

Inedited SVM Application to Automatically Tracking and Recognizing Arm-and-Hand Visual Signals to Aircraft

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Keywords: Visual Signalling, Sensory Glove, SVM.

Abstract: An electronic demonstrator was designed and developed to automatically interpret the signalman's arm-and-hand visual signals. It was based on an "extended" sensory glove, which is a glove equipped with sensors to measure fingers/wrist/forearm movements, an electronic circuitry to acquire/condition/feed measured data to a personal computer, SVM based routines to classify the visual signals, and a graphical interface to represent classified data. The aim was to furnish to the Italian Aircraft Force a tool for ground-to-ground or ground-to-air communication, which can be independent from the full view of the vehicle drivers or aircraft pilots, and which can provide information redundancy to improve airport security.

1 INTRODUCTION

According to the *International Code of Signals*, by National Imagery and Mapping Agency (United States Edition, revised 2003), the Visual Signalling (VS) is *any method of communication, the transmission of which is capable of being seen*. The VS can be implemented by means of different methods, among which the arm-and-hand based one, treated here.

This method of signalling is mandatory for communication of deaf people, can generally improve communication in task collaboration (Gander, 1996), and becomes strategical for particular communications when radios cannot be used or are unavailable. Inter alia, here we consider a VS application suitable to meet the requirements of the "Armaereo" (a Military Aircraft Force of the Italian Ministry of Defence), which funded our research. However, the basic idea can be easily extended to any field where VS is standardized, as it occurs for the Army (reference: visual signals for armor fighting vehicles, GTA 17-02-019), for the Navy and Marine (reference: Offensive combat I and combat signs, by United States Marine Corps, TACT 3022, Apr 2011), for the Road rules (as an example of reference: Washington State Legislature, Rules of the road, Chapter 46.61.310), and for sport activities (as an example of reference: Basic Officials Manual of the USA Hockey, updated August 2013).

The VS refers to code meanings related to specific vocabulary, receipting, acknowledging and identification procedures (Visual Signals, Department of the army, FM 21-60). Here we consider the ground-to-ground or ground-to-air visual signal communications between the signalman and the vehicles or aircrafts, with the aim of furnishing an automatic electronic way of interpreting the signalman's visual signals, so to replicate the decoded signal meaning inside the military vehicle or inside the aircraft, allowing double check to the driver or to the pilot. This system has the advantages of being independent on the full view of the driver or the pilot, of offering information redundancy for management or security improvement, and of allowing information recording for realizing a sort of a "black box airport runway", similar to the well-known "black box flight recorder".

The signalman is in charge of communicating with standard signals (among which: cut engine(s), hook-up complete, release, move right/ left/ ahead/ rearward/ downward/ upward, depart, land, do not land) or emergency signals (among which: ok, affirmative, negative, do not attempt to land, stop). These signals are arm-and-hand based and can be tracked by means of different technologies. Currently, the mostly adopted method of tracking relies on optical cameras (Song et al., 2011), but our project intended to avoid any camera, so to be

independent by camera distance, camera occlusion, number of cameras, and insufficient lighting. In particular, our system implemented a sort of “extended” sensory glove, that is, a glove equipped with sensors to measure not only flex/extensions of the fingers, but also wrist and forearm movements.

The sensory glove has been finding very different applications, among which the real-time control of a granular sound synthesis process (Costantini et al., 2010), the monitoring of hand rehabilitation (Park et al., 2009; Mohan et al., 2013) or clinical hand assessment (Williams et al., 2000), the human-computer interaction (Saggio et al., 2012; Berlia and Santosh, 2014), the sign-to-language conversion (Cavallo et Saggio, 2014), the objective surgical skill assessment (Saggio et al., 2015), the serious games for training of rescue teams (Mugavero et al., 2014), the tele-robotic manipulations for astronauts (Saggio and Bizzarri, 2014), and so on. As far as we know, this is the first time the sensory glove is utilized for Aircraft Force or Army purposes.



Figure 1: The “extended” sensory glove, the electronic circuitry (both the source and the receiving one), the virtual representation on a personal computer.

Here, we present an electronic framework, made of: an “extended” sensory glove, an electronic circuitry, a suitable classifier, and a virtual representation. The framework was aimed to measure, record, recognize and virtually represent the arm-and-hand visual signals. Figure 1 shows the ensemble.

2 MATERIALS AND METHODS

The arm-and-hand tracking framework consisted of hardware and software levels. In particular, we distinguish a sensory glove and an electronic conditioning circuitry for the so termed “source sub-

system”; an electronic receiving circuitry, a mathematical classifier, and a virtual avatar representation for the so termed “receiving subsystem”.

2.1 The Sensory Glove

Our “extended” sensory glove includes a supporting Lycra®-based glove equipped with ten flex/extension sensors placed on-top of the metacarpo-phalangeal (MCP) and proximal-interphalangeal (PIP) joints of each finger, and two 6 degree-of-freedom (DoF) inertial measuring units (IMUs), respectively necessary to measure the wrist and forearm movements (Figure 2). Total source signals were then $10+2 \times 6=22$.

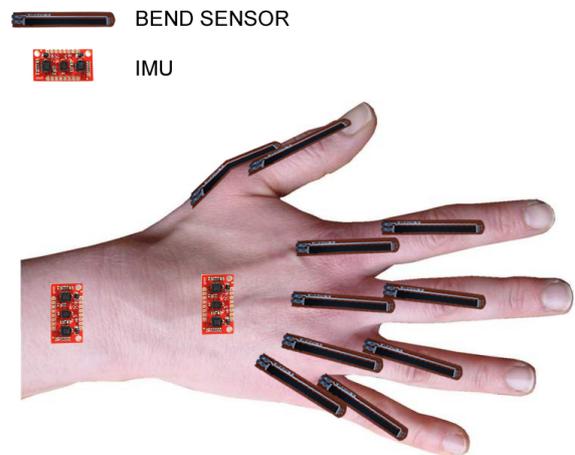


Figure 2: Sensors placings: ten flex sensors on-top of the MCP and PIP joints, one 6DoF IMU on the dorsal aspect of the hand, and one 6DoF IMU on the forearm. The supporting glove is not showed here for clarity reasons.

We did not measure the distal-inter-phalangeal (DIP) joints since their flex/extension capabilities are normally correlated to the PIP ones in known percentages (Ghosh, 2013).

We used ten flex/extension sensors termed “Bend Sensors®”, (by Flexpoint Sensor Systems Inc., Draper, Utah, USA), adopted because of their lightness and suitable repeatability and reliability characteristics previously measured and reported (Saggio and Bizzarri, 2014).

The two IMUs were the Sparkfun Razor ones (by SparkFun Electronics, Niwot, Colorado, USA), each with a 3-axis accelerometer and a 3-axis gyroscope.

2.2 The Electronic Circuitry

For the electronic circuitry we can distinguish the “source” and the “receiving” subsystems.

Let's start considering the source-subsystem (Figure 3a) necessary to acquire signals from the sensors, to provide A/D conversions, and to wired/wireless transmit data to the receiving-subsystem. The wired transmission is intended for testing purposes, while the wireless one to be in-field adopted.

Resistance values from the ten flex sensors have been converted into voltage values by means of an equal number of voltage dividers, while voltage values from the IMUs fed directly the circuitry. The core of the source-subsystem was the integrated circuit PIC18F47J53 (by Microchip, Chandler, AZ, US), 48Mhz-clocked, capable of 12bit A/D conversion.

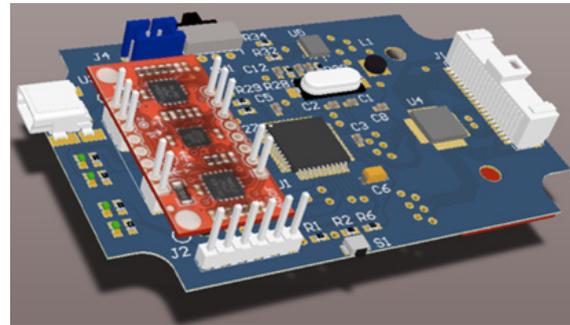
Table 1: Speed, range and consumption transmission values among different protocols/standards.

Protocol/Standard	Speed	Range	Consumption [mW]
IEEE802.15.4 / ZigBee	20-250[kbps]	<1km	40
Bluetooth-Bluetooth Smart/ IEEE802.15.1	1-24 [Mbps]	<100m	200
IEC62591/ WirelessHART	250 [kbps]	<100m	40
ISA100.11a	250 [kbps]	<100m	40
DASH7	27.7-200 [kbps]	<10km	1
Z-WAVE	10-40 [kbps]	<300m	80
ANT	1 [Mbps]	<30m	40
Wavenis	4.8-100 [kbps]	<200m	80

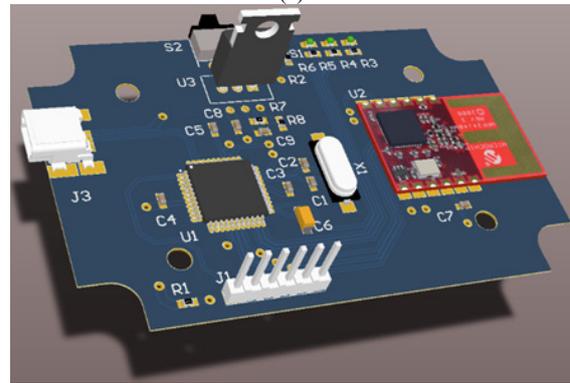
This IC offer only 10 analog inputs so that, in order to acquire all the 22 signals from the extended sensory glove, we used a 2x16 channel multiplexer, the ADG726 (by Analog Devices, Norwood, MA, USA) (its 10 spare input channels can be used for eventually additional requirements).

Requests for the wireless protocol included short (or medium) transmission range, low-medium transmission speed, low-power consumption, and scalability so to handle data of up to four sensory gloves at a time, all in an auto user-independent configuration mode. To respond to these requests, we analysed different protocols/standards, in particular the Bluetooth and Bluetooth smart/ IEEE802.15.1, the IEC62591/ WirelessHART, the ISA100.11a, the DASH7, the Z-Wave, the ANT, the Wavenis, and the IEEE802.15.1/ ZigBee. Table 1 reports a comparison among speed, range and consumption of the aforementioned protocol/standards. The IEEE802.15.1/ ZigBee was our

choice, since it better covers the commitment requirements.



(a)



(b)

Figure 3: The electronic circuitry, designed using an electronic design automation (EDA) tool by Altium Designer (by Altium, Belrose, NSW, Australia), of the (a) source-subsystem and of the (b) receiving-subsystem.

Transmission security was not a mandatory parameter for our purposes; anyway the aforementioned protocols can be considered reasonably “similar” from a cryptography point of view. The interested reader can find a survey comparison in Gomez and Paradells (2010).

Our wireless transmission was then obtained with the IEEE 802.15.4 radio transceiver module MRF24J40MA (by Microchip, Chandler, AZ, USA), which allows a 0dBm transmission within a 100 meters range.

The DC power supply was realized with a Li-Ion single-cell battery, charged and controlled by the IC BQ25015 (by Texas Instruments, Dallas, TX, USA), which includes a DC-DC buck converter capable of 300mA @3,3V.

Let's now consider the receiving-subsystem (Figure 3b), necessary to receive signals and to feed them, via USB port, to the personal computer. It was based on the same integrated circuit MRF24J40MA of the source-subsystem. The USB transmission was based on the inner full-speed module of a second

PIC18F47J53. The DC power supply was obtained from the USB port, with its 5V reduced to the necessary 3.3V adopting an LDO voltage regulator.

2.3 Set of Visual Signals

The visual signals we intended to discriminate come from the *Field Manual No. 21-60 – Visual Signals*, by Defence Department, USA, 1987.

In particular we selected the arm-and-hand signals for ground forces, used for controlling vehicle drivers (Figure 4 a, b, c, d, e), for combat formations (Figure 4 a, c, e, f), for patrolling (Figure 4 g), for recovery operations (Figure 4 b, h, i). In addition, we considered to recognize six numbers (from 0 to 5) represented by the hand, as in Figure 5. These particular set of visual signals were considered as the most representative for our purposes, and included both static (maintained for at least 3secs) than dynamic (repeated cycling at least three times) gestures.

In order to recognize the dynamic visual signals, i.e. the signals performed with arm-and-hand moving and cycling to represent a gesture (Figure 4a-g), it was necessary to acquire electric signals from all the sensors of the “extended” sensory glove, but in order to recognize the static visual signals, i.e. the signals performed keeping the arm-and-hand in a static pose (Figure 4 h and i, Figure 5a-f), data from IMUs were not necessary, therefore omitted.

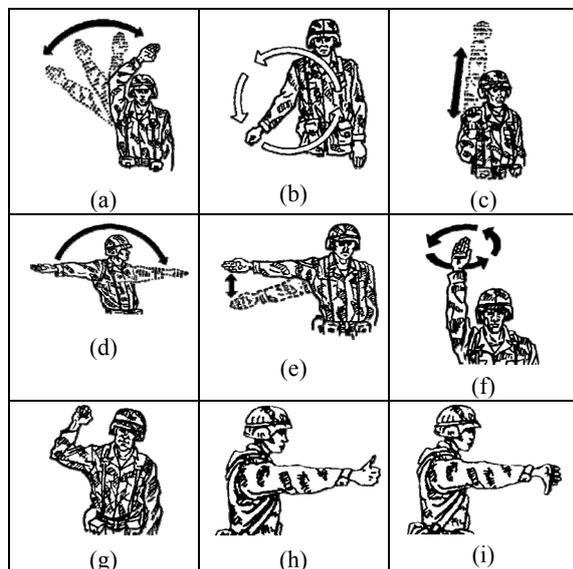


Figure 4: Visual signals selected as representative for our application, in particular: (a) attention or column, (b) start engine or in haul the main winch, (c) increase speed or rush, (d) advance, (e) slow down or quick time, (f) rally or coil, (g) freeze, (h) ok, (i) nack.

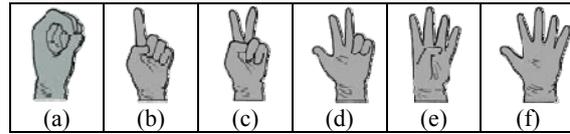


Figure 5: Hand visual signals performing six numbers, from 0 to 6.

2.4 Classifier

We intended to discriminate an arm-and-hand gesture within a subset of visual gestures, and this was possible by means of a suitable classifier.

This classifier could better perform when preceded by pre-processing and feature extraction phases. The pre-processing phase was aimed at reduction of the undesired noise components by means of digital *IIR* (Infinite Impulse Response) filtering. The feature extraction phase involved the use of Fourier and Wavelet Transforms (Walker, 2008), and the calculation of statistical quantities (e.g. energy, mean value, variance).

Concerning the classifier, among the mostly adopted ones for recognition of human upper limb posture and movement, we may include Artificial Neural Network (ANN) (Mitra and Acharya, 2007), Hidden Markov Model (HMM), and Support Vector Machine (SVM) (He, 2011). The latter was here selected as the most suitable for our purposes for some of its peculiarities, in particular: its lower tendency to overfitting (compared, for instance, to ANN), and its good performance even if the data set used in the learning phase is of contained dimension.

The metrics we used to evaluate the SVM performances involved the $Accuracy=C/T$ (C : number of correctly classified trials, T : total number of trials), the $ErrorRate=E/T$ (E : number of wrongly classified trials), the $AbstentionRate=A/T$ (A : number of abstentions).

2.5 Virtual Representation

We implemented software routines to reveal events of connection of new sensory gloves (up to four), to allow training and testing protocols, to acquire and store data from the classifier, to present a graphical interface (GUI, Figure 6) with interactive commands for the user, and to virtually represent, via human avatar, the movements related to the recognized visual commands by the signalman.

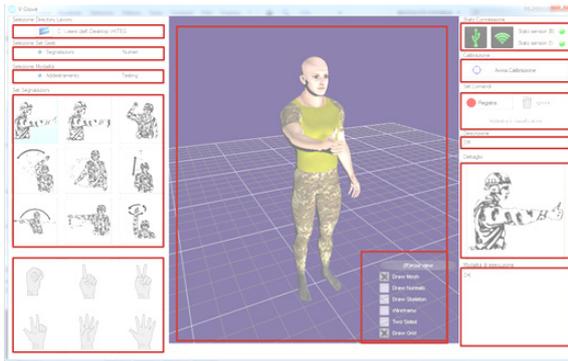


Figure 6: The graphical user-friendly pc-interface for training and testing purposes. On the right column the recognized gesture, on the middle column the animation of the selected gesture via human avatar.

2.6 Training/Testing Protocol

Three subjects took part in the experimental evaluation of the system. They were male 22-35 aged (average 27.6) right handed, with no motor or intellectual limitations.

Our training/testing procedure started with a calibration phase, which consisted in dressing the sensory glove, and posing the hand in a full-open (Figure 7a) and full-closed (fist, Figure 7b) position. The two positions have to be maintained for two seconds each, to allow the acquisition of a sufficient number of sample data, from all the sensors, further averaged.

During full-open/full-closed hand position (Figure 7a/b), we measured both the minimum/maximum electric values (resistances converted into voltages) of each of the ten flex sensors, and the electrical values (voltages) coming from the x,y/z axis of the accelerometers and gyroscopes of both IMUs.

The training/testing protocol always started from the same condition, that is, the user was standing-up with his/her arms along the body, and followed these steps:

1. Glove dressing and calibration;
2. **Training**: three replays of each arm-and-hand visual signal;
3. Glove removal and rest period;
4. Glove dressing and calibration;
5. **Training**: two replays of each arm-and-hand visual signal;
6. **Testing**: five replays of all the visual signals;
7. Glove removal and rest period;
8. Glove dressing and calibration;
9. **Testing**: five replays of all the visual signals.

For the number postures we used a training/testing protocol identical to the one described above. It follows that, both for visual signals and numbers, we acquired 5 training repetitions and 10 testing repetitions of each posture/gesture. We feel it is worth to stress that both training and test data has been acquired in two distinct settings, i.e. after glove removal and re-dressing, so to improve the generalization capability of the classifier (during learning) and better estimate performance in a real-usage scenario (during testing).

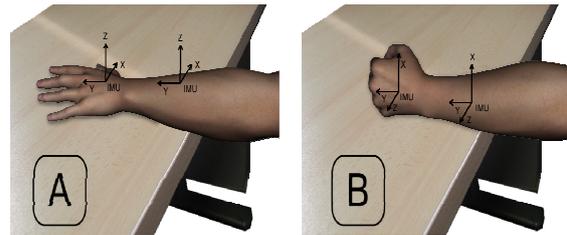


Figure 7: The two hand poses (flat hand and fist) for the calibration steps. The sensory glove is omitted in the figure for clarity reasons.

3 RESULTS AND DISCUSSION

Table 2 and Table 3 show the system performance in visual signals (Figure 4) and number recognition (Figure 5), respectively. It is possible to observe that in the latter task the classifier obtained optimal performance, i.e. 100% accuracy, for all of the involved subjects. In visual signals recognition, performance was also close to optimal. In fact, subject A reached 100% accuracy, and subjects B and C obtained an high accuracy (above 95%) with no errors but only abstentions. This is of particular importance in all those scenarios in which the wrong recognition of a signal could result in damage to persons and/or things.

Table 2: Classifier performances related to the command gestures.

Subject	Accuracy(%)	ErrRate(%)	AbstRate(%)
A	100	0	0
B	97.78	0	2.22
C	95.56	0	4.44

Table 3: Classifier performances related to the gestures of numbering.

Subject	Accuracy(%)	ErrRate(%)	AbstRate(%)
A	100	0	0
B	100	0	0
C	100	0	0

4 CONCLUSIONS

Here we designed and developed a camera-free arm-and-hand tracking framework, and implemented SVM-routines capable to interpret signalman's gestures, so to obtain an automatic tool not prone to human misinterpretation.

Preliminary experimental results with 3 subjects have been quite encouraging (100% mean accuracy for the number recognition task and over 97% mean accuracy for visual signals identification) and thus motivate us for a further investigation involving a greater number of users and, possibly, real-time continuous-recognition too. Future work will also concentrate on the investigation of in-situ usability, i.e. in a real or realistic environment.

ACKNOWLEDGEMENTS

This work was funded by the "Armaereo" (Direzione Generale degli Armamenti Aeronautici, Ministero della Difesa), Contract #a2009.90, for which we would like to thank T.Col. GArm Aldo Spagnolini and T.Col. GArm Salvatore Vignola.

REFERENCES

- Berlia R., Santosh P., Mouse Brace: A convenient computer mouse using accelerometer, flex sensors and microcontroller. In: *Contemporary Computing and Informatics (IC3I), International Conference on: IEEE* pp 558-61, 2014.
- Cavallo P., Saggio G., Conversion of Sign Language to Spoken Sentences by means of a Sensory Glove, *Journal of Software, Vol 9, No 8 (2014), 2002-2009*, Aug 2014.
- Costantini G., Todisco M., Saggio G., A Cybernetic Glove to Control a Real Time Granular Sound Synthesis Process, in: *Proceedings of the International Multi-Conference on Complexity, Informatics and Cybernetics (IMCIC), Orlando, Florida USA*, 2010.
- Song Y., Demirdjian D., Davis R., Tracking body and hands for gesture recognition: Natops aircraft handling signals database, in: *Proceedings of the 9th IEEE International Conference on Automatic Face and Gesture Recognition*, 2011.
- Ghosh S., Capturing human hand kinematics for object grasping and manipulation, *Thesis submitted to the Office of Graduate Studies of Texas and A&M University, for the Degree of Master of Science*, 2013.
- Gomez C., Paradells J., Wireless home automation networks: A survey of architectures and technologies, in *IEEE Communications Magazine*, vol. 48, no. 6, pp. 92-101, 2010.
- He Z., Accelerometer Based Gesture Recognition Using Fusion Features and SVM, *Journal of Software*, vol. 6, no. 6, 2011.
- Mitra S. and Acharya T., Gesture Recognition: A Survey, *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 37, no. 3, pp. 311–324, May 2007.
- Mohan A., Devasahayam S. R., Tharion G., George J., A Sensorized Glove and Ball for Monitoring Hand Rehabilitation Therapy in Stroke Patients. In: *India Educators' Conference (TIEC): IEEE* pp 321-7.
- Park C-Y, Bae J-H, Moon I., Development of wireless data glove for unrestricted upper-extremity rehabilitation system. In: *ICCAS-SICE, 2009: IEEE* pp 790-3.
- Saggio G., Lagati A., Orenco G., Wireless Sensory Glove System developed for advanced Human Computer Interface, *International Journal of Information Science* 2012, 2(5): 54-59.
- Saggio G., Bizzarri M., Feasibility of Teleoperations with Multi-Fingered Robotic Hand for Safe Extravehicular Manipulations, *Aerospace Science and Technology* 39 (2014) 666–674.
- Saggio G., Lazzaro A., Sbermini L., Carrano F. M., Passi D., Corona A., Panetta V., Gaspari A. L., Di Lorenzo N., Objective Surgical Skill Assessment: An Initial Experience by Means of a Sensory Glove Paving the Way to Open Surgery Simulation?, *Journal of Surgical Education*, 2015.
- Walker J. S., *A Primer on Wavelets and Their Scientific Applications*, 2nd ed. Chapman and Hall/CRC, 2008.
- Williams N. W., Penrose J. M. T., Caddy C. M., Barnes E., Hose D. R., Harley P., A goniometric glove for clinical hand assessment construction, calibration and validation, *Journal of Hand Surgery (British and European Volume)* 25 200-7, 2000.