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Article

Dynamic Gesture Recognition using a Smart Glove in Hand-Assisted Laparoscopic Surgery.

Lidia Santos [1], Nicola Carbonaro [2,3], Alessandro Tognetti [2,3], José Luis González [1], Eusebio de la Fuente [1], Juan Carlos Fraile [1] and Javier Pérez-Turiel [1]

[1] ITAP, University of Valladolid, 47011 Valladolid Spain; lidia.santos@uva.es; jossan@eii.uva.es, efuente @eii.uva.es ; jcfraile@eii.uva.es; turiel@eii.uva.es
[2] Research Centre E. Piaggio, University of Pisa, 56122 Pisa, Italy; nicola.carbonaro@centropiaggio.unipi.it (N.C.); a.tognetti@centropiaggio.unipi.it (A.T).
[3] Department of Information Engineering, University of Pisa, 56122 Pisa, Italy
* Correspondence: lidia.santos@uva.es; Tel.: +34-983-423-355

Abstract: This paper presents a system developed for the assistance with a collaborative robot in hand-assisted laparoscopic surgery (HALS). The system includes a sensing glove with piezoresistive sensors which capture continuously the flexion degree of the surgeon's fingers. These data are analyzed using an algorithm that detects and recognize the selected movements. This information is sent as commands to the collaborative robot throughout the surgical operation. The bending patterns, speed and execution times of the movements are modelled in a pre-phase in which it will extract all the necessary information for later detection during the motion execution. The results obtained with 10 different volunteers show a high degree of accuracy and a low false discovery rate.

Keywords: Hand Assisted Laparoscopic Surgery (HALS); sensing glove; wearable; collaborative surgical robot**,** gesture recognition.

1. Introduction

The field of robotics has been entering laparoscopic surgery to facilitate the surgeon's work. The first robots were developed to provide greater stability and precision to the movements of endoscopes or any other additional tools. They consisted of a simple robotic arm and an endoscope or laparoscopic tool attached to it [1]. Since then, they have evolved into semi-autonomous robots that assist the surgeon in the different phases of the operation [2][3][10].

The guidance of these robots is carried out by joystick, in which haptic feedback has been developed [11] or using visual servo-control techniques [4] .

The use of cameras is an early developed technology to sense gestures, but it has not been applied due to challenging problems such as changing light and background [5]. The same problems appear in hand-assisted laparoscopic surgery (HALS), a special laparoscopic surgery in which the surgeon introduce the non-dominant hand inside the patient's abdomen. This allows the surgeon to recover the sense of touch, which is not present during a standard laparoscopic operation. As the entire hand will not always be visible, methods for recognizing hand gestures as [6][7][8][9][10] by artificial vision are not appropriate, so in order to communicate with the collaborative robot in a simple and intuitive way, the use of a sensor glove is proposed.

In the current paper, we have developed a dynamic gesture recognition algorithm using a sensor glove to recognize the commands that the surgeon will send to the collaborative robot. Due to the limited space and bearing in mind that the surgeon must have mobility within the patient's abdominal cavity, a comfortable textile-based motion sensing glove has been chosen, which adapts to the surgeon's hand. The glove we adopted in this study was tailored to a different application (i.e. daily-life monitoring of the grasping activity of stroke patients, as described in [11]) and has a low number of sensors, i.e. three sensors covering the thumb, index and middle fingers. This wearable

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device allows monitoring the surgeon's hand movements throughout the entire operation without detracting from the surgeon's operability. The movement of each finger is detected by the acquisition of the sensor glove data. In this context, cross-talk between sensors appears as a noise signal on one finger when the operator tries to move another. These disturbances are filtered to avoid misclassification of the surgeon gesture. The gesture recognition algorithm developed will be also in charge of discerning them.

To test this algorithm, 10 tests were performed by 10 different subjects to detect the pre-selected movements. Each test consisted of three predefined movements and two others. The inclusion of these two others is due to the need to demonstrate that the algorithm does not erroneously recognize a movement that is not predefined with a predefined one.

With these tests, it has been concluded that a sensor glove can be used to send commands to a robot collaborator during a HALS with a high degree of accuracy.

This paper is organized as follows. Next section introduces the materials and methodologies used in the experiments that are shown in section 3. The results are presented in section 4 and they are discussed in the subsequent section. Finally, section 6 present the conclusions.

2. Materials and Methods

2.1. Sensing glove

The sensing glove adopted in this work is made of cotton-lycra and has three textile goniometers directly applied on the top of fabric (Figure 1).

Figure 1. Sensing glove and the wireless acquisition unit.

The textile goniometers are double layer angular sensors previously described in [12,13]. The sensing layers are *knitted piezoresistive fabrics* (KPF) made of 75% electro-conductive yarn and 25% Lycra [14,15]. The two KPF layers are coupled through an electrically-insulating stratum (Figure 2 a). The sensor output is the electrical resistance difference (ΔR) of the two sensing layers that we demonstrated to be proportional to the flexion angle (θ) [12] that is the angle delimited by the tangent planes to the sensor extremities (Figure 2 b).

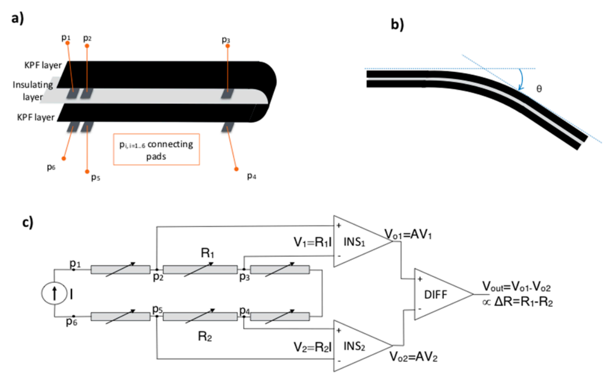

Figure 2 a) Schematic structure of the KPF goniometer. The black stripes represent the two identical piezoresistive ayers, while the gray stripe is the insulating layer. **b)** The output (ΔR) is proportional to the bending angle (θ) **c)** KPF goniometer electrical model and block diagram of the electronics front-end. Two instrumentation amplifiers (INS1 and INS2) and a differential amplifier (DIFF) produce the output ΔV that is proportional to ΔR and thus to Δθ.

The glove was developed in previous studies to perform daily life monitoring of stroke patients' activity to evaluate the outcome of their rehabilitation treatment [11,16]. In [17] we demonstrated the reliable performance of the glove goniometers, showing errors below 5 degrees compared to an optical motion capture instrument during natural hand opening/closing movements. The glove has two KPF goniometers on the dorsal side of the hand to detect the flexion-extension movement of the metacarpal-phalangelal joints of the index and middle fingers. The third goniometer covers the trapezium-metacarpal and the metacarpal-phalangeal joints of the thumb to detect the thumb opposition. We conceived this minimal sensor configuration as a tradeoff between grasping recognition and wear-ability of the prototype.

For the acquisition of ΔR from each of the three goniometers, we designed an ad hoc three-channel analog front-end (Figure 2– c). For each goniometer, the voltages V1=Vp2−Vp3 and V2=Vp5−Vp4 are measured when a constant and known current I is supplied through p1 p6. A high input impedance stage, consisting of two instrumentation amplifiers (INS1 and INS2), measures the voltages across the KPF sensors. These voltages are proportional, through the known current I, to the resistances of the top and bottom layers (R1 and R2). A differential amplifier (DIFF) amplifies the difference between the measured voltages, obtaining the final output ΔV, which is proportional to ΔR and to θ. Each channel was analogically low pass filtered (anti-aliasing, cut-off frequency of 10 Hz). The resulting data were digitally converted (sample time of 100 Sa/s) and wirelessly transmitted to a remote PC for storage and further elaboration.

2.2. Algorithm for movements detection

A HALS operation (Figure 3) has been selected in which the collaborative robot will assist the surgeon. This operation is a cholecystectomy, the surgical removal of the gallbladder. In this case, the robot will receive the following commands from the surgeon's hand gestures: center the image of the endoscope, suture or stretch the thread that will be used in sutures. Therefore, the system must

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be prepared to uniquely recognize the different movements defined as commands for the robot in order to prevent the robot from performing any undesirable operations.

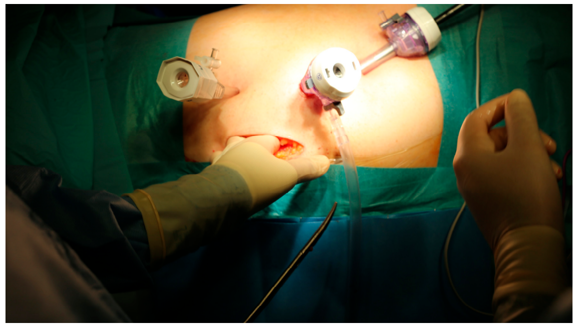
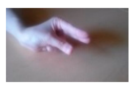
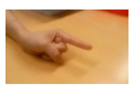


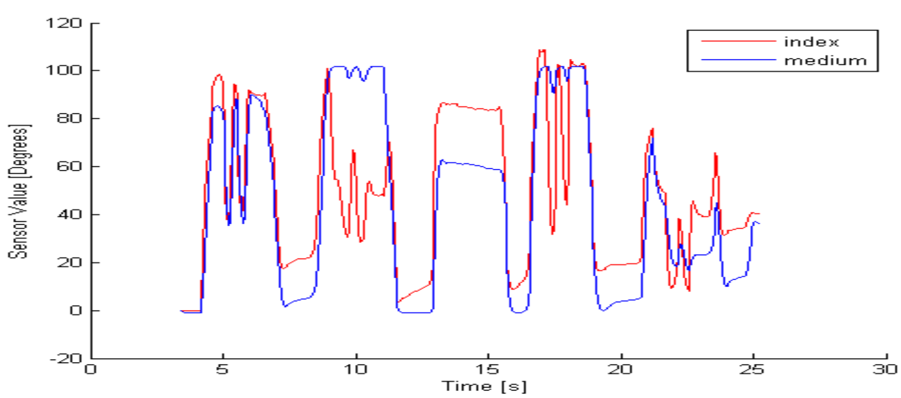
Figure 3. HALS operation. Photo courtesy of Dr.Martín Parada.

For the communication during operation with the collaborative robot, a protocol has been established. This protocol will include these three movements that must be detected as commands for the robot. The selected movements to be recognized as commands are shown on the Table 1.

Table 1. Selected movements to be detected.

Nº	Initial Posture	Final Posture	Description	Command
1			From initial posture to final posture twice	To center the image from the endoscope.
2			From initial posture to final posture twice.	To indicate a place to suture.
3		-	Initial posture for a defined time.	To indicate to stretch the thread.

To detect these movements, the developed algorithm analyses the following parameters: flexion pattern, velocity, execution times and value provided by the sensor of each finger. To evaluate these parameters, there is a previous phase in which the variables of each movement in each person are examined. This previous stage is required for each person because the speed and timing of the fingers movement is very variable as shown in figure 4.



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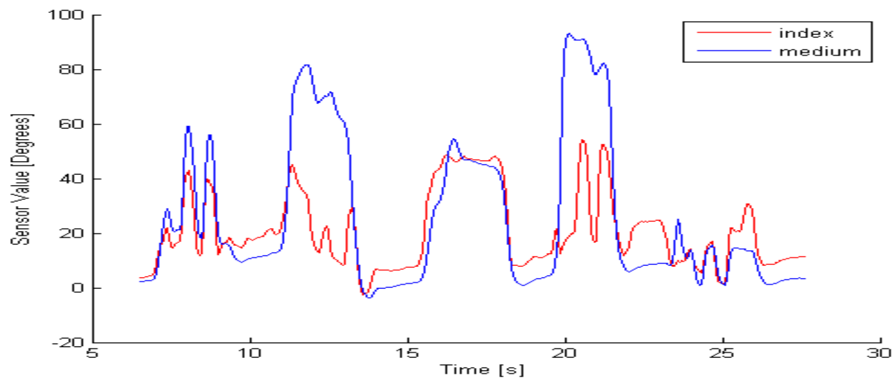
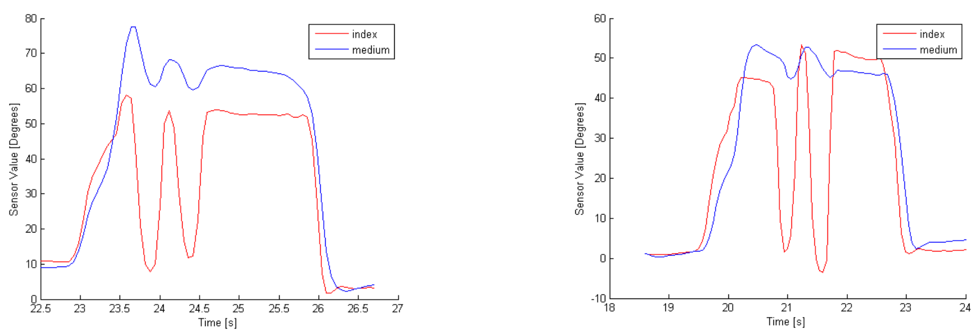


Figure 4. Sensor values during the same test performed by two different people: a) person 1 and b) person 2.

Once these variables are defined, the detection algorithm can identify each of the three movements.

Motion of each finger is detected by the algorithm for the detection of defined movements that scans the data from the sensing glove searching for the previously defined patterns of each movement. Due to the cross talk between sensors, due to the unique textile substrate in which all the sensors are attached, it may be possible to observe a disturbing signal of a finger when the operator tries to move another, as shown in figure 5. These movements are filtered in order to avoid a misclassification



(**a**) (**b**)

Figure 5. Sensor values during movement 2 for the same person. There should be no motion in the middle finger because only the index finger should participate.

Due to the nature of the sensors used, it is possible to determine the degree of flexion that is being applied to the sensor placed on the glove.. However, movement 4 and movement 2 could be mixed up owing to their similarity, as shown in figure 6.

(**a**) (**b**)

Figure 6. a) Sensor values during movement 2 and b) movement 4 performance by the same person.

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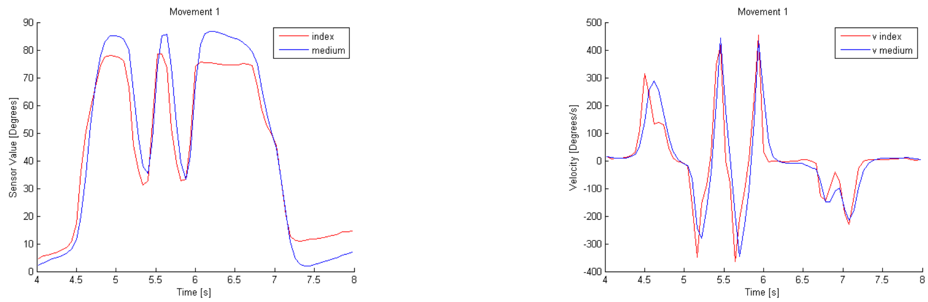

(**a**) (**b**)

Figure 7. a) Glove data which are proportional to flexion of the finger in movement 1. b)Velocity of fingers involved in movement 1.

Movement 1 can be identified by analyzing the data of the fingers index and middle. Each rise and fall in the glove values corresponds to the flexion and extension movements of the fingers. This movement consists of a descent (called D1) and ascent (A1) followed by another descent (D2) and ascent (A2), as shown in figure 5. This is the flexion pattern considered for movement 1.

The velocity of the fingers involved in this dynamic gesture is higher than the cross-talk ones as shown in figure 7 b). To stablish the typical velocity for this movement, the average and the standard deviation of the velocity along D1 and D2, A1 and A2 are calculated. This typical velocity, V_{1u}, is the minimum value obtained from the subtraction of the standard deviation from the average in three tests performed by the same person. Minimum time during descents, t_{1Du}, (D1 and D2) and ascents, t_{1Au}, (A1 and A2) are also calculated and will represent the characteristic ascent and descent execution times of movement 1.

To determine the execution time, t_{1u}, consider the maximum time in which the whole movement is performed; that is D1, A1, D2 and A2.

The last parameters to be defined are the maximum, x_{max}, and minimum, x_{min}, values of the sensor, which set the thresholds to consider if the obtained values are part of movement 1. They are obtained by analyzing three movement samples from the same person.

With these parameters, shown in table 2, movement 1 can be defined and differentiated from others.

Table 2. Characterization of defined movements.

Mov.	Finger	Flexion Pattern	Velocity	Execution time	D time	A time	Sensor value
1	Index Middle	D1 A1 D2 A2	$\lvert V_e \rvert > V_{1u}$	$t_e < t_{1u}$	$t_D > t_{1Du}$	$t_A > t_{1Au}$	$x_{min} < x < x_{max}$
2	Index	D1 A1 D2 A2	$\lvert V_e \rvert > V_{2u}$	$t_e < t_{2u}$	$t_D > t_{1Du}$	$t_A > t_{1Au}$	$x_{min} < x < x_{max}$
3	Index Middle	-	-	$t_e > t_{3u}$	-	-	$x_{min} < x < x_{max}$

Using the graphs obtained during the performance of movement 2, figure 8, we can conclude that to define it we need to determine the movements of the index and middle finger. The flexion pattern for this movement is D1 A1 D2 and A2 for index finger and no movement for finger middle. The velocity, time of execution, minimum time during descents (D1 and D2) and ascents (A1 and A2) and sensor value are defined as described in movement 1.

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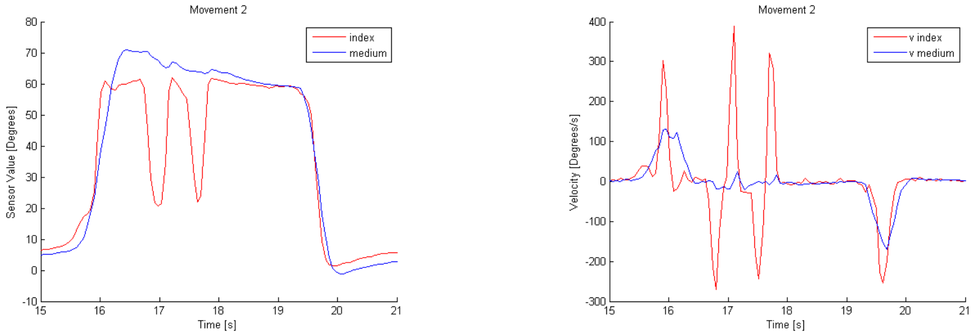
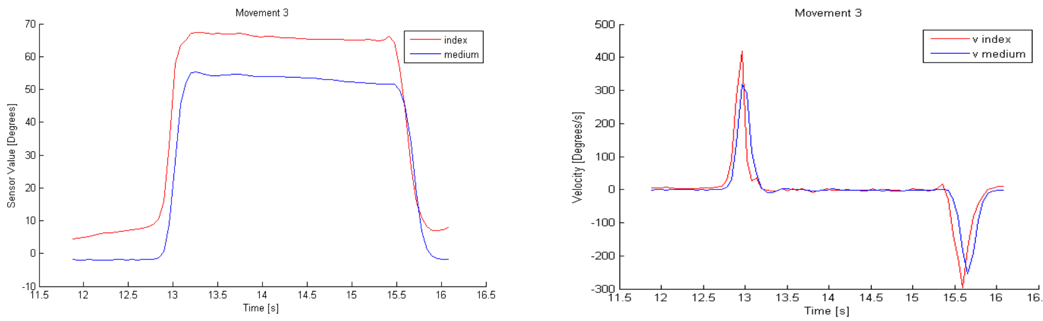


(**a**) (**b**)

Figure 8. a) Glove data which are proportional to flexion of the finger in movement 2. b)Velocity of fingers involved in movement 2.



(**a**) (**b**)

Figure 9. a) Glove data which are proportional to flexion of the finger in movement 3. b)Velocity of fingers involved in movement 3.

Movement 3, in figure 9, differs from the other two by the fact that the velocity must be 0, so it is a static position maintained for a certain time. To identify it, we examine the values of the index and middle finger sensors, whose values will be proportional to the flexion carried out by the sensorized finger.

The algorithm for the detection of defined movements evaluates all the above mentioned parameters and detects when one of these movements is executed.

3. Experiments

The test consists on carrying out the movements shown in table 3 in the same order, performing a flat position between them. The test has been conducted by 10 people 10 times. Movements 1, 2 and 3 are selected to be detected by the algorithm while movements 4 and 5 are introduced to prove that they are not detected as the three selected ones. The two new introduced motions are similar to movements 1 and 2 but there are small differences between them.

The characteristic parameters of each movement are calculated from three tests performed by the same person. These parameters are characteristic of each person, so 10 sets of patterns have been obtained for each type of movement, one per person.

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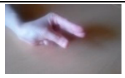
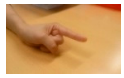
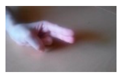
Table 3. Set of movements.

Nº	Initial Posture	Final Posture	Description
1			From initial posture to final posture twice
2			From initial posture to final posture twice.
3		-	Initial posture for a defined time.
4			From initial posture to final posture twice.
5			From initial posture to final posture twice.

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4. Results

As shown in table 14, movements 1, 2 and 3 must be detected by the algorithm while movements 4 and 5 should not be classified as selected motion. Movement 1 is detected between 80% and 100% (98% on overage) and movement 4 is identified as movement 1 only 1%, while movement 2 is detected between 70% and 100% (87%) and movement 4 is recognized as 2 33%. Movement 5 is never mistaken with other movements. Movement 3 is detected between 90% and 100% (97%).

		Actual movement					Positive predicted value	False discovery rate
Volunteer 1		1	2	3	4	5		
Predicted Movement	1	10	0	0	0	0	100%	0%
	2	0	8	0	0	0	80%	0%
	3	0	0	10	0	0	100%	0%

Table 4. Results Volunteer 1.

		Actual movement					Positive predicted value	False discovery rate
Volunteer 2		1	2	3	4	5		
Predicted Movement	1	10	0	0	0	0	100%	0%
	2	0	10	0	2	0	100%	20%
	3	0	0	10	0	0	100%	0%

Table 5. Results Volunteer 2.

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		Actual movement					Positive predicted value	False discovery rate
Volunteer 3		1	2	3	4	5		
Predicted Movement	1	10	0	0	0	0	100%	0%
	2	0	8	0	2	0	80%	20%
	3	0	0	10	0	0	100%	0%

Table 6. Results Volunteer 3.

		Actual movement					Positive predicted value	False discovery rate
Volunteer 4		1	2	3	4	5		
Predicted Movement	1	10	0	0	0	0	100%	0%
	2	0	9	0	5	0	90%	50%
	3	0	0	9	0	0	90%	0%

Table 7. Results Volunteer 4.

		Actual movement					Positive predicted value	False discovery rate
Volunteer 5		1	2	3	4	5		
Predicted Movement	1	10	0	0	0	0	100%	0%
	2	0	9	0	2	0	90%	20%
	3	0	0	10	0	0	100%	0%

Table 8. Results Volunteer 5.

		Actual movement					Positive predicted value	False discovery rate
Volunteer 6		1	2	3	4	5		
Predicted Movement	1	10	0	0	0	0	100%	0%
	2	0	8	0	7	0	80%	70%
	3	0	0	10	0	0	100%	0%

Table 9. Results Volunteer 6.

		Actual movement					Positive predicted value	False discovery rate
Volunteer 7		1	2	3	4	5		
Predicted Movement	1	10	0	0	0	0	100%	0%
	2	0	8	0	9	0	80%	90%
	3	0	0	10	0	0	100%	0%

Table 10. Results Volunteer 7.

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Volunteer 8		Actual movement 1	2	3	4	5	Positive predicted value	False discovery rate
Predicted Movement	1	10	0	0	1	0	100%	10%
	2	0	10	0	0	0	100%	0%
	3	0	0	9	0	0	90%	0%

Table 11. Results Volunteer 8.

Volunteer 9		Actual movement 1	2	3	4	5	Positive predicted value	False discovery rate
Predicted Movement	1	8	0	0	0	0	80%	0%
	2	0	7	0	0	0	70%	0%
	3	0	0	9	0	0	90%	0%

Table 12. Results Volunteer 9.

Volunteer 10		Actual movement 1	2	3	4	5	Positive predicted value	False discovery rate
Predicted Movement	1	10	0	0	0	0	100%	0%
	2	0	10	0	6	0	100%	60%
	3	0	0	10	0	0	100%	0%

Table 13. Results Volunteer 10.

Total		Actual movement 1	2	3	4	5	Positive predicted value	False discovery rate
Predicted Movement	1	98	0	0	1	0	98%	1%
	2	0	87	0	33	0	87%	33%
	3	0	0	97	0	0	97%	0%

Table 14. Total Results.

5. Discussion

Movement 4 is detected as movement 2 or 1 because of, as explained in previous sections, their similarity. Although the study of different patterns, times and speeds, there are 35% of motion 4 detections such as movement 2. Whenever movement 3 has not been detected is due to insufficient time in the static position. This situation would not appear during an operation because the surgeon would wait in the static position until the robot would assist him/her so these non-identifications would not be present.

Reviewing the results, it can be concluded that the effectiveness of the algorithm depends largely on the person performing the test. This is because not all people have the same ability to perform the exact motion with a high repeatability. Results with surgeons are expected to be better because they have greater skills in this field. Tests have shown that the newly developed algorithm can reliably identify the three movements defined in a series of different continuous movements. Movement recognition is accurate because identification is based not only on the initial and final

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pose, but also on intermediate positions and speeds that are continuously analyzed to determine if their pattern is analogous to the model. Different filters are also introduced to make the dynamic gesture recognition algorithm more reliable. The patterns obtained with the sensing glove present sufficient information to be robustly identified preventing failures in those cases where the positions are similar to those of the model but the execution speed of the movement is different.

One of the purposes of this study was to test the validity of our non-specific glove to demonstrate the possibility to employ this kind of devices and define the specification for a HALS-dedicated textile glove to be employed in future studies. In future works, glove-based hand motion sensing could be fused with other sensing modalities, such as artificial vison, to make the system more robust.

6. Conclusions

This paper presents a methodology for movement recognition for a textile-based sensing glove in hand assisted laparoscopic surgery. The glove, using piezoresistive sensors, capture continuously the flexion degree of the surgeon's fingers. However, hand movement recognition is not an easy task due to the high variability in the motion patterns in different people and situations. We propose to analyze the data detected by the sensing glove using the methodology described. First, the patterns of the different selected movements are defined. Afterwards, and for each person, the parameters of their movements are identified and then used to identify them online. Taking into account the results in the conducted tests, the methodology has shown to be robust in identifying the set of movements studied to be commands for the collaborative robot.

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Author Contributions: Alessandro Tognetti and Nicola Carbonaro conceived and designed the sensing glove. Lidia Santos carried out experiments. Lidia Santos processed and analyzed the data. Eusebio de la Fuente, José Luis González, Alessandro Tognetti and Nicola Carbonaro gave advises and discussions. Lidia Santos, Alessandro Tognetti and Nicola Carbonaro wrote the paper. Juan Carlos Fraile, Javier Turiel, Alessandro Tognetti and Nicola Carbonaro supervised the entire work.

Conflicts of Interest: The authors declare no conflict of interest

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