A new multisensor software architecture for movement detection: Preliminary study with people with cerebral palsy

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A B S T R A C T

A five-layered software architecture translating movements into mouse clicks has been developed and tested on an Arduino platform with two different sensors: accelerometer and flex sensor. The archi-tecture comprises low-pass and derivative filters, an unsupervised classifier that adapts continuously to the strength of the user's movements and a finite state machine which sets up a timer to prevent in-voluntary movements from triggering false positives.

Four people without disabilities and four people with cerebral palsy (CP) took part in the experi-ments. People without disabilities obtained an average of 100% and 99.3% in precision and true positive rate (TPR) respectively and there were no statistically significant differences among type of sensors and placement. In the same experiment, people with disabilities obtained 97.9% and 100% in precision and TPR respectively. However, these results worsened when subjects used the system to access a commu-nication board, 89.6% and 94.8% respectively. With their usual method of access-an adapted switch- they obtained a precision and TPR of 86.7% and 97.8% respectively. For 3-out-of-4 participants with disabilities our system detected the movement faster than the switch.

For subjects with CP, the accelerometer was the easiest to use because it is more sensitive to gross motor motion than the flex sensor which requires more complex movements. A final survey showed that 3-out-of-4 participants with disabilities would prefer to use this new technology instead of their tra-ditional method of access.

1. Introduction

Communication is vital for human beings. Great benefits could be reaped from a system allowing people with severe disabilities to access a computer or a communication system reliably, with little effort and quickly. There are several devices on the market, together with scientific papers which translate user intentionality into events. The simplest and most commonly used is based on a mechanical switch. There are several versions of this mechanical switch which depend on the user's level of movement. Thus, there are switches that can be operated by head movements (by pressing the switch with the cheek, head, chin), or by moving the arms, legs, hands, tongue, etc.

Most organizations that care for people with disabilities use such devices on a massive scale so that they can use software applications, particularly those based on scanning methods, by simply connecting the switch to an adapted device which translates user movements into software selections (mouse clicks, enter keystroke, etc).

For people with severe disabilities, these simple devices are still very difficult to use. For this reason, there is a need for devices capable of translating weak intentional movements, without the subject having to target the place where the switch is. We investigated two of these possible devices: accelerometer and flex sensors.

1.1. Accelerometer

Several devices can be employed to detect movements. One of the best known and widely used is the accelerometer. Single- and multi-axis accelerometer models are available to detect magnitude and direction of g-force as a vector quantity, and they can be used to sense orientation, coordinate acceleration or tilt detection. Placing accelerometers on limbs allows us to assess locomotor skills Masci et al. (2013), Palmerini et al. (2013), Yoneyama et al. (2013, 2014), track joint angle El-Gohary and McNames (2012), Chirakanphaisarn (2014) or evaluate recovery after an injury Hurd et al. (2013) or stroke Pas et al. (2011). Accelerometers have also been used to assess movements of people with cerebral palsy who typically have abnormal muscle tone,

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muscle weakness, primitive reflexes or uncoordinated movements. The assessment of physical activity in this population is important for the design and implementation of health, therapy and physical education programs. In Capio et al. (2010), the use of inertial units appears to be a valid instrument for measuring raw activity volume and it is suitable for use in studies attempting to characterize the physical activity of this population. Wearable inertial sensors have also been applied to allow people with disabilities to access a computer. In Raya et al. (2010) an inertial mouse driven by head movements is reported. The accuracy of such a device is about 1º and experimental results with two infants with CP (athetoid and dystonic cases) demonstrates that the children are able to place the pointer near the target but they find fine motor control difficult. In Ranjan et al. (2010) a universal remote control based on an accelerometer is shown. It can be placed on the hand or wrist and it detects four movements: hand up, down, left and right in order to drive an infrared transmitter to control a TV set. Although the movements are easy to execute for a subject without disability, for some people with CP they are very difficult. In fact, the authors do not report experiments with such users. Accelerometers are important devices for detecting intentional movement even in subjects with severe motor problems. The simplest way to use them with such people is putting them on the limbs or head to convert weak movements into switch strokes suggested in Mariano et al. (2014), but the authors do not report any tests with people with disabilities.

1.2. Flex sensor

Another device used to measure or detect movements related to joint bending is based on a flex sensor Saggio (2012, 2014). The flex sensor changes its electrical resistance value depending on the amount of bend it is subjected to. This sensor can be implemented with different techniques. The one most commonly adopted is based on a resistive film element which may consist of a polymer printed on a plastic substrate Tongrod et al. (2010), a conductive elastomer in an elastic fabric Tognetti et al. (2006) or more recently linear potentiometers and flexible wires Park et al. (2014). This technology has been used to measure joint angle Bakhshi et al. (2011a), for example, knee flexion using a supportive cloth in which the flex sensor is embedded. However, in another paper, the same authors, show how inertial sensors units can be used for the same proposal to measure bending angle Bakhshi and Mahoor (2011a) with improved accuracy. Flex sensors can be placed in gloves to detect finger flexion. These sensors can be combined with other kinds of sensors such as contact sensors and/or an accelerometer in the same glove to recognize hand gestures such as Sign Language fingerspelling Tanyawiwat and Thiemjarus (2012), Nelson et al. (2013), Ibarguren et al. (2010), Adnan et al. (2012). Controlling fingers as in fingerspelling is an impossible task for many people with disabilities. They require simpler gestures. In Nelson (2013a) a wearable multi-sensor gesture recognition system is proposed for people with disabilities. The system is based on an electrooculography capture system to detect eye movements by using a textile sensor in a headband and a glove with flexometers and an accelerometer to detect hand gestures. Hand gestures are made by pointing a single finger or a set of fingers from their bend position. Although hand gestures are simpler than in other reviewed articles, people with disabilities still find them difficult to perform. Moreover, putting a glove on is not easy for subjects with muscle stiffness, joint atrophy, etc. such as those with CP. A much simpler system using bending detection on one finger would be easier for such subjects to attach and use.

1.3. System goals

A system that translates weak movements into signals would not generate very high peaks on the signal. Therefore, detecting those peaks, even in situations when the subject is tiring and using less force, is an important challenge for the system and enhances user interface interaction Mezhoudi (2013). Another issue is that intentional movements are sometimes accompanied by uncoordinated movements, which therefore means the signal has several peaks. Although such peaks would be detected as movements, they should be considered as parts of the initial voluntary movement. As soon as the signal has been stabilized, which means that the movement has stopped, the detection of a new voluntary movement will be enabled again.

1.4. Mutilayer architecture

To accomplish these goals, in this article we propose a layered software architecture which can be implemented on external hardware platforms working as if they were mechanical switches, or on a computer.

We tested this architecture using both accelerometers and flex sensors in people with and without disabilities. Each layer can be adjusted by using parameters such as filter length, timeouts, etc, and one of our goals is provide a set of parameters allowing users to operate the system reliably.

Some related work about flexible and layered software architecture can be found in Beuvens and Vanderdonckt (2012a, 2012b) where the authors present a structured method for facilitating the integration of gestures in graphical user interfaces and in Molina et al. (2011a), where the authors propose a system based on infrared light to translate eye movements, blinks, winks or head movements into a set of events that may be configured to emulate mouse actions. The versatility of such a system is constrained to the usage of infrared light and even if it were possible to use such a system with other sensors, to do so, each layer would have to be reprogrammed. In Ibarguren et al. (2010) a layered architecture is also proposed for hand gesture recognition. Two layers are employed, the first, a segmentation layer, splits signals into movement and non-movement segments, and the second, a classification layer, assigns a character to each movement segment.

This paper is organized as follows: Section 2 presents the software architecture and the set of layers it is made up of. Section 3 describes the implementations chosen to test the architecture: Section 4 the methodology, including the system user profiles and how the experiments were conducted. This is followed by Sections 5, 6 and 7 with the results, discussion and conclusions, respectively.

2. Software architecture

The software as a whole receives data from the acquisition system and delivers commands to a computer to emulate a mouse click. To accomplish this main goal the software has been split into 5 different layers: the lowest is the hardware layer, which receives data from the analog to digital converter; the top layer is the finite state machine (FSM), from which events (mouse clicks) to the computer are dispatched Fig. 1. The data flow upwards from the hardware to the FSM layer, going through three other layers. Each one acts as a system receiving input data, then processing, and sending output data to the next layer in the data pipe. A queue between each two adjacent layers holds output data coming from layer number n before being accepted by layer $n+1$. A task manager is in charge of executing the processes on each layer as the queue connected at its input receives new data.

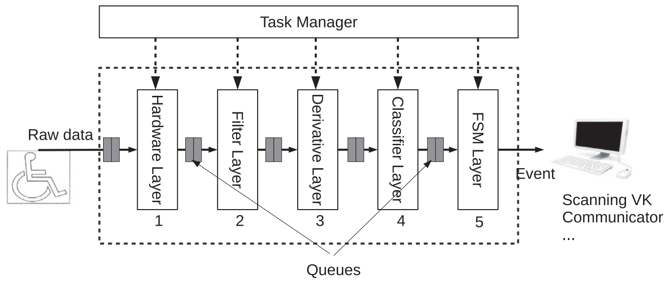

Fig. 1. The set of layers in the proposed software architecture. Data flows from movement detection sensors from layer 1 up to 5. The top layer emulates a mouse click sent to a computer to control a Virtual Keyboard for instance.

2.1. *Layer 1: The hardware layer*

This contains the set of routines that reads digital data coming from the sensor and sends it to the filter layer at a fixed rate. Depending on the sensor, an interpolation sublayer may be activated if the input data does not come at a fixed rate. The sampling frequency, F_s, and type of interpolation must be selected according to the type of sensor.

2.2. *Layer 2: The filter layer*

Most data coming from the hardware layer contains noise and may be downsampled to reduce computational load in the following layers. Noise reduction is also better for estimating the velocity of movement, because several algorithms, in particular those based on derivatives, are very sensitive to noise. For these reasons, this layer contains a set of routines enabling both noise reduction and downsampling of input data by using a polyphase low-pass filter Proakis and Manolakis (2007), which is efficient for computing a new data output using a subset of input data at a lower rate. The length, L, of the filter, and the decimation factor, D, must be tailored to the type of data.

2.3. *Layer 3: The derivative layer*

A steady signal coming into this level, no matter what its value, is associated with a user's non-movement state, whereas an unsteady signal is associated with user movements. For this reason, a good estimator of movement could be based on the signal derivative, since it is zero when the user is at resting state and non-zero otherwise. This layer contains a L_d-length queue which stores the latest L_d values of input data with which the output is calculated by applying a SavitzkyGolay filter (SGF) Schafer (2011), Press et al. (2007). The coefficient of the SGF for estimating the first-derivative depends on the length of the queue containing the data to be convolved. For instance for $L_d=5$ they are $[1,-8,0,8,-1]/12$. The last step is to calculate the absolute value of the SGF output and send it to the upper layer.

2.4. *Layer 4: The classification layer*

Data coming from the derivative layer is classified into two main categories: movement (M) and non-movement (NM) samples. NM samples are associated to values closer to zero, whereas M samples must be much greater than zero. Thresholding may be a viable solution for classifying samples, but it requires the user to move with a minimal intensity.

An adaptive K-means, storing the last 32 inputs, classifies each input as NM or M according to the distance to the centroids of three classes. In turn, these centroids are continuously adjusted as new data come into the layer. Data closer to centroid number 3 are labeled as M samples, otherwise they are classified as NM samples. To filter out a certain amount of input noise centroids are only updated if the distance between a new sample and the centroid is greater than a preset value. Centroid number 1 is associated to very low movements and centroid number 2 to slight ones. Data classified as belonging to centroid 2 updates its value and also that of centroid number 3. This takes centroid 3 closer to centroid 2, thereby adapting to movement intensity as soon as possible.

The algorithm can be summarized as follows where v_n is the sample in time n, $centroid_j$ is the value of centroid number j, where $j=1,2,3$ and L_c an arbitrary weight. All samples classified as M-samples belong to centroid $j=3$. The samples classified as NM-samples belong to centroid j=1,2, but when $centroid_2$ is updated, the $centroid_3$ is as well.

Algorithm 1. The classification layer algorithm.

1: $[d_{nj}, pos] = min_j(|v_n - centroid_j|)\ j = 1..3$
2: **if** $d_{nj} > 2$ **then**
3: $\quad centroid_{pos} = \frac{(Lc-1)\times centroid_{pos}+v_n}{L_c}$
4: $\quad$ **if** pos==2 **then**
5: $\quad centroid_3 = \frac{(L_c-1)\times centroid_3+v_n}{L_c}$
6: $\quad$ **end if**
7: **end if**

2.5. *Layer 5: The FSM layer*

Labeled samples usually come into this layer grouped in packets. Each single M-sample packet may only send out one mouse click (see Fig. 2). We propose a finite state algorithm with two states to detect packets. State S0 is called the resting state and S1 the movement state. As soon as the subject moves, the finite state machine goes to S1. Transition from S0 to S1 delivers a mouse click. Each M sample starts a timer which sets the time-lapse, t_f, the finite state machine has to wait for to go back to state S0.

Many people with cerebral palsy present uncontrolled movements after initiating an intentional one and they take some time to stop. To a certain extent, the timer guarantees the subject has stopped making movements before returning to state S0, and thus, false mouse clicks are prevented from being sent to the computer. This time, t_f must be empirically estimated according to the user's profile.

3. Implementation

The software architecture has been implemented on a hardware platform called Arduino Banzi and Shiloh (2014). Two shields have been developed to adapt flex sensors and an accelerometer to

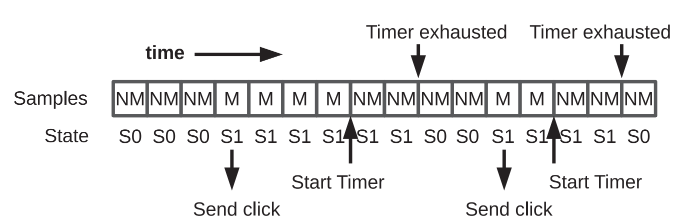

Fig. 2. Example of operation of FSM layer. A mouse click is sent whenever there is a transition from S0 state to S1 (reception of the first M-sample). When the movement finishes, the FSM layer starts receiving NM samples. The first NM-sample triggers a timer. When it exhausts the finite state machine returns to S0. The reception of an M-sample when the timer is running re-triggers it.

Table 1
Parameters used for different layers in the implementation of the architecture. The global delay or the system response time for movement detection is also shown for accelerometer and flex sensors.

Layer	Parameter (units)	Flex Sensor	Acceler.
Hardware	N channels	1	3
	$F_s/ch(Hz)$	250	250
Filter	L	32	64
	$F_C(Hz)$	7.8	3.9
	D	16	16
Derivative	L_d	5	5
Classifier	L_c	32	32
FSM	$t_f(s)$	2.5	2.5
Global delay	$t_d(s)$	0.19	0.26

the platform. Both include a switch-type connector which interfaces to a computer just like any other mechanical switch.

3.1. Flex sensor

We selected a 2.2″ flex sensor model SEN-10264[1] connected to a shield which also contains an amplifier with gain equal to 2 and a low pass filter with a cutoff frequency equal to 70 Hz. A digital output is also included in the shield to turn a led on and off to indicate the state of the finite state machine and as a feedback mechanism to show users when to start a movement. The hardware layer only uses one channel of the analog to digital converter sampled at $F_s = 250$ Hz and the filter layer contains an FIR filter with a Hamming window and cutoff frequency equal to 1/L, where L, the length of the filter, is equal to 32. Table 1 summarizes the parameters chosen for the implementation of the software architecture, including the global time delay (latency) t_d.

3.2. Accelerometer

The selected sensor is an ADXL335,[2] a tri-axis accelerometer with a range of measurement of $\pm 3g$. An amplifier of a gain equal to 10 and a low pass filter with a cutoff frequency equal to 70 Hz have also been included in the shield for each channel. Signals go into the Arduino analog to digital converter which samples them at a rate of $F_s = 250$ Hz/ch. The shield also contains the led as described above in the Flex sensor section. Table 1 summarizes the chosen parameters. As the accelerometer sends three signals, the filter and derivative layers receive three data streams that are independently processed. This requires three instances of filter and derivative layers and queues to hold data for them, but in the end, the three first-derivative estimations must be combined into one value (Eq. (1)).

$$v = \frac{|v_x| + |v_y| + |v_z|}{3} \tag{1}$$

3.3. Sensor Setup

An accelerometer detects movement in any part of the human body where the sensor is placed. Fig. 3 shows possible placements of such a sensor. For head movement detection, the accelerometer is attached to an adjustable harness similar to the ones used in safety helmets. A small strap with tiny buckles wraps both sensor and a portion of the harness and prevents the sensor from coming loose. The head has three possible movements: roll (neck lateral bending), yaw (neck rotation) and pitch (forward and backward

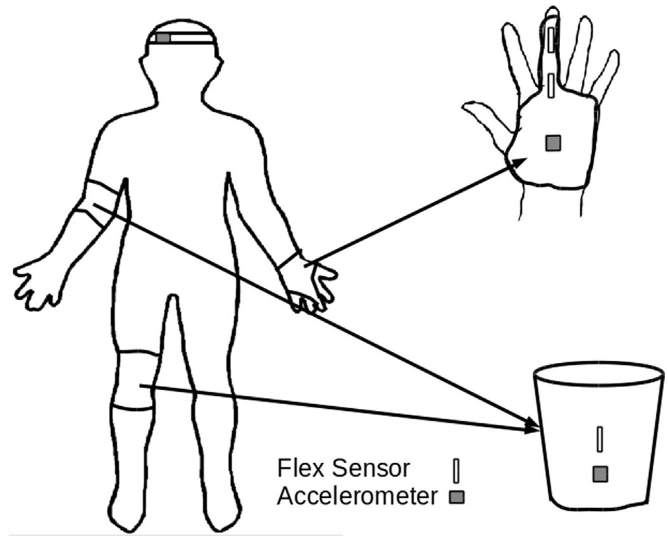

Fig. 3. Garments to host sensors: head harness, armband, glove, knee-brace. Flex sensor is placed in rectangular receptacles attached to the garments. Accelerometer is placed in squared receptacles.

bending). The further the position of the accelerometer from the rotation axis of the head, the better the sensitivity to head movement the sensor will have. Such a place could be the middle point of the forehead. However, we preferred to place the accelerometer by the right temple, where it is more comfortable because the harness exerts less pressure and accelerometer wires do not have to be routed along the harness.

For upper limb movement detection, the accelerometer can be placed in an armband by the elbow or in a glove covering the hand. A receptacle made of elastic fabric was sown in both armband and glove to host the sensor and parts of the wires. Movements in upper limbs are more complex than in the head due to greater degrees of movement allowed by joints. Nevertheless it is not easy to perform an upper limb movement without moving the hand, so placing the accelerometer in a glove might be enough.

For lower limb movement detection a knee- or ankle-brace can be used to sew the receptacle which will host the accelerometer. For the same reasons stated above, the further away it is placed, the greater the sensitivity it will have. However, to avoid having to take shoes off, which may be uncomfortable for some people, the knee was the preferred place. The knee-brace consists of a rectangular elastic fabric ending in two complementary pieces of velcro which make it easy to put on the subject's knee.

The flex sensor needs to be placed over a joint to measure bending. Four positions were chosen to detect grasping, extension or flexion of the finger, leg, or forearm by placing the flex sensor on knuckles, finger, knee or elbow respectively. The same glove, armband and knee-brace with receptacles for this sensor were used.

3.4. Example of operation

To illustrate how the whole system works, Fig. 4 shows the output from layer 2 of the proposed architecture when the input signal is acquired by a flex sensor placed over the elbow.

Fig. 5 shows the outputs of layers 3–5. The derivative signal is drawn in a thick blue line. M samples or samples classified as movements are shown with a filled square. FSM layer output is drawn in a thin green line and scaled to emphasize the fact it covers the derivative signal. Note this output is activated as an M sample goes into it. The evolution of three centroids has also been drawn in dashed red lines. Centroid 3 values correspond to the

[1] https://www.sparkfun.com/products/10264
[2] https://www.sparkfun.com/products/9269

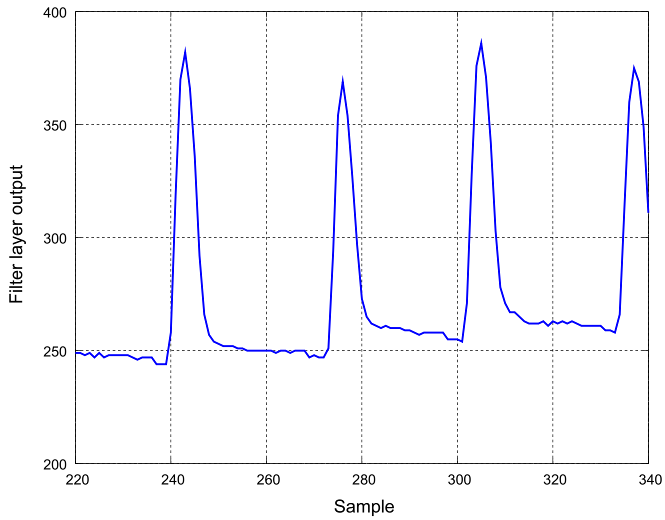

Fig. 4. Typical filtered signal from the flex sensor detecting elbow bending.

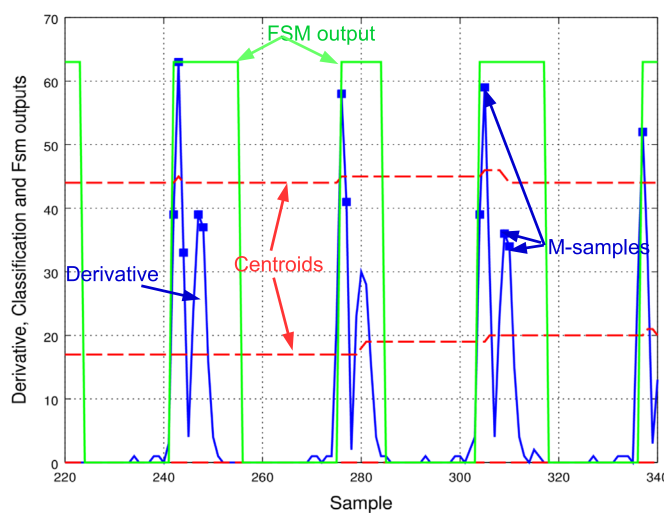

Fig. 5. Derivative, classification and FSM layer signal outputs shown in Fig. 4. The derivative signal shows two peaks for each bending. Classification layer labeled each sample as NM or M. Figure shows the values of the two higher centroids (dashed lines). Each M-sample has been shown using a square. The FSM layer output has been scaled to the size of the movement and how it covers the movement.

upper line and centroid number 1 is hidden by the baseline. Fig. 6.

4. Methodology

To test the feasibility of this implementation we conducted three experiments with 8 people. The first experiment, or Exp1, was performed by people without disabilities (group A) and people with CP (group B). Group A performed the experiment first of all as a mandatory step before the system could be used by the other group. Basically, Exp1 tested whether the system could properly identify subjects' movements. We obtained three measurements: tp or true positives (correctly identified movements); fp or false positives (the system incorrectly indicated there was a movement); and fn or false negatives (undetected movements). Combining such parameters we estimated precision and TPR (Eq. (2)). Precision is the proportion of positive outcomes that are correct, whereas TPR measures the proportion of positives that are correctly identified as such.

$$Precision = \frac{tp}{tp + fp}$$
$$TPR = \frac{tp}{tp + fn} \qquad (2)$$

To obtain such measurements, the Arduino platform delivered the output signals of each level of the architecture to a computer in which they were stored. A computer web-cam recorded the subject's movements during the experiments. Video and off-line analysis of data allowed us to quantify true and false positives and false negatives. Moreover, in the case of group A participants, they also counted the number of false positives and false negatives made by the system. At the end of the experiment the participants reported such information to the researcher.

The second goal of Exp1 was to estimate the theoretical maximum speed of operation of the system without decreasing its precision and TPR. This mainly required estimating the lowest (or optimal) value for the parameter t_f and the movement time t_m. The former sets the time that a user must remain still before initiating a new movement whereas the latter, t_m, is the time to execute a movement. The total time for the system to detect a movement properly is equal to $t_m + t_f$. Reducing this time can be done by just reducing t_f down to its optimal value t_f^{opt}. Most people with disabilities are accustomed to using different switch-operated communicating systems. In such systems, each item (or icon) is highlighted for a time t_{scan} or dwell time to show the focus. A user's movement (or switch press) makes the selection of the focused icon. The dwell time must be equal to or higher than the time employed for the user to execute a movement, which in our proposal would be $t_{scan} \geq t_m + t_f$. In this relationship, t_f is a constant factor whereas t_m is a random variable. To fix a value of t_{scan} knowing the average time of t_m the 0.65 rule was proposed Simpson and Koester (1999), Simpson et al. (2007), Lesher et al. (2000). With the 0.65 rule, the minimal dwell time is equal to the response time divided by 0.65. This response time includes the reaction time t_r (the amount of time it takes to initiate a movement from the onset of the stimuli) and the execution time t_m (Eq. (3)).

$$t_{scan} \geq t_{scan}^{0.65rule} + t_f^{opt} = \frac{t_r + t_m}{0.65} + t_f^{opt} \qquad (3)$$

Exp1 allowed us to obtain all the parameters explained above. The participants had feedback from the FSM layer, so they knew when to start a movement and when to remain still. Group A performed one session whereas the other group attended two sessions. In each session the participant had to perform at least 15 movements.

Participants in group B performed two other experiments. In the second experiment, Exp2, users accessed a communication board through the proposed system. The main difference between Exp1 and Exp2 lay in the fact that there was no feedback to let the user know when the timer had exhausted and they could perform a new action. In this experiment we obtained precision and TPR following the procedure described above.

The last experiment, Exp3, was basically the same as Exp1 but, in this case, subjects were asked to use their usual input devices (based on a switch). This helped us gain a point of comparison between the proposed method and the traditional one.

Finally, group B participants were asked whether they would prefer to use this system instead of their usual input devices and those who had tested the sensor in different parts of their bodies were asked where they preferred it to be placed.

Table 2 summarizes the experiments performed by the two

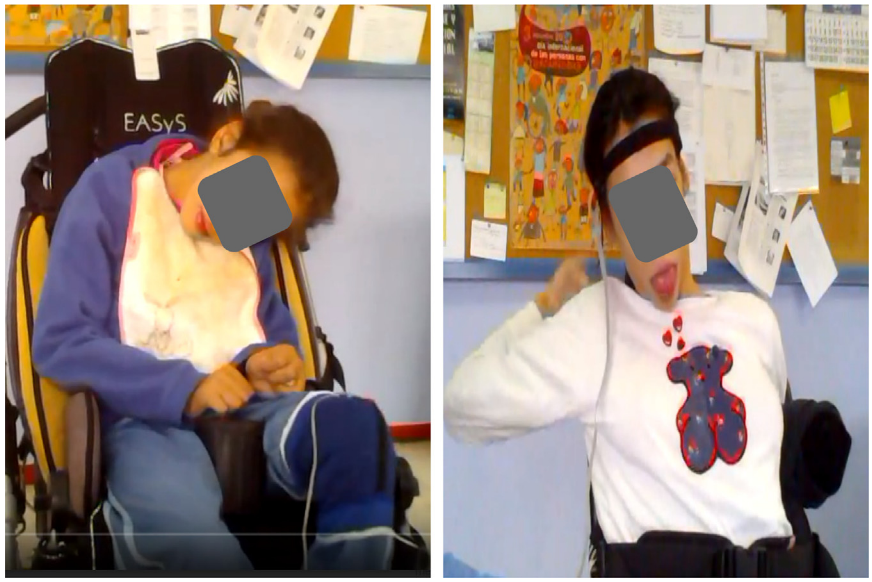

Fig. 6. Pictures of B1 (on the left) and B4 (on the right) when they were performing the experiment. B1 wears a knee-brace that hosts the flex sensor whereas B4 wears a harness containing the accelerometer placed close to the right temple.

Table 2
Experiments performed by each group.

Group	Exp1	Exp2	Exp3	Survey
A	x			
B	x	x	x	x

groups.

4.1. Participants

Four people with disabilities (Group B) and four without disabilities (Group A) took part in the experiments. The Ethics Committee of the University approved the experiment and their parents were informed and agreed to allow them to take part in this study.

4.1.1. Group A

We called the four people who belonged to this group: A1 to A4. There were three males and one female aged 38.75 ± 10.2. They each tested both the flex sensor and accelerometer performing seven experiments overall. For the flex sensor, they performed four kinds of movement: grasp, extension and flexion of middle finger, elbow and knee. The accelerometer was placed in three positions: head, hand and knee, but, unlike the flex sensor, the participants were just asked to move the sensor in any direction.

4.1.2. Group B

We called the 4 subjects with cerebral palsy B1, B2 and so on. They were all recruited from a special educational needs school called *Colegio de Educación Especial Directora Mercedes Sanromá* which is dedicated to work with motor disability students in Seville. All participants with CP had good intellectual, visual and hearing capabilities but very poor motor skills, including inability to speak. Table 3 summarizes their description according to Gross Motor Function Classification System (GMFCS), the Communication Function Classification System (CFCS) and Manual Ability Classification System (MACS).

The Gross Motor Function Classification System Palisano et al. (1997) is a 5 level clinical classification system that describes the gross motor function of people with cerebral palsy on the basis of self-initiated movement abilities. Particular emphasis in creating and maintaining this scale rests on evaluating sitting, walking, and wheeled mobility. Distinctions between levels are based on functional abilities; the need for walkers, crutches, wheelchairs, or walking sticks.

The Communication Function Classification System Hidecker et al. (2011) is a tool used to classify the everyday communication of an individual with cerebral palsy into one of five levels according to effectiveness of communication. For example, at level I, a person independently and effectively alternates between being a sender and receiver of information with most people in most environments. However at level V, a person is seldom able to communicate effectively even with familiar people.

The Manual Ability Classification System Ann-Christin et al. (2014) describes how children with cerebral palsy use their hands to handle objects in daily activities. This scale has five levels. For example, at level I a person handles most objects but with some reduced quality and/or speed, but at level V the child is not able to do it or complete even simple actions with their hands.

Subject B1 is a 12-year-old girl with dystonia. She can execute coarse movements with left-side body limbs and has bad control of head position. It is very difficult for her to reach a target with her left hand showing involuntary movements after the completion of a intentional one. She finds it easiest to control her left leg, which also shows short-time involuntary movements. Her usual computer interaction is by means of a leg-controlled switch.

Subject B2 is a 13-year-old girl who has muscle spasticity, no postural head control and she has difficulty reaching a switch to access a computer. Her upper limbs are quite stiff due to the spasticity so she is unable to open or close her hands or flex her arms. She rarely accesses a computer, but when she does she uses a switch rod operated by her head or leg.

Table 3
Description of group B participants according to GMFCS, CFCS and MACS.

Subject	GMFCS	CFCS	MACS
B1	V	II	IV
B2	V	III	V
B3	V	IV	IV
B4	V	III	IV

Table 4
Sensor positions for each participant.

Subject	Flex sensor				Accelerometer		
	Finger	Knuckle	Knee	Elbow	Head	Hand	Leg
A1–A4	x	x	x	x	x	x	x
B1			x		x	x	x
B2			x		x		x
B3				x		x	
B4					x		

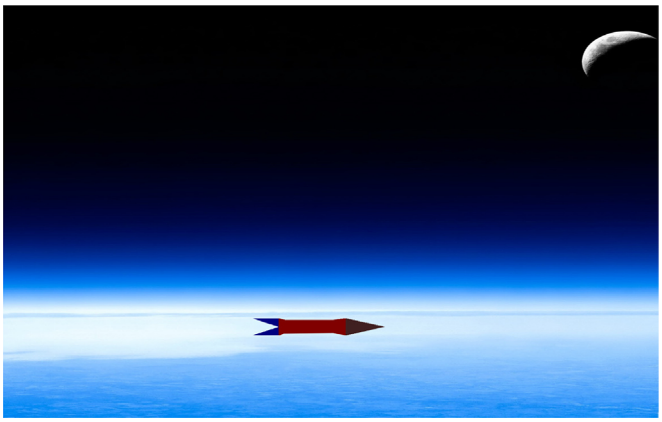

Fig. 7. Screenshot of the rocket shown in Exp1. The color of the rocket indicates whether the user may or not may perform a movement: green means yes. In this case the user needs to be still. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Subject B3 is a 12-year-old girl who can coarsely control her upper left arm. She executes movements very slowly and can flex and extend her knee. She can also open and close her hand but she was excluded from this part of the experiments because there were no gloves of her size at the time of performing them.

Subject B4 is a 17-year-old girl; although she is able to coarsely control her upper limbs she preferred to use just her head to access the computer. She can say yes and no and accesses a computer by means of a headwand.

Table 4 summarizes the type and position of sensors for participants in the experiments.

4.2. Experiments

4.2.1. Experiment Exp1

A software program trained users and collected information about their interaction with the computer. This software shows a rocket which is continuously blown from the right side of the screen to the left by a cosmic wind Fig. 7. To stop the rocket from disappearing off screen its engine must be started and the rocket then moves back towards the right side of the screen. The color of the rocket changes according to the FSM layer output. A green rocket indicates the user is still and can perform a movement. The rocket turns red when the user has accomplished a movement and stays red for t_f=2.5 s after the user has stopped executing it. One of the main goals of this experiment was to find the optimal t_f^{opt}. To avoid an excessive number of experiments, particularly with the users with disabilities, t_f was set high enough to guarantee a correct use of the system for almost all participants. Subsequent offline analysis will gauge how much this parameter can be lowered without altering the number of false positives and negatives in movement detection.

The time the rocket is red is equal to the time the subject performs a movement t_m plus the timeout set in the FSM layer, t_f. Therefore, t_m is then easily estimated by subtracting t_f from the time the rocket is red. Finally, as participants were asked to perform a movement as the rocket turned green, the reaction time t_r could also be calculated by subtracting the time the rocket remained green before turning red again. These three parameters could be used to estimate t_{scan} (Eq. (3)).

4.2.2. Experiment Exp2

Participants from group B were now invited to use a communication board (see Fig. 8) based on 12 pictures. Each of these pictures or icons was highlighted for a preset dwell time (Eq. (3)) using cyclic scanning. The icons were highlighted one by one from left to right starting with the icon on the left of the top row. If the user performed a movement, the icon highlighted at that moment was selected and an action, such as playing a recorded message, was executed. The pictures marked for selection by the participant were: water, sleep, cold and TV (blue square in Fig. 5) In two out of

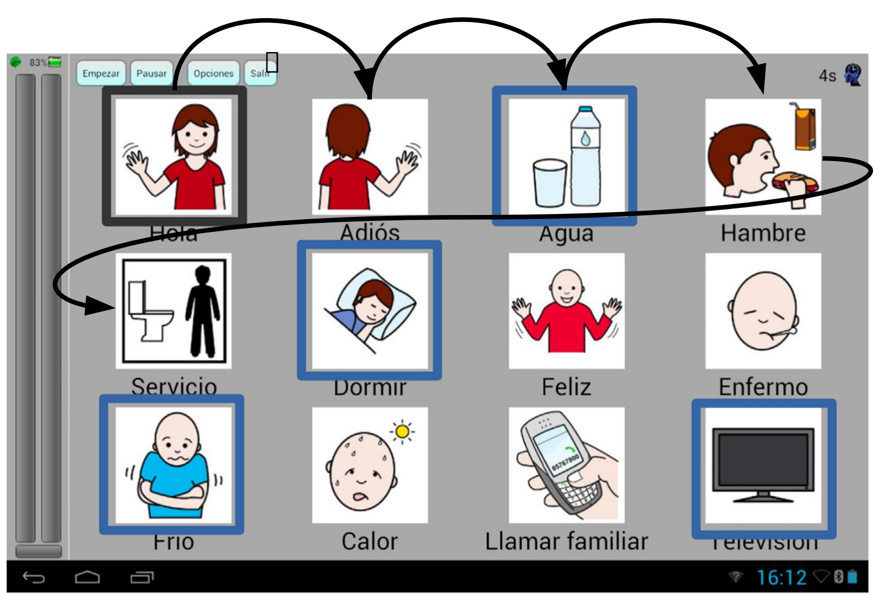

Fig. 8. Communication screen for experiment Exp2. Captions read from top, left to right: Hello, Goodbye, Water, Hungry, Toilet, Sleep, Happy, Ill, Cold, Hot, Call, Television. The subject has to select the four framed icons: Water, Sleep, Cold, and TV.

three icons the subject had to remain still while they were highlighted, then, the scanning reached the preselected icon where subjects were able to perform a movement. This process was repeated several times.

The communication board ran in a tablet which recorded the target icons and any kind of subject activity during the experiment so it could be reproduced later on. Apart from the fact this software stored information for the experiment, it did not differ from any other kind of software that people with disabilities are used to. The important issue here was to find out how many errors the participants would make using this software when the visual feedback, showing subjects when to perform the movement, was masked.

4.2.3. Experiment Exp3

This was basically the same as Exp1, but, in this case, the participants from group B used a mechanical switch that was placed at their usual positions (leg for B1 and B2, hand for B3 and head for B4). We also placed an accelerometer to record the movements the subject made during the experimental sessions. Both switch activity and the information from layers 2-5 of the proposed architecture were stored for further analysis. A webcam recorded the participants performing the sessions.

The main goal of this experiment was to compare between the traditional and the proposal method of access. This was be done in three dimensions: efficiency (precision and TPR), time to perform a movement, t_m and latency (as a measurement of the time elapsed between the beginning of the movement and its detection).

As explained above, precision and TPR had to count the number of true positives, false positives and false negatives. Signals and video were analyzed to obtained such parameters. Firstly, we identified the number of movements the participant made during the session by watching the video and studying the stored signals. From those movements, we counted the ones which ended with pressing the switch (true positives) and the ones that did not (false negatives). The rest of the detected switch pressings resulting from uncontrolled movements were considered false positives.

To measure the difference in latency between the two systems (Δt_l), firstly we calculated the latency of each system individually from the time the rocket changed to green, which enabled participants to perform a movement. Then, we subtracted both latencies, so a positive (Δt_l) value means that the proposed system is faster than the mechanical switch.

Finally, to estimate t_m we followed the same procedure as explained above in Section 4.2.1.

5. Results

Table 5 shows the results for group A participants: precision, TPR, optimal t_f^{opt}, t_m and t_r averages and the estimated dwell time t_{scan} (given by Eq. (3)) for each experiment. The participant who obtained the lowest t_{scan} and could potentially have obtained the fastest speed in a communication board was A1 for the flex sensor placed on her finger, the same position where, paradoxically, the slowest speed was obtained by participant A2. By averaging precision and TPR for each participant and then for all of them we obtained 100% and 99.3% for those parameters respectively.

Fig. 9 shows the results of t_{scan} versus sensor position. The lowest mean value (2.87 s) for four participants was obtained when the accelerometer sensor was placed on the leg, and the highest value (3.70 s) was when the same sensor was placed on the head.

Table 6 shows the results for group B participants and Experiment Exp1. The information format is the same as the one used for group A participants. Following the same procedure as explained above, the average precision and TPR for all participants were 97.9% and 100% respectively. Results of experiment Exp2 are shown in Table 7 which also includes the percentage of targets

Table 5
Data collected from group A participants in Exp1. Precision is the proportion of positive outcomes that are correct; TPR or true positive rate is the proportion of positives that are correctly identified as such; t_f^{opt} is set by off-line analysis and it establishes the minimum time the user must remain still before initiating a new movement; t_m is the movement time; t_r the reaction time and t_{scan} is the dwell time calculated by Eq. (3).

Subject	**Parameter**	Flex sensor				Accelerometer		
		Knuckles	**Finger**	**Knee**	**Elbow**	**Head**	**Hand**	**Leg**
A1	Precision (%)	100	100	100	100	100	100	100
	TPR (%)	100	100	100	100	100	100	100
	t_f^{opt} (s)	0.75	0.25	0.5	0.75	0.75	1	0.75
	t_m (s)	0.70	0.42	0.62	0.70	0.86	0.76	0.35
	t_r (s)	0.92	0.73	0.86	0.90	1.12	1.33	0.98
	t_{scan} (s)	3.24	2.03	2.78	3.21	3.80	4.22	2.81
A2	Precision (%)	100	100	100	100	100	100	100
	TPR (%)	100	100	100	100	100	100	**93.75**
	t_f^{opt} (s)	0.5	1.25	0.75	0.5	0.75	0.75	0.25
	t_m (s)	0.70	0.89	0.65	0.79	0.89	0.67	0.29
	t_r (s)	1.38	1.21	1.34	1.14	1.13	0.92	1.44
	t_{scan} (s)	3.69	4.48	3.83	3.47	3.86	3.19	2.92
A3	Precision (%)	100	100	100	100	100	100	100
	TPR (%)	100	100	100	100	100	100	100
	t_f^{opt} (s)	0.25	0.5	0.5	0.25	0.75	0.5	0.75
	t_m (s)	0.85	0.39	0.60	0.62	0.85	0.51	0.35
	t_r (s)	0.97	0.82	1.14	0.98	1.01	0.99	1.29
	t_{scan} (s)	2.34	2.68	3.05	2.72	3.86	3.21	3.27
A4	Precision (%)	100	100	100	100	100	100	100
	TPR (%)	100	100	100	**93.75**	**93.75**	100	100
	t_f^{opt} (s)	0.75	0.75	0.75	1	0.75	0.5	0.25
	t_m (s)	0.76	0.78	0.61	0.89	0.27	0.35	0.45
	t_r (s)	1.24	0.80	1.35	0.95	1.52	0.89	1.00
	t_{scan} (s)	3.83	3.17	3.78	3.82	3.52	2.41	2.49

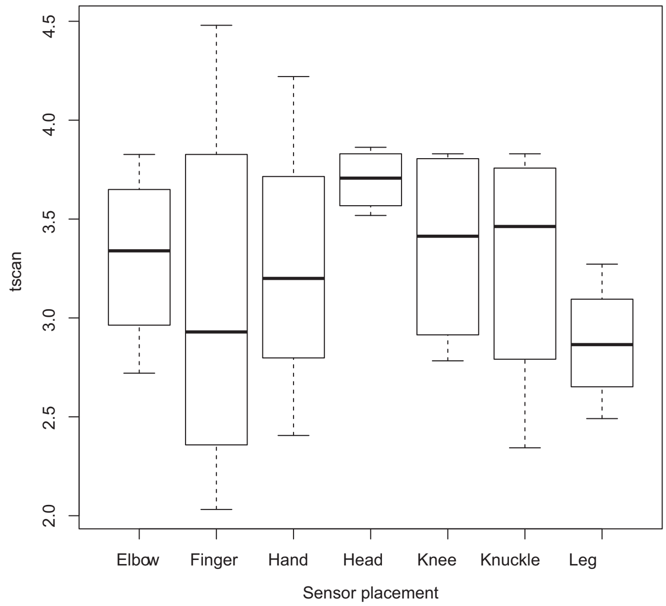

Fig. 9. Boxplots of t_{scan} versus sensor placement for group A subjects.

Table 6
Data collected from group B participants in Exp1.

Subject	**Parameter**	Flex Sensor		Accelerometer		
		Knee	**Elbow**	**Head**	**Hand**	**Leg**
B1	Precision (%)	100	–	100	100	100
	TPR (%)	100	–	100	100	100
	t_f^{opt} (s)	2	–	0.75	1.00	0.75
	t_m (s)	1.32	–	0.51	3.96	0.48
	t_r (s)	1.13	–	1.20	1	1.47
	t_{scan} (s)	5.78	–	3.38	8.65	3.74
B2	Precision (%)	100	–	**86.7**	–	100
	TPR (%)	100	–	100	–	100
	t_f^{opt} (s)	1.75	–	2.5	–	2.5
	t_m (s)	2.27	–	6.17	–	3.69
	t_r (s)	2.25	–	1.41	–	1.23
	t_{scan} (s)	8.7	–	14.17	–	10.07
B3	Precision (%)	–	**93.75**	–	100	–
	TPR (%)	–	100	–	100	–
	t_f^{opt} (s)	–	2	–	2.5	–
	t_m (s)	–	2.07	–	3.76	–
	t_r (s)	–	6.25	–	5.65	–
	t_{scan} (s)	–	14.8	–	17	–
B4	Precision (%)	–	–	100	–	
	TPR (%)	–	–	100	–	
	t_f^{opt} (s)	–	–	2.5	–	–
	t_m (s)	–	–	6.5	–	–
	t_r (s)	–	–	1.31	–	–
	t_{scan} (s)	–	–	14.5	–	–

correctly selected and the percentage of non-targets that were incorrectly selected. In this case average precision and TPR (89.6% and 94.8% respectively) were worse than in Exp1.

Table 8 shows the results obtained in Exp3. The average precision and TPR considering all the participants were 86.7% and 97.8% respectively. Fig. 10 shows details of some signals captured during the experiment. For each subject, the absolute value of velocity is shown in blue, the centroids in red, the output of the FSM layer in green, the switch state in black and the state (color) of the rocket in cyan. A rising edge in the state of the rocket signal sets the time the participants can perform a movement. The rising

Table 7
Data collected from group B participants in experiment Exp2. It includes percentage of targets correctly and incorrectly selected.

Subject	**Parameter**	**Tablet**
B1	Precision (%)	100
	TPR (%)	100
	Target (%)	100
	Non Target(%)	0
B2	Precision (%)	78.2
	TPR (%)	90
	Target (%)	62.5
	Non Target(%)	25
B3	Precision (%)	80
	TPR (%)	89
	Target (%)	87.5
	Non Target(%)	12.5
B4	Precision (%)	100
	TPR (%)	100
	Target (%)	100
	Non Target(%)	6.25

Table 8
Data collected from group B participants in experiment Exp3. Δt_l is the time difference in detecting the movement between the switch-based system and our proposal. A positive value shows the proposal was faster.

Subject	**Parameter**	**Tablet**
B1	Precision (%)	88.6
	TPR (%)	91.2
	Δt_l (s)	0.13
	t_m (s)	3.5
B2	Precision (%)	58.2
	TPR (%)	100
	Δt_l (s)	0.15
	t_m (s)	6.1
B3	Precision (%)	69.5
	TPR (%)	100
	Δt_l (s)	0.43
	t_m (s)	3.7
B4	Precision (%)	100
	TPR (%)	100
	Δt_l (s)	-0.72
	t_m (s)	2.6

edges of the switch signal and FSM output set the time the switch and the proposed architecture detected such a movement. The average time delay, Δt_t, is also drawn for some subjects and shown in Table 8. For three out of four participants the new architecture was slightly better than the switch in detecting the movement, whereas for the other subject, the switch was significantly better than our system. The average of Δt_t for all participants was -0.03 s Table 8 also shows the average of the movement duration t_m for each subject calculated as explained in Section 4.2.1.

Finally, Table 9 shows the results of the survey.

6. Discussion

6.1. The proposed architecture

6.1.1. Group A

The four participants in group A carried out overall 420 voluntary movements of which 417 were correctly identified. This makes 417 true positives, 3 false negatives and no false positives. The number of errors was very low (<1%) and there were no false positives which led to a precision score of 100%.

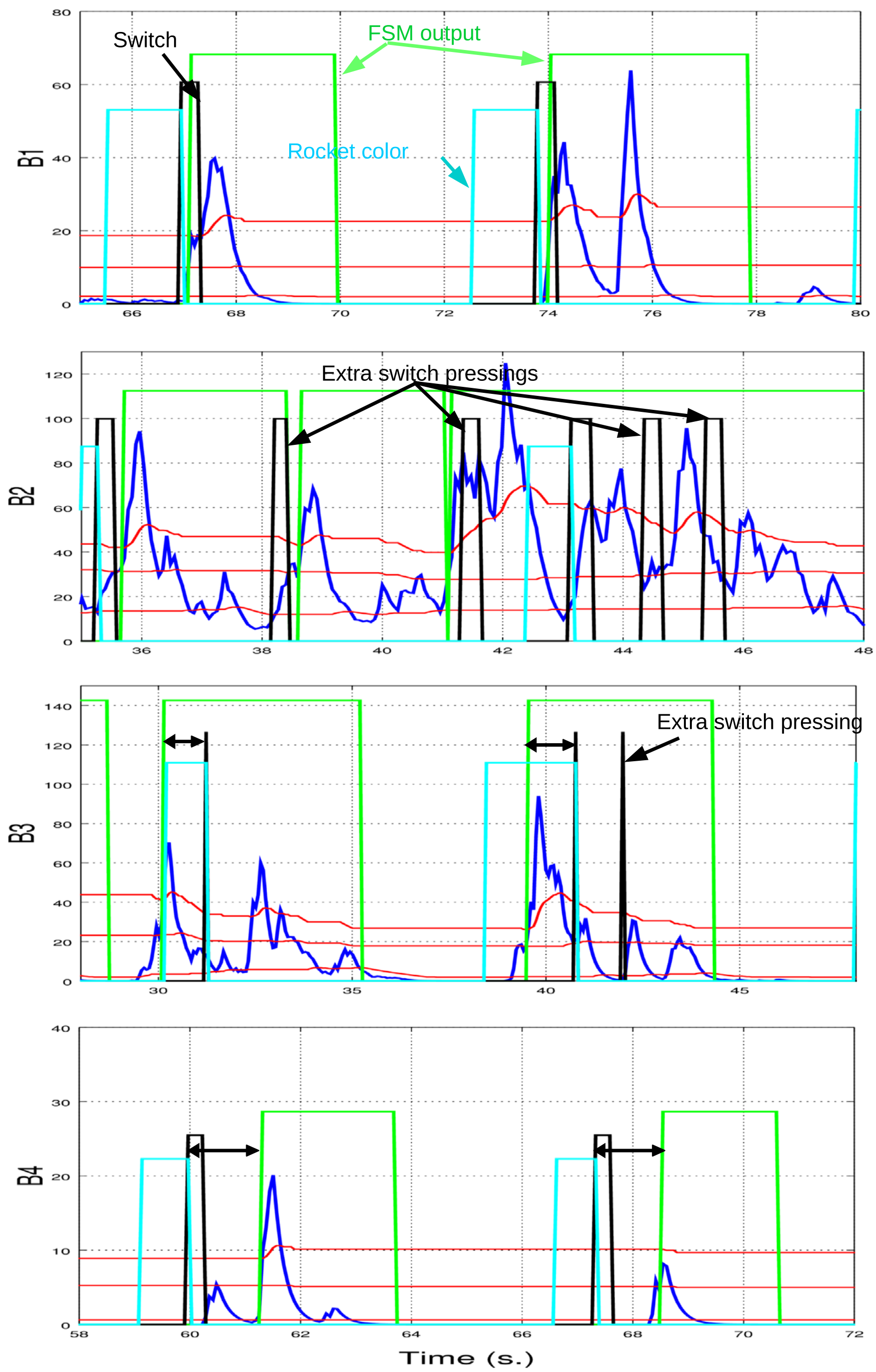

Fig. 10. Signal samples collected in Exp3. The absolute value of the movement velocity is shown in blue, the centroids positions in red, the switch state in black, the output of the FSM layer in green and the color of the rocket in cyan. A change from low to high in the rocket signal sets the time that the participant could start a movement. In some pictures the delay between the keystroke and the movement detection for the proposed architecture is shown. The new architecture shows slightly better latency times for B1-B2, it is faster for B3 and, in general reduces the number of false positives. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The timeout t_f results varied depending on sensor, position and subject. In general, for all participants, this time was around 1 s without losing performance in movement prediction. This parameter is very important because the lower the t_f, the greater the communication ratio with this system. However, as t_f drops, the time to block involuntary movements following intentional ones is shorter, and the probability of false positives increases.

In Molina et al. (2011b) the authors proposed a model to estimate the wpm (words per minute) ratio by using a virtual keyboard knowing only the t_{scan}. According to that study and extrapolating data from our group A participants, the highest ratio of 1.11 wpm would be obtained by participant A1 with the flex sensor over the finger. The lowest one of 0.50 wpm would be obtained by participant A2 with the same sensor on the middle finger. An average around 3.26 s for t_{scan} for all participants would have given an average of 0.59 wpm.

Results in Fig. 9 show that there were differences among the values of t_{scan} obtained depending on the type of sensor and its position. Statistical analysis using a data set of 4×7 t_{scan} samples (Subject x Sensor placement), where t_{scan} is the output variable (normally distributed – Shapiro test $p = 0.85$) and the sensor placement is the treatment (Bartlett test $p = 0.17$ suggests

Table 9
Survey results.

Survey questions	Subject	Answer
Which part of the body?	B1	Leg
	B2	Leg
	B3	Hand
	B4	Leg
Do you prefer this system ?	B1	Yes
	B2	Yes
	B3	No
	B4	Yes

homocedasticity), allows us to apply ANOVA (F=0.66, p=0.68). This shows that the position does not influence t_{scan} significantly. However, the low number of users in the study limits the validity of the statistical analysis.

A comparison between types of sensor gave t_{scan} averages of 3.27 s and 3.25 s for the accelerometer and flex respectively, which showed there was no difference between using either device. In fact, users A2 and A4 obtained better performances with the accelerometer, whereas the flex sensor was used better by the other participants.

6.1.2. *Group B*

To begin with, we shall discuss the results of group B case by case. We will look at its global results at the end of this section.

Participant B1 performed quite well and she had no false negatives or positives in experiments Exp1 and Exp2. Her reaction time t_r was around 1.2 s on average which was similar to the ones obtained by participants in group A. Her movement time, t_m, showed some variability depending on the position and type of sensor used. The best results, similar to the ones for people without disabilities, were obtained when the accelerometer was placed on her leg (0.48 s) or head (0.51 s). The worst results were obtained when the flex sensor was placed on her knee (1.32 s) or the accelerometer on her hand (3.96 s). When it was on her knee, she did not flex or extend the joint, she just moved her leg up and down. This movement was enough for the flex to detect the user action but the amplitude of the signal was very low compared to the signal coming from flexion and extension. This implies that the signal peaks associated to intentional movements were quite close to the baseline noise which made the classifier increase the number of movement samples (M samples) and, in turn, extend the range of motion detection. This also explains the high value of t_f. When the accelerometer was placed on her hand, the highest t_m value was obtained because that was the part of her body which showed most uncontrolled movements. Although this girl developed her own strategy to stop her hand movement against her belly it was not enough to reduce this time to similar values obtained with other parts of her body. Participant B1's best results for t_{scan} were obtained with the accelerometer on her head, even though she can not control the position of her head properly, and this made it difficult for her to keep the computer screen in her visual field. However, she preferred to use this system with the accelerometer on her leg which gave similar results.

Participant B2 performed Exp1 perfectly with the accelerometer or flex sensor on her knee (preferred position) but precision decreased with the accelerometer placed on her head. She has bad control of the vertical position of her head having lots of uncontrolled and swinging movements. This explains the high t_m values that were obtained. Results of t_f showed difficulty to stop moving and is an indicator suggesting this subject will be prone to committing false positives with this system unless t_f is increased. Reaction time, t_r, was also high because, after starting a movement, the whole body moved and the computer screen went out of her visual field. This partly explains why the percentage of target pictograms on the tablet was low in experiment Exp2 while at the same time the percentage of non-target ones was high. Moreover, the large number of involuntary movements (see Fig. 10) led to false positives and selecting non-target pictograms as well.

Subject B3 has good control of her right arm but performs movements slowly, sometimes swinging her arm; this explains the high t_m and t_f values. Different reasons made the reaction time be high. On one hand the participant either got distracted several times and/or she did not understand the dynamic of the experiment very well, which, in turn, may explain why she rejected this access method preferring her traditional one. On the other hand, she performed movements very slowly so it took longer for the system to recognize a intentional movement from the moment she started it. Even with the flex sensor, the reaction time was slightly higher than with the accelerometer because she tried to perform movements with her arm straight and rigid, delaying the detection of the movement. This may also be the reason this person preferred the accelerometer sensor placed on her hand. The penalty in precision was due to slow movements with swinging and this was why she obtained false positives and negatives in Exp2, selecting non-target pictures on the tablet and failing to select the target ones.

Participant B4 has good control of her head, and in the experiment she performed short and fast movements, which were correctly classified by the system, usually followed by slow swinging. The acquired signal shows small peaks over a very noisy baseline. As in the cases explained above, this swinging made the t_m and t_f high. She performed Exp2 almost perfectly. Precision and TPR were at the maximum, all the targets were correctly selected with very few non-targets being chosen. This girl preferred to use this system even though she is to typewriting with a handwand.

As for the type of sensor, it seems that people with CP find it easiest to use the accelerometer to access a computer with this system. This is because the accelerometer is more sensitive to gross motion than the flex sensor which needs more complex movements that are difficult to be performed by people with CP who took part in the experiments.

A final comment concerns the clothing used to carry the sensors. It is not easy to put gloves on people with CP who usually have atrophied joints and very stiff muscles. In Simone et al. (2004) a sensor sleeve holding the flexometer is attached to the back of each finger with toupee tape to locate the sensor directly over the joints and leave the joints free of adhesive that would otherwise restrict movement. One important finding in that study is that when the fingertips are uncovered it is much easier for subjects to forget that the sensors are there because sensory function is not masked. An additional advantage is that this tape could also be used to extend movement detection to other uncovered parts of the body, such as for example the shoulder, neck Al-Rahayfeh and Faezipour (2014), etc.

6.1.3. *Group A vs. Group B*

For group B participants, the time t_m was on average greater ($\approx$ 3 s) than the average obtained by group A (less than 1 s for all participants). The difficulty these participants had moving and their involuntary movements explain these results. Reaction times t_r were also greater for this group because participants found it difficult to keeping the screen in the visual field or paying attention when doing the experiment. Their swing movements could pose a problem for the classifier by getting too close to the second one and increasing the number of non-movement samples (NM samples) and, consequently, the number of false positives.

6.2. Mechanical switch vs. proposed system

It would seem plausible to think that the accelerometer will always detect the approaching of the limb towards the switch before it can be pressed. Therefore, the latency of the proposed system will be always lower than the switch. However, experimental results did not confirm that assertion. We found that the latency in detecting the movement was better for 3-out-of-4 participants with disabilities using the proposed architecture. To explain this we have to take into account several factors. On one hand, there is a delay in processing data throughout the layers (we can see this delay in the time elapsing between the switch pressing and the movement velocity in Fig. 10). The main source of delay lies in the filter layer which introduces a delay proportional to the length of the low pass filter (Table 1 summarizes the global delay according to the chosen parameters). On the other hand, the latency also depends on how the user performs the movement and how far away the switch is placed from the limb or head. For example, subject B2 performs slow movements and she has to move her hand at a relatively long distance compared to her peers. This is why the proposed system is clearly better for her (on average 0.43 s faster than the switch). In contrast, participant B4 only had to move very slightly her head to reach the switch. For her the mechanical switch was much faster than our proposal. For the other participants, B1 and B2, the mechanical switch delay was slightly higher on average.

Bad limb control leads to repeated and unintentional hitting the switch. We can see these extra switchings in participants B2 and B3 in Fig. 10 and how the proposed system deals with them as part of the same movement. As Table 8 shows, the precision of the mechanical switch is slightly lower (86.7%) on average than the one obtained in Exp2 (89.6%) and in Exp1 (100%). As for TPR, the switch obtained a value of 97.8% in average, slightly better than in Exp2 (94.8%) and slightly worse than the one obtained in Exp1 (99.3%) with our proposal.

For participant B1, the proposed system was highly beneficial. The precision and TPR was higher (100%) and the time to perform a movement lesser (t_m=0.48 s versus 3.5 s with the switch). Participant B2, who showed rather uncontrolled movements, obtained better results with the accelerometer placed on her leg than with the switch (precision=86.7% in Exp2 and TPR=100% versus 58.2% and TPR=100% in Exp3). Trying to press a switch seemed to produce more uncontrolled movements than with just the accelerometer. This explains why the time t_m with the switch was somewhat higher (t_m = 6.1 s vs. 3.69 s). Subject B3 got slightly better results with the accelerometer, because the precision was better (100% in Exp1 and 80% in Exp2 versus 69.5% in Exp3), although the TPR was similar (100% in Exp1, 89% in Exp2 versus 100% in Exp3) and the time to perform a movement very similar (t_m=3.76 s versus 3.7 s with the switch). Only the proposed architecture's latency of movement detection alone (0.43 s faster than the switch) could have shifted the performance towards our proposal. However, this subject preferred to go on using the traditional method of access. The subject who obtained best performances with both systems was participant B4 (100% in precision and TPR). For her the switch was faster in detecting the movement and the duration of the movement. t_m = 2.6 s, was also shorter than in our proposal (6.5 s). To explain such a big difference in t_m we had to watch the video recorded to realize that Exp1 or Exp2 were performed in slightly different conditions to Exp3. In Exp3, the wheelchair had a headrest which reduced the head swinging after a movement, thereby reducing the interval of time associated to a movement, and avoiding a noisy baseline in the signal captured (Fig. 10).

Finally, we would like to highlight the comments of participants' caregivers about this new system which has been used for several months. They see it as being faster than the mechanical switch, allowing people with disabilities to make fewer errors without needing to make a big effort to performing movements, while at the same time letting them use a computer longer. Moreover, when people have lots of uncontrolled movements, not having to strike a mechanical switch prevents her/him from hurting themselves the limbs, neck, face, etc.

7. Conclusions and future work

In this work we developed a software architecture to translate movements into switch events. For experiments this architecture was implemented on an Arduino platform and two specific hardware shields were designed to amplify flex sensor and accelerometer signals. This five-layered architecture contained low-pass and derivative filters, a classifier that was continuously adapting to the intensity of user's movements and an finite state machine that generated the event and contained a timer to prevent involuntary movements from triggering false positives.

Most of the participants in this study obtained good results, better than with the traditional switch, even though the number of trials was low and they did not have much time to get used to the new system. It is noteworthy that 3 out of 4 of the participants with disabilities preferred this system to their traditional computer access device.

Further work must be carried out to make the system more efficient for people who show swinging, lots of uncontrolled movements or perform them slowly.

Finally, it seems that people with CP found it easier to use the accelerometer to access a computer than the flex sensor.

Conflicts of interest

There is no conflict of interest.

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