PhD Program in Bioengineering and Robotics

INNOVATING CONTROL AND EMOTIONAL EXPRESSIVE MODALITIES OF USER INTERFACES FOR PEOPLE WITH LOCKED-IN SYNDROME

by

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To my parents Jean and Nathalie Larradet

DECLARATION

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 65,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

Fanny Larradet
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ABSTRACT

Patients with Lock-In-Syndrome (LIS) lost their ability to control any body part besides their eyes. Current solutions mainly use eye-tracking cameras to track patients' gaze as system input. However, despite the fact that the interface design strongly impacts the user experience, only a few guidelines have been used so far to ensure an easy, quick, fluid and non-tiresome computer system control for these patients. On the other hand, the emergence of dedicated computer software has been greatly increasing the patients' capabilities, but there is still a great need for improvements as existing systems still present low usability and limited capabilities. Most interfaces designed for LIS patients aim at providing internet browsing or communication abilities. State of the art augmentative and alternative communication systems mainly focus on communication based on words to form sentences without considering the need for emotional expressions inextricable from human communication.

This thesis aims at exploring new types of system control and expressive modalities for people with LIS. Firstly, existing gaze-based web-browsing interfaces were investigated. Page analysis and high mental workload appeared as recurring issues with common systems. To address these issues, a novel user interface using an innovative menu control reducing eye movements and therefore fatigue was designed and evaluated against a commercial system. The results suggested that it is easier to learn and to use, quicker, more satisfying, less frustrating, less tiring and less prone to error. The mental workload was greatly diminished with this system. Other types of system control for LIS patients were then investigated in particular using a gaze-controlled game. It was found that galvanic skin response may be used as system input and that stress related bio-feedback helped lowering mental workload during stressful tasks.

Improving communication was one of the main goals of this research and in particular emotional communication. A system including a gaze-controlled emotional voice synthesis and a personal emotional avatar was developed with this purpose. The assessment of the proposed system highlighted its capability to enhance dialogs and to allow emotional expression. Enabling emotion communication in parallel to sentences was found to help with the conversation. Automatic emotion detection seemed to be the next step toward improving emotional communication. Several studies established that physiological signals relate to emotions. The ability to use physiological signals sensors with LIS patients and their non-invasiveness made them an ideal candidate for this study. One of the main difficulties of emotion detection is the collection of high intensity affect-related data. Studies in this field are currently mostly limited to laboratory investigations,

using laboratory-induced emotions, and are rarely adapted for real-life applications. A virtual reality emotion elicitation technique based on appraisal theories was proposed here in order to study physiological signals of high intensity emotions in a real-life-like environment. While this solution successfully elicited positive and negative emotions, it did not elicit the desired emotions for all subjects and was therefore, not appropriate for the goals of this research. Collecting emotions in the wild appeared as the best methodology toward emotion detection for real-life applications. The state of the art in the field was therefore reviewed and assessed using a specifically designed method for evaluating datasets collected for emotion recognition in real-life applications. The proposed evaluation method provides guidelines for future researcher in the field. Based on the research findings, a mobile application was developed for physiological and emotional data collection in the wild. Based on the appraisal theory, this application provides guidance to users to provide valuable emotion labelling and help them differentiate moods from emotions. A sample dataset collected using this application was compared to one collected using a paper-based preliminary study. The dataset collected using the mobile application was found to provide a more valuable dataset with data consistent with the literature. This mobile application was used to create an open-source affect-related physiological signals database.

While the path toward emotion detection usable in real-life applications is still long, we hope that the tools provided to the research community will represent a step toward achieving this goal in the future. Automatically detecting emotion could not only be used for LIS patients to communicate but also for total-LIS patients who have lost their ability to move their eyes. Indeed, giving the ability to family and caregiver to visualize and therefore understand the patients' emotional state could greatly improve their quality of life.

This research provided tools to LIS patients and the scientific community to improve augmentative and alternative communication, technologies with better interfaces, emotion expression capabilities and real-life emotion detection. Emotion recognition methods for real-life applications could not only enhance health care but also robotics, domotics and many other fields of study.

A complete system fully gaze-controlled was made available open-source with all the developed solutions for LIS patients. This is expected to enhance their daily lives by improving their communication and by facilitating the development of novel assistive systems capabilities.

CONTENTS

LIST OF ABBREVIATIONS

AAC	Augmentative and alternative communication
Acc	Accelerometer
ALS	Amyotrophic Lateral Sclerosis
ANS	Autonomic Nervous System
AoE	Area of action
AP	Airway pressure
BP	Blood pressure
BPC	Blood pressure cuff
BVP	Blood volume pressure
ECG	Electrocardiogram
EDA	Electrodermal activity
EEG	Electroencephalogram
EMA	Ecological momentary assessment
EMG	Electromyogram
EMSR	Emotion mood and stress recognition
EOG	Electrooculogram
F	Force
GP	General public
GSR	Galvanic skin response
GUI	Graphical user interface
GY	Gyroscope
HR	Heart rate
HRV	Heart rate variability
IBI	Interbeat interval
L	Load
LIS	Locked-In Syndrome
MA	Magnetometer
PPG	Photoplethysmogram
PS	Preliminary study
R	Research
Resp	Respiration
SC	Skin conductance
SP	Several products
SpO2	Peripheral oxygen saturation
ST	Skin temperature
T	Torque
TEMP	Temperature
UD	User dependent
UID	User independent
UP	User-picked
W	Weight

1

INTRODUCTION

1.1 Motivations

Amyotrophic Lateral Sclerosis (ALS) is an “idiopathic, fatal neurodegenerative disease of the human motor system”, which can lead to a locked-in syndrome (LIS) [Kiernan et al., 2011]. LIS is a medical condition “characterized by quadriplegia and anorthic with preservation of consciousness. Patients retain vertical eye movement“ [Jacob, 1995]. LIS patients’ abilities are limited, especially in terms of computer system control and communication. Their remaining ability to control their eyes is often used as input for user interfaces thank to eye-tracking technology. However, few guidelines are available to build gaze-controlled interfaces and other types of system input may be investigated. When it comes to communication, most patients use spelling boards (Fig. 1.1) or simple blinking codes in order to express themselves. Several systems provide adapted communication modalities using gaze-controlled software systems. However, existing dedicated systems usually focus on word spelling not taking into consideration that human-human communication goes way beyond words. It also includes actions such as face expressions, hand gestures, para-verbal signals and physical contacts. While written expressions like emoticons are commonly used in Computer-Mediated Communication (CMC) to transfer those emotions, it is not a naturalistic way to express emotions and it is not adapted to text-to-speech communication systems used by ALS patients. Considering this context, the main goal of this research is to build novel modalities of technologically mediated communication designed to improve ALS patients’ quality of life. Such solutions must provide novel interfaces adapted to LIS patients capabilities and provide them a more extensive, and complete communication systems. It should improve their ability to express emotions as well as words. To further explore this goal, this research also aims at providing tools for research in emotion detection from physiological signals for real-life applications.

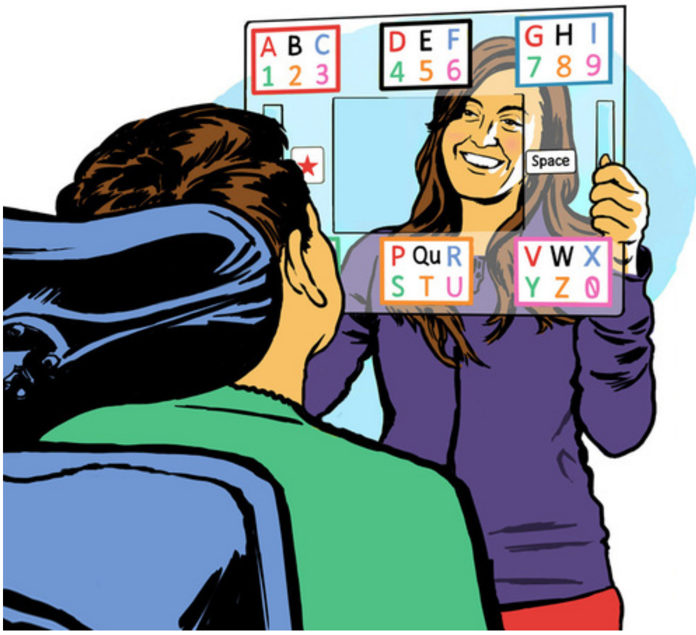


Figure 1.1: E-TRAN letter board. Image Courtesy of Low Tech Solutions.

1.2 Hypothesis

Based on the previously presented motivations, two hypothesis were raised:

- Novel interface designs can increase user experience.
- Emotion expression can improve the communication abilities of LIS patients

1.3 Approach

In order to improve interface control for LIS patients, available inputs were investigated, in particular, eye-tracking solutions and physiological signals. The extent of their usability and limitations were established. A gaze-controlled speaking tool was then developed aiming at expressing emotions as well as words. While selecting the desired emotion was possible, studying the possibility of an automatic detection seemed like the next step toward an improved communication experience. A virtual reality (VR) game aiming at inducing emotion for physiological signal data collection was developed. However, the limits of induced emotion studies seemed too important and a decision to move toward real-life emotional data collection was made for investigations in ecologically valid settings. The possibility of detecting real emotions better meets the end needs of the research. The state of the art in terms of emotion recognition outside the laboratory and emotion recognition for real-life application was established. Only few studies investigated emotion recognition outside of the laboratory and this research line remains at an early stage. Considering that no emotionally labelled physiological signal dataset in the wild were available in open-access, a data collection had to be conducted. In order to comprehend the challenges of data collection in the wild, a preliminary study was carried out using standard paper-based methods. It showed great flaws in user-labelled data making the collected data nearly unusable. It then seemed necessary to develop a better way of collecting data to acquire the ground truth. To do so, a mobile application was developed using both the guidelines found in the literature and the lessons learnt from the preliminary study. A data collection using the mobile application confirmed the validity of the developed mobile application compared to the paper-based solution. The application was then used to collect a great number of data in order to create an open-source dataset available to researchers desiring to pursue this topic. Finally, a complete system fully gaze-based was designed for LIS patients including all developed tools.

1.4 Contributions

This thesis aims at improving user experience regarding both computer system control and communication for LIS patients.

1.4.1 Improving control

Two types of system controls were considered. First of all, the limitations of the classic and most commonly used computer system input was studied: gaze. The guidelines for gaze-based interface designs are limited. The impact of internet browsing interfaces on capabilities, speed and mental workload was studied. A novel design was developed using an innovative menu control reducing eye movements and therefore fatigue.

Secondly, other types of inputs were explored. Especially, voluntary physiological signal alteration based on Galvanic Skin Response (GSR). GSR-based control associated with gaze-based control were used as inputs for a video game. It was found that GSR could be voluntarily controlled by users and successfully used as computer system input. Additionally, bio-feedback display was found to lower mental workload in stressful environments.

1.4.2 Improving communication

A classic gaze-controlled keyboard interface with word autocompletion was first developed. In order to improve communication, the later was enhanced to provide emotion communication in addition to words. The interface provides emoticon selection managing an emotional avatar as well as a emotional voice synthesis. The emotional system was found more helpful for communication compared to a classic system. Additionally, the possibility of an automatic emotion detection system was considered to improve such system. A VR-game was developed successfully inducing positive and negative emotions on subjects. Tools helping research towards emotion detection in real-life settings were developed. Notably a review of existing works on emotion stress and mood recognition outside of the laboratory for real-life applications, and the creation of new method for assessing these studies. In order to improve the quality of self-report collection in the wild, a mobile application was created to help the user provide ground-truth emotion labels. The application was then used to create a large dataset of emotionally-labeled physiological signals in real-life settings.

1.5 Overview of the Thesis

The thesis is organized as follow: Chapter 2 presents research contributions regarding user interfaces control. Chapter 3 focuses on emotion communication systems. Chapters 4, 5 and 6 discuss emotion detection for real-life application in greater details. Chapter 4 investigates emotional data collection methodologies. Chapter 5 focuses on alternative data collection methods in the laboratory while Chapter 6 presents a novel solution for emotion detection for real-life application and the database created using this solution. Chapter 7 presents the resulting system made available to LIS patients. Finally, conclusions and possible future research directions are provided in Chapter 8.

2

IMPROVING USER INTERFACES CONTROL

Eye-tracking technologies greatly assist the interactions and communication acts of motor-impaired people, specially of those only able to control their ocular movements (Locked-In Syndrome, LIS, as in late stages of Amyotrophic Lateral Sclerosis, ALS) [Kiernan et al., 2011]. It allows, for instance, to select letters on a screen to compose a message in an intuitive fashion [Söderholm et al., 2001]. However, eye-tracking technologies can show limitations in terms of user experience [Majaranta and Räihä, 2002]. For instance, it can increase users' mental workload due to repetitive ocular movements in demanding tasks [Yuan and Semmlow, 2000]. It can lead to users' frustration, and to a degradation in the engagement and motivation in using eye-tracking. Thus, it is necessary to design novel solutions improving the user experience with particular attention to its aspects related to users' workload. Other types of input may also be investigated to extend the range of LIS capabilities.

2.1 Design and Evaluation of an Open-source Gaze-controlled GUI for Web-browsing

Few ocular control modalities have been explored so far, with a dearth of guidelines to build gaze-controlled systems [Majaranta, 2011]. In particular, most gaze commands are based on dwelling [Jacob, 1995] (activating a UI item when the user looks at it for a certain time - dwell time) or on eye gestures [Porta and Ravelli, 2009] (e.g., looking from left to right). Gaze control often represents the LIS people's sole interaction method, thus it is essential to make it easier, quicker and more efficient. The interaction mechanic of the system should, therefore, avoid inducing actions known to be tiring such as repetitive saccadic eye movements [Yuan and Semmlow, 2000].

With the purpose of increasing LIS people's web-surfing experience, this section presents an open-source internet browser design based on eye-tracking. It promotes a way of quickly controlling the browser while imposing minimal screen clutter and requiring minimal eye movements. The interface provides the user with full freedom to control any website, generally including the ones not specifically designed for people with disabilities. Here, the usability, user experience, and performance of the proposed browser were compared to those of a typical eye-tracking Graphical User Interface (GUI): the default configuration of The Grid 3 [ThinkSmartBox, 2011]. The new open-source system is referred as SightWeb. It can be freely downloaded with technical documentation [Larradet, 2018].

2.1.1 Internet browsing control modalities

Only solutions proposed by dedicated gaze-controlled internet applications are discussed here such as The Grid 3 [ThinkSmartBox, 2011] rather than systems available to control a complete operating system such as Optikey [Sweetland, 2015].

The main functions for internet browsing are link selection, scrolling and text typing. In the case of common accessible and gaze-controlled web-browsers such as The Grid 3, links and buttons are extracted from the page by the system. They can then be selected using different techniques. Side buttons might allow to travel from link to link or a menu might contain all links displayed as buttons [ThinkSmartBox, 2011]. Many solutions consist in gazing at the desired link. An increased precision might be done by progressively zooming in the gazed area [Menges et al., 2017] or by confirming the desire to click on a specific link through color coding [Kondaveeti et al., 2016]. Other methods might include gaze gesture such as performing an upside then downside gaze movement [Porta and Ravelli, 2009].

To perform scrolling, existing solutions include side buttons [ThinkSmartBox, 2011] that might trigger an additional speed selection menu [Porta and Ravelli, 2009]. Those methods do not provide contextual scrolling of specific areas and therefore would not be able to deal with a website containing several windows with several scroll bars, such as the one in Figure 2.2.a. Additional methods allow to contextually scroll an area by looking at the corner of it [Menges et al., 2017].

When it comes to text input, most existing solutions require manual trigger of the keyboard using side buttons [ThinkSmartBox, 2011]. Gazable buttons added to the top of the page when textfields are detected represent another solution found in the literature [Menges et al., 2017] (Fig. 2.1). However, this solution occludes the page and might induce erroneous selections. Displaying the keyboard presents a choice between providing comfortable size buttons [Menges et al., 2017] or allowing the user to visualize the page while writing by diminishing the size of the keys [ThinkSmartBox, 2011]. The first solution however prevents from modifying an existing text (e.g., a draft email), and viewing text proposals (e.g., Fig. 2.2.c).

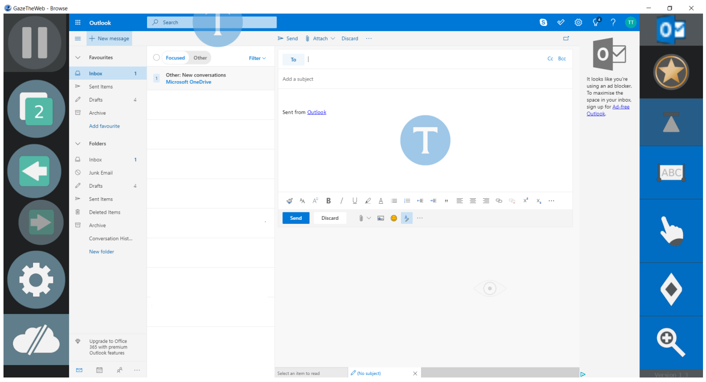


Figure 2.1: Gaze The Web interface, example of gazable buttons for text input

An important limitation for most of the previously cited techniques is the need for page analysis. Indeed, the systems must know where the links are in the page, what is a text-field, what is scrollable. Because of rapidly changing web technology, such system should be frequently updated to detect which UI items are clickable or can be written in. It is risky and challenging to use page analysis in order to provide functionalities for actions as an oversight or a fail to upgrade might make the page features inaccessible.

Finally, most gaze-controlled internet applications include side buttons which require constant movement back and forth from the action buttons to the web view. This motion could cause fatigue [Yuan and Semmlow, 2000]. Such buttons should therefore be limited as much as possible. Next subsections will present SightWeb in details and compare its design with The Grid 3, notably in terms of speed, appreciation, eye movements and screen usage.

2.1.2 GUI design approach

The ideal gaze-controlled internet browser must satisfy several requirements. First of all, it needs to be quick to use (high ‘action-speed’) and have a minimally invasive screen-space usage. It should be able to understand users’ actions without confusing their natural eye movements with a command [Jacob, 1993]. In terms of gaze detection, several solutions are available for a great range of prices (increasing with precision). However, financial accessibility is a priority to provide systems to many patients. Thus, it is necessary to overcome the low control precision and the risk of errors through proper design.

Furthermore, a system that is too demanding in terms of mental workload also induces fatigue [Ahsberg et al., 2000]. Therefore, two factors affecting mental workload should be considered. First of all, the intuitiveness of the system [Naumann et al., 2007] is important so that the user do not have to intensely and repeatedly think about how to use the system to perform actions. Secondly, repetitive eye movements must be minimized as they have a negative impact on mental workload [Yuan and Semmlow, 2000]. Consequently, the design of the proposed system took as requirements the needs to work with low-cost eye-tracking devices, to provide an intuitive interaction paradigm, and to minimize necessary eye movements for control.

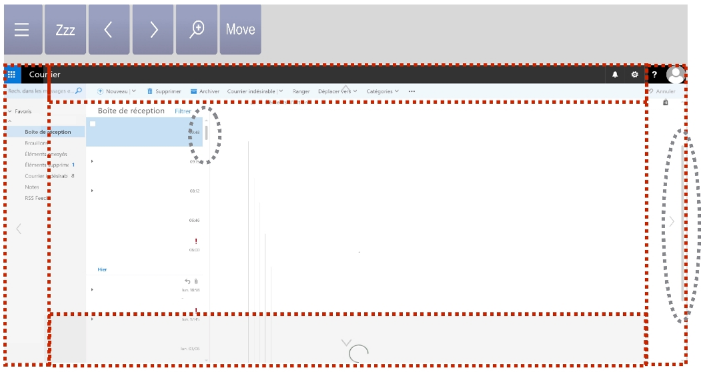
The ideal system would permit a LIS person to perform the same actions as a regular user, such as: clicking on regular buttons, clicking on links, clicking on other items such as form-like items (e.g. drop-down menu, radio buttons), hovering (which includes mouse aspect changes, color changes, and contextual menus opening), scrolling in the case where there are several windows and several scroll bars, e.g. Figure 2.2.a. It is important to be able to update an already written text (modify a draft for example), see the suggestions from the website while writing (Fig. 2.2.c), and be able to select this suggestion.

Lastly, the system needs to stay usable regardless of new web technologies updates. Building a system dependent on knowledge of the web components in the page would need constant system updates to keep it usable. For this reason, the system should not depend on current web technology knowledge and therefore would not need updating.

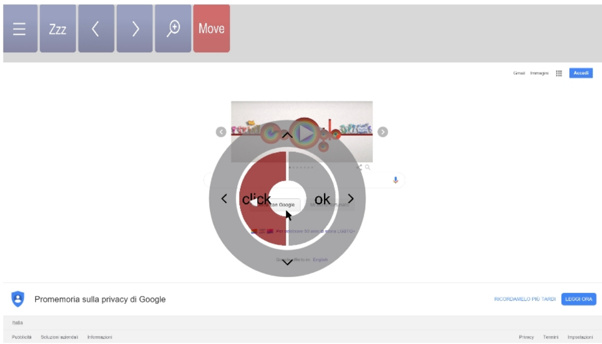
2.1.3 Proposed design

To control any kind of website (including web-based instant messaging and social networking) with general-purpose interfaces, not designed for people with motor disabilities, the control of the cursor was given to the user in the same fashion as a computer mouse. This provides all interface possibilities such as ‘hovering’, which is used in websites, for example, to temporarily display a menu as the mouse passes over specific components, change menu color, or change the mouse aspect. Mouse control also provides the possibility to scroll in specific areas, in the case of websites containing several screen parts with several scrolls (Fig. 2.2.a), or clicking on items that are not buttons or links such as dropdown form options.

For the general aspect of SightWeb (Fig. 2.2), the size of the browser itself was maximized and, therefore, the number of buttons on the main page were greatly limited. At the top, 6 buttons are available to the user to control the system. Firstly, a menu button; it opens a menu to allow user customization of dwell times. The second button puts the system into ‘sleep mode’, which allows the user to look at the page or simply rest without worrying about unwanted button clicks. The next two buttons are used to go backwards or forwards a page while the following button zooms the page. The last button allows control of the mouse and therefore the performance of actions.
In the browser’s page itself, 4 semi-transparent scrolling buttons are placed on each corner of the page (Fig. 2.2.a). Looking at a corner of the page will scroll it in the desired direction. In case of a multiple window page, the area of the page containing the mouse will be scrolled. A classic dwell time control was implemented for all menu buttons. The dwell times may be changed by the user in the customization menu (Fig. 2.3).



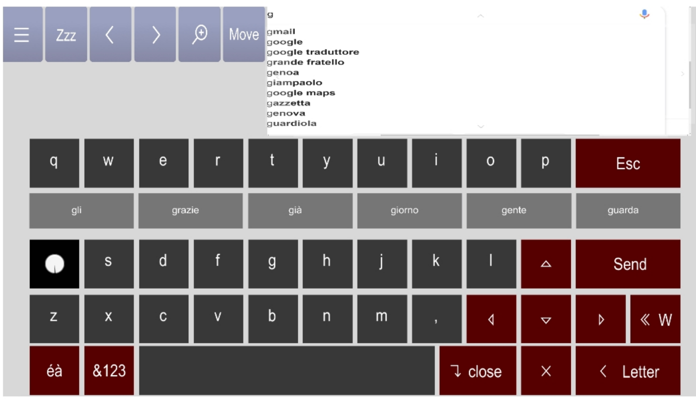
a) General aspect of SightWeb, with scrolling buttons (here highlighted with dotted red squares) and a dual scroll website (here highlighted with dotted grey ellipses).



Action buttons (for clicking and fixing the mouse in position)

Mouse position adjustment buttons

b) Sightweb's temporary radial menu.



c) Sightweb's keyboard and text proposal from the page

Figure 2.2: General aspect of SightWeb.

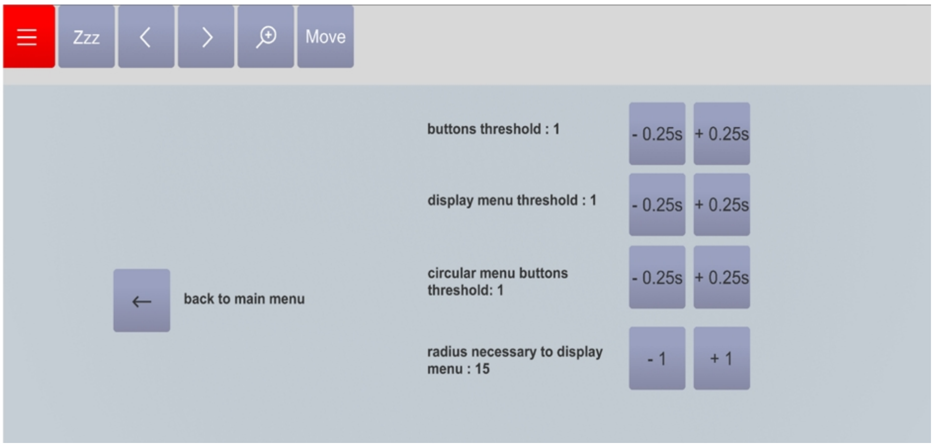


Figure 2.3: SightWeb customisation menu

The system first opens the home page selected by the users. The mouse is fixed in the middle of the screen by default. To perform an action, it is needed to look at the 'Move' button for the selected dwell time (default dwell time is set to one second). The Move button will change color according to its state as a visual feedback (Fig. 2.4). Once the 'Move mode' is on (red button), the users may control the computer mouse.

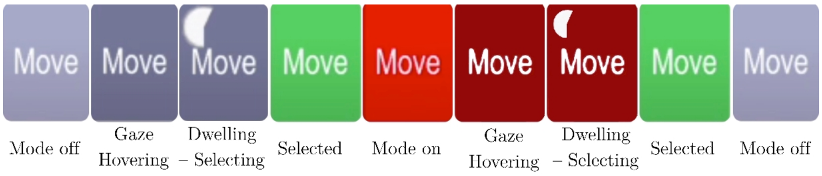


Figure 2.4: Move button states.

When "Move mode" is on, the browser's mouse follows the users' eyes. The gaze position is filtered to create fluid movement and remove jittering. The users can move the mouse around freely for as long as they want, explore the hover actions on the buttons, discover the hover menus etc. They then need to fixate their gaze on the position where they want to do the action. A fixation is established when all the gaze points are within a certain radius (dwell activation radius) during a certain time. Both the radius and the time are customizable by the users in the menu. A large radius will allow for an easy fixation of the mouse but, if too big, could induce false fixation detection and a less precise final position. On the other hand, a smaller radius will have more precise positioning but would be more difficult for users to fixate. Customization is then necessary considering the great differences in the capacities of users.

Once a fixation is detected, a circular menu similar to Huckauf and Urbina [2008] temporarily appears around the mouse (Fig. 2.2.b) and the scroll buttons are temporarily removed from the screen (in case there is not enough space to display the menu around the mouse, it is displayed to the side of the mouse). This solution enables the users to directly access the menu without moving their eye gaze from the side of the screen and,

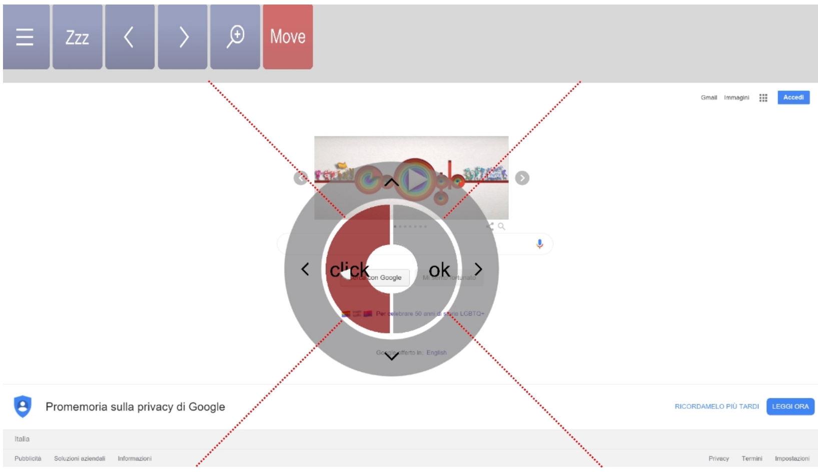


Figure 2.5: Radial menu functionality explanation.

therefore, it helps minimize the required amount of eye movements. The center of the menu is left empty to permit the users to see the mouse and to provide a ‘safe area’ to look at the screen without triggering any actions. Around it, two buttons permit performing a mouse click where the mouse is positioned or to fix the mouse position without performing a click.

The system was designed to work with Tobii 4C [Tobii Group, 2001], an entry level eye-tracker, in order to be a low-cost and easily accessible system. However, using a device for the general public results in an inaccurate gaze position measurement. Furthermore, websites can often have very small buttons, links, and GUI items that necessitate precise actions. For this reason, SightWeb provides a way to readjust the mouse position with high precision to facilitate access to desired UI elements. This is done with buttons built in a radial design (Fig. 2.2.b). Users can look anywhere in the direction of the button in order to select it (Fig. 2.5). This allows a greater range of flexibility in clicking buttons without impacting the visual interface. The menu itself is slightly transparent to not obscure the view.

The ‘Ok’ button permits either the dismissal of the menu or the fixation of the mouse without performing an action. It is necessary for the contextual scrolling and zooming. Indeed, the scroll action (corner buttons) can act in the area where the mouse is positioned. For instance, in Figure 2.2.a, fixing the mouse in the left area and then scrolling would scroll the messages. On the other hand, positioning the mouse in the right area would scroll the selected message. This functionality allows to fix the mouse once and then always scroll from this point of the screen.

The ‘click button’ allows clicking at the position of the mouse. The keyboard is brought up automatically when the users click on a text-field-like item (Fig. 2.2.c). It is detected through the change of mouse appearance and not through the name of the html element making it independent of web technologies updates. The web browser will stay displayed while the keyboard is up so that the users can see the direct effect of their writing in the page, for example propositions from the page (Fig. 2.2.c). The browser is automatically

Actions	SightWeb	The Grid 3
Click on a UI item	• Look at the « Move » button for 1 second • Look at the desired item for 1 second *The menu appears* • [Eventually look at the menu's arrow to more the mouse in a more precise position if necessary] • Look at the « Click » button for 1 second *The menu disappears*	• Look at the « Link up », « Link down », « Previous link » and « Next link » buttons until you reach your link • Look at the « Activate link » button
Write in a textfield	• Click on the textfield (see previous line) *The keyboard automatically appears*	• Navigate to the textfield (see previous line) • Click on the « Keyboard » button
Scroll (only one screen part case)	• Look at the desired scrolling arrow	• Look at the desired scrolling arrow
Scroll (Several screen parts case)	• Look at the « Move » button for 1 second • Look at a point within the desired window for 1 second *The menu appears* • Look at the « OK » button *The menu disappears and the mouse is fixed at the position* • Use the scrolling arrows	Not Possible
Zoom	• Look at the zoom button in the top menu	• Look at the « View » button • Look at the zoom button
Page forward/ backward	• Look at the desired button in the top menu	• Look at the desired button in the bottom menu
Prevent any action	• Look at the « Zzz » button	• Look at the « Zzz » button

Figure 2.6: Steps to perform several actions with both systems.

zoomed on the text field. Pressing the up and down arrow keys in the keyboard allow navigation through the page propositions. Pressing 'send' simulates the 'entry key' and closes the keyboard. The steps to perform actions with each system can be found in (Fig. 2.6)

For the radial menu directional arrows and scrolling buttons, the users will likely repeat the same action in the same direction until the desired position is reached. Therefore, the dwell time is reduced after the first time if the gaze rests on the same button. It is reset to default if the users look anywhere else. The scrolling buttons were not integrated in the radial menu as adding 4 buttons would require a 2-stage menu as in pEYE [Huckauf and Urbina, 2008], increasing the time to do any action. Furthermore, while actions such as clicking are punctual, scrolling may need to be done many times in the same page to read a text for instance. It needed to be more accessible and always present while the radial menu only appears when needed.

This design aims to provide a safe reading zone, with convenient scrolling functionality and a responsive and easy way to control the mouse. The browser was made in Unity with the "Embedded Browser" asset [LLC, 1016]. Unity was used in order for it to be included with the other works presented in this thesis, therefore using only one technology.

2.1.4 Experimental evaluation

To assess SightWeb, it was compared to the default design of the reference product in this class of assistive solutions: The Grid 3 [ThinkSmartBox, 2011] (Fig. 2.7), which was regularly used by the 2 patients involved in this research. Only irrelevant buttons were removed (favorites, back to main menu, web address).

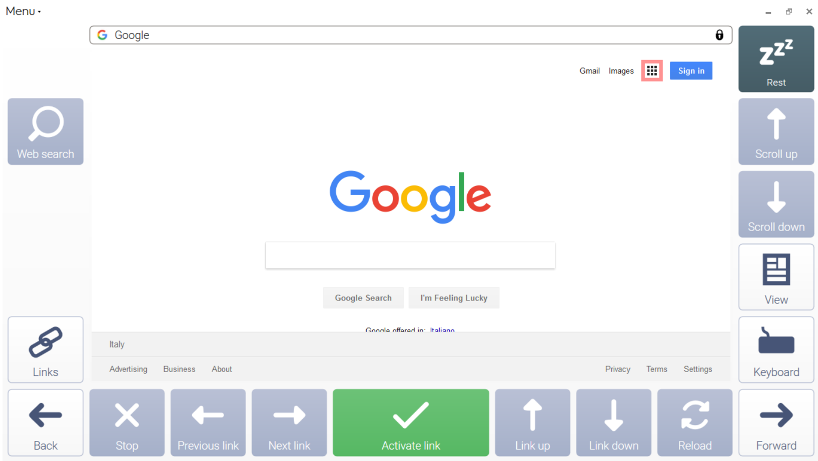


Figure 2.7: The Grid 3.

18 subjects without motor impairments were involved, 14 males and 4 females, according to the IIT ADVR TEEP02 protocol (approved by the Ethical Committee of Liguria Region). They were separated into two equal groups with similar average age (M=29 years, SD=5.9 years for group 1, SD=2.7 years for group 2) and gender balance. The subjects were divided by condition according to a within-group experimental design with 2 factors, each one with 2 levels: task-factor (task 1, task 2), GUI-factor (The Grid 3, SightWeb). The experiment was designed as within-subject as adaptative capabilities greatly differ from subjects to subjects according to preliminary studies. A between-subjects experiment design would therefore be biased or require a great number of participants. None of the participants used an eye tracker before. The preliminary trial period was designed to make sure participants understood its usage. While learning how to use an eye-tracker may take many trials, it was considered here that both systems were tested using the same knowledge and capabilities and therefore comparable. The alternation of which system was tested first prevented the learning of the eye-tracking usability and the learning of the tasks to bias the results.

Each participant accomplished two tasks with each system. Both tasks were achievable by both tools. The first group of participants started the session with The Grid and the other with SightWeb (Fig. 2.8). The first task consisted of searching for a personal page on the IIT website. It was a short and simple task, without complex buttons or actions. The second task was more complex yet very common. It included actions such as drop-down menus and auto-scrolling. It consisted of typing “eyetracker" into Google search, sorting the results by month, going to the “Tobii gaming" page, clicking on the “device/monitor" menu and following the “buy on Amazon" link, going to the reviews and adding the device to the basket.

After signing the informed consent, the subjects were presented the first design (either The Grid or SightWeb, according to the group) and the controls were explained. A demonstration of the system was performed by the experimenter including basic actions

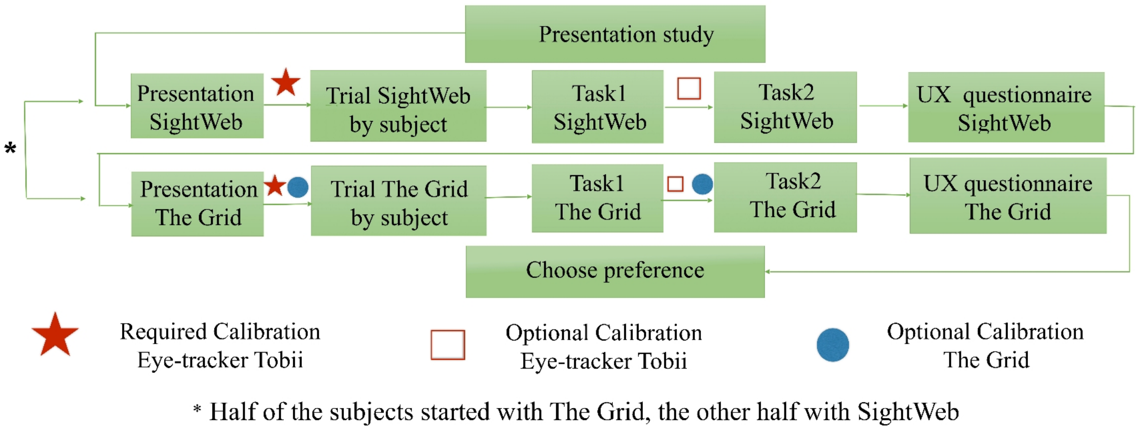


Figure 2.8: Experimental flow.

such as clicking on a desired link, scrolling a page and writing on a text field. The subject then assumed a comfortable position in front of an external monitor equipped with a Tobii 4C eye-tracking device. The participants calibrated the eye-tracker using the Tobii software. This step was repeated as many times as necessary until the calibration was considered successful. The proprietary calibration from The Grid was also used when necessary (i.e. if the user was not able to click on certain buttons). The subject was then asked to reproduce the same basic actions demonstrated by the experimenter. Help was provided if necessary. Once the subject understood the controls of the software, the experimental tasks were performed. Recalibration was performed between tasks, if necessary (e.g., participant moved, software seemed unusable). Questions from the subject were not answered during the tasks unless they were related to the usage of the system itself or to the task. Questions such as “I don’t remember how to scroll" were answered but not questions such as “How do I reach this link, should I click “next link"?"

The subjects were then asked to fill in a user experience questionnaire with 9 statements:

- (q1) My performance required too much time;
- (q2) The task was extremely demanding in terms of mental effort;
- (q3) Controlling the system was easy to learn so I could start using it quickly;
- (q4) Considering all the difficulties I experienced with the control system, the task was frustrating;
- (q5) It was satisfying to use the tool;
- (q6) The system control was easy;
- (q7) The control of the system induced fatigues, stress and discomfort in my eyes;

- (q8) My performance with this system in this task was frustrating;
- (q9) It is easy to make errors with this system.

While traditional questionnaires like SUS and NASA-TLX do not consider gaze control-specific features, this questionnaire was designed according to Barresi et al. [2016] to evaluate the user experience in such conditions. According to preliminary tests with both people with and without motor impairments, default values of 15 pixels (0.4 cm) for the SightWeb dwell activation radius and 1 second for the dwell time were selected. This was the best compromise between accessibility and speed.

For each statement, the subjects were asked to answer using a rating scale from 0 to 100 (0 being "strongly disagree", 50 "neither agree nor disagree" and 100 being "strongly agree"). These Likert-type scales allow for the adoption of many inferential statistical analyses, since they are perceptually similar to visually continuous scales [Jaeschke et al., 1990]. The same steps were then repeated with the second system. When both tasks and questionnaires were completed for both systems, the subjects were asked which system they preferred. During tasks 1 and 2, a separate application was running in the background to calculate the total distance covered by the eyes during the task and the elapsed time. The same experiment was conducted with two people with ALS in the late stages of the disease, with preserved voluntary gaze movements (a 55 year-old male and a 58 year-old female) to assess the system with the intended end-users following the IIT ADVR TEEP03 protocol (approved by the Ethical Committee of Lazio Region 2).

2.1.5 Data analysis and results

All measures (questionnaire scores, times, accumulative eye distances) collected from subjects without motor impairment were analyzed through the Wilcoxon signed-rank test because of a lack of normality in the distributions.

In terms of browser size (only page content, without buttons), on a 34.5cm by 19.4cm screen, SightWeb displayed a 34.5cm x 16cm browser and The Grid 3 a 27cm x 14cm one.

2.1.5.1 User experience questionnaire

The questionnaire showed an overall significant preference of SightWeb compared to The Grid (Fig. 2.9). The system control was found to be easier to learn (W=28.5 - p=0.08) and to use (W=18 - p=0.02), more satisfying to use (W=4 - p=0.004) and less easy to make errors (W=158 - p=0.002). The participants estimated that SightWeb was less demanding in terms of mental effort (W=108.5 - p=0.006), they were more satisfied with their performance (W=0 - $p < 0.001$) and less frustrated (W=113.5 - p=0.02) during the tasks. The participants estimated that their tasks required less time with SightWeb (W=155.5 - p=0.002), which correlated with the actual execution times. Finally, SightWeb induced less fatigue, stress and discomfort in the eyes (W=103.5 - p=0.01), which correlated with the actual accumulated eye distance for the task. Both patients preferred SightWeb to The Grid in all aspects of the questionnaire.

Overall, 16 subjects without disabilities and the 2 patients preferred SightWeb. 2 subjects without disabilities preferred The Grid even if they ranked SightWeb better on average in almost all questions beside the overall satisfaction for the system (Q5). Once the experiment finished, they were interviewed on such choice: they explicitly stated that The Grid was good but, in their opinion, they were simply lacking skill in using The Grid. However, the objective data (see sections 2.1.5.2 and 2.1.5.3) of the 18 participants showed that the difficulty in using The Grid is not related to the skills of the individual.

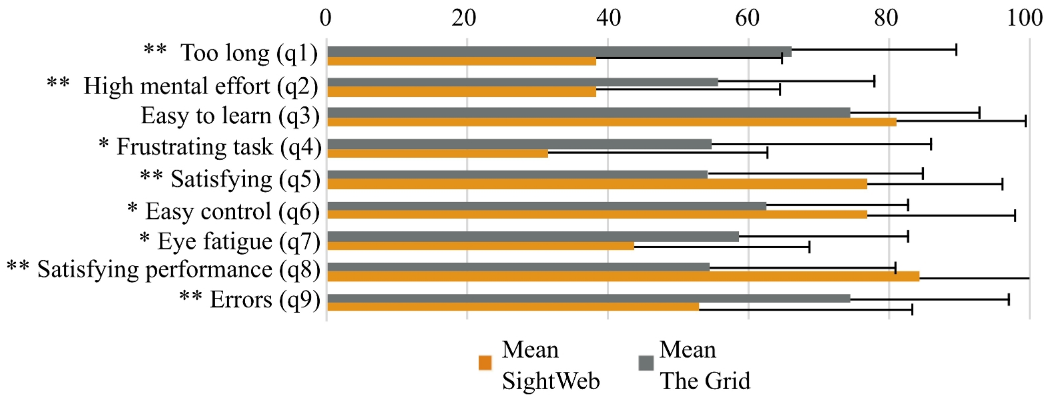


Figure 2.9: Questionnaire results (means with standard deviations) for subjects without motor impairment (* $p < 0.05$; ** $p < 0.01$).

2.1.5.2 Time

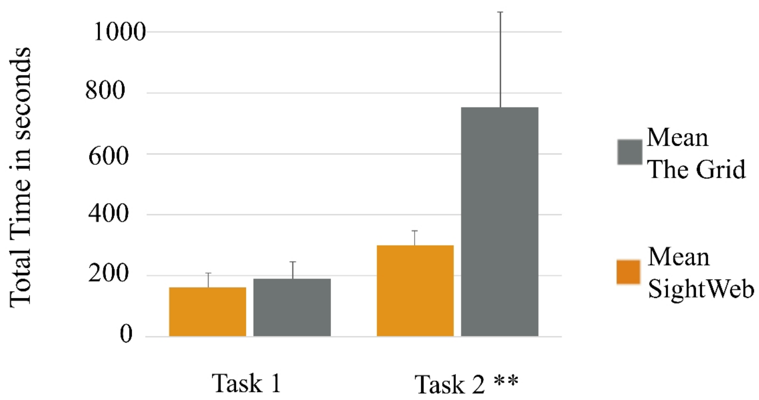


Figure 2.10: Total time (means with standard deviations) for each task and each system. (** $p < 0.01$).

The average time to complete the first task was similar for both systems (Fig. 2.10): 2.7 minutes (162.2s) for SightWeb against 3.15 minutes (188.5s) for The Grid. On the first task, SightWeb was quicker on average but not significantly (W=121 - p=0.130). The second task, more complex, took an average of 5 minutes (301.1s) for SightWeb and 12.5 minutes (754.57s) for The Grid. SightWeb was significantly superior in terms of speed (W=171 - $p < 0.001$). Similar results were found with the 2 patients in both Task1 (302s and 234s with The Grid; 166s and 201s with SightWeb) and Task2 (1024s and 1228s with The Grid; 474s and 285s with SightWeb).

2.1.5.3 Accumulated gaze distance

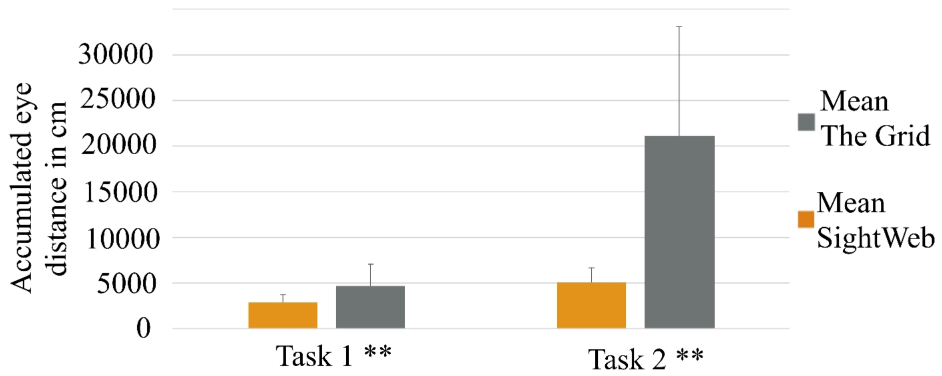


Figure 2.11: Total accumulated eye distance (means with standard deviations) for each task and each system. (** $p < 0.01$).

Accumulated eye distance during the tasks was calculated (Fig. 2.11). A shorter distance would imply less saccades, therefore less fatigue. For each task, the total accumulated eye displacement was compared for both systems (1000 px is displayed 1 Kpx). Total accumulated eye distance equivalence in pixel, cm and cm/s can be found in Table 2.1. The equivalence in cm was calculated using a 60 cm diagonal screen. The results of the 2 patients show similar scores in both Task1 (167Kpx and 142Kpx with The Grid; 109kpx and 83kpx with SightWeb) and Task2 (514 kpx and 779 kpx with The Grid; 313 kpx and 95 kpx with SightWeb).

Table 2.1: Total accumulated eye distance equivalence in pixel, cm and cm/s for people without motor impairment.

	Task1			Task2		
	SightWeb	The Grid	Wilcoxon test	SightWeb	The Grid	Wilcoxon test
Kpx	105	169	W = 161 p< 0.001	187	773	W = 166 p< 0.001
cm	2846.9	4608.5		5107	21054.9	
cm/s	17.5	23.6		16.9	26.5	

Since only 2 subjects with ALS were available to participate, no statistical inference could be performed on their (subjective and objective) data. However, their appreciation of SightWeb can be highlighted.

2.1.6 Discussion

On similar tasks, the subjects were significantly quicker with SightWeb. The time for completing the second task took on average over double the time for The Grid compared to SightWeb. Furthermore, due to the radial menu being around the target area, our design allowed for the reduction of the eye movements, diminishing fatigue and effort. This is corroborated by both the reduced accumulative eye distance in SightWeb and the questionnaire answers (statements 2 and 7). SightWeb was found to be easier to learn and to use, more satisfying, less prone to errors, and less frustrating.

SightWeb needs less accumulative distance than The Grid for completing the same tasks which confirms that side buttons increase the need for eye travel (and therefore fatigue), while a circular menu centered on the point of interest greatly decreases this distance. In terms of browser size, SightWeb represents the best option for screen real-estate for the browser.

The test conducted with ALS patients confirms that this design is appropriate for this type of user and their enthusiasm for this system is very encouraging. Figure 2.13 shows an ALS patient using WhatsApp Web [1] for the first time. Figure 2.12 shows the same patient writing on her own home system (Dialog) her opinion on SightWeb and The Grid 3. The text is written in Italian with the following translation: "It [SightWeb] was essential, with few commands and easy to use even for people with little expertise in computer systems. The other [The Grid3] was too confusing, with too many commands that scare people that approach this system for the first time.". Testing with patients highlighted the great importance of customization (dwell time, fixation time fixation radius) as their capabilities differed greatly. This customization must be available at any time by the patient

[1] https://web.whatsapp.com/

as those capabilities may improve over time when regularly using the system or decrease as their disease progresses or due to their age.

Overall, all results confirm that SightWeb represent an important open-source software contribution to both patients and the research community. While this study focuses on systems specifically designed for web-browsing, additional study could be done to analyze different methodologies used by systems designed to control complete computer systems. This study was published in the CEEC 2019 conference [Larradet et al., 2018]

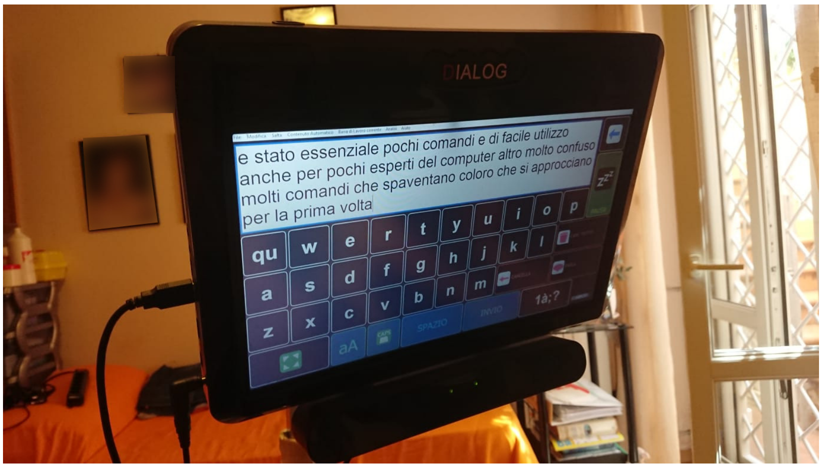


Figure 2.12: ALS patient's opinion on SightWeb and The Grid 3.

Figure 2.13: ALS patient using WhatsApp Web for the first time.

2.2 Effects of galvanic skin response feedback on user experience in gaze-controlled gaming

Additional input solutions for computer system available to LIS patients were investigated. While ALS patients lost the ability to perform any movements, their vital body function are still intact as well as their Autonomic Nervous System (ANS) reactions to emotions [Lulé et al., 2005]. Such physiological signals such as Galvanic Skin Response (GSR) could therefore be accessed and used to alter specific variable in an interface. Previous studies have demonstrated that adapting the parameters of eye-tracking to the users' physiological indices related to their mental processes can be useful to improve both the system performance and the user experience [Barresi et al., 2016]. Furthermore, physiological data are consistent with user experience-related measures of stress, frustration, and workload experienced by the user during the control of a device [Lin et al., 2005]. Accordingly, such physiological signals can be monitored to provide a biofeedback designed to shape the user's affective states. This could be used, for example, to maintain optimal engagement by adapting the difficulty level in computer games [Chanel et al., 2011].

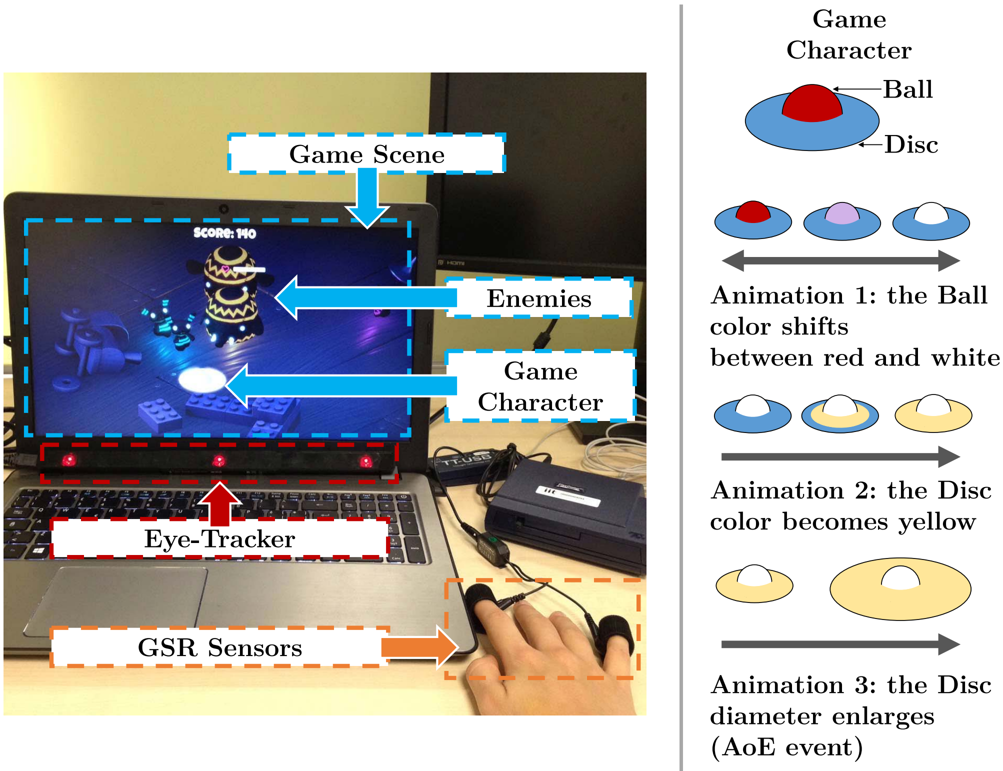
Following this approach, the effects of a relaxation-biofeedback solution on different dimensions of user experience during eye tracking control were investigated. In particular, subjects tested a gaze-controlled system that is mentally and temporally demanding: an eye-tracking-based video game designed to be compatible with a biofeedback system controlled by the user's Galvanic Skin Response (GSR). This methodology has also been implemented in portable systems [Dillon et al., 2016]. Here, different aspects of user experience were estimated, through a questionnaire, under two test conditions: eye-tracking-gaming without biofeedback, and eye-tracking-gaming with GSR biofeedback to provide an additional control modality to the scenario.

2.2.1 Experimental study

2.2.1.1 Experimental setup

The experiment was conducted using a laptop and a game based on the Unity3D asset Survival Shooter tutorial (Fig. 2.14). The controls and the object (Game Character) moved by the user were changed to be based on eye-tracking. The Tobii EyeX was used as the eye-tracking device. Each subject performed a calibration task and each calibration profile was sent to the dedicated Unity3D software that managed the gaze-control. The Thought Technology FlexComp Infiniti system was used to measure GSR through two SC-flex sensors, strapped around two fingers (index finger and little finger) of one hand of each participant, according to the FlexComp manual. The Biograph Infiniti software processed the GSR data in real-time. Finally, a GSR interface (developed throughConnection Instrument SDK) allowed to send those data to the Unity3D software for producing visual feedback (Fig. 2.15).

The experiment consisted of a game (Fig. 2.14.a) in which the player moved the Game Character: a ball intersected with a disc (Fig. 2.14.b). The Game Character's movements



(a) Game Scene and Setup

(b) Game Character Animations

Figure 2.14: The setup (a) and the animated Game Character (b).

were controlled by the gaze in a 3D environment (isometric perspective). Enemies progressively appeared in the game, and the primary player's goal was to move of the Game Character to escape such enemies. The secondary player's goal was to release an omnidirectional attack covering a wide area-of-effect (AoE) to defeat the surrounding enemies. Before the AoE event, 3 animations of the game character occurred according to the control options of the game (see section 2.2.1.2). The first animation was a change in the ball color, shifting between red and white (Fig. 2.14.b, Animation 1). The second animation was a circular yellow area filling out the disc from the center to the periphery (Fig. 2.14.b, Animation 2). When the disc became completely yellow, the AoE animation occurs: the disc enlarged to hit all enemies (Fig. 2.14.b, Animation 3). The AoE design was a choice defined by the limitations of eye-tracking control. Since the game was designed to fit the conditions of typical eye-tracking users with motor impairments, implementing a control modality for aiming the Game Character's weapon would have required controls that were too complex. Thus, an omnidirectional AoE attack presented an optimal design concept for producing a fast gaze-controlled gameplay.

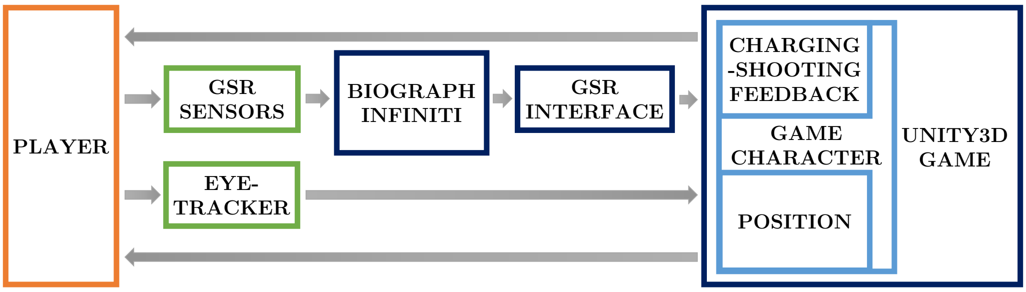


Figure 2.15: The flow of information between player and game.

2.2.1.2 Experimental conditions

Two conditions (Fig. 2.16) defined how the Animations occurred, and both were related to the modality and timing used to release an AoE attack against the enemies. In the Biofeedback condition the AoE attack was released thanks to the GSR-estimated voluntary relaxation. In the No Biofeedback condition the AoE attacks were triggered by time.

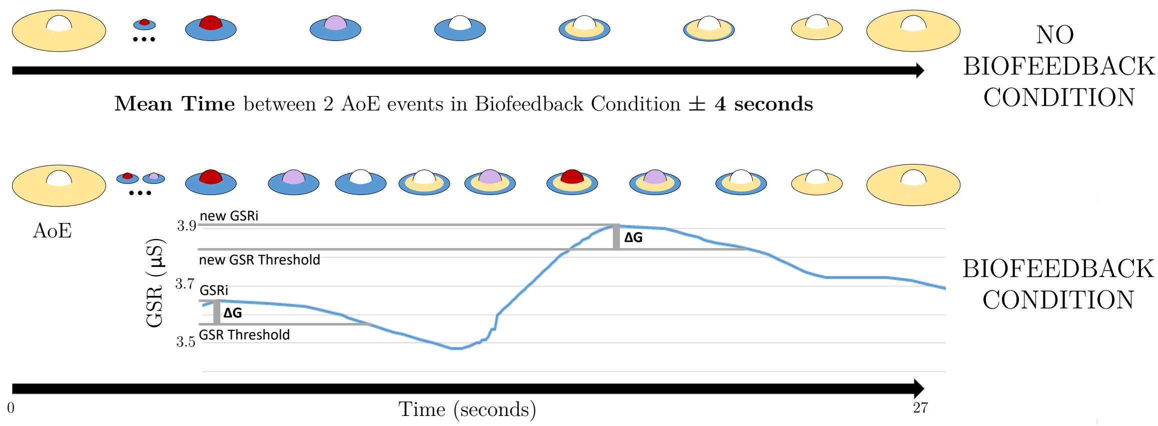


Figure 2.16: The animation features of the Game Character in the No Biofeedback and Biofeeedback conditions.

The subjects in Biofeedback condition (BF) recharged their attack power thanks to their voluntary relaxation, identified through lowering values of their GSR [Fehring, 1983]. Each subject of BF undertook a GSR training session of 30 seconds to test how much they were able to lower their GSR from a value to another without any intermediary oscillations. This reduction in GSR was labeled as ΔG. Positive changes of GSR lower than 0.01 (0.07% of maximal range) were ignored during the decreasing periods. Once this training was done, the game started and the users were required to lower their GSR the previously recorded ΔG in order to change the color of the ball (Animation 1 - relaxation makes it shifts from red to white). To do so, a GSR threshold to reach was set to GSRi-ΔG (GSRi being the current GSR value, as described later). Once this level has been reached, the disc started to change color radially from the center to the periphery (Animation2). The AoE event occurred automatically once the disc changed color completely (Animation 3).

Since GSR typically increases quickly but decreases slowly, it would takes too much time for anyone to lower their GSR to a previously set threshold after their GSR increased. For this reason, the threshold is adaptive. Indeed, if the current GSR went over the GSRi, the GSRi and the threshold were updated as previously. Once the threshold was reached by the user, the GSRi and the threshold were updated progressively which incites the user to keep relaxing. The relaxation was represented as the ball color shifting from red to white. Red was for high stress, white was for relax, this way the subjects were able to see their relaxation level over time. The subjects were also able to monitor when the AoE was ready from the amount of disc colored in yellow before the transition from Animation 2 to Animation 3. When the stress level increased and the ball became red, the portion of the disc not yet yellow-colored was indicating how long the person had to relax again in order to completely change the color of the disc and trigger the AoE. Indeed, the design choice to display all information on the Game Character was necessary, since the eye-tracking users cannot look elsewhere while they are controlling the object motion with their gaze. Furthermore, having a visual feedback about their relaxation level on the Game Character enabled the user to see continuously the effects of relaxation during the game session.

In the No Biofeedback (NBF) condition the GSR was not recorded. The Animations were controlled only by a timer and their sequence was similar to BF: the ball first went from red to white, then the disc was filled up by the yellow area, and finally the AoE shooting occurred. This presented in NBF a condition perceptually similar to BF. Considering how task success can affect time estimation when measuring mental workload [Hertzum and Holmegaard, 2013], the time required for AoE events in NBF had to be similar to the average one in BF. Thus, the mean time needed for BF subjects to relax and trigger AoE was calculated (27 seconds) and labeled as MeanTimeBF. The time required to shoot in NBF was calculated randomly in a range from MeanTimeBF±4 seconds (the optimal range according to an assessment performed before this study). This solution allowed to obtain an equivalent number of AoE events in both conditions, making them comparable.

2.2.1.3 Experimental design

18 healthy people were involved, 16 males and 2 females: 9 passed the BF condition and 9 the NBF condition. The composition of the two groups balanced the age and gender of the members: each group was composed of 1 female and 8 males with an average age of 27.33 years (SD=3.32 years) for the BF group, and 27.56 years (SD=4.42years) for the NBF group. The gender was not balanced within each groups due to difficulties in recruiting females. The participants' gaming time per week was also balanced between the two groups, with 4 playing less than 1 hour per week and 5 playing more than 1 hour per week in each group. The investigation was included into the IITADVRTEEP01 protocol,

approved by the Ethical Committee of Liguria Region on June 14th, 2016.

In both conditions, subjects were first seated in front of the computer in a self-adjusted ergonomic position to perform the eye-tracking calibration. The subjects in BF condition had to pass also 30 seconds of GSR calibration. All subjects played the game a first time for 2 minutes of training, before undertaking the experimental session for 7 minutes. If the Game Character was defeated (each collision with an enemy was consuming part of its life-points according to the duration of the contact) the game would automatically start again.

The number of AoE events, score (how many enemies were destroyed during a session), and defeats were recorded during the experimental session as performance measures. For BF the GSR level was also recorded.

After the 7 minutes of gaming, each participant was asked to say how many minutes they thought the experimental sessions had lasted: according to the literature, such perceived task time can be used to evaluate the workload of a person during that task [Block et al., 2010]. Here, subjects were not told in advance that they would have to estimate the time spent playing.

After answering the question on perceived time, each subject filled out a questionnaire designed to measure different aspects (represented by 7 statements) of their user experience in playing the game. The subjects had to mark their degree of disagreement or agreement with each of the 7 statements on the session (Fig. 2.18) along evaluation scales with 100 points each one (from 0 for strong disagreement to 100 for strong agreement). This solution was used to match the criteria for performing a wider range of statistical analyses than with traditional Likert-type scales.

Summing up, the experimental design was characterized as a between-group with 2 levels of the independent variable ”Animation Control”: BF and NBF. The dependent variables were the recorded performance measures (AoE events, score, defeats), the answer to the question on perceived session time estimation to evaluate the workload, and the questionnaire scores on user experience.

2.2.2 Data analysis and results

Firstly, we can notice that subjects in the BF group took an average of 27 seconds to voluntarily relax and trigger the shooting effect. Secondly, the analyses (t-tests) on the performance (Tab. 2.2) and the questionnaire (Fig. 2.18) indices did not show any significant effect. However, a significant between-group difference was observed for the perceived time through the Welch's t-test with t (12.63)=32 and p-value=0.0072 (Fig. 2.17). The test normality assumption was checked through Shapiro-Wilk test in both groups, with p-value>0.05: for BF, W(8)=0.92439 with p-value=0.4298; for NBF, W(8)=0.8762 with p-value=0.1431.

Table 2.2: Performance Measures

Performance Measures	Conditions			
	No Biofeedback		Biofeedback	
	M	SD	M	SD
AoE events	26.11	1.3	26.11	17.65
Score	1605.56	101.38	1252.22	385.09
Defeats	1.11	1.17	2.22	1.2

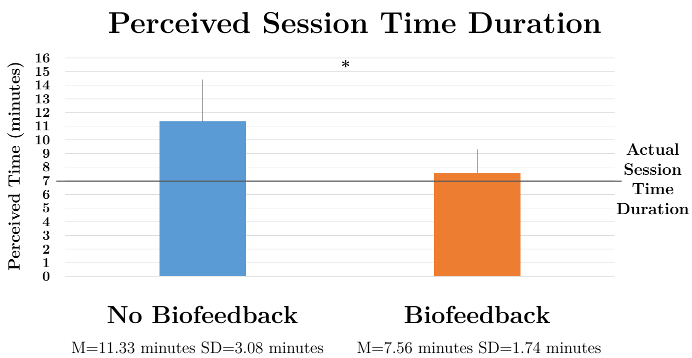


Figure 2.17: Means and Standard Deviations of the session time duration estimated by the subjects in each group (actual time: 7 minutes).

It is interesting to note how different scales of the user experience questionnaire (Fig. 2.18) suggest differences between the two groups that can enrich the explanations for the significant difference of perceived times. In particular, BF could improve the relaxation (Statement 2) of the players more than NBF. On the other hand, NBF could provide a more satisfying performance than BF (Statement 3) because of the automated generation of the AoE events that defeats the enemies - losses in BF are more frequent than in NBF (Tab. 2.2). Moreover, BF was more engaging and entertaining (Statement 5) than NBF, which is also reflected in the higher desire to continue to play the game (Statement 7). This study was published in the EMBC 2017 conference [Larradet et al., 2017]

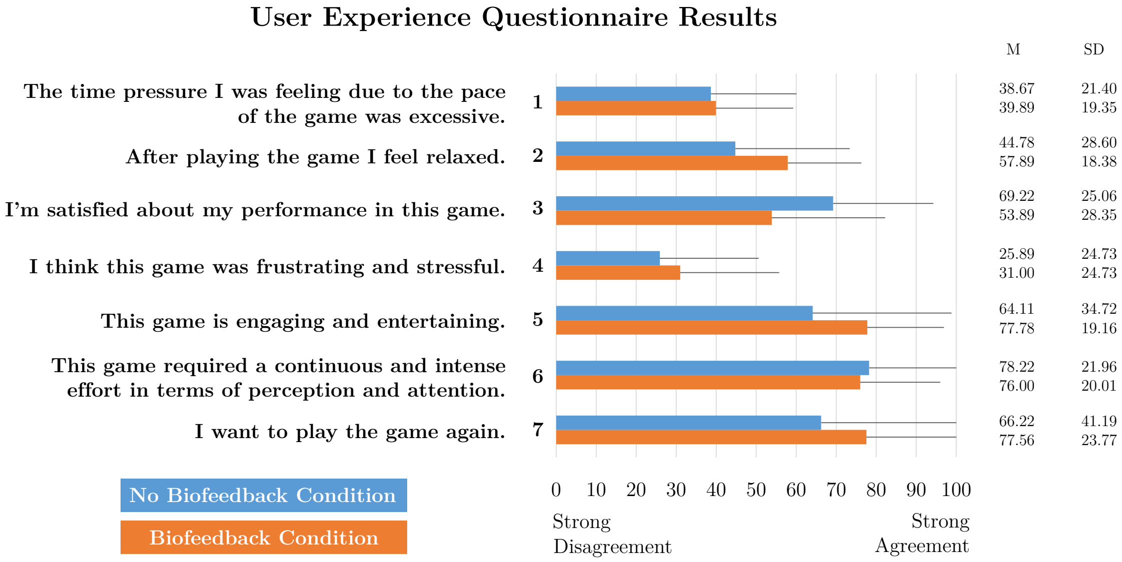


Figure 2.18: The results of the subjective questionnaire: Means and Standard Deviations of agreement scores per statement in each group.

2.2.3 Discussion

The average time needed (27 seconds) for BF subjects to lower their GSR level suggest that they were able to voluntarily relax when necessary to trigger the shooting event even in a stressful environment. This result highlights possibilities to design alternative interfaces for LIS patients including both eye-tracking and GSR as system input. Additionally, data analysis has shown a significant session time-estimation difference between BF and NBF. Participants in BF declared significantly lower estimated time than the ones in NBF. According to the premises on estimated time and mental workload, BF can be considered as less demanding in terms of mental workload than NBF. One would expect that the task in NBF would require less user's attention and effort than the one in BF since the AoE was timed. Indeed, users ranked BF as more frustrating and stressful than NBF(Statement 4). The low workload in BF could have derived from the voluntary relaxation process or from the user's engagement (Statements 5 and 7), regardless of the player's satisfaction (Statement 3). The results implied that self-relaxation through GSR-based feedback can indeed reduce the workload during demanding eye-tracking tasks, while potentially increasing the user's relaxation state and engagement.

2.3 Conclusions

Eye-tracking is the most common technique used by LIS patients to control computer systems. However, the design of assistive GUIs needs advances to facilitate access, diminish errors, and reduce the fatigue and mental workload for the users.

A new minimalistic gaze control paradigm, implemented within an open-source standalone web browser, was proposed: SightWeb. This system enables LIS patients (as in late stage of ALS) to navigate the web with minimal effort, high freedom, and precise actions. SightWeb was designed to achieve better performance than typical gaze-controlled GUIs, allowing for precise actions even with entry-level sensors for eye-tracking, while also minimizing screen obstruction. It imitates the original mouse control to stay relevant regardless of website technology updates. While at this time it does not include advanced interactions such as copy-pasting or text selection, it allows people with LIS to use common websites.

This system fulfills all of the design requirements, maximizing precision, browser size, and interaction simplicity. According to the presented results (gaze movements, execution times, user experience questionnaire scores), this new solution was found to be quicker, easier to learn and to use than a state-of-the-art system adopted by many patients today. It decreases the amount of eye movements required to perform a task, thus, it reduces fatigue and mental workload. The subjects felt higher satisfaction and reduced risk of error with this new system. Nonetheless, Gaze-controlled web surfing needs further improvements to perfect the balance between user capabilities, system intuitiveness, and screen space usage.

SightWeb exploits an interaction paradigm analogous to the Microsoft Eye Control system [Microsoft Corp., 2018] which was first released to control Windows machines when this study was already in progress. SightWeb has the peculiarity and benefit of being an open source system specifically dedicated to web browsing. Moreover, given the similarities, the assessment methods and key results presented here are also valid for the Microsoft EyE Control and other eventual future systems based on the interaction concepts presented above.

Additional system input may be considered such as physiological signals monitoring. The ability to voluntary control one's GSR to control a specific UI variable was studied as well as the effects of a relaxation-biofeedback system on user experience dimensions during a demanding eye-tracking-based gaming task. It was shown that the presence of GSR biofeedback contributes to lowering the level of mental workload required by such tasks. This confirms the opportunity to use relaxation-biofeedback features in eye-tracking systems to improve the user experience. Further results allow to assume that the biofeedback game enhanced also the users' relaxation level and engagement.

In both presented systems, all of the information, whether it was for menu display (SightWeb) or for relaxation feedback (ball color), was displayed in the area of action. This type of display was found to be a reliable way to make information easily accessible by users without the need for tiring eye movements. While the ability of subjects to willingly decrease their GSR to control a UI is a promising result for LIS-specific GUIs, the time necessary to do so needs to be taken into account. Indeed, this type of input seems to be too slow to be used as classic control such as a mouse click. It can however be used for less crucial commands such as a background color adapting to one's stress level for self-awareness, similarly to the work done by Roseway et al. [2015].

3

AFFECTIVE COMMUNICATION ENHANCEMENT SYSTEM

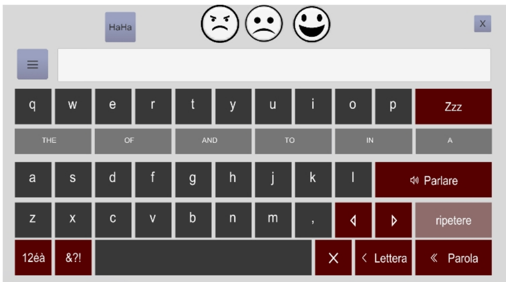
The first communication systems for LIS patients consisted in codes using eye blinking to signify yes and no or more complex sentences using techniques such as Morse codes [Laureys et al., 2005]. Other types of communication exist such as transparent letter board held by the interlocutor [Laureys et al., 2005] (Fig. 1.1). The patients may then indicate a letter by gazing at it. The interlocutor must then write down or remember the letters sequence to form words. This systems is still widely used nowadays.

More advanced systems have been established since. Notably, the ability to control their gaze was used to send commands to computer systems through eye-tracking cameras [Majaranta and Räihä, 2002]. This technique enabled LIS patients to select letters through keyboards displayed on computer screens and to "read" the written sentence out loud using voice synthesis [Majaranta and Räihä, 2002]. Such systems mostly focus on composing words letter by letter. However, when we communicate, we do not only use words but also a great range of additional non-verbal communications cues such as voice intonation, facial expression or body gesture [Mehrabian, 2017]. Such additional input helps the interlocutor to properly understand the context of the message itself. A simple sentence such as " let's go now" can be read with excitement or anger and deliver a completely different message.

This need for enriching words with emotional features has led to the creation of additional textual communication cues in Computer-Mediated Communication (CMC) such as emoticons [Lo, 2008]. These solutions are now widely used in text communications such as SMS or in social medias. For this reason, it is essential for LIS patients to also be able to communicate such affective state to their interlocutors in the most natural way possible. Focusing on the most common emotional cues in communication, voice and facial expression, we may find a great number of work in recreating such concept for CMC. For instance, emotional speech synthesis has been widely studied in the past [Burkhardt, 2005; Lee et al., 2017; Xue et al., 2015]. Additionally, facial expression was often associated with avatars and 3D characters as a way to express emotions online [Fabri et al., 1999; Morishima, 1998; Neviarouskaya et al., 2007]. The usage of those two technologies together were also studied in the past for CMC [Tang et al., 2008].

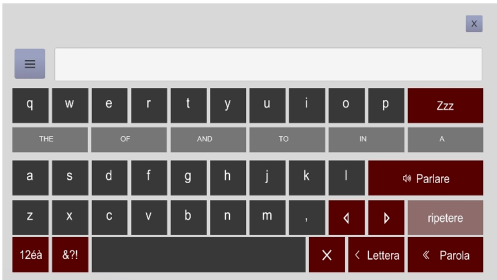
However, to our knowledge, those advances in technology related to emotion expression haven't yet been adapted for LIS patients. Augmentative and Alternative Communication (AAC) systems for persons with disabilities rarely provide tools for emotion expression [Baldassarri et al., 2014]. Focusing on children with disabilities, [Na et al., 2016] reviews the past studies on AAC and exposes the great need for emotional communication in such tools. Additionally, the effect of such affective capabilities on communication abilities for patients with LIS haven't been studied so far. To fill this gap in the literature we propose a novel open-source system controlled with eye gaze, including emotional voice synthesis and an emotional personalized avatar for enhance affective communication.

3.1 The proposed solution



a) AG display - Neutral

b) AG display - Happy



c) CG display

d) Dwell time settings menu

Figure 3.1: General aspect of the keyboard display (AG: Affective Group; CG: Control Group).

In order to allow LIS patients to communicate their emotions in addition to words, we proposed a system including a gaze-based keyboard, an emotional voice synthesis and a personalized emotional avatar. We focused on the 3 most common basic emotions: Happy, Sad and Angry. An additional option allowed the patients to generate a laughing sound. The system display was done using the Unity platform.

3.1.1 Gaze-based keyboard

The general aspect of the keyboard can be found in Fig. 3.1. It uses a standard dwell time system for key selection [Jacob, 1995]. A menu button allow for the settings of this dwell time. Autocompletion words were proposed using the Lib-face library [Matani, 2011] and displayed in the center of the keyboard to reduce gaze-movements that have been proven to induce fatigue [Yuan and Semmlow, 2000]. Additionally, we thought that users would most likely see the proposed words positioned in this way rather than above all the keys as their gaze would often pass over the words.

3.1.2 Emotional voice synthesis

The open-source voice modulation platform Emofilt [Burkhardt, 2005] was used to modulate the voice according to emotions. To tune the emotional voice, we took as an hypothesis that a great voice differentiation between emotions was primordial to insure the emotion recognition by the interlocutor in the long-term. The selected Emofilt settings for the happy (H), sad (S) and angry (A) voice can be found in Figure 3.2.

		Angry	Sad	Happy
pitch	f0Range	80		
	f0Mean			230
	lastSylContour		30 - straight	
	variability			10
	firstWordLevel*			120
	lastWordLevel*	90		160
duration	durationUnstressedSyls	70	170	
	durationFocusStressedSyls	130	170	120
	durationWordstressedSyls		170	
	speechRate	110	90	110
	dur vowel		170	130
	durpause		200	
	lastSylDuration*		140	80
	durNasal			130
phonation	jitter	3		
	vocal effort	loud	soft	loud

Figure 3.2: Emofilt settings.

The settings containing an asterisk are additions to the original system. The pitch were capped to a maximum and a minimum to avoid unnatural voices. The user are able to select the desired emotion using 3 emoticons buttons positioned above the keyboard (Fig. 3.1). If no emotion is selected the voice is considered as neutral.

3.1.3 Emotional avatar

Because LIS patients are not able to communicate their emotion through facial expression, we decided to simulate this ability using a 3D avatar shaped to look-alike the user.

To do so, the AvatarSDK Unity asset [ItSeez3D, 2014] was used. It allows to create a 3D avatar using a simple picture of the user. 3D animations such as blinking and yawning are provided. We created additional 3D animations of the 3 previously cited emotions. An example of such avatar expressions can be found in Figure 3.3. The avatar facial expressions are triggered using the same emoticons buttons used for the emotional voice. The selected facial expression is displayed until the emotion is deactivated by the user.

Figure 3.3: Example of the emotional avatar generated from a picture.

3.2 Methodology

In order to test the capability of this system in enhancing patients' communicative abilities, we performed a between-subject study with 36 subjects without motor disabilities (26 males, 10 females) separated into two gender-balanced group (5 females, 13 males, avg. age 29 years): a control group (CG) and an affective group (AG). The experimental flow may be found in Figure 3.4).

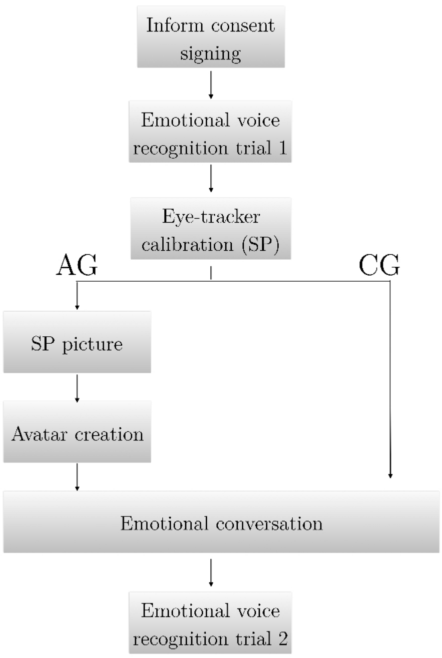


Figure 3.4: Experimental flow.

For the control group, unlike the affective group, the affective features (emoticon buttons, emotional voice, emotional avatar, laugh button) were hidden and therefore inaccessible. During each session, a subject was assigned to represent either "the patient" (SP) or "the healthy interlocutor" (SI). After signing the inform consent, we first tested the validity of the emotional voice. 5 sentences were randomly picked among 10 sentences (Table 3.2) and were each played in the 3 different emotions.

Therefore, in total, 15 sentences were played to the subjects in random order who had to decide if it was a Happy, Sad or Angry voice (Trial 1). Both SP and SI rated the emotional voices separately, in written form, without consulting each other. SP was then seated in front of a commercial eye-tracking monitor system (Tobii 4C [Tobii Group, 2001]) and SI next to him. The eye-tracker was calibrated using the dedicated Tobii software. For the affective group, a picture of SP was taken using the camera from the computer. The 3D avatar was then built from this picture. A second screen displayed the emotional avatar positioned so that both subjects could see it. For both groups, the dwell time was originally fixed to 1 second but SP was able to adjust it at any time through the menu. They were then given a talk scenario designed to simulate an emotional conversation (Table 3.1).

Table 3.1: Conversation scenarios.

SP	Your friend come to see you after not having seen you for a long time. This friend is in control of the company you spent your entire life building. You left him the control of the compagny when you started being sick because you trusted him. You are very happy to see him and express this joy to him. He will make a joke that makes you laugh. Then, he will tell you something that is very upsetting , you get angry at him. Finally after he explained the reason of his actions you forgive him but this situation made you very sad. You express this sadness to him
SI	You come to see an old time friend that has ALS. You tell him how happy you are to see him and start a casual conversation. You tell him a joke of how you fell in the parking lot on your way over. Later, you inform your friend that you have sold for money the company that he has built from his own hands. You defend yourself by explaining you sold the compagny because it was not bringing any money anymore and it was dommed. It was the only way to save it. You can't appologize enough.

The subjects were asked to have a conversation with each other. They were free to say whatever they desired while respecting the scenario. AG-SP was instructed to use the emotional buttons as much as possible. Once the conversation finished, both subjects were asked to answer a questionnaire on a 7 point Likert-type scale (Table 3.3). The first part of the study was then repeated with the remaining 5 sentences (Table 3.2) (Trial 2).

Table 3.2: Emotional sample sentences.

He saw your father	You played the game
We smelled your cake	They made some food
She went this way	She said my name
We came home early	I know this person
You read the paper	I drove this car

Table 3.3: Questionnaire.

<table>
<tr><th colspan="2">Subject "patient" (SP)</th><th colspan="2">subject Interlocutor (SI)</th></tr>
<tr><th>Control group</th><th>Affective group</th><th>Affective group</th><th>Control group</th></tr>
<tr><td colspan="4">(Q1) The conversation was similar to a normal dialog (in terms of communication abilities, not in terms of scenario)</td></tr>
<tr><td colspan="2">(Q2-SP) I could express my emotions with the system</td><td colspan="2">(Q2-SI) I could identify the emotions felt by my interlocuter</td></tr>
<tr><td>(Q3-CG-SP) The ability to convey my emotions would have helped with the communication</td><td>(Q3-AG-SP) The ability to convey my emotions helped with the communication</td><td>(Q3-AG-SI) The ability to identify his/her emotions helped with the communication</td><td>(Q3-CG-SI) The ability to identify his/her emotions would have helped with the communication</td></tr>
<tr><td>-</td><td>(Q4-AG-SP) The emotions I tried to express were well represented by the emotional voice</td><td>(Q4 -AG-SI) I could identify the emotions felt by my interlocuter through the emotional voice</td><td>-</td></tr>
<tr><td>-</td><td>(Q5-AG-SP) The emotions I tried to express were well represented by the emotional avatar</td><td>(Q5-AG-SI) I could identify the emotions felt by my interlocuter through the emotional avatar</td><td>-</td></tr>
<tr><td>(Q6-CG-SP) A controlled animated 3D representation of myself virtually making facial expression would have helped with the communication</td><td colspan="2">(Q6-AG) The emotional avatar helped with the communication.</td><td>(Q6-CG-SI) A controlled animated 3D representation of my interlocuter virtually making facial expression would have helped with the communication</td></tr>
<tr><td>(Q7-CG) An emotionaly modulated voice would have helped with the communication</td><td colspan="2">(Q7-AG) The emotional voice helped with the communication</td><td>(Q7-CG) An emotionaly modulated voice would have helped with the communication</td></tr>
</table>

3.3 Results

3.3.1 Speech synthesis emotion recognition

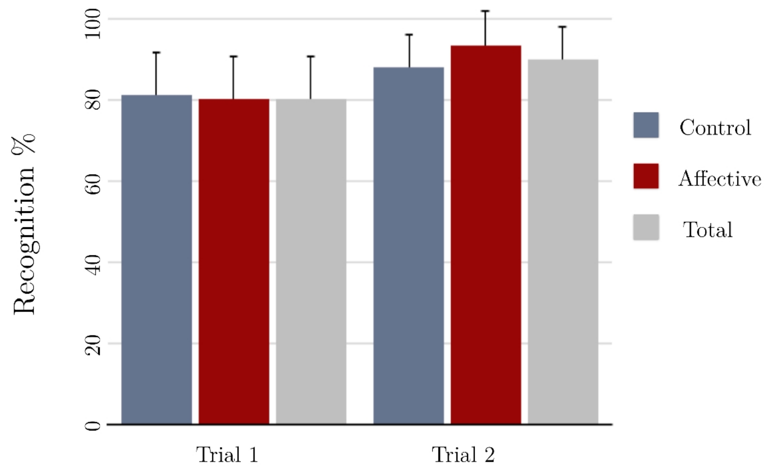


Figure 3.5: Recognition of emotional sentences for each trial.

The control group were able to recognize 81% of the emotions from the emotional voice synthesis in the first trial and 87% in the second trial. The affective group had a 80% recognition in the first trial and 92% in the second trial (Fig. 3.5).

3.3.2 Questionnaire

The answers to the questionnaire may be found in Fig. 3.6. The conversation was found closer to a normal dialog for the affective group (Q1-AG-SP: 4.5 and Q1-AG-SI: 4.75) than for the control group (Q1-CG-SP: 3.375 and Q1-CG-SI: 3.25). An ordinal logistic regression analysis was performed to obtain the results of an Omnibus Likelihood Ratio Test that showed a significant effect of the affective condition (chi-squared (1)=13.277 with $p<0.001$).

The questionnaire data are analyzed through appropriate non-parametric tests because of the dependent variables are constituted by ordinal scale measures. The assumptions of the tests are checked

The "patients" from the affective group found that they were more able to express their emotions (Q2-AG-SP: 5.875) compared to the control group (Q2-CG-SP: 3.25). A significant difference was found between the 2 conditions (AG and CG) (Mann-Whitney $U(16)=1.5$ with $p<0.001$).

The "healthy subjects" from the affective group found that they were more able to identify emotions from their interlocutors (Q2-AG-SI: 5.5) compared to the control group (Q2-CG-SI: 3.75). A significant difference was found between the 2 conditions (Mann-Whitney $U(16)=10.5$ with $p=0.008$).

The “patients” in the affective condition found that the ability to convey their emotions improved the communication (Q3-AG-SP: 5.875) and the ones from the control group thought that it would have helped (Q3-CG-SP: 5.2). The “healthy subjects” in that affective condition found that the ability to identify their interlocutor’s emotion helped with the communication (Q3-AG-SI: 6.1) and the ones from the control group thought that it would have helped (Q3-CG-SI: 5.5).

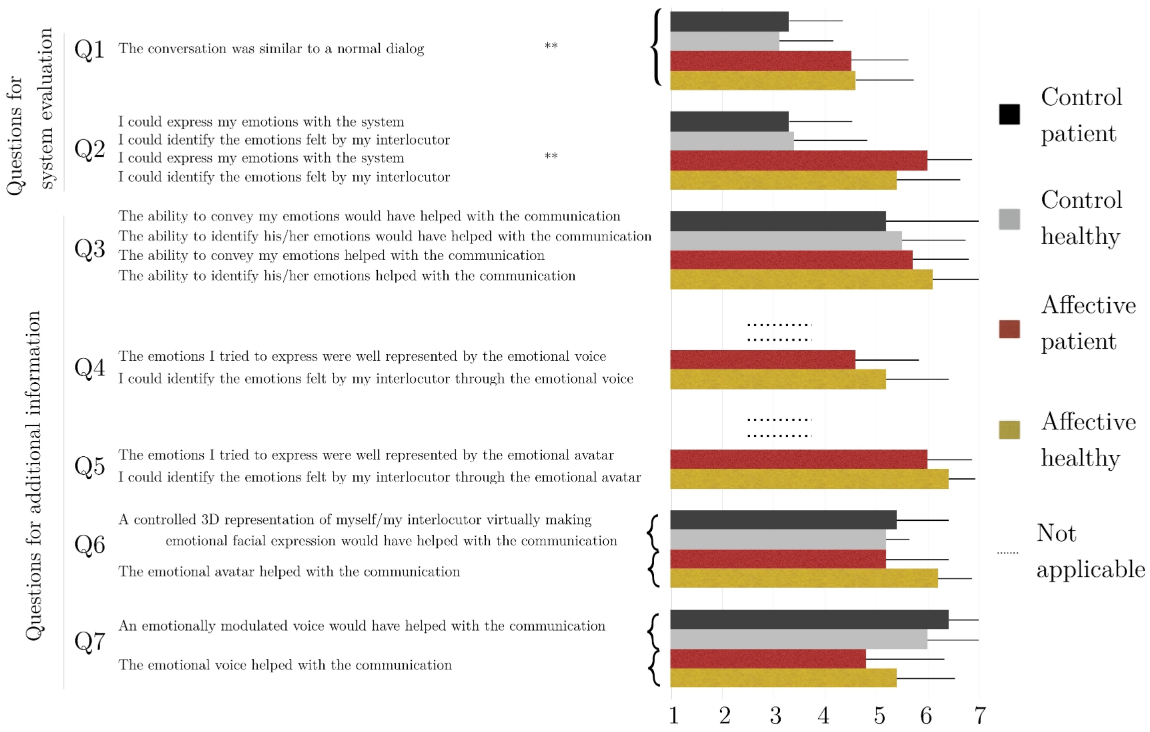


Figure 3.6: Questionnaire results (** p < 0,01).

3.4 Discussion

Firstly, we can see that the overall recognition of the emotional voice in the first task was sufficient for it to be used meaningfully in this experiment. Additionally, we can see that this recognition quickly increases with time since the recognition on task2 is much higher than the one on task1. This increase is higher for the affective group that had additional time to familiarize with the voice modulation during the scenario part of the experiment, reaching a score of 92 %. This ability to successfully express emotion (Q4-AG-SP) and identify emotions (Q4-AG-SI) through the voice synthesizer were confirmed by the questionnaire. Furthermore, the affective group found this emotional voice helpful for the communication (Q7-AG) and the control group thought it would be a useful feature (Q7-CG). It confirms our hypothesis that strongly distinctive emotional voices are easily recognizable in the long term and improve communicative abilities.

The emotional avatar was found to successfully represent the desired emotion (Q5-AG-SP), to provide easily identifiable emotions (Q5-AG-SI) and to help with the communication in the affective group (Q6-AG). It is interesting to notice the affective group found the avatar to be more helpful for the communication than the voice (Q6-AG and Q7-AG).

Overall, the communication was found more natural to the affective group than to the control group (Q1). SP subjects found that they were more able to express their emotion (Q2-SP). It highlights the positive impacts of both the emotional avatar and the emotional voice on the communication which is confirmed by Q3-AG-SP and Q3-AG-SI. Concurrently, the control group that did not have access to any emotional tools, also found that the ability to express emotion (Q3-CG-SP) and to identify emotion (Q3-CG-SI) would have helped with the communication.

It is interesting to notice that in the affective group the “healthy” subject ranked higher how much the avatar and the voice helped (Q6-AG-SI and Q7-AG-SI) compared to the “patient” (Q6-AG-SP and Q7-AG-SP). This highlights the fact that this system is particularly useful for the interlocutor who is the one looking for cues about the emotion felt by the patient. The “patients” subjects often stated that they did not really pay real attention to the avatar as they were focused on writing on the keyboard.

3.5 Conclusions

People in LIS have limited methods to communicate. In the past decades, technology have greatly improve their quality of life by providing a great range of communication tools. However AAC are still constrained in communicating words and rarely include ways of expressing emotions. This work proposes to study the impact of expressing emotion on communicative ability for LIS patients. To do so we created a platform that allows the user to select an emotion between happy, angry and sad. A 3D avatar representing the user was then animated according to the selected emotion along-side with an emotionally modulated voice synthesis. This system was tested by 36 subjects who were successfully able to recognize the emotions from the voice modulation and the avatar. They found that the two emotional tools helped with the communication as they were more able to convey and identify emotions. This system is available in open-source [Larradet, 2019b].

While today the avatar is only expressing fixed emotions it shows the need for extending AAC tools to include more non-verbal communication cues. This system could in the future include additional animations such as lip synchronization, visual reaction to detected skin temperature (sweating, shivering), additional gesture (wink, hand gesture, eye raised...), additional type of sounds ("waaaw", "uhm uhm", "oooh"). The avatar could therefore become an extensive communication tool as well as a quick visual aid for the interlocutor, family and caregiver to understand the internal state of the patient. Advanced avatar control could be used for instance to perform art [Aparicio, 2015].

While voice modulation and facial expression are the most common in non-verbal communication, other types of natural communication may be simulated such as physical contact. Indeed, systems such as heating wristbands placed on family and loved ones may be activated by the patient using gaze control and therefore convey the idea of arm touching.

In the future, the emotion could be automatically detected for instance from physiological signals [Jerritta et al., 2011]. However it would raise the concern of the patients' willingness to constantly display their emotion without a way to hide their true feelings from their interlocutor [Petronio and Bantz, 1991]. This capability to detect users' emotions will be further discussed in next chapters. This study was accepted to the HCI international 2020 conference.

4

INVESTIGATING EMOTIONAL DATA COLLECTION METHODOLOGIES

The capability to detect patient's emotions from physiological signals would allow to greatly improve the system presented in the previous chapter. For this reason, this particular topic was investigated further in this chapter.

Emotion, mood and stress recognition (EMSR), whether it is from facial expression [Fasel and Luettin, 2003], speech [El Ayadi et al., 2011], full-body motion [Castellano et al., 2007], words [Hirschberg and Manning, 2015], physiological signals [Jerritta et al., 2011] or other data type, have been studied intensively for at least two decades. While all the previously cited techniques follow similar methodologies in terms of data collection, this chapter will focus on physiological signals.

One of the biggest challenges in EMSR consists in collecting and annotating data for both model creation and testing [Constantine and Hajj, 2012]. This chapter will address this challenge by providing a thorough discussion of existing methodologies for physiological dataset creation as well as proposing evaluation criteria and tools to compare datasets.

4.1 Introduction

The studies on EMSR can be differentiated according to the type of emotion theory adopted to characterize the data. While using labels such as anger, disgust, fear, joy, sadness, and surprise [Lazarus and Lazarus, 1991] present the advantages of being meaningful to non-expert , many researchers use multi-dimensional models such as valence-arousal [Russell, 1980] or pleasure-arousal-dominance [Mehrabian, 1996] to classify emotions in a two 2 or 3 dimensional space. Valence is defined as the perception of a situation from positive to negative, the arousal can refer to a level of physiological activation (from calm to agitated), and the dominance defines how in control an individual is toward a situation. Finally, appraisal theories such as the OCC model [Ortony et al., 1990] or Ira Roseman's theory [Roseman, 1984], which explain emotion elicitation in terms of cognitive evaluations of significant events, are more rarely used in recognition and detection studies.

As for the classification method, most works use approaches based on feature extraction and machine learning (e.g., support vector machine [Hovsepian et al., 2015], decision trees [Plarre et al., 2011]), while the solutions based on expertise knowledge (e.g., rule-based) are more rare. Recently deep learning methods were proposed (e.g., convolutional deep belief networks [Ranganathan et al., 2016]). The later are, however, limited by the capacity to collect a sufficient amount of data. EMSR methods might be user-dependent (or person-specific), built from the data of a specific user to detect his/her own emotions, or user-independent, built from the data of multiple users to detect emotions of any user.

Building physiological datasets for EMSR was usually performed in laboratory settings by purposely inducing emotions to subjects at specific time intervals. It allows experimenters to control the stimuli and reduce the number of contextual factors that may influence the subjects' reactions.

On the other hand, to this date, only few studies have attempted to create real-life (not induced) emotions datasets, i.e., collections of affect-related data, outside of the lab, in reaction to everyday events. In the literature, the terms "in the wild" [Dhall et al., 2013], "in the fray" [Healey et al., 2010], and "in real-life" [Devillers et al., 2005] are used to describe such approach, in which the experimenters do not control the emotion elicitation process. In this methodology, the subjects can be, for example, monitored during their everyday activities over long time periods in order to collect their most natural reactions. This kind of study can either be *ambulatory* [Healey et al., 2010] where people are able to move freely, or *static* where people experience real-life emotions but constrained to a specific location (e.g., a desk in a workplace [McDuff et al., 2012] or during an exam [Melillo et al., 2011]). This similarity to real-life settings defines the ecological validity of a study.

In this chapter, the term EMSR for "real-life applications" includes methods able to recognize emotions, moods or stress, in the wild (not induced, elicited by real-life events) with the potential to enable many useful application. The previously described system aiming at detecting real-life emotions for patients with Locked-in Syndrome is an example of such real-life application. In this case, there is no need to be concern about ambulatory challenges. However, the difficulty to find patients in this state might compromise the capacity to build a successful EMSR model. Additionally, it might be tiring or difficult to involve such patients in early testing stages of the model. In those cases preliminary testing might be required with subjects without motor impairments. Such data model creation and testing would then need to be performed in ambulatory settings to access the subjects' emotions during their daily lives.

The perspective of the researcher or software developer who needs to create a new dataset to be used for EMSR was taken. The categories to consider when building "real-life application"-focused datasets in-the-wild are discussed. Differences between each data collection method are presented, their advantages, challenges and limitations. In particular, the focus was made on physiological data collection outside of the laboratory as it represents a way to access people's emotional state without invading their privacy (e.g., using video, audio) and without being cumbersome (thanks to the minimal size of the sensors). The set of guidelines presented may be used by future researchers aiming to build physiological datasets for EMSR. Furthermore, a method to assess the readiness of specific studies toward ambulatory real-life applications is presented.

In order to facilitate the comparison and evaluation of such studies, a visual method is introduced to assess EMSR studies in terms of their ability to be used in real-life applications. This graphical method is used to visually compare the existing dataset collections of the literature and their different approaches. Then, an overview of the studies that took a step toward EMSR using physiological data outside of the laboratory is presented. The graphical assessment focusses on studies including detection or classification methods (not the one presenting observations only).

The main contributions are:

- while other recent surveys on EMSR make a census by considering expressive modality (e.g., Castellano et al. [2007]; El Ayadi et al. [2011]), this work brings a new point of view to the field by focusing on methodologies for physiological data collection to build real-life EMSR applications in the wild,
- A complete list of criteria is proposed as well as a novel graphical aid to compare and evaluate any existing and future affect-related datasets in terms of their applicability in real-life applications.

The currently (1st July 2019) available commercial devices for ambulatory physiological data collecting are listed in the annex.

4.2 Existing affect related data collection techniques

While here the focus is given to physiological signals, established techniques to elicit emotions are common for all types of signals [Kory and D'Mello, 2015]. Techniques described in the literature to collect emotion-related data provide a great range of realism and genuineness of emotions.

Some techniques involved the participation of actors simulating emotions through facial expressions and speech [Wallbott and Scherer, 1986]. In this case, however, there is no emotion elicitation protocol as the participants do not actually feel any affective state but only pretend to react in an emotional way.

Several researchers, however, claim that the spontaneous expressions of emotions are different from the acted ones [Ekman, 1997]. For instance, Hoque et al. [2012] found significant differences in facial expressions of acted and induced emotions. Consequently, the EMSR models trained on acted data may not work properly in real-life applications. Using actors is not viable for physiological signals collections as people may not simulate their own physiological reaction.

Actors may use some techniques such as the Stanislavski's method [Cole, 1995] to make their acting more natural. Other methods of self-induction of emotion were used in scientific literature: e.g., in Vrana [1993] where subjects are asked to apply the guided imagery method that consist in thinking about specific situations to elicit emotions. Retrospection is another commonly used techniques where participants are asked to narrate a story from their past when they experienced a given emotional state, e.g., [Pasupathi, 2003]).

Some studies on emotion, mood or stress try to induce more genuine reactions in their participants by using established experimental protocols. These usually consist of exposing the subjects to some pre-defined and pre-validated stimuli for emotion induction. In such studies the experimenter has control over the environment such as the type, duration, order of the stimulus and the position of subject (e.g., whether he is sitting or standing). Various type of stimulus have been used in the past. For instance, the widely used IAPS database [Lang et al., 2008] contains 956 images chosen to elicit emotions and rated on valence and arousal by 100 participants. It was used in a great number of studies [Dikecligil and Mujica-Parodi, 2010; Fox et al., 2010; Schmidt et al., 2011; Walter et al., 2011]. In addition, the Geneva affective picture database (GAPED) [Dan-Glauser and Scherer, 2011] contains 730 pictures similarly rated. Showing video-clips is another frequently used method, adopted for instance by Soleymani et al. to create the MAHNOB-HCI dataset [Soleymani et al., 2011]. While music stimuli on its own is only used in few studies [Kim and André, 2008], they are commonly associated with other input such as light and storytelling [Kim et al., 2004]. Methods requiring active participation of subjects were also used, e.g., by using video games [Tognetti et al., 2010] or virtual reality [Ververidis et al., 2008].

Other less common emotion induction methods such as performance of specific facial expressions or postures (without being aware of corresponding affect) [Zajonc et al., 1989] can be found in the literature. These are based on the facial feedback theories [Izard, 1977; Tomkins, 1962] according to which the emotional facial expression induce the emotion and not the other way around.

Making a step closer toward real-life scenarios, some researchers induce emotion by creating social scenarios in the lab simulating some realistic social interactions. For instance, Harmon-Jones and Sigelman [2001] asked the participants to write about an important subject to them, which was then pretendedly negatively rated (regardless of the content) by a second participant. An aggressive comment and a low mark was expected to induce anger in the subjects. Niewiadomski et al. [2016] elicited expressions of amusement by having participants playing social games. This type of study, especially the ones focusing on negative emotions, usually require that the participant is not aware of the experimental procedure.

Amodio et al. [2007] presents additional guidelines for building such scenarios such as a the elaboration of a credible cover story, a constant experimenter behavior and the conduct of post-experimental interviews.

Avatars or robots have been also used to create highly controlled experimental social scenarios with high reproducibility. For instance, [AlZoubi et al., 2012] used an avatar to induce boredom confusion and curiosity for expression detection. [Kim et al., 2009] demonstrated that humans can indeed empathize with robots . Using this concept, Turner-Cobb et al. [2019] studied the stress elicited by subjects performing a mock interview in front of a robot audience.

Some studies have tried to collect spontaneous affective reactions while controlling the experimental environment by doing supervised real-life studies. These consist in putting the subjects into situation usually bringing strong emotional reactions such as sky-diving [Dikecligil and Mujica-Parodi, 2010] or driving in difficult conditions [Healey et al., 2005]. However, these studies usually focus only on stress.

To introduce stress, additional techniques are available [Karthikeyan et al., 2011]. The Stroop test from 1935 [Stroop, 1935] – presenting words representing a color written in a different color and asking to verbally state the written color – have been used in many studies [Pehlivanoğlu et al., 2005; Zhai and Barreto, 2006]. Hassellund et al. [2010] used a cold stressor, which consists in immerging one's hand in cold water. Other popular stress induction stimuli include, for instance, performing mental arithmetic exercises [Ring et al., 2002], voluntary hyperventilation [De Santos Sierra et al., 2011], public speaking [Von Dawans et al., 2011], or computer games [Rani et al., 2002].

The previously presented techniques all have their own set of advantages an limitations. They will be further discussed in comparison with the "in-the-wild" methodology in next subsection.

4.3 The “in-the-wild” methodology

4.3.1 Why are datasets in-the-wild needed?

A large number of studies on automatic emotion recognition from physiological signals obtained good recognition rates [Jerritta et al., 2011] but very few of the proposed methods were then tested on data collected in the wild. Their applicability in real-life applications is therefore not confirmed.

Wilhelm and Grossman [2010] presented the risks of such approach in terms of physiological signals, comparing laboratory induced stress and the ones occurring in ecological settings. They studied the case of physiological reaction to stress and compared laboratory induced stress to real-life ones such as watching a soccer game. They found the heart rate during the latter greatly superior to the former. Similarly, Xu et al. [2017] considered the validity of using in-lab collected data for ambulatory emotion detection. Their findings suggested that EDA, ECG and EMG greatly differ between real-life and laboratory settings and that using such methodology results in low recognition rates (17-45%). Thus, it is necessary to validate EMSR methods in the wild to be able to automatically recognize people's emotional states in real-life applications, such as the ones previously introduced. Additionally, even if emotion laboratory induction techniques use highly controlled experimental procedure there is no certainty that the subjects will actually experience the desired emotion. Indeed, people are very different and can react in various ways to the same stimuli [Kret and De Gelder, 2012]. For instance, someone might enjoy horror movies and find the experience entertaining, while someone else might find it scary and stressful.

Furthermore, it is known that people's physiological signals adapt with age [Kostis et al., 1982] or fitness level [Melanson and Freedson, 2001]. Developers of commercial user-dependent models may then need to either develop adaptive models to include such changes or allow the users to punctually re-train the model to adapt to their new self which may be difficult for laboratory created models (see section 4.3.2.3).

Theoretically, a method addressing the previously stated issues would be able to use data collected in the lab for training and in-the-wild for testing and still be valid. However, using in-the-wild data for both the model building and testing phases brings additional advantages.

Firstly, using in-the-wild data allows for iterative learning. By using data collected in the wild to build a model, it becomes possible to improve the learnt models over time. The longer the user provides data, the better the model might become. Such approach requires the usage of the in-the-wild data collection combined with self-reports (see section 4.3.3.2).

Secondly, as mobiles phones and personal sensors become more and more popular, this data collection approach also allows the usage of big data [Laurila et al., 2012] allowing the application of the latest techniques of data mining and deep learning. Indeed, model created from users self-report input and real-life emotions could allow for the collection of an extensive database feeding the model and greatly improving it over time. People are already reporting their emotion on mobile apps for the sole purpose of self-monitoring (eg. "The Mood Meter"[1], "Pixels – mental self awareness"[2], "Mood diary"[3]). There is only a small step to associate such data labelling to physiological sensors using mobile applications such as the one that will be presented in section 6.1.

4.3.2 Advantages

In order to present the advantages of the in-the-wild methodology, it was compared with the previously presented techniques for data collection and model testing in the lab (see section 4.2).

4.3.2.1 Ethical issues

Inducing negative emotions such as anger or sadness can be problematic due to some ethical constraints. Usually only low intensity emotion induction methods such as IAPS images or movie clips (see section 4.2) are acceptable by Ethical Committees Institutions. The model would therefore not be able to learn from high intensity reactions as they would not be present in the collected dataset. On the other hand, real-life emotions collected using the “in-the-wild” methodology can be of any level of intensity and valence.

4.3.2.2 Context

Although the creation of emotion elicitation procedures in the lab usually allows for a better control of the context (by minimizing unrelated factors that may influence the emotion elicitation process), several other factors may alter the affective reactions. For

[1] https://moodmeterapp.com
[2] https://play.google.com/store/apps/details?id=ar.teovogel.yip&hl=en_US
[3] https://play.google.com/store/apps/details?id=info.bdslab.android.moodyapp

instance, some participants may already feel stressed or discomfortable when participating in an experimental study in a laboratory [Britton et al., 1983]. Emotions collected in the wild appear in a natural context without the presence of an experimenter to alter the subject’s affects.

4.3.2.3 Experimental effort

Whether the data collection is performed in the lab or in the wild, a certain effort is necessary to build the dataset. In the laboratory, the experimenters need to prepare and validate the experimental protocol for emotion elicitation (e.g., trying interactive scenarios, preparing emotion induction games, finding appropriate images datasets. See more in section 4.2). In the wild, this effort is given to the subjects that need to report their emotions. In this case, no effort is required from the experimenter as the stressors/emotional situations are provided by life itself.

In the case of EMSR models based on induced emotions datasets, the need of retraining the model (see section 4.3.1) would imply a need to reproduce the elicitation process. However, for most emotion induction methods cited earlier (see section 4.2), it would be difficult and probably ineffective to reproduce the method using the same materials. This problem exists for most visual or auditory stimulation. The previous knowledge of the material may reduce or totally suppress the emotional reaction. New material compilation is then needed to reproduce the emotion elicitation, which requires additional effort from the experimenter. It would therefore be difficult to use a user-dependent emotion-induced system in a commercial application as it would need manual intervention (research and compilation of the new materials) each time the user needs to rebuild the classifier. User-dependent models are often used in the case of physiological signals because of the important interpersonal differences in people’s baselines and reactions to stimuli. Therefore, they tend to give better emotion classification results [Jerritta et al., 2011].

On the other hand, since user-dependent EMSR models built using the in-the-wild methodology only need self-reporting effort from the user and do not need any material compilation they can be re-trained when the user requests it and agrees to self-annotate additional data. This approach then is more suitable for real-life commercial applications.

4.3.3 Challenges and limitations

4.3.3.1 Absence of a controlled environment

In-lab data collection provides a controlled environment, similar for all subjects. It allows for the comparison of different subject reacting to a similar stimuli for a same period of time. Using a real-life dataset implies an unknown environment. The experimenter is unable to predict the emotional stimuli that will occur. Additionally, those stimuli will most likely be different for all subjects which makes inter-subject data comparison difficult.

For instance, two subjects might both experience happiness but one due to an accepted publication and the other because of a conversation with a friend. While both events will be labelled as "happy", they are elicited in very different environments. Because of this unpredictability and uncontrolled experimental procedure, the experimenter is unaware of the emotions felt by the subjects and therefore this information needs to be determined. Several ways of acquiring such information will be presented in the next paragraph.

4.3.3.2 Emotion labelling

There are 2 main methods to acquire the emotions labels, starting and end times in uncontrolled environments:

Self-report

The most commonly used data labelling technique is achieved by the subjects themselves. In this method, participants are asked to report the time in which they felt an emotion, which emotion, and, eventually, some other parameters such as its intensity or context. This emotion self-labelling may be done following different types of emotion theories such as writing labels or estimating valence and arousal. However, it may be difficult for the subjects to estimate valence and arousal as it is a concept non-expert are usually unfamiliar with. Consequently their report might not be reliable. Indeed, Healey et al. [2010] found that subjects' valence and arousal reports did not correlate with their comments. They identified that subjects misunderstood the functionality of the 2 dimensional map. Techniques such as the SAM images [Bradley and Lang, 1994] makes this process more accessible to the subjects. Asking the subjects to self-report emotions by using the labels such as “angry” or “sad” can also lead to problems. Indeed, Widen and Russell [2010] highlights the need for a distinction between “descriptive definition” of emotion, as it is used in everyday life, and a “prescriptive definition”, as it is used by the scientific community. The concept of an emotional label might differ from the one understood by the experimenter. Similarly, the label concepts might differ within participants due to different gender [Kret and De Gelder, 2012], or cultural differences [Mesquita et al., 1997]. All these differences in labels conception might alter the capacity to recognize emotions for user-independent model. A user-dependent model might not be affected as the conception of a label would most likely stay constant for each subject. This problem will be addressed in section 6.1 using an appraisal theory-based questionnaire tree to help the subjects providing precise information about the emotion elicitation stimuli, without the need for them to choose a specific emotion label.

Oversight is another problem derived from subject labelling their own data. One may not immediately report the felt emotion and then, simply forget to do it. Depending on the type of application and model used, rating the emotion in terms of intensity might also be necessary. However, subjects might underrate their emotions for several reasons such as ego (e.g., subjects may not admit that they felt sad or scared), or time (emotion self-reports tend to be less valid when performed long time after the experienced emotion [Mauss and Robinson, 2009]).

Furthermore, user-given annotation of emotions beginning and end times might not be precise. Subjects will tend to give approximated times, making the exact data labelling more difficult. Instead of asking the subject to voluntary report emotions when they feel them, some studies use alternative electronic systems that prompt the user to report his emotions at regular intervals [Plarre et al., 2011]. This solution is based on the Ecological Momentary Assessment (EMA, in Shiffman et al. [2008]) designed to improve typical self-reports during clinic visits. It is not clear, however, what is the optimal frequency of such prompting. Asking too often can easily become bothersome to the subjects and therefore affect the emotional data collection. Asking too rarely would increase the chance of the subject lowering the strength rating of the emotion [Mauss and Robinson, 2009], or forgetting a previously felt emotions. Schmidt et al. [2018] advise to perform an EMA every 2 hours or five times a day coupled with a possibility to manually report emotions. Asking at a regular time interval would allow to know the emotions felt the last hour for instance but it would not provide the precise time it happened. This technique may be more appropriate to collect information about moods which are longer and less momentary [Mauss and Robinson, 2009], rather than emotions that are usually short [Gray et al., 2001]. Indeed, Robinson and Clore [2002] states that increasing the time between two consecutive prompts increases the chances to collect semantic (related to beliefs and generalizations about oneself) memory of emotions instead of episodic (related to a particular event) ones. Accessing events details of the day may improve the recall [Lang et al., 1980; Robinson and Clore, 2001]. However, the retrospective thinking about too many details may disproportionately bias the emotional report [Kahneman et al., 1999]. Asking subjects details about their daily lives might not meet the ethical regulations as it would provide an easy way to recognize the subject. Asking the subjects to mentally reproduce the event without giving details to the experimenter might be a solution [Clore et al., 2001]

The other issue linked with emotion labelling is the amount of information not given by the subjects. Researchers may have research constraints for a particular study. For instance, a study might focus on happiness and anger and therefore only ask the participants to report those events. However, the subjects will still experience the whole range of emotion. Additionally, subjects might do unrelated actions such as smoking or drinking which may not be in the scope of the study and therefore would not be reported by the participants. These other emotions or actions might however have an impact on the studied signal (for example coffee intake can affect HR [Green and Suls, 1996]). A real-life emotion study will therefore include parts of the data affected by unannotated events which makes machine learning training difficult. Schmidt et al. [2018] recommends to collect in parallel the physical activities and the sleep quality of the subjects and to conduct data-driven screenings interviews with the participants to gather additional context information.

Expert labelling

This method consists in having one or several experts examining the data and using his/their knowledge and expertise to annotate emotions. This can be done either using the same physiological signal(s) as the one that will be used in the EMSR model [Yin et al., 2006] or using a different type of signal (e.g., facial expressions, body movements). For instance, Healey et al. [2005] conducted an experiment where both physiological signals and video were recorded in the wild. Video was analyzed by experts to validate the data labels given by the subjects and physiological data was used later on to create an emotion detection model.

However, this method often requires multimodal synchronized recordings which can be difficult in-the-wild. Additionally, the modalities which are most often used by experts when performing the annotation, such as video or audio, are usually the most intrusive. Additionally, even experts may still misclassify or miss some emotional states of subjects. If more than one expert is used to perform the annotation, they may disagree on perceived emotions. Thus, a combination of expert labelling with user post-experiment cross-validation is often a preferred solution [Yin et al., 2006].

4.3.3.3 Ambulatory

When it comes to real-life dataset collection, there is a distinction to be made between ambulatory and static studies. Indeed, as previously stated, real-life emotions happen at unpredictable times. Collecting of such data often implies long-term studies during which people can more freely. This implies a necessity for ambulatory systems able to collect physiological signals while the person is moving. Some existing studies focused on real-life emotions felt by the subject but they limited the collection to a specific physical space, e.g., to a desk space [Roseway et al., 2015]. This type of studies will be referred as "static studies" (as opposed to ambulatory ones previously mentioned).

In ambulatory studies, more issues need to be addressed. First of all, the devices recording the data must be both mobile and comfortable as they must allow the subjects to move freely for extended periods of time. This is the main reason why studies using HR or GSR are among the most common real life emotion recognition studies as some signals such as EEG would be difficult to achieve without very bothersome wearable devices. There are a few devices available in the commerce for physiological signals-based ambulatory studies which are presented in the supplementary materials. Some studies chose to develop their own device [Wilhelm et al., 2005].

The choice of sensors for ambulatory studies presents another challenge. While it is important to choose small sensors to improve the wearability of the device, some sensors might be more affected by movement than others. For instance, in order to calculate HR, it is possible to use small PPG sensors, from which the BVP is read, the InterBeat Interval (IBI) calculated and the HR extracted. This technique is reliable but very sensitive to sensor movement. Another solution to measure HR is to use ECG. Chest ECG, while being a much more invasive sensor provides more precise data which are less affected by movement [Ge et al., 2016]. The choice between the two is then a compromise between wearability and accuracy. There are techniques in order to improve the accuracy of the IBI calculated from PPG [Torres et al., 2016]. The most common is the use of a 3D accelerometer to detect movement [Lee et al., 2010]. Furthermore, HR is also greatly affected by physical activity (e.g., sports). It is advised to remove from the physiological data the periods of such activities, so that they would not be mistaken by an emotion. Once again accelerometer may help detecting such activities with some limitation, for instance stairs may increase HR and may not be easily detectable by the accelerometer [Foerster et al., 1999]. Additional elements may need to be considered when conducting ambulatory studies such as EDA asymmetry. Indeed, while EDA signal might be found similar in both side in the lab, Picard et al. [2016] noticed differences in EDA measures in left and right wrists during ambulatory studies. They concluded that the right wrist acquired stronger signal overtime. It is therefore recommended to place this sensor in the right side in the field.

4.3.3.4 Long-term experiment

In-the-wild conditions implies an unpredictability of the emotions. It is uncertain how many time the subject will experience a certain emotion during the study or if they will experience it at all. However, some techniques exist to increase the likelihood of the emotion during the collection period. For instance, some subjects might know specific event in their future that are likely to trigger emotions (e.g., public presentation, important meeting, job interview). Performing the data collection during this specific period would increase the likelihood of collecting the desired emotional data without providing any certainty. Studies involving multiple emotions might require all subject to experience all studied emotions (e.g., anger, sadness, happiness, frustration) during the data collection period. While it would be unlikely to happen in a short period of time (a day), increasing the duration of the experiment (several days, week, months), would increase the chances of having subjects experiencing a specific emotion or a different ranges of emotions. This method will however, greatly impact the length of the study or the number of subjects. Additionally, the wearability of the device chosen will impact the possible length of the study. Indeed, the more comfortable the device, the more it would be acceptable for a subject to wear it over a long period of time.

4.3.3.5 Lack of databases

Considering the great differences between people when it comes to emotion, it is important to word with data from a large number of subjects. For this reason, open access databases are very valuable for EMSR research. However, while induced emotion-based open access databases exist [Abadi et al., 2015; Dan-Glauser and Scherer, 2011; Koelstra et al., 2011; Sharma et al., 2018], to the best of our knowledge, there is no open access database of emotional data collected in the wild. Such database was built during this research (see section 6.2) using the protocol that will be presented in section 6.1

4.4 The GARAFED method

In this subsection, a new assessment of the data collection methodologies is presented based on their readiness toward ambulatory real-life application usage: GARAFED (Graphical Assessment of Real-life Application-Focused Emotional Dataset).

Eight criteria were selected, each containing sub-classes that allow assessing the distance from the ambulatory real-life EMSR goal. While specific application cases might have different needs and requirements (e.g., work focusing on detecting stress during an exam would not need an ambulatory setup), the assessment will be made on the capacity for the proposed method to be used in any ambulatory real-life applications.

In addition, even though other methodology choices must be considered for EMSR research (e.g., emotion labelling methods, see sections 4.2 and 4.3), they are not included in this assessment model. This is because such choices cannot be ranked from the most to the least suitable for real-life applications as each decision is equally valid. Here, when categories ranges include numbers (e.g., between 3 days and 7 days), the lower number (e.g., 3 days) is included and the higher number (e.g., 7 days) is not included.

4.4.1 The GARAFED categories

- Emotion origin

  As previously presented, there are many possible origins for the emotions. The origin of the emotion may be induced by an experimenter, or, in real-life, can be caused by other agents, events or objects [Ortony et al., 1990]. By collecting data in situations closer to ecological settings the creation of a more appropriate dataset is insured. Here the following emotion origin possibilities are defined.

  1. Simulation of the emotion (e.g., actors).
  2. Induction of emotions in-lab (e.g., movies, IAPS images).
  3. Induction of emotions through supervised real activities (e.g., car driving, sky-diving).
  4. Real-life emotions, static monitoring.
  5. Real-life emotions, ambulatory monitoring.

- Invasiveness

  The size and portability of the system used to collect data in the wild impacts how easy it is for the subjects to carry it for longer periods and thus the possibility to conduct longer experiments. This invasiveness factor has been separated in 4 categories from "Non portable" to "Portable and non-invasive".

  1. Non portable: the system needs to be linked to a power supply and/or require the experimenter intervention, such as sampling of salivary cortisol level.

2. Portable and highly invasive: the system is heavy bulky or invasive. It may include sensors such as nasal respiration sensors. It is not possible to wear it for many hours a day without it being uncomfortable for the subject. (ex: Vu-ams [De Geus and Van Doornen, 1996]).
3. Portable and slightly invasive: The system is light. It can be worn for several hours a day but it is noticeable and/or potentially uncomfortable for the subject after a certain time. (e.g., Shimmer3 GSR+ Unit).
4. Portable and non-invasive: The system is light and non-invasive. Others may not notice the device. It is similar to a commonly worn object such as a watch, a belt etc. (e.g., Empatica E4).

- Privacy

  The input data used to classify emotions can infringe the privacy of the subject. Indeed, input data such as video, voice or calendar activity would give the experimenter access to very personal data. They may also allow for the identification of the subjects. While the focus is given to physiological data that are usually non-intrusive, other studies were also consider, using physiological data combined with other types of data which may be intrusive. Papers will be classified using the 4 categories bellow.

  1. Intrusive data: personal data or data that allows identification.
  2. Non-intrusive data: non personal and does not allow identification.

- Number of experimental days

  Collecting data over many days increases the probability to gather data in a variety of situations and environments. It therefore ensures the creation and validation of a better model.

  The number of collection days in papers in the first paragraph in 4.5.1.1 and the first paragraph in 4.5.2.1 were aggregated. From this data, 4 quartiles were extracted that will be used to separate each papers proposing an EMSR model into the following 4 categories.

  1. Less than 3 days.
  2. Between 3 days and 7 days.
  3. Between 7 days and 34 days.
  4. 34 days or more.

  For papers giving a range of experiment days (e.g., 4 to 6 days), the maximum time was taken (e.g., 6 days).

- Number of hours per day

  The number of hours for data collection per day also greatly impacts the value of the dataset. Indeed, physiological signals may vary with the time of day [Gjoreski et al., 2017]. Here again the same studies were used to extract the 4 quartiles that will represent the following 4 categories.

  1. Less than 4h a day.
  2. Between 4h and 8h a day.
  3. Between 8h and 16h a day.
  4. 16 hours a day or more.

  For papers giving a range of experiment time per days, (e.g., 12to 14 hours) the maximum time was taken (e.g., 14h).

- Number of subjects

  As previously stated, emotions are experienced very differently by people. In order to validate an emotion recognition system, it is necessary to test it on as many subjects as possible. Similarly, the studies quartiles were used to create the following categories.

  1. Less than 6 subjects.
  2. 6 to 12 subjects.
  3. 12 to 24 subjects.
  4. 24 subjects or more.

  Quartiles were averaged to the superior round number.

These criteria represent a data collection paradigm that can be used to build an emotion recognition model usable in any ambulatory real-life application, such as the ones previously presented. Ideally, the data collection would be done using small non-invasive and non-intrusive sensors, with a model close to reality and tested in real life. Such study should be done for an extensive time with a great number of subjects to prove its efficacy.

4.4.2 The GARAFED visual aid

In order to ease the assessment of existing and future studies toward this goal, a visual aid is proposed (Fig. 4.1). Inspired by the Adapted ECOVAL framework [Labonte-LeMoyne et al., 2018], it allows to evaluate any study based on this readiness toward real-life application at a glance.

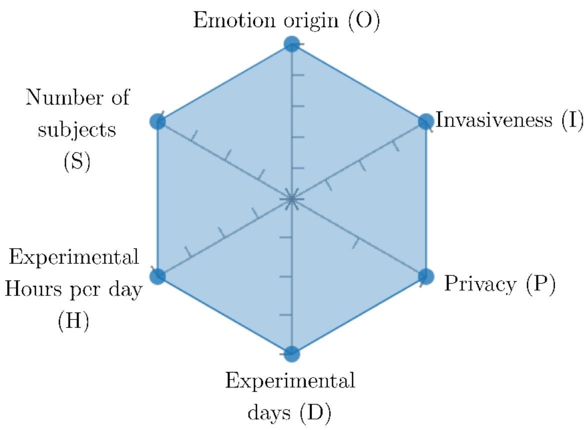


Figure 4.1: The GARAFED method.

4.5 Assessment of existing datasets

This subsection presents works involving real-life or supervised real-life environment. To build this corpus of studies combinations of the following keywords were used: "emotion", "emotion recognition", "emotion classification", "emotion detection", "valence", "arousal", "affect", "in the wild", "in the field", "in the fray", "in real life", "ambulatory", "physiological signals" , "biosignals" , "heart rate", "HR", "galvanic skin response", "GSR", "electrodermal activity", "EDA", "skin Conductance", "SC", "photoplethysmogram", "PPG", " blood volume pressure", "BVP".

Although the GARAFED may be applied to different types of input data, in this subsection it is used to assess papers focusing on physiological signals acquisition. Here, are distinguished:

- works using solely physiological signals (see section 4.5.1),
- studies collecting physiological signals and additional inputs such as audio or video (see section 4.5.2).

Acceleration sensors, while not collecting physiological signals, are wildly used in combination with physiological signals as an indicator of excessive movement and for filtering purposes. Therefore, a study using physiological signals and acceleration is considered as a physiological signals-only study instead of a multi-modal one.

In both cases, research papers will be separated in 3 categories:

- First of all, the studies proposing an EMSR detection or classification method tested in the wild.

- Secondarily, the empirical studies exploring physiological signals reactions to emotions, mood or stress in real-life settings without proposing a detection or classification method.

- Lastly, the studies using laboratory knowledge or real-life established methods to recognize emotions, mood or stress for specific real-life applications.

Only the first category will be displayed using the previously presented visualization method as only them are proposing an EMSR method. The second category represent the step before EMSR and may help researcher wishing to build such method by providing empirical information about emotions. The third category represents the step after EMSR as it presents studies using established models for specific applications. A list of the currently (2019) available devices to perform such ambulatory studies are available in the supplementary materials.

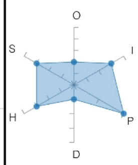
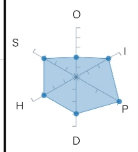
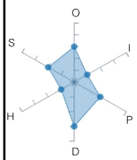
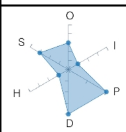
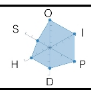
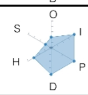
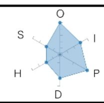
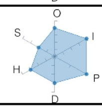
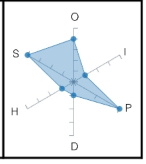
4.5.1 Physiological signals-based studies

Here, the studies focusing solely on physiological signals will be presented.

4.5.1.1 In-the-wild detection and classification studies

Studies on stress

Table 4.1: Physiological signal-based stress studies providing a detection or classification method.

Authors	Signal	Model emotion	Testing method	Emotional states	User dependency	Accuracy	Approximate duration	Number of subjects	Graphical Representation
Plarre et al. 2011	ECG RESP Acc	Public speaking period Mental arithmetic Cold pressor Self report	self report Smartphone 25 EMA/day	Psychological stress Perceived stress	UID	Psychological 90% Perceived stress: lab :72% field: 71%	2 days 12-14h/day	Lab: 21 Field: 17	
Hovsepian et al. 2015	ECG RESP Acc	Public speaking period Mental arithmetic Cold pressor Self report	self-report Smartphone 15 EMA/day	Stress	UID	lab:89% field: 72%	7 days 10-16h/day	Lab: 26 Field: 20	
Healey et al. 2005	ECG EMG EDA Resp	Driving (rest, highway, city) Validated by Self report & Score derived from video	Leave-one-out	Stress	UD	97,40%	1-7 days 2h/day	9	
Rigas et al. 2011	ECG EDA Resp	Driving Self-report voluntary oral	Leave-one-out	Stress	UID	82%	~40 days 50 min / day	13	
Dobbins et al. 2018	HR GSR	Self-report Smartphone 2 / day	Leave-one-out	Stress	UID	70%	10 days Waking hours	6	
Gjoreski et al. 2016	HR GSR ST Acc	Mental arithmetic	Self-report Smartphone 4-6 EMA/day	Stress	UID	92%	55 days	Lab: 21 Field: 5	
Muaremi et al. 2014	ECG Resp ST GSR	Self-report 1 / day	Leave-one-out	Stress	UID	73%	18 nights ~6h30/n	10	
Hernandez et al. 2011	EDA	Self-report 1 / call	Leave-one-out	Stress	Both	UD :78.03% UID: 73.4 %	7 days work hours	9	
Melillo et al. 2011	HR	Stressor: University evaluation - Control: After holidays	Leave-one-out	Stress	UID	95%	2 days 5m/day	42	

A few studies propose methods to estimate stress in real-life settings. Plarre et al. [2011] , Hovsepian et al. [2015] and Gjoreski et al. [2016] trained a model with 21 participants in the laboratory and tested it in real-life settings with respectively 17, 20 and 5 subjects obtaining 71%, 72% and 92% accuracy.

Using a different approach, Dobbins et al. [2018] , Muaremi et al. [2014] and Hernandez et al. [2011] used data from respectively 6, 10 and 9 participants collected in-the-field to estimate stress obtaining 70%, 73% and 78% accuracy.

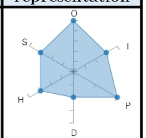
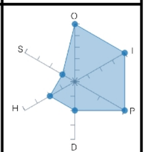
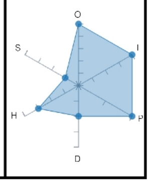
Other researchers constrained their studies to supervised environment such as Healey et al. [2005] and Rigas et al. [2011] who aimed to detect stress in drivers obtaining respectively 97% and 82% accuracy. Similarly, Melillo et al. [2011] used a real evaluation from a university to collect data from 42 students estimating stress with an accuracy of 95%. Table 4.1 summarizes those studies and present their respective GARAFED .

Studies on emotions and moods

There are much fewer studies proposing emotion or mood recognition methods tested in the wild. Carroll et al. [2013] aimed at studying emotional eating by detecting mood using a dimensional method. They reached 75% recognition for arousal and 72.62% for valence. Zenonos et al. [2016] aimed a recognizing moods in work environments. They proposed a model that reach an accuracy of 70%. Finally, Healey et al. [2010] studied emotion recognition in the wild with 19 participants and reached an accuracy of 85% for arousal and 70% for valence.

Table 4.2 presents those studies as well as their graphical representation.

Table 4.2: Physiological signal-based emotion and mood studies providing a detection or classification method.

Authors	Signal	Model emotion	Testing method	Emotional states	User dependency	Accuracy	Approximate duration	Number of subjects	Graphical representation
Healey et al. 2010	GSR HR Acc	Self-report Voluntary Smartphone 2D map	Self-report Smartphone	Valence-Arousal	UID	85% Arousal 70% Valence	5 days 8+ h/d	19	
Carroll et al. 2013	Resp HR EDA Acc	Self-report Smartphone 1 EMA/h 2D map	Leave-one-out	Valence-Arousal	UID	Arousal : 75% Valence : 72.62%	4 days 4-6 h/d	4	
Zenonos et al. 2016	HR ST Acc	Self-report Smartphone 1 EMA / 2h Emotions %	Leave-one-out	Excited Happy Calm Tired Bored Sad Depressed Angry	Both	Max Average : UD: 70% UID : 62%	5 days 8h/d	4	

4.5.1.2 Empirical studies in real-life environment

Studies on stress

Most studies on stress in the wild are preliminary studies and present findings and observations of physiological reactions to natural stressors without proposing a detection model.

The disparities in stress experiences in-lab compared to in-the-wild are assessed by Dikecligil and Mujica-Parodi [2010] that compared HRV obtained from 33 subjects during 2 short term laboratory measurements (aversive then benign IAPS images), a long-term hospitalized monitoring (24h) and a supervised real-life study (180 min including a first-time tandem skydive). They found strongly predictive correlations between laboratory results and supervised real-life study.

Similar supervised real-life studies were conducted notably by Fenz and Epstein [1967] that monitored HR and respiration in 10 novice and 10 experienced parachutists during a jump. They found a sharp rise in physiological activity in novice jumpers and an inverted V-shaped curve in experimented ones. Wilhelm and Roth [1998] similarly studied HR and respiration during a plane trip with flight phobics which pointed additional HR as a reflection of participants anxiety. Kusserow et al. [2012b] present their finding when monitoring people in the wild as well as a musician, an Olympic ski jumper and a public speaker. They found correlations between HR and stress arousal. Baek et al. [2009] tried to evaluate stress in driving using a custom car equipped with sensors (ECG, GSR, Resp). In this supervised real-life study, temperature, noise, time of day (night vs daytime) and simultaneous arithmetic calculations separated were altered to create stressful environments. They found meaningful changes in physiological signals during simulated stress environment. Different physiological reactions in participants were obtained for the same stressor. This highlights individual differences in reaction to emotional triggers.

Ambulatory in-the-wild studies were also conducted. Verkuil et al. [2016] proposed an in-lab calibration using rest, standing cycling and stairs to improve the capabilities of categorizing metabolic and non-metabolic HRV reductions in the wild (24h) using ECG and 3D accelerometer. Additional HRV was found associated with negative affect and worrying. Johnston and Anastasiades [1990] studied the relation between HR and stress, arousal and time pressure in real life with 32 subjects for 24h. No significant relation were found between the HR and the emotional state in most participants. A significant relation was obtained only in a small subset of subjects which were found more anxious, angry and with higher systolic blood pressure. Ramos et al. [2014] attempted to simulate out-of-the lab environment by introducing movements. They found a great need in detection methodologies adapted to real-life applications and assessed the possibility to use detection of physical activity to improve stress detection increasing stress classification (f-measure improved of 130%).

Studies on emotions and moods

Studies on mood and emotions are less common than the ones focusing on stress. Myrtek and Brügner [1996] studied ECG associated with a 3D Accelerometer to compare laboratory induced emotional events to real life ones. The self-reports of 500 participants during a 23h ambulatory study were used and highlighted disparities between emotional arousal in the wild compared to results obtained in laboratory.

Kusserow et al. [2012a] proposed an evolved solution to the additional heart rate method to determine arousal by improving the physical activity detection. They used such technique to assess arousal in daily activities such as taking public transport or office work.

Picard and Rosalind [2000] proposed innovative ways to gather physiological signals for ambulatory emotion recognition, notably EDA sensors in earrings, shoes and glasses

Schmidt et al. [2018] collected 1081 EMAs from 10 subjects over 148 days and proposed several guidelines for ground truth data labelling as presented in the second paragraph in 4.3.3.2.

4.5.1.3 Usage of laboratory knowledge

Studies on stress

While no gold standard in terms of stress detection in the wild has been established, some studies used the previously presented findings in physiological signal reactions to stressors to assess stress for further purposes. For instance, Massot et al. [2011] uses physiological signals to evaluate stressful part of a walking path for blinds in ambulatory settings. Al-Fudail and Mellar [2008] evaluate teachers' stress level when using technological tools in the classroom through GSR.

Myrtek et al. [1999] studied 29 blue and 57 white collar workers to determine stress and strain at work using HR. Several indices were used to define each type of strain: HR for total strain, physical activity for physical strain, HRV for mental strain. Later, Myrtek et al. [2005] took the same approach to evaluate stress and strain in female students. They found that there is two type of persons "cool" or "emotional" . The subjects in the first type do not consider anything as moods (no emotion perception) and the ones in the second type are very aware of their emotions (high emotion perception). Kimhy et al. [2009] evaluated the relation between stress and arousal for 20 patients with psychosis using both EMAs and the Life Shirt [Grossman, 2004] during 36h ambulatory studies. Zhang et al. [2012], designed a mobile application that estimate stress using HRV and prompted the user to relax through breathing exercises. Rahman et al. [2014] studied stress in illicit drug users, daily smokers and drinkers. They used the previously mentioned model of Plarre et al. [2011] to access stress and found after the first week a significant learning effect from the subjects in how to provide valuable data. Karlsson et al. [2011] studied the reaction of ambulance professionals to alarms. They showed that all subjects experienced increased heart rate when there was an alarm regardless of their experience, education and gender which implies a physical arousal detected by the heart rate.

Studies on emotions and moods

Similarly, researchers used knowledge of emotions and mood's effect on physiological signals established in the lab to use in application conducted in the wild. For instance, Kim and Fesenmaier [2015] used EDA to estimate 2 travelers' emotions during a 4 days trip. Their mean EDA level correlated with their experience of each activity. Roseway et al. [2015] used EDA to determine arousal and HRV to determine valence in 10 participants during a 10 days study. Arousal was displayed using a color-changing emotional crystal to help mood-awareness at work in the workplace. The device improved stress control abilities in the subjects. Similarly, Snyder et al. [2015] used the color of a desk lamp to reflect subjects internal state estimated from EDA. It provided information on the way arousal feedback affects understanding of ourselves and others.

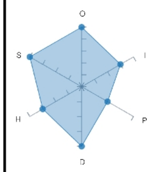
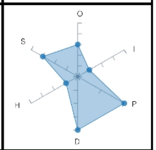
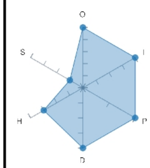
4.5.2 Multimodal approaches

Collecting additional signals in addition to physiological signals might ease the recognition of emotions moods and stress. Here, the studies using a multi-modal approach including physiological signals will be presented.

4.5.2.1 In-the-wild detection and classification studies

Studies on stress

Table 4.3: Multimodal stress studies providing a detection or classification method.

Authors	Signals	Model emotion labeling	Testing method	Emotional states	User dependecy	Accuracy	Approximate duration	Number of subjects	Graphical representation
Muaremi et al. 2013	Microphone, Acc GPS Phone calls Address book Calendar Battery HR	Self-report Smartphone Audio 4 EMA /day	Leave-one-out	Stress	UD	61%	4 month 12-14h/d	35	
Rigas et al. 2011	ECG EDA Resp Driving event	Driving Self-report voluntary Oral	Leave-one-out	Stress	UD	96%	~ 40 days 50 min / d	13	
Gjoreski et al. 2017	HR EDA ST Acc Activity Hour of the day Type of day	Self-report Smartphone 4-6 EMA & Voluntary	Leave-one-out	Stress	UD	Recall :70% Precision : 95%	55 days	5	

A few studies used physiological signal combined with additional inputs to study stress. For instance, Muaremi et al. [2013] used smartphone information such as phone calls and calendar associated with heart rate to detect stress. They reached a 61% accuracy. Rigas et al. [2011] associated driving event information to physiological signals to detect drivers' stress and obtained an accuracy of 96% .

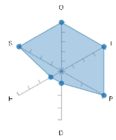
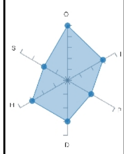
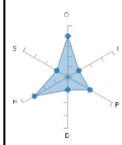
The presented studies and their representation may be found in Table 4.3

Studies on emotions and moods

Moods and emotions have also been studied using multimodal inputs. Kanjo et al. [2018] associated noise environment, ambient light levels and air pressure to physiological signal to predict emotions with a 86% accuracy. Exler et al. [2016] used smartphone extracted data such as calls and calendar associated with HR to evaluate valence with a 91% accuracy. McDuff et al. [2012] limited their study to a working desk. They added devices to the subjects desk such as cameras and position sensors. The reached an overall accuracy of 68% to recognize valence arousal and engagement.

Those studies are presented in Table 4.4 alongside with their GARAFED.

Table 4.4: Multimodal mood and emotions studies providing a detection or classification method.

Authors	Signals	Model emotion labeling	Testing method	Emotional states	User dependency	Accuracy	Approximate duration	Number of subjects	Graphical representation
Kanjo et al. 2018	HR EDA ST 3D Acc Air pressure Light GPS Noise	Self-report Smartphone SAM Constant evaluation	Leave-one-out	Valence	UID	86%	45 min	40	
Exler et al. 2016	Location Current app Microphone Messages Calls Light Connectivity Calendar Activity HR	Self-report Smartphone Emotions % 1 EMA / h & 1 / specific event & Voluntary	Leave-one-out	Valence	UD	Avg: 68% Max: 91%	4 weeks Waking times	6	
McDuff et al. 2012	Video Posture Microphone EDA 3D Acc GPS File activity Calendar	Self-report 2D map EMA	Leave-one-out	Arousal Valence Engagement	UID	68%	2 days 10h /d	5	

4.5.2.2 Empirical studies in real-life environment

Pärkkä et al. [2008] studied the relationship between physiological signals, behavioral variable, exterior variables such as temperature, room illumination and self-reports of moods and stress for 3 months with 17 subjects. Self-reported stress reported by the subjects correlated with the variables. Sarker et al. [2016] studied the GPS, activity data and physiological data of 38 subjects during a 4 weeks experiment. They highlighted patterns such as the predictability of stress events durations using previous data and likelihood of stress events depending on the time of day. They proposed a way for predicting the likelihood of a momentary stress episode to become significant, Adams et al. [2014] collected EDA, microphone input and stress self-reports of 7 participants for 10 days. The found a correlation between audio profiles , EDA and self-reports of stress. Kocielnik et al. [2013] used GSR to evaluate arousal during a workday. The system created a 5 level arousal map (very high arousal to very low arousal) associated with calendar activities. 91% of the users found the generated arousal map a good reflection of their feelings.

4.6 Conclusions

Accurate emotion recognition in the wild has a great potential to support affective science research and to develop applications designed for the general public. Whether it is applied to robotics, with robots understanding humans emotions, in health care, for an increased capacity to understand our own emotions or the one of others, in domotics, with smart homes adapting settings to your moods or other domains, emotion recognition has been a goal we are trying to achieved for decades. Emotion recognition is of particular interest in this research since, as previously stated, it would allow to automatically detect patients emotion and create an affect-aware and adaptative system.

However, research has mainly be limited to laboratory environment and needs to be broaden out to the wild to really achieve meaningful progress. In this chapter the main differences between classification and detection of emotions in the wild and in the laboratory were presented. The main decisions to take, according to the goal of the desired study, their advantages, challenges and limitations were pointed out, and a visual method to categorize studies based on those main choices was proposed. Studies focusing on physiological signals were assessed using such method and existing devices suitable for ambulatory studies, whether they are designed for research or for the general public were listed. Studies, past or future, using physiological signals or other types of input for emotion, stress or mood recognition may be assessed using this method in the future.

The reason why there is a real need for research to be done in emotions recognition in the wild was highlighted. It was shown that while a tendency toward this goal has been seen, very few papers focus on this matter today. The quantified-self trend associated with the smaller and more portative sensors technology nowadays makes it easier for researcher to step in this path. This review was submitted to the journal "frontiers in psychology - emotion science".

5

EMOTIONAL DATA COLLECTION IN THE LABORATORY USING VR GAMES

As seen in the previous chapter, one of the greatest challenges in Affective Computing is the creation of ecological multimodal datasets for emotion detection and recognition. Ideally, such datasets would contain affective expressions recorded in the wild, i.e., in a real-life setting. Unfortunately, reproducing these ideal conditions is time consuming and very challenging. This chapter investigate alternative data collection methods in laboratory settings that would elicit strong emotions.

5.1 Introduction

Currently, Virtual Reality (VR) technologies are widely applied to investigate complex human behaviors and to elicit similar-to real-life emotions. For example, VR is a well-established medium for investigating fear perception and treatment [Diemer et al., 2014; Mühlberger et al., 2007; Rothbaum, 2009]. A characteristic of VR is the possibility to elicit emotional reactions as, by its nature, it mainly relies on perceptual, visual and auditory stimulation (including perceptual feedback of one's own actions). Recent studies have highlighted the need to consider both bottom-up and top-down perceptual processes, in order to understand how VR can become emotionally engaging (e.g., how background narrative can enhance emotional experience [Peperkorn and Mühlberger, 2013]). In Diemer et al. [2015], authors reviewed the factors influencing presence perception, with emotional states (e.g., fear) being crucial, according to clinical psychology. In their analysis, they considered the central role of perception in eliciting emotional reactions and the role of arousal as a basic dimension of emotional experience. Finally, in Meuleman and Rudrauf [2018] the authors used a set of VR consumer games to elicit emotions in participants in lab conditions. According to Scherer's model [Scherer, 2009], they asked participants to self-report appraisal components, physiological reactions, feelings, regulation and action tendencies in addition to emotion labels and dimensions. Using multivariate analyses, they shown the relation between reported labels and affect components.

Several works attempting to create emotional states in the laboratory for scientific aims are based on appraisal theories. For instance, Conati and Zhou [Conati and Zhou, 2002] implemented a probabilistic model, using Dynamic Decision Networks, to recognize student's emotional states in an educational game context, following the OCC appraisal theory [Ortony et al., 1990] and considering the students' goals and personality.

In the video game context, Johnstone [1996] analyzed the relation between the acoustic features of the player's vocal responses and the manipulations of some appraisal properties of Scherer's Component Process Model [Scherer, 2009]. Another attempt at using a video game for the manipulation of appraisals was proposed by Kappas and Pecchinenda [1999], while van Reekum et al. [2004] used a simple video game to study physiological effects of the same properties addressed by Johnstone.

5.1.1 Roseman's appraisal theory

In affective sciences, emotion elicitation refers to the use of emotionally valanced stimuli to evoke affective responses. Emotion research often relies on appraisal theories of emotions, considering emotion as a process, rather than a state.

These theories highlight the central role of appraisal, suggesting that it can trigger and differentiate emotional episodes, determine intensity and quality of action tendencies, physiological responses, behaviors and feelings [Lazarus, 1991; Scherer, 2001]. In this framework, it can be argued that appraisal elicits emotions [Moors et al., 2013].

This chapter relies on the appraisal theory of emotions proposed by Roseman et al. [1996] for emotion elicitation . According to this theory, the appraisal process categorizes a given situation according to five dimensions:

- situational state: assessing whether the appraised event is consistent or not with someone's motives;
- probability: indicating the certainty or uncertainty of the outcome of the appraised event;
- agency: indicating whether the person is in control over the event or if some other agent (or external circumstance) is in charge;
- motivational state: assessing whether the event is consistent with the motive of obtaining reward or of avoiding punishment;
- power: referring to a person's control power over the situation.

For instance, the event of receiving a prize would elicit pride, as it is (1) consistent with one's motives of being rewarded, (2) certain, and (3) appraised as something depending on the person's ability or performance. In the Ironman game, the elicitation of the positive emotion of joy and of the negative emotion of frustration is the focus. More precisely, the game play is designed to re-create the situational circumstances that, according to Roseman's appraisal theory, elicit joy and frustration. Details about the emotion eliciting events exploited in the game are provided in Table 5.1.

Table 5.1: Appraisal variables of the Ironman VR game for emotion elicitation.

Emotion	Appraisal variables	Emotion eliciting events in the game
Frustration	Circumstance-caused, strongly uncontrollable events inconsistent with personal appetitive motives	Uncontrollable circumstances (i.e. time constraints) make it impossible for the players to win the game
Joy	Circumstance-caused, controllable events consistent with personal appetitive motives (e.g. obtaining a reward)	Having enough time to complete the task, players can satisfy their desire to win the game

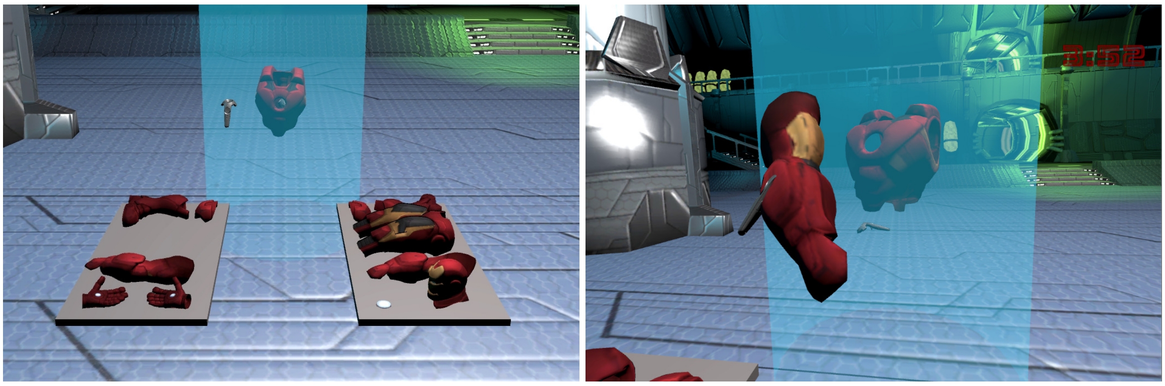


Figure 5.1: Two screenshots of the appraisal theory based VR game: at the beginning of the game the suit pieces are randomly arranged on two tables (left); the player has to assemble the Ironman suit inside the light blue cylinder as fast as possible (right); a timer is visible in the top right corner.

5.2 A VR game for emotion elicitation

To address the limitations encountered by previous research, and to investigate alternative data collection in laboratory settings that would elicit strong emotions, a virtual reality game was developed here (Fig. 5.1). It aims at eliciting emotional states and providing a system for recording synchronized multimodal data streams. Most of the existing works in the field of affect detection and recognition focus on facial expression and audio. Here, a system recording a novel combination of modalities: physiological (HR, GSR, ST, muscle contraction), kinematic (acceleration), visual (video of the user and the VR environment seen by the user) and auditory (user's respiration) was designed. While some previous works address them separately (e.g., [AlZoubi et al., 2012; Loghmani et al., 2017; Lussu et al., 2019]), this system collects all of them at the same time and in sync, with the possibility to add other sensors and devices thanks to its modular nature.

This emotion elicitation game was designed leveraging the Roseman theory. The choice of an immersive VR environment affords better control and manipulation of the emotion-eliciting stimuli and ensures the replicability of the conditions among participants. It is also expected that the immersive environment will produce stronger emotional elicitation.

5.2.1 Game flow

The "Ironman Game" is a single user VR game designed to elicit joy and frustration in the player. The game is based on the manipulation and assembly of virtual objects to be performed within a limited amount of time. The HTC Vive headset is used for visualization, while interaction is made simple and intuitive through the use of HTC Vive controllers: objects can be grabbed and released by pressing and letting go the controller's trigger button.

Following Meuleman & Rudrauf's guidelines on game design for emotion elicitation [Meuleman and Rudrauf, 2018], this VR game exploits relatively simple game controls and cognitively demanding tasks and elaborate narratives were intentionally avoided. The futuristic environment was chosen to give the player the impression of a familiar environment, similar to that many commercial games, so they can feel engaged and are not distracted by the data collection process going on during the playing session. Moreover, a soundtrack was played in the background in order to facilitate immersion.

In the introductory scene, the players are provided with the game instructions. Next, they play a demo scene in which some pieces of the suit are pre-assembled, to familiarize with the game interaction modality. Then, the actual game starts and the players have a limited time to complete the task of assembling the entire suit. On the top left part of the VR display, a timer is shown only at the beginning and during the last 10 seconds of the game. During some preliminary tests, indeed, it was noticed that players do not pay attention to the timer in a continuous manner. Audio messages are also played back during the game to announce that only 10 seconds are remaining to complete the task.

The game has two playing conditions: normal vs. manipulated. In the manipulated condition, the duration of the game turn was shortened without announcing it to the player. Whenever the player is close to accomplish the task (i.e., when 11 of the 13 suit parts have been correctly positioned), the timer appears and a voice announces that only 10 seconds are left until the end of the turn, making accomplishing the task and successfully complete the game in time highly improbable. Consequently, even if the player managed to easily finish the game in time in the normal condition, performing the same task using similar skills in the manipulated one will result in a failure.

The game was designed to elicit two emotional states: joy and frustration. By accomplishing the task in time in the normal condition, the player will probably, according to the theory, feel joy. Consistently, it was expected that the proposed manipulation would elicit frustration, as the unexpected game ending would be seen as a certain undesirable event caused by circumstances.

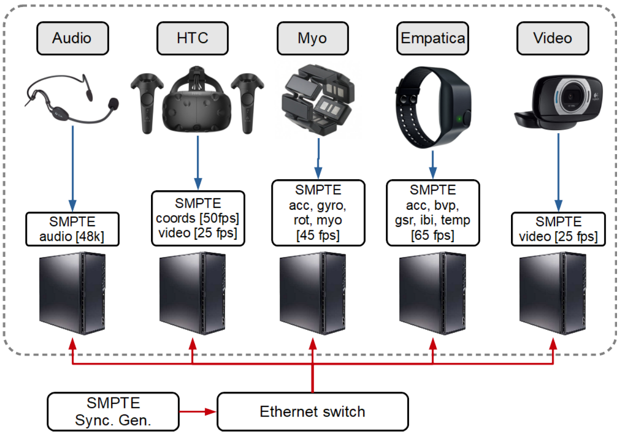


Figure 5.2: Multimodal recording system. Several machines connected through a wired network receive a SMPTE timecode at 100 Hz. Each one of them manages the communication with one of the sensors and records the corresponding data along with timestamps.

5.2.2 Multimodal recording system

A multimodal recording system was implemented by exploiting the EyesWeb XMI open research platform, a modular application that allows researchers to quickly design and develop real-time multimodal systems [Volpe et al., 2016]. The platform is based on modules, or *blocks*, that can be visually and intuitively assembled to create programs, or *patches*, to process input data streams and generate multimodal output in real-time. Figure 5.2 illustrates the system architecture.

The recording system has the following main characteristics:

- it can process data from multiple sensors;
- it generates a synchronization signal that is used to add a time-stamp to the recorded signals;
- it is distributed over a network of wire-connected workstations;
- by adding workstations, it can be extended in order to record a larger number of sensors without introducing latency.

As reported in Figure 5.2, several machines are connected through a wired network, on which a SMPTE timecode[1] signal is constantly transmitted via UDP packets and acts as a synchronization clock between the machines. Each machine has an internal clock that is used to generate timestamps for the recorded data. Whenever a SMPTE timecode is received, the internal clock is updated, if needed, to match the timecode. The wired network is a local gigabit Ethernet connection which ensures a high speed transmission of the UDP packets containing the SMPTE timecodes. The system is an extension of the

[1] https://en.wikipedia.org/wiki/SMPTE_timecode

SIEMPRE recording platform [Glowinski et al., 2013], which exploited dedicated hardware, instead of a common network connection, to ensure the time sync between the machines.

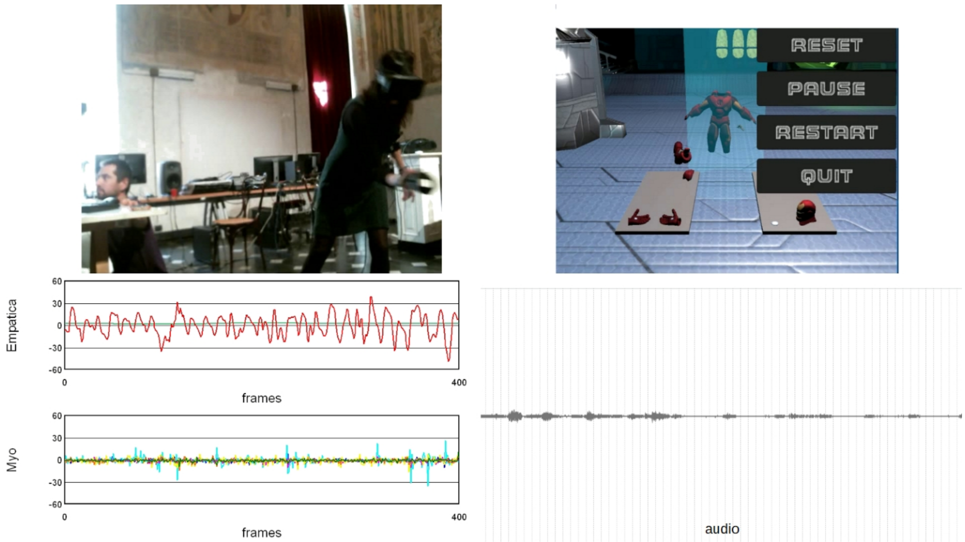


Figure 5.3: A screenshot of multimodal data playback from the EmoVR corpus: physical (upper-left) and VR (upper-right) environment videos, physiological sensor data (lower-left) and audio data (lower-right).

Each machine connected to the system acts as an independent recorder and manages the communication with one of the recorded sensors. The recorded data is always timestamped, that is, each single datum (e.g., an audio or video frame, a physiological datum) is associated to the internal clock of the machine that received and recording it. Figure 5.3 shows an example of the sensors and data streams that our system allows to record and synchronize, as described next.

5.2.2.1 Sensors and Data

Physiological signals

The Empatica E4[1] wristband was used to collect physiological data. It is designed to collect physiological signals related to emotions: PPG for BVP as an indicator of HR, EDA and ST. This device is medically certified and provides reliable data [McCarthy et al., 2016].

During the experiment, it was connected via Bluetooth to an iOS mobile application. Once the data was transferred, the application forwarded it to EyesWeb via UDP packets.

Forearms EMG

Some existing works used EMG signals to detect expressions of specific emotions, e.g., amusement [Perusquía-Hernández et al., 2017] or movement expressive qualities [Ward

[1]https://www.empatica.com/en-eu/research/e4/

Table 5.2: List of tasks used in the data collection session

Name	Code	Description	Expected emotions
Kitty Rescue game[1]	T1	rescue the kitten lost a tall sky scarper in construction (i.e., virtual height exposure)	fear, joy satisfaction
Set of videos used in Chirico et al. [2018]	T2a	combination of YouTube clips	amusement
	T2b	video of hens wandering across grass	neutral
	T2c	video of high mountains took with the drone camera	awe
	T2d	video sequence of tall trees in a forest	awe
Ironman Game	**T3**	**see section 5.2.1 for description**	**frustration, joy**
Shinrin-yoku: Forest Meditation and Relaxation[2]	T4	relax in a virtual forest inspired by "Forest Bathing" Japanese relaxation method	awe
RideOp - VR Thrill Ride Experience [3]	T5	experience attractions of VR luna park	fear

et al., 2016]. More frequently, however, researchers developed multimodal systems to detect emotion-related movement qualities using a combination of signals, including EMG (e.g., [Girardi et al., 2017; Nakasone et al., 2005]).

In order to increase the portability of our system and to give the player the impression of an ecological gaming experience, the use any high precision EMG devices were avoided as they are often bulky. Instead the consumer-level MYO device[2] was chosen, which is shaped as a lightweight band attached to the player's forearm. The MYO SDK and Bluetooth communication were used to transmit EMG data to EyesWeb XMI via UDP.

Video

While it will not be used for emotion recognition, multiple synchronized video streams are recorded for other purposes: it allows to keep track of how the player reacts to stimuli in the physical environment and the actions they carry in the VR environment.

By looking at those streams it is possible to better identify the player's actions during the data segmentation phase. For example, large/energetic body movements may be excluded from the dataset, as it is demonstrated that physical activity have detrimental effects on the reliability of physiological sensors (e.g., PPG) [Ge et al., 2016].

Video is recorded in EyesWebXMI by capturing a portion of the screen of the machine running SteamVR[3] (to record what the payer is seeing in the VR environment) and by receiving frames from a webcam (to record how the player is moving in the physical environment). Both video streams are synchronized by timestamping them with the current sync clock.

Respiration Audio

The work presented in Lussu et al. [2019] demonstrated the possibility of guessing movement by analyzing the audio of respiration captured with a normal voice microphone placed near the participant's nose. It has been also shown that emotional states can be recognized from movement expressivity [Castellano et al., 2007]. For this reason, it was expected that audio from respiration can be exploited to detect emotional states.

[2] https://support.getmyo.com/hc/en-us
[3] https://www.steamvr.com

A head mounted wireless microphone was placed close to the mouth of the player. This approach is similar to the one adopted in Lussu et al. [2019], where user's respiration data was extracted from an audio signal. Audio is recorded in stereo at 48 KHz: the first channel contains the actual respiration audio while the second one contains the SMPTE clock encoded as an audio signal. In this way, the SMPTE clock may be decoded and the respiration audio played in sync with the other data streams at a later stage.

5.2.3 EmoVR multimodal corpus

A preliminary data collection was carried out by exploiting the VR game described in Section 5.2.1 and the recording system illustrated in section 5.2.2. The outcome was the EmoVR multimodal corpus of emotional states elicited by VR games.

Our long-term goal is to build multimodal classifiers to detect non-basic emotions. To this purpose, the set of tasks to be performed in the VR environment were chosen to collect the physiological responses of two negative and two positive affective states, to avoid that our classifier will classify emotions along the valence axis only. Along with the Ironman game designed to elicit joy and frustration, other commercial games and contents available on SteamVR were exploited, half of them focusing on eliciting fear of height [Meuleman and Rudrauf, 2018], the other half eliciting awe [Chirico et al., 2018, 2017].

5.2.3.1 Protocol

All participants had to perform 5 tasks in a fixed order, as shown in Table 5.2. The games requiring an active participation of the user were interleaved with video contents requiring a passive participation only. The purpose was to alternate the tasks that may possibly elicit high arousal in participants, with less agitating sessions.

After each data collection stage, participants were asked to self-report their affective state, by selecting from a list of 16 labels (see Table 5.2), including most of the emotions from Roseman's theory. Each participant could report more than one emotion per task. The 4 stimuli used in Task T2 were considered separately as it was expected that each of them might induce a different emotion (see [Chirico et al., 2018, 2017]).

5.2.4 Results an Discussion

Five participants took part in the data collection (2 males, 3 females). From the participants self-reports (see Table 5.3) it emerges that a large spectrum of positive and negative emotions were successfully elicited during Tasks T1-T5, showing that VR-based methods can be used to collect affect-related data. In particular, the emotion that was the focus here, i.e., frustration, was successfully elicited in 3 out of 5 participants.

Other reported emotions were: joy, pride and surprise. One participant, however, did not report any emotion. It is important to notice that, according to appraisal theories, the same event can result in different emotions being elicited, depending on how the person experiences the event. Therefore, although carefully designed stimuli were used,

Table 5.3: Self-reported emotions for each task.

Task	T1	T2				T3	T4	T5
		a	b	c	d			
awe/delight	0	0	0	1	1	0	3	3
surprise	1	1	0	0	2	1	1	0
hope	0	0	0	1	0	0	0	0
joy	1	3	0	1	2	1	2	1
relief	2	0	0	1	0	0	2	1
fear	5	0	1	0	1	0	0	4
frustration	2	0	0	0	0	3	0	0
anger	0	1	1	0	0	0	0	0
pride	0	0	0	0	0	1	0	0
guilt	0	0	0	0	0	0	0	0
regret	0	0	0	0	0	0	0	0
sadness	1	0	1	0	0	0	0	0
distress	1	0	0	0	0	0	0	0
no emotion	0	1	3	1	1	1	0	0
other emotion	0	0	1	0	0	0	0	0

the elicited emotions may differ from the ones expected by the experimenter, at least for some of the participants. For instance, in our experiment, one participant reported the disgust emotion (the "other emotion" row in Table 5.3) in response to the supposedly emotionally neutral stimuli (i.e., hen-house video, stimuli T2b). After the experiment, the participant reported a personal repulsion for that animal. Regarding the elicitation of the positive emotion of awe (T2c and d, T4),it was experienced by three participants, confirming the previous results in [Chirico et al., 2018, 2017].

This study was published in the MIG 2019 conference [Bassano et al., 2019]

5.3 Conclusions

This game is the first immersive VR game inducing emotional states based on appraisal psychological theories and a system for collecting synchronized multimodal data, exploiting a novel combination of modalities, i.e., physiological data (Empatica and MYO), kinematic data (MYO), video recordings and audio. Preliminary experimental results show that it is possible to successfully induce a spectrum of positive and negative emotions in VR scenarios, even if there are some limitations in using a simplified questionnaire for emotion self-reporting.

In the future, more sophisticated validated tools (e.g., GRID [Fontaine et al., 2013]) could be exploited to check whether the participants' reactions not only corresponded to the experimenter's expectations in terms of emotional labels but also in terms of single appraisal evaluations. Finally, deep learning techniques may be used on the collected corpus to develop models for automatically recognize of emotional states.

While this system successfully elicited strong positive and negative emotions on subjects and can be used for other type of research, it did not successfully elicited the desired emotion on every participants. Therefore, adapting it for LIS patients as a way to elicit emotion for emotion recognition would not be an adequate route to pursue the goal of this research. Collecting emotions in the wild seems to be a more adapted solution for the purpose of this research and will be investigated further in next chapter.

6

TOOLS FOR EMOTION DETECTION FOR REAL-LIFE APPLICATION

As seen in Chapter 4, several works have shown that physiological signals can constitute indices for automatic emotion recognition [Shu et al., 2018]. Differences were observed when comparing physiological data of emotions induced in the lab to real-life emotional reactions [Wilhelm and Grossman, 2010]. Difficulties in building the affect-related datasets in ecological settings, e.g., establishing the ground truth, are well documented in the literature [Schmidt et al., 2018]. Proper data segmentation and labelling is one of the main challenges [Healey et al., 2010]. This chapter will investigate novel ways to collect physiological data in the wild while taking into account the challenges of data labelling. Open-source tools will be proposed to researchers wishing to work toward this goal.

6.1 Appraisal Theory-based Mobile App for Physiological Data Collection and Labelling in the Wild

As seen in Chapter 5, appraisal theories have been greatly used in emotion-related applications in the past. It was used in this section in order to help collecting and labelling physiological data in the wild through an open-source mobile application (app). The Ortony, Clore and Collins (OCC) model [Ortony et al., 1990] (Fig. 6.1) has been chosen as it was successfully used in affective computing applications in the past [Bartneck, 2002; Conati, 2002]. It can predict 22 emotion labels based on valence and the emotional trigger type (event, object or agent). The app detects additional heart rate to predict emotional events from physiological signals [Myrtek and Brügner, 1996]. Once relevant events are detected, the app prompts the users to provide the appraisal evaluation of the event, helping them to define their emotional state. Unlike existing solutions, which often only use a constrained list of emotional labels [Nasoz et al., 2004] or dimensions [Carroll et al., 2013], here, a questionnaire is introduced based on appraisal theory to help the user provide the ground truth for his/her emotional states. By collecting the information about appraisal process, the hope is to improve the ground-truth labelling and to provide more consistent annotation of corresponding physiological signals.

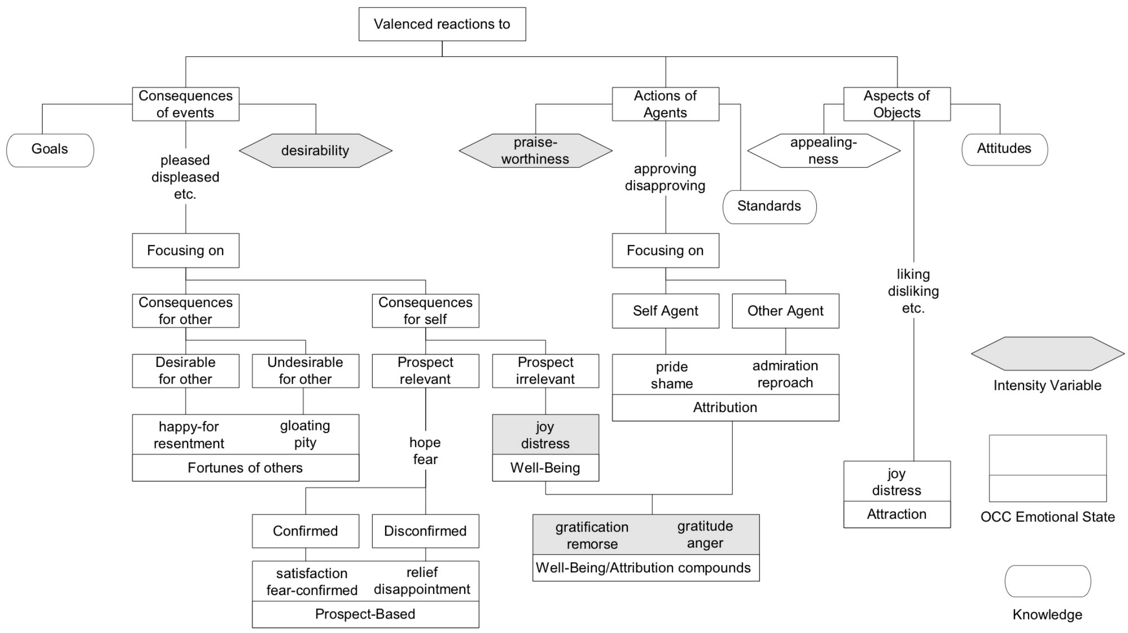


Figure 6.1: OCC model

6.1.1 Emotion recognition from physiological signals

Emotion recognition from physiological data collected in the lab was often addressed [Shu et al., 2018]. Most of the studies use measurements of Heart Rate (HR), Skin Conductance (SC), ElectroDermal Activity (EDA), Galvanic Skin Response (GSR), Skin Temperature (ST), and Respiration. Fusions of several signals were also studied. For instance, the combination of HR, EDA and ST, also used in this work, has been studied in the past in Nasoz et al. [2004] to classify anger, surprise, fear, frustration, and amusement with an average recognition rate of 83% [Nasoz et al., 2004].

Studies using data collected in ecological settings are rare, and most of them focus primarily on stress detection [Gjoreski et al., 2017; Hovsepian et al., 2015; Plarre et al., 2011]. Some studies investigating affective states focused on moods [Zenonos et al., 2016] as they can be measured at any time of the day. It is more difficult to collect and label the data of emotions in ecological settings, as they are usually much shorter and more momentary than moods [Gray et al., 2001]. Therefore, methods which ask the user to report emotions at fixed time intervals, e.g., Plarre et al. [2011], might not be appropriate to collect such data.

6.1.2 Methods for emotional self-reporting in the wild

According to Scherer [2005], existing techniques for emotional state self-reporting can be divided into two groups: free response and fixed-response labelling. While the first group allows for a higher precision of labelling (custom labels [Isomursu et al., 2007], verbal reports [Muaremi et al., 2013]), it makes it difficult to develop machine learning recognition models due to a potentially wide range of emotion labels selected by users. Constrained solutions include the usage of a finite list of labels (e.g., Nasoz et al. [2004]) or dimensional models such as valence-arousal (e.g., Healey et al. [2010]) or pleasure-arousal-dominance (e.g., Kocielnik et al. [2013]). More user-friendly techniques may be used for reporting such as emoticons [Meschtscherjakov et al., 2009]. Affect dimensions are usually reported through the Self-Assessment Manikin (SAM) method [Isomursu et al., 2007] or through 2D point maps [Carroll et al., 2013].

In Schmidt et al. [2018], guidelines are provided for emotional labelling in the wild by comparing the results of different methods. A combination of manual reports and automatically triggered prompts is advised, as well as providing the means to the user to manually correct the timespan of an emotional event. Unlike Schmidt et al. [2018], that used time-based trigger, in this study prompting based on physiological cues [Myrtek and Brügner, 1996] was used and an experimenter-free data gathering protocol was implemented. The role of the experimenter was reduce in order to help different research teams to contribute in future to the creation of a large shared dataset.

6.1.3 Methods for emotional physiological data collection

In real-life settings, the physiological data labelling and segmentation (i.e., defining the start and end of an emotion) are the main challenge [Healey et al., 2010]. A few studies used mobile apps to collect both physiological data and affect related states. The most common ones collect stress levels [Hovsepian et al., 2015; Muaremi et al., 2013] or moods [Carroll et al., 2013; Zenonos et al., 2016] .

Healey and colleagues [Healey et al., 2010] conducted a real-life experiment using a mobile phone app to study different labelling methodologies for physiological data collection. They collected data and self-reports in the form of discrete labels and dimensional models (valence and arousal) and drew attention to some difficulties linked to self-reporting. For instance, from the reports, the label "anxious" was annotated both as a positive and negative emotion. This example highlights a need for a scheme to help users pick labels. They reached a rate of 85% for classifying arousal and 70% for classifying valence using GSR and HR on manually extracted data segments of various durations.

6.1.4 Preliminary study

In a preliminary study (PS) physiological data was collected in ecological settings using a standard paper-based self-reporting method. 4 subjects (3 males, 1 female; avg. age 29 years) participated in the study. The experimental procedures follow the IIT ADVR TEEP02 protocol, approved by the Ethical Committee of Liguria Region on September 19, 2017.

6.1.4.1 Study protocol

The subjects wore the Empatica E4 bracelet [Empatica, 2012] for 5 days, 12 hours a day. They were asked to remove the bracelet at night, during sport and showers. They kept a hand-written journal of their emotions. The focus was given to the 3 most common basic states: happy, sad and angry. For each emotional event, participants were asked to report its start and end time as well as the intensity using a 5 point Likert scale. The focus was made on those emotions because of the end goal to use this emotion detection for automatically modulating the voice and the avatar in the system presented in chapter 3. Additionally, emotional labels were collected instead of valence and arousal for the same reason.

6.1.4.2 Issues and lessons learned

Blood Volume Pressure (BVP), EDA and ST data were collected for a total of 234h 02m 29s. This pilot study gave us a great number of insights into the problems faced when collecting physiological data in ecological settings. It also confirmed the issues previously discussed in the literature e.g., Healey et al. [2010]; Schmidt et al. [2018]. Several subjects forgot to wear the device and failed to report some relevant events. When the data was analyzed after the study, some participants were asked about moments in the day where the physiological signals was particularly different from the baseline. Only then they remembered the events which they had failed to report before. Additionally, some subjects forgot to rate the intensity of certain emotions.

Furthermore, our participants had difficulty with distinguishing what constitutes an emotion. For instance, an event "Happy: 8AM to 8PM intensity rating 1" was reported by a participant. However, the long duration and low intensity makes us believe that in this case the user was referring to a mood rather than an emotion [Gray et al., 2001].

6.1.5 The proposed solution

Collecting and labelling the physiological data of emotions in ecological settings brings many difficulties. In order to address them, a mobile application was created with the aim that it:

1. can be used to capture physiological signals of spontaneous emotions during every-day activities;
2. is minimally intrusive;
3. guides the user through the process of reporting relevant events, by acquiring the necessary information to infer the related affective states, and without asking the user to pick any emotional labels;
4. helps the user to provide meaningful annotation by differentiating emotions from moods;
5. detects the relevant events from the physiological data and prompts the user about it;
6. provides a limited set of ground-truth labels to be used in recognition and classification models.

Taking into account the results of the preliminary study (see section 6.1.4) a solution based on appraisal theory was proposed using a commercially available physiological sensor, a mobile application, as well as a state-of-the-art event detection algorithm.

6.1.5.1 Self-reporting about relevant events

To fulfil the requirements 3, 4 and 6, appraisal theory was used for self-reporting which acquires the whole appraisal process around the event. The resulting annotation consists of a limited set of labels (single appraisals or emotional labels corresponding to a combinations of appraisals), and it can, therefore, be used to build classifiers with machine learning.

Unlike user-picked (UP) label-based datasets that use a specific set of labels for a specific application, exploiting appraisal theory to annotate the data allows one to build application-independent datasets. Indeed, the same dataset can be used in different application-specific recognition models, by choosing the relevant subset of emotional labels, or by detecting single appraisals. It provides for a greater information about the event (additional details on what led to the emotion) and a large number of labels to the experimenter without being cumbersome to the user since they do not need to choose such complex labels from a long list. Additionally, using appraisal theories allows for the creation of a single appraisal recognition model from physiological data [Mortillaro et al., 2012]. Such models have rarely been studied so far but the results are promising [Smith, 1989]. The OCC model was chosen for its simplicity to create an adapted questionnaire comprehensible by non-experts.

6.1.5.2 Sensors

The Empatica E4 bracelet allowed us to fulfil requirements 1 and 2. This medical device was chosen for its sensors relevant to emotion detection: BVP, EDA and ST as well as kinematic data through a 3D accelerometer. Its small size allows for long duration experiments without being bothersome. The device comes with an API for mobile applications and an already processed BVP to Inter Beat Interval (IBI). Both raw BVP and calculated IBI are collected by the app to allow experimenters to perform their own peak detection method. The sensor has also been used in the past for research purposes [Gjoreski et al., 2017].

The iPhone-based (iOS) mobile app use a Bluetooth connection to collect physiological data from the E4 bracelet.

6.1.5.3 The application modules

The emotion definition module

This module is designed to collect information about relevant emotional events. Using this module, the users first provide the duration of a relevant event. The maximum duration of the event was set to 5 minutes to limit the collection of moods as emotions are

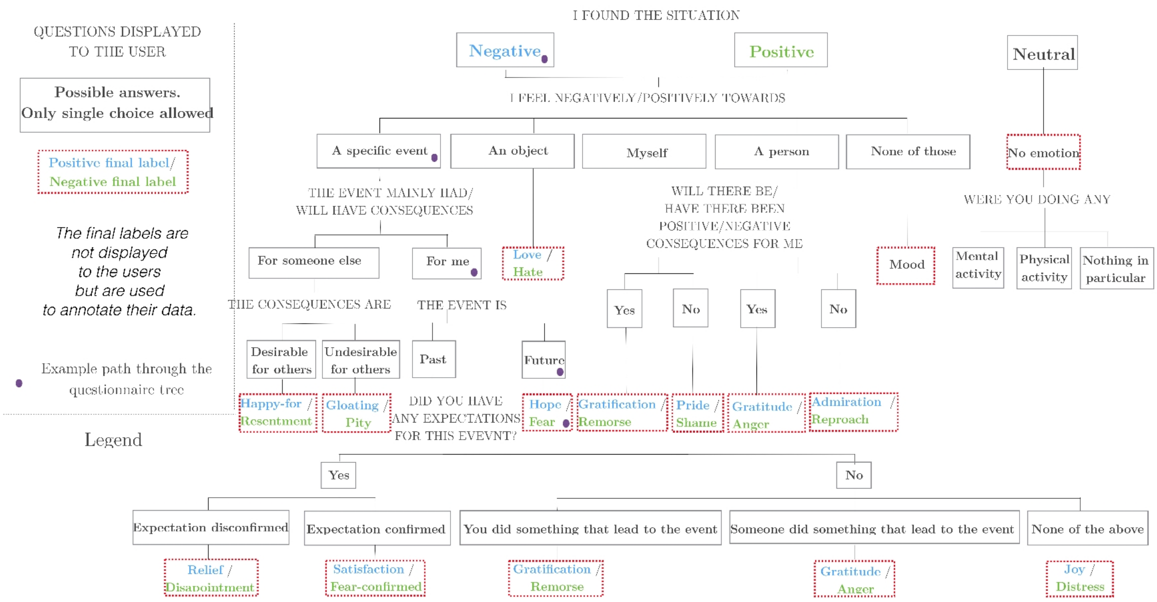


Figure 6.2: OCC-based questionnaire.

usually shorter. Next, they answer a series of questions according to the questionnaire (Fig. 6.2) and give the strength of the emotion.

To collect the information about the relevant events, the OCC model was converted into a question tree (see Fig. 6.2). For instance someone frightened by an incoming meeting would probably answer the example path in Fig. 1. Small changes were introduced to the original model to differentiate mood from emotions. Indeed, according to Clore and Ortony [2013], moods are *unconstrained in meaning*, while emotions are directed at specific objects, events or people. Therefore, a branch was added to the tree to provide the possibility to report such "unconstrained in meaning" experiences (see "Mood" branch in Fig. 6.2).

The event detection module

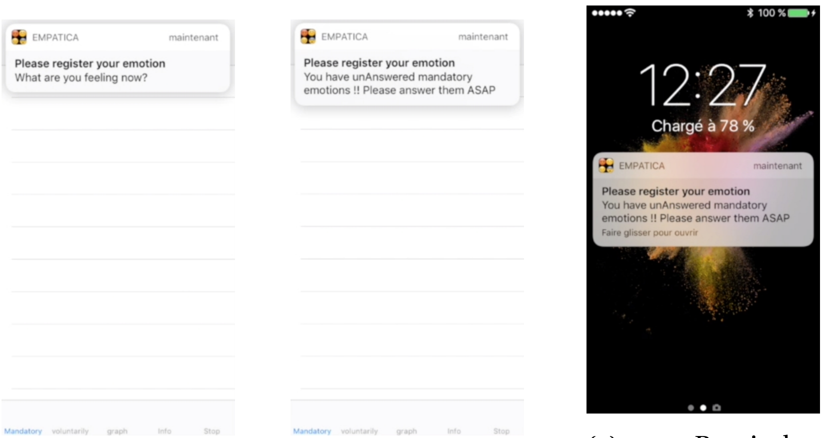
This module is used to detect relevant events from the data in real-time. The additional heart rate method [Myrtek and Brügner, 1996] was used to detect relevant events and prompt the user to report his/her emotion at this time. It consists in detecting heart rate increases that are unrelated to activity (estimated using the accelerometer). Detected events create a *mandatory events* list, which is always accessible to the user on a separate tab of the app. By implementing this algorithm requirement 5 was fulfilled from the list presented in 6.1.5.

As the exact length of the detected event is unknown, it was set to the maximum time allowed for voluntary report: 5 minutes, 150s before and after the detected peak. The minimum time interval between two detected mandatory events is fixed at 1 hour to avoid life disturbance with too many prompts. If two or more events are detected within an hour, only the first event is added to the mandatory list and the remaining ones are ignored.

6

The Notification module

It reminds the user to wear the device when needed and to report the events from the mandatory event list, if any. Reminders, when needed, are done at a rate of once every 15 min since emotional reports become less accurate as time passes [Mauss and Robinson, 2009]. When connection with the wristband is lost, notifications are prompted by the phone every 15 seconds until reconnection.



(a) Prompt. (b) Reminder. (c) Reminder, locked screen.

Figure 6.3: Mandatory emotion.

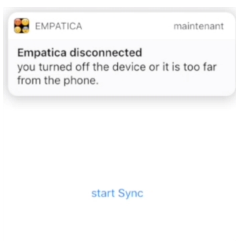


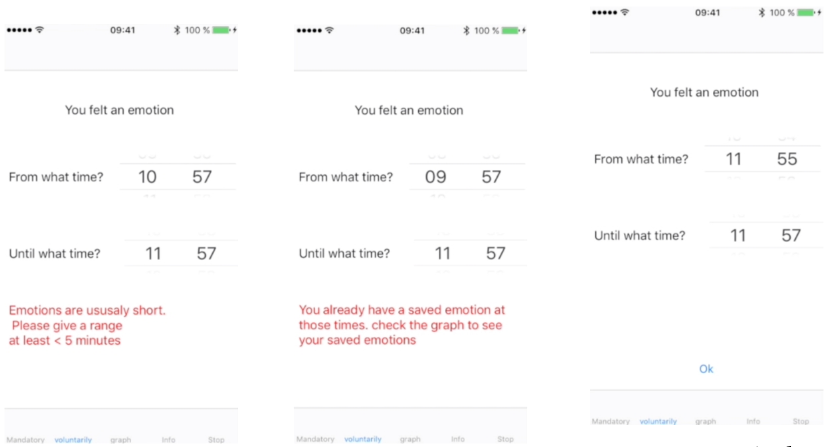
Figure 6.4: Notifications - Disconnection.

6.1.5.4 The application functionalities

The mobile application is separated into 5 tabs:

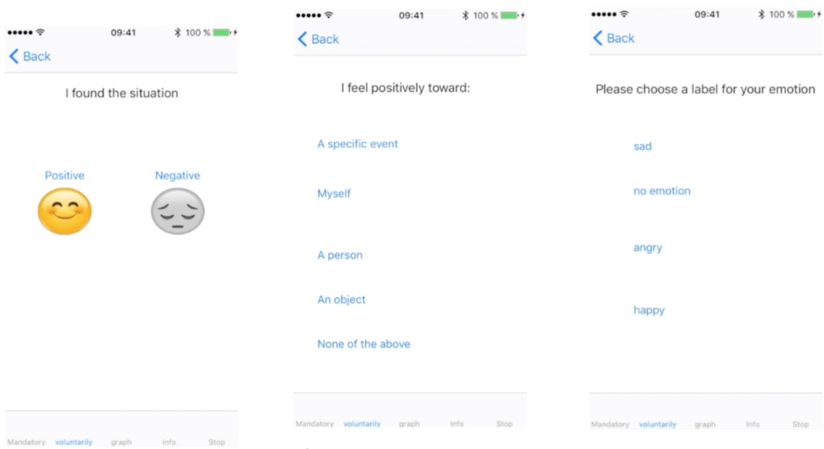
Voluntary reports

The users can voluntarily report an undetected event. They select the start and end time (max. duration of 5 min) then continue with the emotion definition module.



(a) Prompt. (b) Reminder. (c) Reminder, locked screen.

Figure 6.5: 1/ Time selection

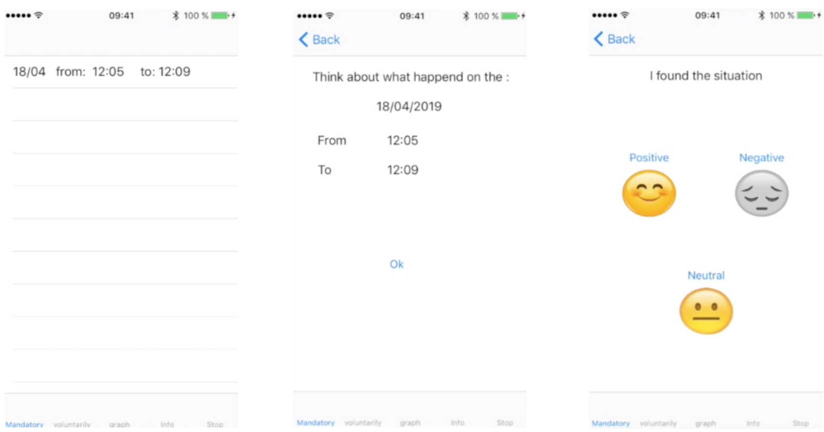


(a) 2/ Valence. (b) 3/ OCC questionnaire. (c) 4/ User-picked labels.

Figure 6.6: Voluntary tab.

Mandatory event list tab

When an event is detected by the event detection module (see second paragraph in 6.1.5.3, a mandatory event is added to the list. An event will also be added if the E4 bracelet's button is pressed. Our preliminary study highlighted that reporting the events as they happen may be difficult. However, referencing them later may decrease the time range precision. By pressing the button, the users manually add a new entry to the mandatory list with a precise timing (150s before and after the button press). They can then report the event later.



(a) 1/ Event list. (b) 2/ Event picked. (c) 3/ Valence.

Figure 6.7: Mandatory tab.

The remaining 3 tabs allow for a better experience with the app: to temporarily stop the notifications, check the battery level and visualize the reports using appropriate graphics. A video of the app is available in the supplementary materials.

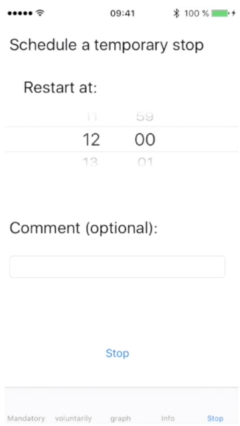


Figure 6.8: Stop tab - temporary stop.

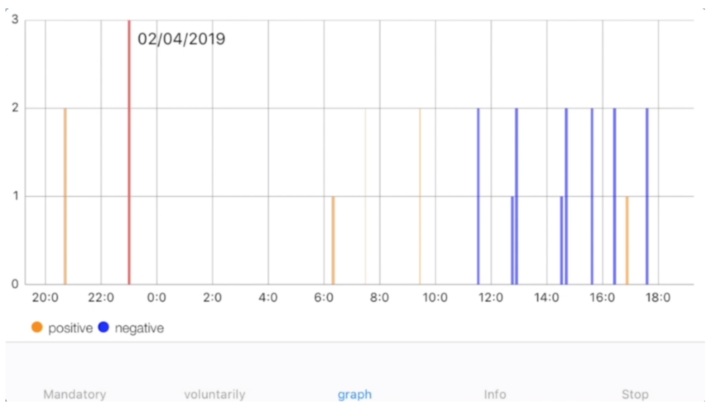


Figure 6.9: Graph tab - Visualize emotional reports.

6.1.6 Data collection

Figure 6.10: IBI averages for anger and baseline for each dataset (UP-PS: Database from the Preliminary using User-Picked labels; UP-App: Database using the mobile application and User-Picked labels; OCC-App: Database using the mobile application and the OCC-inferred labels.

A data collection was performed with 4 subjects (3 males, 1 female, avg. age 28 years) who wore the Empatica E4 bracelet and an iPhone 5C running the app for 5 days each. An additional question was added at the end of the appraisal tree where the users were asked to choose an emotional label between "happy", "sad", "angry" and "no emotion" (User-Picked- UP - labels). 65% of the automatic prompts were rated as emotions, which suggest the suitability of the event detection.

Additionally, some OCC labels were associated to both "angry" and "sad" user-picked labels. This highlights the shortcomings of the user-picked choice list to report emotional states. Finally, while HR is known to rise during anger events (lower IBI) compared to baseline [Schwartz et al., 1981], the normalized IBI average (aIBI) from anger events in the preliminary study (0.41) is higher that the aIBI from no emotion periods (0.39) (Fig. 2) which is not consistent with literature and might indicate a poor quality dataset. While the aIBI from the user-picked anger events collected with the app (0.34) is lower than the one from no emotion periods (0.39), they are still very similar. The aIBI during OCC-labelled anger collected with the app is much lower (0.24) than the one during no emotion periods (0.39), which is consistent with literature and supports our hypothesis that this mobile application allows for the collection of valuable emotional labels.

Only anger was used to validate this dataset collection as it was the only emotion label present in all datasets. Other emotions may be used in the future for validation using different protocols.

6.2 An emotional physiological signal database built in-the-wild.

As previously discussed, open-access databases represent therefore very useful tools for researchers allowing them to test various machine learning methodologies on one single dataset. There are some emotionally labelled physiological signals open-access datasets in the literature e.g. Abadi et al. [2015]; Dan-Glauser and Scherer [2011]; Koelstra et al. [2011]; Sharma et al. [2018]. However, in all cases, emotions have been induced in laboratory settings. To the best of this author's knowledge, there is no, to this day, equivalent with in the wild data.

This section proposes an open-source dataset of emotionally labelled physiological signals collected in the wild. It uses both emotional labels created from appraisal theory using the methodology described in section 6.1 as well as arousal and valence [Russell, 1980].

6.2.1 Data collection protocol

15 subjects participated in this study. 4 females and 11 males, average age 31 (SD: 5,2). The experimental procedures follow the IIT ADVR TEEP02 protocol, approved by the Ethical Committee of Liguria Region on September 19, 2017. Subject first came to the laboratory where they were explained the goal of the research. After signing the informed consent, they wore the Empatica E4 [Empatica, 2012] wristband for 7 days. During this time they were asked to report their emotions using the mobile application previously described in section 6.1.

The collected reports are of 3 types : Mood, Emotion or No emotion. All reports contained a start time, an end time, an optional comment and a path form the question tree (Fig. 6.11). Mood and emotions also had an intensity, an integer between 1 and 3. The Arousal and Valence were integers between 1 and 5.

The Valence rating was used to identify "No emotion" reports (rated as 3 - neutral). While they therefore had a path to the question tree, the Valence is not reported in the database.

The collected physiological signals had the following frame rates :

- GSR : 4 data point per second
- BVP : 64 data point per second
- ST : 4 data point per second
- ACC : 32 data point per second
- IBI : Calculated from BVP, one data point for each BVP peak.

6.2.1.1 Mobile app alteration

For this data collection the question tree from the previously validated mobile application (see section 6.1) was adapted to collect in addition valence and arousal estimates. While this modification do not alter the collected data and therefore do not compromise its validity, it provides additional information on the collected emotions that can be used by researcher working on recognition model with this dataset. Indeed, as seen in section 4.5, the valence-arousal model was greatly used in emotion recognition research. It

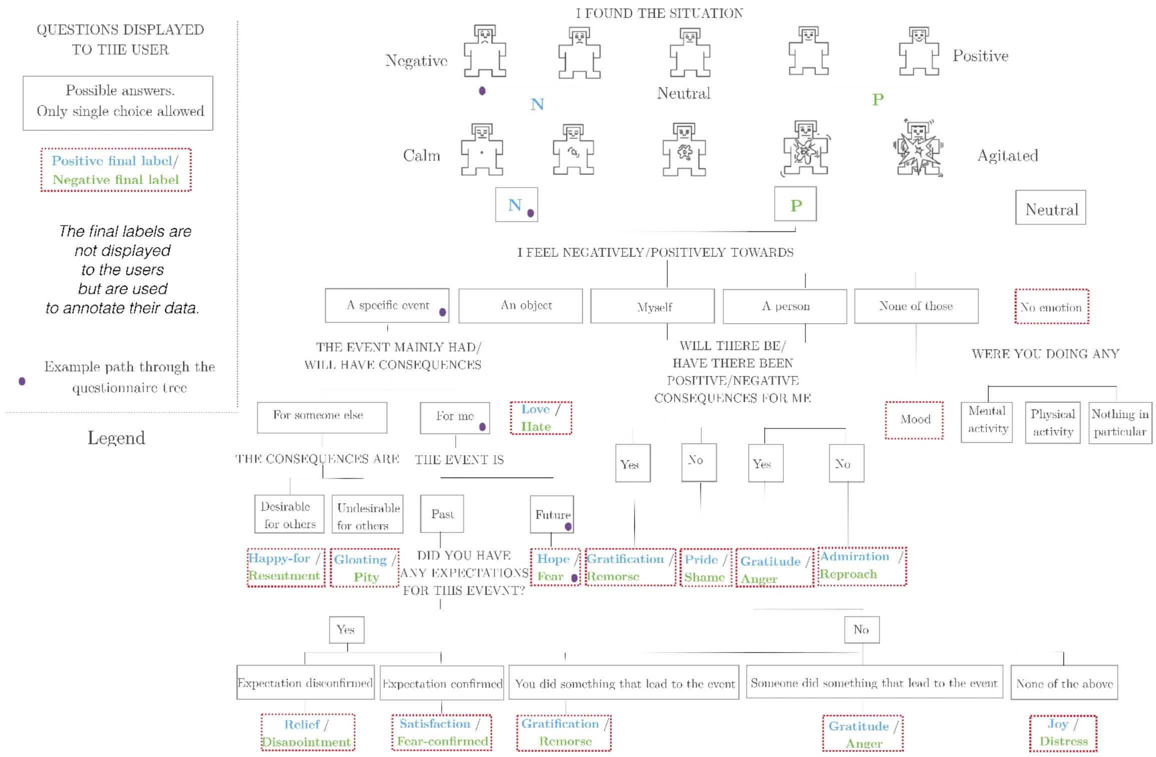


Figure 6.11: OCC-based questionnaire with valence and arousal estimation.

would therefore add additional insight to collect both OCC inferred labels and Valence-Arousal ratings. In this section, collected "labels" will refer to the labels inferred from the OCC path chosen in the question tree since, as previously explained in section 6.1, the users of the application do not provide labels to annotate the emotion but appraisals instead.

6.2.2 Results

In total, 822 hours of data were collected. This represents an average of 7.8 hours per day per subject. 336 emotion reports, 49 mood reports and 50 no emotion reports were collected. It represents in average, 3.2 emotion reports, 0.5 mood reports and 0.5 no emotion reports per day per person.

The average duration of emotional labels was 136 seconds (2min 16s) which confirm the short duration of emotions found in the literature [Gray et al., 2001]. It also shows the need for precise timespan reports when collecting data about emotional events in the wild.

Out of 15 persons, only 11 wore the wristband for the 7 days as required by the protocol.

Analysis was performed on the collected data. Firstly, relation between positive,

Table 6.1: Number of time a label was felt for each subject.

	s1	S2	S3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15	Total	
Happy-for	3	2	0	0	1	0	0	0	0	1	0	0	0	0	0	7	Happy-for
Gloating	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2	Gloating
Hope	3	0	0	1	0	2	13	2	0	8	0	2	0	2	0	33	Hope
Love	0	1	0	1	0	0	5	4	0	4	2	4	0	1	1	23	Love
Gratification	3	0	3	2	1	1	10	15	8	2	1	0	1	2	0	49	Gratification
Pride	0	0	7	0	0	0	1	0	6	0	0	3	0	0	0	17	Pride
Gratitude	3	2	5	3	1	1	6	3	2	4	2	1	1	3	0	37	Gratitude
Admiration	0	2	0	0	1	1	0	0	11	4	0	3	2	0	0	24	Admiration
Mood	0	3	2	1	1	10	0	0	1	1	0	10	3	0	3	35	Mood
Relief	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Relief
Satisfaction	1	1	0	8	0	1	1	3	2	3	2	0	0	0	0	22	Satisfaction
Joy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	Joy
																0	
Resentment	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	2	Resentment
Pity	0	0	1	1	0	0	0	2	0	0	1	1	1	0	1	8	Pity
Fear	0	0	3	2	2	2	3	1	0	2	1	1	0	0	1	18	Fear
Hate	0	0	0	0	0	0	2	0	8	0	1	3	0	0	0	14	Hate
Remorse	2	1	0	1	0	0	0	0	0	2	0	0	0	1	0	7	Remorse
Shame	2	2	0	1	2	0	1	1	1	0	1	1	0	0	1	13	Shame
Anger	1	0	2	1	0	0	1	2	0	0	0	0	0	0	2	9	Anger
Reproach	0	2	3	2	0	2	3	7	6	2	1	3	2	1	2	36	Reproach
Disapointment	0	0	0	0	0	0	0	0	2	0	0	0	0	1	0	3	Disapointment
Fear-confirmed	2	0	0	0	0	0	1	0	0	2	0	0	0	0	0	5	Fear-confirmed
Distress	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	6	Distress
Mood	0	1	0	0	1	3	0	0	2	1	0	1	0	4	1	14	Mood
Total	20	17	29	24	11	23	48	42	50	36	12	34	11	15	13	385	**Total**

negative emotions and their number of occurrence was investigated. Table 6.1 identifies how many times each emotion was felt. Additionally, the relation between valence and the mandatory or voluntary character of the report was calculated. Table 6.2 references the number of positive, negative, mandatory and voluntary reports collected. Table 6.3 presents how may time each label was associated with one arousal value (valence/label association was not analyzed as valence was used to deduce the label). The average arousal from the database (μ) was compared to the average arousal found in the literature (L) [Whissell, 1989]. For each label, it was ensured that :

$$F1 : \mu - \sigma < L < \mu + \sigma$$

With σ, the arousal standard deviation from the collected database.

Additionally, participants were able to add comments when they desired. Such disclosure of personal information was made optional in order to respect the subjects' privacy. These comments associated with the inferred label as well as the subject number are reported in Table 6.4.

Table 6.2: Number of positive, negative, mandatory and voluntary reports.

	+	-	Total
Mandatory	183	90	273
Voluntary	67	45	112
Total	250	135	385

Table 6.3: Arousal and valence association with each label (in percentages).

	Arousal					Average arousal datanase (μ)	Standard deviation arousal database (σ)	Arousal from literature (L)	F1 (Whissel 1989)	Equivalent label from literature
	1	2	3	4	5					
Joy	0	100	0	0	0	2,0	0,0	3,9	-	Joyful
Satisfaction	52	13	13	22	0	2,0	1,3	3,1	TRUE	Satisfied
Gratification	37	37	10	10	6	2,1	1,2	2,8	TRUE	Boastful
Hope	45	9	6	18	21	2,6	1,7	2,8	TRUE	Hopeful
Gratitude	30	22	19	14	16	2,6	1,5		-	-
Pride	6	41	24	29	0	2,8	1,0	3,5	TRUE	Proud
Admiration	8	28	28	36	0	2,9	1,0		-	-
Love	17	22	9	35	17	3,1	1,4	3,5	TRUE	Content
Happy-for	0	43	0	57	0	3,1	1,1		-	-
Gloating	0	0	0	0	100	5,0	0,0		-	-
Relief	0	0	0	0	0	-	-		-	-
Remorse	0	29	29	43	0	2,6	0,9	2,4	TRUE	Remorsful
Disappointment	0	33	0	67	0	3,3	1,2	3,8	TRUE	Disappointed
Fear	13	17	13	35	22	3,3	1,4	3,6	TRUE	Affraid
Shame	8	23	8	46	15	3,4	1,3	2,5	TRUE	Ashamed
Fear-confirmed	20	20	0	20	40	3,4	1,8	3,3	TRUE	Sorrowful
Hate	0	29	29	7	36	3,5	1,3	3,7	TRUE	Disagreeable
Reproach	3	8	17	47	25	3,8	1,0	3,9	TRUE	Antagonistic
Pity	0	13	13	50	25	3,9	1,0		-	-
Resentment	0	0	0	100	0	4,0	0,0	3,7	-	Resentful
Anger	0	11	11	44	33	4,0	1,0	3,1	TRUE	Angry
Distress			33	33	33	4,0	0,9	4,3	TRUE	Anxious

Table 6.5: Ratio mood emotion per subject.

subjects	Ratio mood/emotion (%)
1	0,0
2	23,5
3	6,9
4	4,2
5	18,2
6	56,5
7	0,0
8	0,0
9	6,0
10	5,6
11	0,0
12	32,4
13	27,3
14	26,7
15	30,8
Average	15,9

Table 6.4: Comments reported by subjects associated with the end label of the report. In green hunger and pain reports, in yellow mood reports.

ID	Comment	Emotion	subject
1	software crash and I lost 3 hours of work	Distress	3
2	food & chatting	Gratification	4
3	meeting	Fear	4
4	itchy annoying mosquito bite	Anger	4
5	experiment with robot	Love	4
6	really hungry	Shame	4
7	pre work out	Hope	4
8	eating & chatting	Satisfaction	4
9	pity watched someone else get a ticket	Pity	4
10	annoying phone all with electrician	Reproach	4
11	eating lunch with friends	Satisfaction	4
12	excited to visit new town	Satisfaction	4
13	playing with dog	Satisfaction	4
14	playing video game	Gratification	4
15	eating food with friends	Satisfaction	4
16	writting work email	Reproach	4
17	A bit agitated for a repetitive request from a person	Mood	6
18	talk about topic I like	Mood	6
19	Funny jokes	Mood	6
20	Talking about my next job	Hope	6
21	Making fun of <Name>	Mood	6
22	Reading	Mood	6
23	Empatica disconnection	Distress	12
24	Review	Hate	12
25	I hurt myself	Shame	12
26	Music I like	Mood	12
27	Driving fast	Mood	12
28	Bored	Mood	12

Table 6.5 presents the percentage of mood in reports by each subject.

The mobile application was programmed in such a way that it was possible to identify when subjects changed their mind half way through the question tree. For instance, one may select "A specific event", then, once the next question is displayed, go back and select "A person" instead. This allowed to record 28 times where people change their opinion which represents 0.1% of all emotional reports.

6.2.3 Discussion

Firstly, it can be noticed that positive emotions are reported more often than negative ones (Table 6.2). This may be because those specific subjects did not experience negative emotions as often or because they felt less comfortable reporting them. In addition to the low number of emotional reports (3.7 reports/day/subjects in average), reported emotions are unevenly distributed (Fig. 6.1) with labels such as "gratification" counting a total of 49 reports when labels such as "disappointment" counting only 3 reports. This suggests the need for longer data collection times, lasting several weeks or months in order to collect sufficient emotion labels for each person, especially for user-dependent models. However, the fact that only 11 subjects wore the wristband for required duration suggest the need for a method to reward the participants based on their respect of the protocol, especially for long data collection.

Some people reported few emotions, such as subject 5 with a total of only 11 emotional labels in 1 week, when others reported much more, such as subject 7 reporting up to 48 emotions. This disparity might come from a difference in the number of emotional stimuli during their respective weeks. It is however known that some people are less subject to emotions and more aware of them than others [Myrtek et al., 2005]. The first type of person would require a much longer data collection time than the second type in order to gather the same amount of data.

Table 6.3 highlights the fact that negative emotions were in average rated as higher arousal compared to positive ones. All average arousal from each labels calculated from the collected database were found similar to literature (Table 6.3).

The comments that were gathered (Table 6.4) brought light to certain aspects of the data collection. For instance, subjects 4 and 12 reported hungry and pain as emotions (ID 6 and 25). The path chosen was "Negative [emotion] /[toward]Myself/No [There have not been consequences for me]" and therefore, according to the model, were labelled as "Shame". The question on whether or not hunger and pain are emotion has been debated in the literature. Hunger often induce impulsivity, aggressivity or negative moods in people, an emotional state also called "Hanger" [MacCormack and Lindquist, 2018]. Hunger have been found to have effect on physiological signals notably on pulse pressure and temperature [Engel, 1959]. Specific instructions on whether or not physical drives such as pain or hunger should be considered in the data collection should be given to the participants. A specific path for such internal state may be needed in the question tree. Alternatively it is also possible that the subjects felt shameful of being hungry or in pain.

Most of the comments seem to fit the emotion label, a "software crash" (ID 1) is likely to induce "distress", and a meeting to induce "fear" (ID 3). The comment " itchy annoying mosquito bite" (ID 4) is particularly interesting as it could be classified in the "pain" category previously discussed, however, in this case, the participant's emotion appears to be directed toward the reason of the pain, the mosquito, as the subject selected the path

"[I feel negatively toward] A person" which resulted in the label "Anger". This shows the advantages of using appraisal theory for labelling as this theory states that emotions do not depend of the event that brought the emotion but rather by the way the person experienced it.

Table 6.4 also allows to notice the trend of certain subjects to always select " None of those" in the question tree resulting in a Mood label such as subjects 6 and 12. However, comments bring additional insights suggesting that this labelling might not be correct in certain cases. For instance, "A bit agitated for a repetitive request from a person" (ID 17) could have probably be labelled as anger or reproach. It is surprising that this person wrote such a comment but did not pick the "person" or "event" categories. The cause might be that such participants were less able to understand the categories and were less able to match the emotion to the category that were the most appropriate. It might also be a technique to answer the form quicker as no other question is asked after the "none of those" answer, however, it is less likely as those participants took the time to write a comment which was optional. Additionally, the subjects giving inconsistent comments were also the ones with a disproportionally high ratio of mood reports compared to emotion reports (Table 6.5). Indeed, while the average number of moods report is 17%, subject 6 reported more moods than emotions (56%) and subject 12 reported an unusually high amount of moods (32%). While the "none of those" option was added to the question tree in order to detect mood as they are unconstrained in meaning (see section 6.1.5.3) , it seems that it might be necessary to rename it "Nothing" in order to avoid participants selecting "None of those" when their emotion is constrained in meaning but they think that it does not match with the other options. In this way they would most probably be more willing to analyze the situation and try to find the most appropriate category between "An event", "An object", "Myself", "A person". Unfortunately, only 4 participants decided to use comments, which constrained the possibilities of analysis.

On the one hand, the mandatory reports were rated as emotion 56% of the time and 78% of the emotional reports were mandatory, which highlights the usefulness of the mandatory prompts as they allowed to collect many additional emotional reports to the database. On the other hand, 10% of the mandatory reports were labelled as mood and 88% of the Mood labels were picked in mandatory reports. The reason is most probably that participants feel the need to provide an emotion report when a mandatory trigger is raised. However, those reports appear to be mainly of moods. This findings confirms the need for differentiating moods from emotions in the question tree to validate emotional reports especially mandatory ones.

A high number of times subjects seemed to have change their mind half way through the question tree. It is likely that by reading the next question they realized that this path was probably not appropriate for their emotion and that another path would be a better fit. It would be interesting to reproduce this experiment adding post-experiment interviews to ask the thought process behind the change to understand it better. It is interesting to notice that those changes only occurred at the first layer of the OCC tree.

Finally, the Empatica E4 wristband that was used in this data collection resulted in many disconnection due to Bluetooth sensibility. Unfortunately, the Empatica API did not provide the possibility to save the data internally until the connection was restored or to automatically reconnect once the Bluetooth device was in range again. This resulted in a significant amount of lost data. The mobile application was designed to alert the user of this disconnection through vibrations, however, subjects reported leaving the room without the mobile phone and returning long time later, only then realizing their oversight and loosing many hours of data. Subjects also reported many disconnections and need for reconnection to be irritating. A different device including both automatic reconnection and internal data saving would be advised for future research.

The collected database is made open-source [Larradet, 2019a] and might be used by future researchers to unravel the challenges of emotion detection in the wild. It proposes a large spectrum of emotional labels rarely used in emotion studies nowadays.

6.3 Conclusions

Based on the in-the-wild methodology presented in chapter 4, a new tool was proposed to collect and label physiological signals, acquired during relevant events in ecological settings. This solution was designed according to appraisal theories, allowing the user to self-report the whole appraisal process around relevant events. The system is able to prompt the user to report the emotional self-assessment. The hypothesis is that the possibility of precise selection of relevant events timing and duration, the assistance given to the user to differentiate moods from emotions and the ability to report appraisals instead of emotion labels will improve the quality of the dataset compared to standard paper-type collection.

To our knowledge, this is the first app for emotion reporting based on appraisal theory. It is open-source [Larradet, 2019a] and can be used by other researchers to extend the existing dataset. It provides the novel methodology to evaluate the physiological data collection of emotions in the wild. It allows to collect application-independent dataset containing an increased number of information about the emotional trigger and a great variability of label without it being cumbersome for the user. The same dataset might be used in the future, e.g., to create different application-specific classifiers, by choosing the relevant subset of the appraisals and emotional labels. The increased information of the event accessed thanks to the use of appraisal theory, allow researchers to make informed decision about how to use each event according to the need of their research. This study was published in the Ubicomp 2019 conference [Larradet et al., 2019].

This mobile application was used to collect data from a great number of subjects to create an open-source database of emotionally labelled physiological signals collected in the wild. It was collected using a state of the art mobile application to ensure ground truth. Both appraisals and valence-arousal sets were collected. Analysis of the data showed that a single week of data collection might not be enough for user-dependent detection or classification models. Participants reported consequently more positive emotions than negative ones and some subject reported much more emotions as a whole compared to others. Negative emotions were found to be associated to higher arousal in average compared to positive ones. Additionally, it was found that specifications must be given to the participants on whether or not to report affects related to physical states such as hunger or pain. It was found that mandatory prompts provides useful information and requires mood filtering. Hopefully, this open-source dataset will help future researchers to make a step forward toward emotion detection in the wild.

The three tools introduced(dataset assessment method, mobile application, database) in this research advance the field of emotion recognition in the wild and represent stepping stones for future researcher working on such topic. Indeed, emotion detection for real-life application has a great potential in many different fields. Roboticists have already started to design affect-aware robots using emotion recognition from speech for instance [Hegel et al., 2006]. Giving a robot the ability to detect its owner's emotions from physiological signal in a natural context would allow it to react accordingly [Kim et al., 2009], for instance by proposing relaxing or positive activities. Similarly, domotics may use such emotion detection capability to adapt the environment such as the music [Khowaja et al., 2015]. Detecting emotions from physiological signal has the advantage to work in environment were typical methods such as video-based or audio-based detection would fail. For instance, cases where the user is away from cameras, not speaking or in dark environments would be challenging for classical methods while physiological signals would still be accessible. It is also logical to assume that using several methods in parallel for emotion recognition would increase the validity of the detection.

While this data collection was made on people without motor impairment, a similar collection can be done on LIS patients. Indeed, similarly to the mobile app, the gaze-controlled system provided in this thesis used on daily basis for communication, can be adapted to prompt the patients to register their emotions based on their physiological signals accessed using the Empatica wristband. A separate menu can be added to the main menu to allow for voluntary emotion registration. In this way, a user-specific model can be created for emotion detection of the patient, and later, used for emotional voice modulation and avatar facial expression modulation.

7

A COMPLETE SYSTEM FOR LIS PATIENTS

All developed systems presented in the previous chapters were combined to form a complete system for LIS patients allowing efficient web browsing, emotional communication, gaming, telepresence robot control and stress reduction. This computer-based system (laptop or desktop) is fully controlled using eye-tracking technology. This work was part of a bigger project called TEEP-SLA: "Tecnologie Empatiche ed Espressive per Persone con SLA" (Empathic and Expressive Technologies for People with ALS) aiming at satisfying the patients' social interaction and communication needs with innovative patient interfaces and associated robotic technologies [1].

7.1 System structure

7.1.1 Menu

The first menu allows the patient to choose between the different options (web browsing, emotional communication, gaming, telepresence robot control and stress reduction) using dwell time selection.

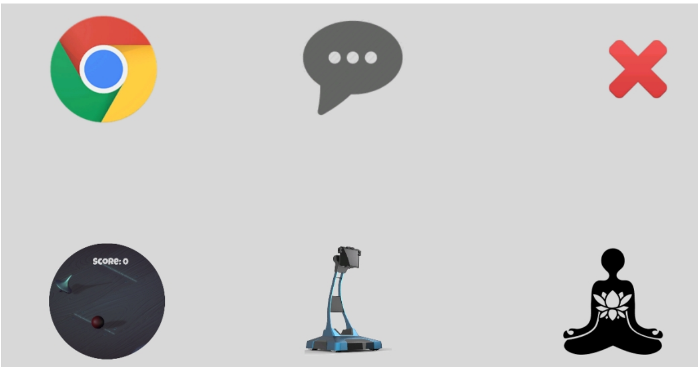


Figure 7.1: Main menu.

[1] https://teep-sla.eu/

7.1.2 Web browsing

In the path toward designing the most efficient web-browsing several designed were developed. While chapter 2 demonstrated the efficiency of the presented design, the advantages of flexibility and customization were also considered. The choice of browser were therefore given to the user between 4 different designs.

7.1.2.1 version 1

The first version of the browser is similar to classic interfaces. It contains side control buttons that are constantly present. The browser's size is therefore diminished. The control system is similar to the one described in chapter 2. This system, while requiring more screen-space, being less efficient and more tiring, will be preferred by users affected by changes and appreciative of more classical interfaces.

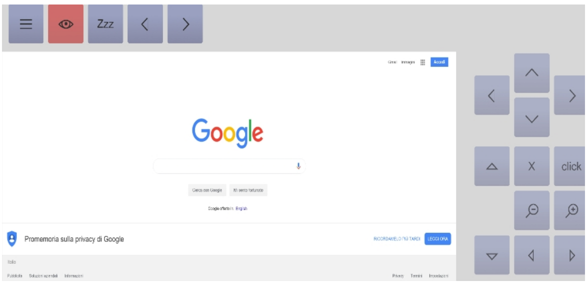


Figure 7.2: Web browser version 1.

7.1.2.2 version 2

The second version of the browser still uses a classical side button interface but that is displayed only when necessary and on top of the browser's page in the opposite side of the area of action. This classical interface also allow for a greater browser size. However, it will be tiring because of the necessary eye movements as seen in chapter 2.

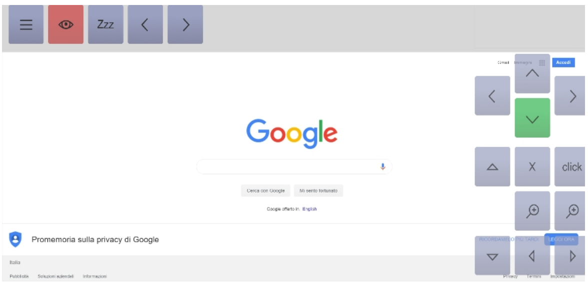


Figure 7.3: Web browser version 2.

7.1.2.3 version 3

The third version of the browser introduce a radial menu as the one described in chapter 2. However, In this interface, unlike version 4, all the commands are present in the menu.

While increasing simplicity and comprehension it decreases speed of actions since they are performed in two steps and therefore need twice the dwell time.

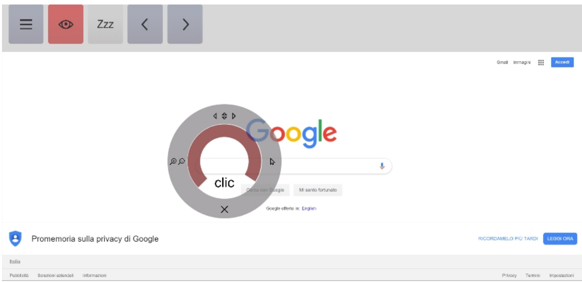


Figure 7.4: Web browser version 3.

7.1.2.4 version 4

Finally, the fourth version of the browser is the one described in chapter 2. It represent the best choice in terms of screen-space usage and mental workload. It is selected as the default browser on download.

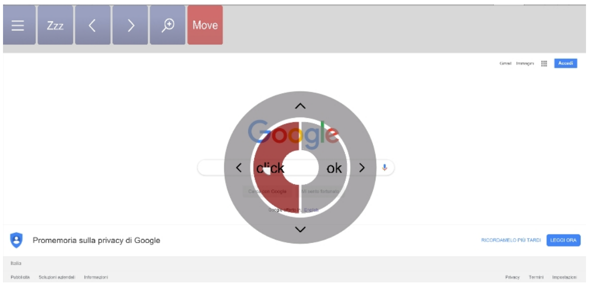


Figure 7.5: Web browser version 4.

7.1.3 Communication

The enhanced communication system presented in chapter 3 was included in the final system.

7.1.4 Gaming

The game presented in chapter 2 was included in the final system. Two choices were given to the user: they could either play using a random shooting (not controlled by the player) or using a shooting control by the player's GSR using the Empatica wristband.

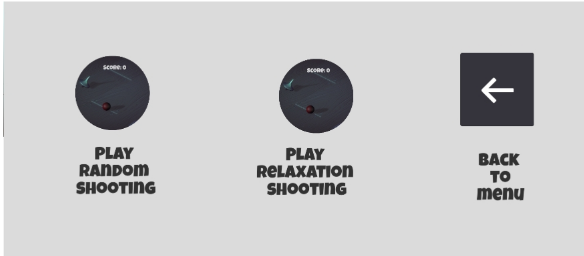


Figure 7.6: Game menu.

7.1.5 Telepresence

The system also included the work from another team as part of the TEEP-SLA project allowing the control of a telepresence robot using eye-tracking.

7.1.6 Relaxation

The method to display stress levels using a ball color as biofeedback seen in chapter 2 was reproduce to control a relaxation game. It was designed to help users lower their mental workload as seen in chapter 2 .

Figure 7.7: Relaxation game.

7.1.7 Affect-aware system

This system was designed to be aware of patients' critical emotional states. Indeed, using the additional heart rate method (see section 6.1), high arousal was detected, activating propositions of calming activities such as the relaxation game or speaking to family online using the web browser system.

Figure 7.8: Relaxing proposition after stress detection.

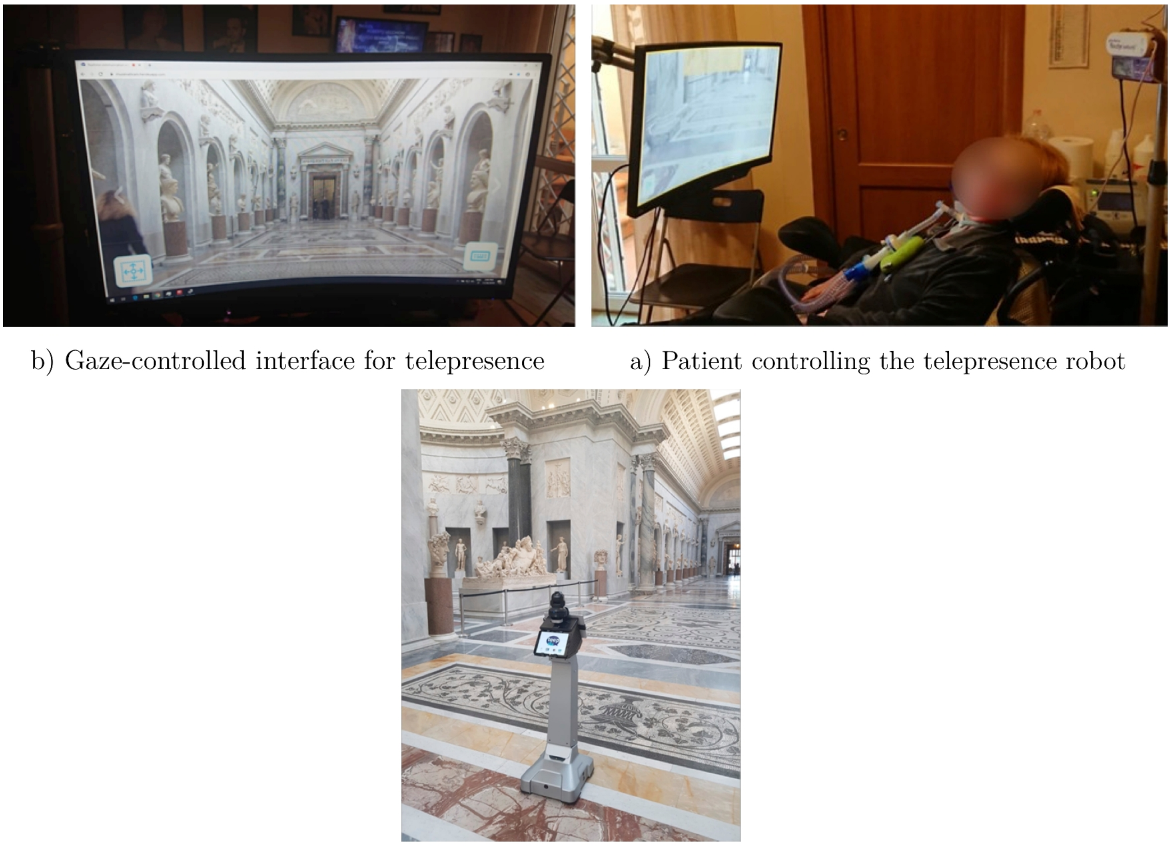
7.2 Overall system evaluation

The evaluation of each part of the system was individually assessed as presented in the previous chapters (see Table 7.1).

Table 7.1: Overall evaluation of the system.

	Evaluation
Web browser (see section 2.1)	• Quicker • Easier to learn and to use • Decreases required eye movements • Reduces fatigue and mental workload • Higher satisfaction • Reduced risk of error
Game (see section 2.2)	• Decreases mental workload • Increases engagement
Emotional speech (see section 3)	• Helped with the communication • Increased capability to convey and identify emotions

The final system was greatly appreciated by ASLS patients. This was specially noted during the final presentation of the system, which included a private visit of the Vatican museum using a telepresence robot and the gaze-based communication system (Fig. 7.9).



b) Gaze-controlled interface for telepresence

a) Patient controlling the telepresence robot

c) Telepresence robot in the Vatican museum

Figure 7.9: Gaze-controlled telepresence visit of the Vatican museum.

8
CONCLUSIONS AND FUTURE WORK

People with LIS have reduced capabilities due to their loss of movements. Systems available to such patients are limited and can be tiring when used for long periods of time. This thesis aimed at improving computer system control and enhancing communication for people with LIS.

Firstly, gaze-based system control was improved by proposing a novel web-browsing interface using a menu centered in the area of action. This solution was found to improve the action-speed and reduce mental workload. Users found this interface easy to learn and to use, less frustrating, more satisfying and less prone to error. It was found to induce less fatigue stress and discomfort in the eyes. Using this concept, a dedicated video game controlled by eye gaze was designed. The player's stress level was estimated from GSR and represented by the character color. The users appeared to be capable of voluntarily controlling their stress level to activate a specific UI in the game. This biofeedback display associated with the reward following the relaxation was found to decrease mental workload. These findings represent new solutions for LIS dedicated computer interfaces. Their abilities being limited, interfaces design matter much more to ensure a satisfying experience. Developing, testing and comparing different GUIs with both healthy subjects and patients allows to better understand their needs and helps to determine the advantages and disadvantages of each solution. Exploring new types of input can increase the patients abilities and open the door to different and more empathic user interfaces.

The main concern for LIS patients is communication. Their inability to speak make them dependent of novel communication systems or technologies to express themselves. While common systems allow users to communicate through eye gaze commands, they rarely involve any emotion communication system that is intrinsic to human-human exchanges. A novel solution was developed simulating humans most natural emotion expression: voice modulation and facial expression. Users were given control of an emotional voice synthesis as well as an emotional avatar. This solution allowed user to have more natural dialog and to better express their emotions.

While this system was found to help with the communication, it seems that it could be improved by automatically detecting emotions from the user rather than manually selecting the emotion. However, this would require an emotion detection model able to recognize the patients' emotion for real-life applications. However, to this day very few studies have been conducted outside the laboratory and there is still a long way to go before detecting emotions in real-life. In order to help toward this goal, several tools were developed and made available to the scientific community. Firstly a method was proposed to assess emotion, mood and stress detection based on their readiness toward real-life applications. Secondly, an open-source mobile application was designed using psychology concepts and state of the art guidelines to help gathering valuable ground truth from users when collecting emotional self-reports. Finally, this mobile application was used to collect a large dataset of emotionally labelled physiological data in the wild.

Those tools are made open-source in order to help future researchers willing to make a step toward detecting emotion in the wild. The data labelling was purposely broad enough and informative enough to be used by different types of research. State of the art machine learning methods may be applied in the future to this dataset to detect or classify emotions in the wild whether it is from valence and arousal, emotion labels or appraisals. While emotion detection may be used for enhancing communication for LIS patients, it would be especially useful to build systems for total LIS patients that lost there eye movement capabilities. Indeed, today their communication abilities are reduced to binaryEEG systems [Mir et al., 2019] or no communication at all. Providing the patient's family and caregivers the ability to visualize their emotional state via tools such as the avatar system presented in chapter 3 would be a great improvement to understand the affective states of such patients. Emotion recognition in the wild may also be applied to a great range of other types of applications such as healthcare, self-awareness, robotics or domotics. It would open new doors to have affect-aware systems in our lives. A final system was made available open-source to patients including all the developed novel tools.

Being in Locked-in state represent an every-day challenge. Fortunately, thanks to technology we have the power to provide new solutions to such patients and to improve their daily life. It is to be hoped that future technological development will allow additional solutions to enable even greater capabilities in such patients.

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A
SUPLEMENTARY MATERIALS

In order to collect physiological signals in the wild, researchers must choose which device to use. As mentioned in the previous sections , decisions must be done regarding comfort, invasiveness and data accuracy. A list devices available for ambulatory data collection are listed below with indications of their characteristics. Companies with several similar products are marked with SP. Invasiveness is marked from 1 to 3, 1 being the bulkier and 3 the less invasive as described in section 4.4.1. If several combination of sensors are available for a certain product a range of invasiveness will be displayed. It will be specified for each device if it was made for research (R) or for the general public (GP).

A

Table A.1: Commercialy available devices for ambulatory physiological signal collection

Name (company)	Physiological signal	Other	Invasiveness	Research(R) / General Public (GP)
E4 – SP (Empatica)	EDA, PPG, ST	Acc, GY	3	R & GP
Shimmer – SP (shimmersensing)	ECG,EMG,GSR, PPG, RESP	3D Acc, 3D GY, 3D MA,L,W,F,T,P	1-2;	R
Lifeshirt (VivoMetrics)	ECG, RESP, GSR, ST, PPG, EEG, EMG	Acc , TEMP	1	R
Bisigma - SP	ECG,EEG,EMG,EOG, EDA, RESP,ST, PPG, GSR, SpO2	TEMP, Limb movement, Acc, Body position, Microphones, Light, Air humidity, AP	1	R
Biofeedback 2000x-pert(Schuhfried)	EDA, PPG, ST, RESP	Acc	2	R
movisens - SP	ECG, EDA	Acc , Barometric AP, light, TEMP	2	R
BITalino - SP	Resp, PPG, ST, Glucose, BPC, SpO2,EMG,EEG, ECG, EDA,	F, TEMP, Acc, Light	1-3;	R
somnomedics - SP	RESP, EEG, ECG, EOG, EMG, ST, BP, SpO2	TEMP, Light, Body position, Snoring	1-3;	R
NeXus-4(Mindmedia)	EEG,EMG,ECG, ST, EDA, EOG, RESP, BVP		1-2;	R
vu-AMS	ECG, RESP, EDA	Acc	1	R
Vitamove - SP	ECG, EMG, EEG, EOG , Resp,	Acc , light	1-2;	R
Equiviatal (EQ02)	ST, SpO2,GSR, BP cuff, PPG, ECG, RESP,	Acc, GPS, Body position	1-2;	R
G.MOBIlab (Gtec)	EEG,ECG, EOG, EMG, Resp, GSR, ST , BP, SpO2	Limb movements, Snoring	1-2;	R
Mobile Impedance Cardiograph (Mindwaretech)	ECG, GSR, EMG, RESP	Acc	1-2;	R
Zephyr SP	ECG, Resp, ST	Acc, time, location	2	R & GP
Feel	BVP, EDA, ST	Acc	3	P
Jawbone SP	BVP, EDA, ST,	Acc	3	P
Moodmetrics	EDA		3	P
Spire	Resp		3	P&R