, however, the surgeon's direct view is often restricted, thus requiring a higher degree of manual dexterity. The complexity of the instrument controls, restricted vision and mobility, difficult hand-eye co-ordination, and the lack of tactile perception are major obstacles in performing laparoscopic procedures. To date, a number of techniques have been developed for objective assessment of operative skills during laparoscopic surgery. Most existing techniques are concentrated on the assessment of manual dexterity and hand-eye coordination with the combined use of virtual and mixed reality simulators. These environments offer the opportunity for safe, repeated practice and for objective measurement of performance. Current methods of assessing surgical skills in MIS are mainly based on subjective and objective criteria. Subjective assessment relies on expert examiners to judge the skills of the trainees based on observation [1]. The use of objective methods avoids the drawback of subjectivity and can provide a fairer and more constructive way of skills assessment. OSATS (Objective Structured Assessment of Technological Skill for Surgical Residents) is a well-known technique for evaluating operative skills where structured criteria are used [2]. With this approach, the procedures are usually video taped for scoring and analysis. This, however, is a time consuming task and a more efficient method is required. Surgical procedures can be viewed as a series of gestures performed in a sequence with an end objective. By recognising these gestures, it is possible to determine how the task is performed and the intermediate steps leading to the task. Existing research has shown that different surgeons can have different approaches to performing a given task, and their manoeuvre is characteristic of the basic skills attained. For instance, an expert surgeon may require much less movements than a novice in performing a similar task, therefore identifying the intrinsic pattern of the hand movement can provide important information on basic surgical skills.

Human hand is a highly articulated object with approximately 30 degrees of freedom (DoF) [3]. This presents a challenge to track its detailed movements. Thus far, a number of tracking methods have been developed, and many of them involve the use of glove based input devices primarily for use in Man Machine Interfacing (MMI) [4]. The sensors involved include LEDs, colour markers, fibre optics, electromagnetic (EM) and flex sensing devices. The models used for decoding basic hand-gesture include Hidden Markov Models (HMM) [5,6], particle filters [7] and specialized maps [8]. For basic surgical skills assessment, EM tracking devices have been widely used for measuring 3D hand motion. Objective measures such as the number of manoeuvres made, distance travelled, velocity, acceleration and time used are combined together as basic indices for elucidating the manual dexterity of the surgeon [9].

Although EM sensors provide accurate 3D positional readings, the sensors are relatively large and require a series of cables to connect to the data-capturing device. They can affect the free-movement of the surgeon and potentially alter the natural behaviour of the operator. Furthermore, the EM tracker is sensitive to interference from metal objects and detailed calibration procedures are required before each experiment. In this paper, we will describe the use of a novel fibre optic sensor combined with BSN nodes for unobtrusive skills assessment. The method provides a pervasive sensing environment that is suitable for large class teaching and skills assessment.

3. IMPLEMENTATION

Fig. 1 demonstrates the basic hardware set up of the system, where wireless sensors are mounted onto a glove to measure the bending motion of the hand and fingers. The sensor data can be sent wirelessly to a PDA or PC for data storage and analysis. The system allows both global motion (3D accelerometers) and local motion analysis. We have used a fibre optic bend sensor to measure the gripping motion while performing laparoscopic procedures. The sensor data is captured and digitised by a BSN node developed by Imperial College. The BSN node is a small ($26mm^2$) device that provides a flexible platform to aid the research and development of wireless body sensor networks [10]. The BSN node runs the TinyOS operating system [11] that provides the software building blocks necessary to gather and transmit the data. Once the data is collected, temporal features are extracted from the data for performance classification based on HMM or Bayesian Networks.

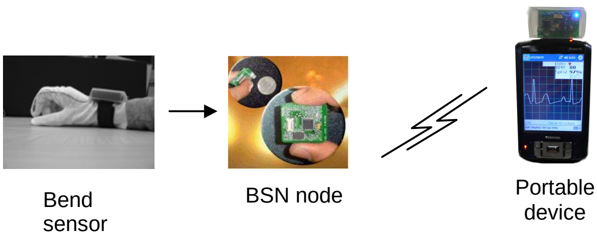

Fig 1: Hardware setup of the proposed skills assessment system based on BSN.

3.1. WIRELESS SENSOR

With this study, the flexion of the palm is measured by using a S720 Miniature Joint Angle ShapeSensor developed by Measurand Inc. [12]. The sensor as shown in Fig. 2b, uses a specially treated optic fibre to measure the curvature along a given one plane of motion within a range of ±90º. The fibre has been treated such that only one section of the fibre emits the light transmitted through it. As the bend in the fibre is increased, more light escapes the fibre reducing the final intensity detected, thus allowing the extent of the curvature to be measured. The ShapeSensor is thin and light, making it completely unobtrusive to the user.

To provide a wireless link, the bend sensor is connected to a BSN node via its analogue channel. To capture detailed hand movement pattern, the sampling rate of the BSN was set at 200 Hz. Fig 2a. shows the glove design with the fibre optic integrated into the BSN node. The small box holds the BSN node and an encapsulated LED and photodiode to illuminate the optic fibre.

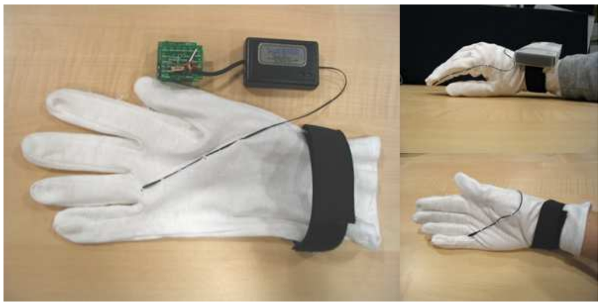

Fig 2: (a) The glove design that encapsulated the BSN node and the bend sensor. Fibre optic ShapeSensor positioned on (b) the index finger (c) the palm

4. RESULTS

To demonstrate the value of the proposed framework, an experiment based on a simple laparoscopic procedure using a grasper with rotating tip was conducted. Figure 3 demonstrates the sensitivity of the optical fibre when attached to the index finger by measuring the motions of the first joint. Figure 3a gives the range of the finger when straight and fully bent (just over 90º) where values reach 1 and 0 respectively.

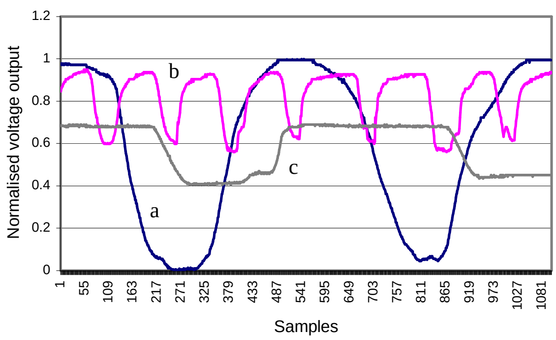

Fig 3: Sensor output for actions with sensor on the index finger. (a) Full motion range (b) Twisting grasping tool tip (c) grasping with laparoscopic tool tip.

For a laparoscopic tool, the grasping jaws are rotated by operating the dial near the handle of the tool with the index finger; the output is shown in Figure 3b with a faster motion and smaller bending range. Figure 3c shows the trace recorded as the grasper jaws are closed demonstrating a small motion range but within a different angle range to the twisting motion.

The second experiment aimed to use the collected data to differentiate between experienced and novice surgeons. The sensor was relocated to the palm making it more sensitive to grasping motions, the most common action. Under laparoscopic training conditions three experienced and three novice surgeons perform a simple procedure wearing the sensor glove relying on a 2D image from an endoscopic camera for visual feedback. Each participant gave three fast gripping motions at the start and end of the procedure for synchronisation. Using the laparoscopic tool an object was picked up, held, and then replaced. This was repeated three times.

Figure. 4 show the readings of the task performed by an experienced surgeon. Part (a) and (e) shows the synchronisation, (b) indicates the grasper opening and closing while picking up the object, (c) is the time the object is held, and (d) corresponds to the object being released. Figure 5 show novice results where section (a) and (c) indicate the beginning and end synchronisation pulses and (b) shows the time taken to complete the task. Unlike the experienced surgeon it is not possible to distinguish between the different phases of the procedure.

The average time taken to complete the procedure and the variance are extracted and showed in Table 1. By comparing these measurements, the difference between the expert and novice is apparent. The expert surgeons were faster to complete the procedure while the novice may take up to twice as long. Also the sensor data from both experts have a higher variance to the novice who often needs many movements to grip the object.

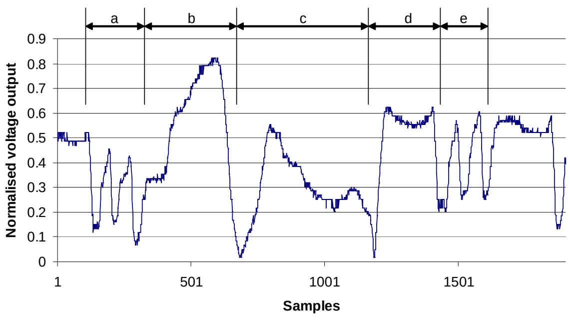

Fig 4: Laparoscopic procedure with palm sensor readings from an experienced surgeon

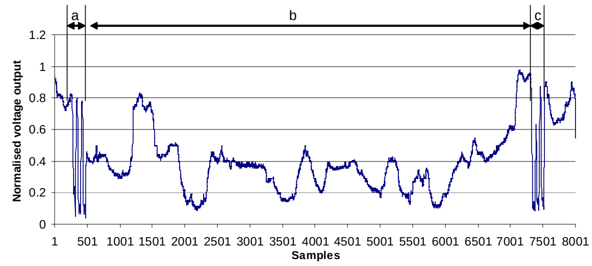

Fig 5: Laparoscopic procedure with palm sensor readings from a novice

Participant	Av. Time (samples)	Variance	Skill Level
1	1975	0.081405	●●●●○
2	1145	0.070029	●●●●○
3	4596	0.031086	●○○○○
4	9316	0.033035	●○○○○
5	3836	0.0373	●●○○○

Table 1: Extracted results from glove data.

5. CONCLUSION

This paper introduces the use of wireless BSN nodes for a gesture recognition system with applications in surgical skills training and evaluation. The proposed glove is discrete, light and allows full freedom of movement without reducing sensor accuracy making it idea for use in the operating theatre or skills laboratory. It can be seen that differentiating between a novice and expert surgeon is possible. Preliminary results demonstrate that movement features can be captured and used in an automated classification system such as HHM or Bayesian network. However, the number of unique motion signatures is limited by using only one sensor. Refinements of the glove would integrate more sensors to the fingers and use a more general sensor such as a 3D accelerometer to measure the global position of the hand.

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