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An Elicitation Study on Gesture Preferences and Memorability Toward a Practical Hand-Gesture Vocabulary for Smart Televisions

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ABSTRACT With the introduction of new depth-sensing technologies, interactive hand-gesture devices (such as smart televisions and displays) have been rapidly emerging. However, given the lack of a common vocabulary, most hand-gesture control commands are device-specific, burdening the user into learning different vocabularies for different devices. In order for hand gestures to become a natural communication for users with interactive devices, a standardized interactive hand-gesture vocabulary is necessary. Recently, researchers have approached this issue by conducting studies that elicit gesture vocabularies based on users' preferences. Nonetheless, a universal vocabulary has yet to be proposed. In this paper, a thorough design methodology for achieving such a universal hand-gesture vocabulary is presented. The methodology is derived from the work of Wobbrock *et al.* and includes four steps: 1) a preliminary survey eliciting users' attitudes; 2) a broader user survey in order to construct the universal vocabulary via results of the preliminary survey; 3) an evaluation test to study the implementation of the vocabulary; and 4) a memory test to analyze the memorability of the vocabulary. The proposed vocabulary emerged from this methodology achieves an agreement score exceeding those of the existing studies. Moreover, the results of the memory test show that, within a 15-min training session, the average accuracy of the proposed vocabulary is 90.71%. Despite the size of the proposed gesture vocabulary being smaller than that of similar work, it shares the same functionality, is easier to remember and can be integrated with smart TVs, interactive digital displays, and so on.

INDEX TERMS Hand-gesture interaction, gesture elicitation study, preferences and attitudes, gesture set, human-computer interaction.

I. INTRODUCTION

Recent trends in technology have been rapidly improving everyday life, making tasks more efficient, by helping people achieve them in simpler and faster ways. For example, in the 1950s, when the television remote control was initially introduced, watching television became effortless. However, with the development of new features and control options, present-day remote controls have become highly complex devices, which might require adaptation and learning for some users. Hence, the development of more natural and user-friendly interfaces to control multimedia devices and interactive applications has become the ultimate desideratum in multimedia and interactive computing research.

Interaction devices such as the Microsoft Kinect sensor and other types of depth/IR cameras have facilitated the advancement of innovative and natural user interface (NUI)-enabled mechanisms for human-computer interaction (HCI) [2], [3]. These mechanisms have so far relied on generic hand tracking algorithms or recognition engines of a minimal set of hand gestures, all of which are device-specific and not standardized. To develop the next generation of interfaces for smart televisions, a universal interactive hand gesture vocabulary must be derived and implemented. This vocabulary should be intuitive and properly sized to increase memorability. Additionally, to become seamlessly adopted by users, it should be simple, easy to perform, and universally standardized.

The continuing demand for a universal gesture vocabulary, together with the advances in new sensing technologies, have encouraged researchers to apply a diverse range of approaches towards its development. Wobbrock *et al.* [1] introduced a methodology for developing gesture vocabularies based on user-elicited studies, which many researchers have followed. Bhuiyan and Picking developed an open gesture system to help elderly people in everyday activities [4]. Ni *et al.* introduced a new menu design policy and interaction mechanism [5]. Rempel *et al.* attempted to use the maturity of hand sign language as a guideline for user interface design [6]. In our study, we follow Wobbrock's method and extend it with user-elicited studies on natural attitudes, preferences and memorability in order to generate and implement a basic set of television control commands (e.g., changing a channel, increasing the volume, etc. with hand gestures).

The main contribution of this work is the proposal of an interactive hand gesture vocabulary for potential interactions between users and smart televisions. A two-phase user survey was conducted in order to investigate the preferences and attitudes towards all possible control commands for navigating television menus using hand gestures recognized by depth-sensing technologies (e.g., Kinect). After a thorough statistical and qualitative analysis of the survey's results, the proposed gesture vocabulary was generated and implemented to control a television with a gesture recognition engine based on dynamic time-warping (DTW) [7]. An external user agreement evaluation test was conducted to validate the vocabulary and confirm the results of the survey. The vocabulary and its size were then examined by a memorability experiment, showing that, even though the size of the vocabulary is smaller than that of similar studies, it has the same functionality and is easier to remember.

The paper is organized as follows: Section II presents an overview of previously published user-elicitation studies that generated gesture vocabularies for interactive devices and applications. Section III presents the proposed design methodology, describing each step towards the gesture vocabulary generation in detail. Section IV briefly discusses the achieved results and challenges faced throughout the design process. Finally, the conclusion of our study and future work is presented in Section V.

II. RELATED WORK

Most HCI systems, such as surface, mobile, and hands-free computing, integrate gestures created by system design experts. Having solely the system design experts develop the gesture vocabulary deliberately favors gestures which enable better performance of the recognition engines over user comfort and preferences. This might be ideal for the system designer, but burdening for the user. As an initial approach to deal with this issue, Nielsen et al. outlined a procedure for designing a gesture vocabulary for hands-free computer interaction in ubiquitous computing, which took into account a user's viewpoint regarding intuition, learning rate, and ergonomics [8]. A few years later, Wobbrock et al. started conducting user-elicited studies for gesture set design targeted at unistroke gestures and introduced the concept of guessability and agreement score, which is used in the majority of subsequent user-elicited studies [9].

In Table 1 a comparison of several user-elicited studies relevant to our research scope and goals is presented. The different gesture set design studies are compared based on their salient characteristics, such as interaction media, number of participants, demographics, etc. The comparison begins with the seminal work of Wobbrock et al., which introduced a user-elicited gesture set for surface computing applications based on the Microsoft Surface prototype [1]. They demonstrated that three HCI experts designing the same gesture set generated solely 60% of the user-elicited gestures. Moreover, 19.1% of expert-suggested gestures were completely disregarded by the participants. These results confirm that user preferences tend towards simpler patterns for gestures both conceptually and physically [10]. Following this trend, Nacenta *et al.* [11] conducted a comparative study between user-defined and pre-defined gesture sets. The study focused on evaluating the memorability of each set, corroborating that user-defined gestures have higher memorability than pre-designed gestures.

Ruiz *et al.* proposed a user-defined motion gesture set for mobile devices (i.e., movements of the device to invoke specific commands such as answering phone, ignoring call, navigating mail, etc) [12]. Similarities were found between their proposed gesture set and our study. Seyed *et al.* elicited usable gestures for data transfer tasks in multi-display environments (e.g., touchscreen tablet, touchscreen tabletop, and a wall display) [13]. However, the agreement level between the proposed gestures was low, and no gesture set was derived due to several implications, mainly the lack of familiarity with a multi-display environment. Even though people tend to quickly adapt to new technologies, this study showed that we still find difficulty in adapting to multiple interconnected devices.

User-elicited studies have been successful not only for surface and mobile computing applications but also for hands-free interaction applications. Morris explored user preferences when using the Kinect sensor to navigate the web on a living room TV with gesture and speech recognition [15]. Their study found that participants were enthusiastic about web browsing on televisions and the idea of using multiple modalities (e.g., gesture, speech), which is also beneficial for recognition. Similarly, Vatavu conducted a preliminary study investigating user preferences for designing a gesture set for TV control tasks [14]. More recently, he adopted this methodology in the augmented reality (AR) area by developing interaction commands using a Wii remote control within a prototype hybrid-physical augmented TV, where multimedia contents span the physical space of the TV [18]. He then extended his preliminary study, presenting the comparison of handheld gestures versus freehand gestures [19]. Likewise, Piumsomboon *et al.* proposed a user-defined gesture set of an impressive 40 AR tasks such as object manipulation, object transformation, editing, menu navigation, etc. [17]. A recent study claimed that child-defined gestures are an equally important and ignored area of study, as a child's gesture performance and preference is not similar to that of adults [16].

TABLE 1. **The comparison of user-elicited studies for gesture vocabulary design.**

Study	Interactive Media	Participants	Demographics	Commands (referents)	Methodology
Wobbrock et al. [1]	Surface computing *(Microsoft Surface prototype)*	20	Non-expert users, never used a touchscreen device before.	27	Demonstrative (Participants see the simulated effect of a referent and ask to perform a corresponding gesture). *Format: Interview*
Ruiz et al. [12]	Mobile computing *(Multi-platform)*	20	Non-technical high-tech company workers.	19	Inquiry (Participants designed and performed a motion gesture for a specific referent). *Format: Interview*
Seyed et al. [13]	Multi-display environments (Apple iPad, Microsoft Surface 2 and SMART Board Display)	17	Variety of backgrounds (no exclusion based on experience).	16/device	Same as [1]
Vatavu [14]	Free-hand gesture recognition *(Microsoft Kinect sensor)*	12	Students coming from computer science major with no experience in interaction design or using a Kinect.	12	Demonstrative (Participants read and watched a video of the effect of a referent and ask to perform a corresponding gesture). *Format: Interview*
Morris [15]	Free-hand gesture recognition and speech recognition *(Microsoft Kinect sensor)*	25	Varied professions with wide age-range and prior experience using Kinect.	15	Same as [1]
Connell et al. [16]	Free-hand gesture recognition *(Microsoft Kinect sensor)*	6	Children age 3 - 8 with experience using touch-screens and smartphones.	22	Same as [1]
Piumsomboon et al. [17]	Free-hand gesture recognition *(Sony head mounted display, HD webcam and Asus Xtion depth sensor)*	20	Participants with minimal knowledge of AR. Experience with PCs, touch-screens, Wii and Kinect	40	Same as [1]
Vatavu [18]	Hand-held motion sensing *(Wii Remote Controller)*	20	From technical to research level backgrounds.	12	Same as [14]
Ours	Free-hand gesture recognition *(Microsoft Kinect sensor)*	49 in preliminary study, 81 in online questionnaire, 20 in technical evaluation	People from different backgrounds in the preliminary study. University faculty and students from various departments for the online questionnaire and technical evaluation.	12	Two-phase online inquiry (Phase 1: Participants suggested a mid-air hand gesture for a specific referent, Phase 2: Participants selected the most preferred gesture from suggestions of phase 1). *Format: Online-survey* User agreement and memorability test to validate our results. *Format: Lab-based user study*

The study targeted object manipulation, navigation-based tasks, and spatial interaction with whole-body gestures, however, as it lacked context, no acceptable level of agreement was achieved for a single command.

All of the aforementioned user-elicited studies converge to one same conclusion, including the users in interactive technologies development is not only an advantage but a necessity. Most of these studies, as shown on Table 1, follow the same methodology introduced by Wobbrock *et al.* [9]. We introduce a new methodology that yields better agreement levels. With our inquiry-style online survey, we gather information not only of suggested gestures but also regarding preferences and attitudes towards interactive hand-gesture technologies for smart televisions. Moreover, we conduct external user agreement evaluation and memory tests on the proposed vocabulary, which to our knowledge, have never been integrated in any user-elicited studies in this field.

III. METHODOLOGY

People easily learn and rapidly adapt to new ways of interaction. The best example of this behavior has been the rapid adoption of touchscreen devices (e.g., smartphones, tablets) in our every-day life. However, adopting a gesture language to interact with devices is much more challenging, both for the designer and the user. Despite active research in gesture recognition and related user-elicited studies, higher requirements are still needed in real-time processing of such recognition systems. Due to this reason, the focus of this study is directed towards building a vocabulary inferred by the users' preferences, which could give an indication of the complexity level of the selected gestures. To target the users' preferences, a series of studies has been conducted based on a set of control commands applicable to televisions or digital displays. This set of control commands are actually the effects of gestures, defined in linguistics literature as *referents*. We follow this this terminology as it widely used in previous user-elicited studies [1], [14]. The twelve most frequently used referents for smart television controls were selected as the initial set of desired commands for our user-elicited study (Table 2). These referents were, furthermore, classified into four groups: (a) menu navigation, (b) channel surfing, (c) volume control, and (d) override.

TABLE 2. Referents that are used for the design of our user-elicited gesture vocabulary for controlling smart televisions.

Group	Referents	Description
(a) Menu Navigation	Open	Open menu
	Up	Move up in menu
	Down	Move down in menu
	Enter Option	Enter option in menu
	Enter Submenu	Enter a Submenu
(b) Channel Surfing	Previous	Go to previous channel
	Next	Go to next channel
	Last	Go to last visited channel
(c) Volume Control	Increase	Increase volume
	Decrease	Decrease volume
	Mute	Mute volume
(d) Override	Shut down TV	Shut down TV

Involving users in the development process is a challenging task. Although users have no limits regarding the boundaries of current technology, they might be biased towards their own experience. To overcome this issue, the proposed methodology has a two-phase user survey: preliminary survey and gesture vocabulary design. These two phases share the same questions but differ in the way the participant answers them. The first phase is an open-ended questionnaire while the second is a multiple-choice questionnaire. After the second phase was completed, the resulting gesture vocabulary was implemented and subsequent tests for evaluation and memorability were conducted to support our design.

A. STUDY 1: PRELIMINARY SURVEY (FIRST PHASE SURVEY)

The goal of this preliminary survey was to create a vast set of gestures for the desired control commands. In order to span over a wide spectrum of personal backgrounds, the participants considered were *general public*, such as our friends and acquaintances, with no specific background on multimedia or interaction design. In total, 49 people participated in this study, with an average age between 30 to 40 years old. The geographical background of the participants was positively diversified, having participants from North America, the Iberian Peninsula and the Middle East. It was conducted both in English and Spanish.

The participants were asked open-ended questions to obtain a list of possible answers for each referent. In order to remove *the gulf of execution*,[1] we averted from giving any feedback on the suggested gestures regarding the feasibility of these gestures being recognized by state-of-the-art recognition technologies. Compared to previous studies, the open-endedness in this preliminary survey allowed the participants to freely suggest any kind of gestures they could imagine, as they were not limited to the boundaries of current technologies. The participants were encouraged to complete the questions and provide as multiple gestures for each command. Incomplete and vague answers were dropped from the analysis.

As a result, they proposed gestures by using different body parts (such as hands, ears, and mouths) in two and three dimensional spaces. In this study, only 34 out of 49 sets of answers were valid as the rest were either incomplete or vague. In total, 511 gestures were suggested by the participants through this preliminary study (an average of 42.58 suggestions per command). Similar gestures were grouped to reduce the size of the possible gesture set for the second phase of the study. A good example of this grouping process is for the ''shut down TV'' command, where some participants suggested clapping once and some others mentioned clapping twice. Thus, they were grouped together and defined as a *clapping option* for this command. Table 3 shows the complete results of this survey. It is shown that the total number of suggestions for each command was always greater than the total number of participants (34 people). The third column of Table 3 shows the number of different groups of gestures for each command. ''Shut down TV'' had the most variety of suggestions with 22 gestures; ''next/previous channel'' had only 11 distinctive suggested gestures. On average, 14.75 distinct gestures were anticipated by participants for each command.

TABLE 3. The result of preliminary survey to elicit gestures for proposed commands.

Referent	Total No. of Suggestions	No. of Different Gestures
Next Channel	44	11
Previous Channel	45	11
Last Visited Channel	42	16
Turn Up Vol.	44	12
Turn Down Vol.	46	13
Open Menu	45	15
Open Submenu	40	18
Up	42	12
Down	41	12
Enter Option	41	19
Mute	42	16
Shut down TV	39	22

[1] Popular term in HCI used to describe the gap between the user's goal and the commands and mechanisms that are capable of executing that goal.

B. STUDY 2: GESTURE VOCABULARY DESIGN (SECOND PHASE SURVEY)

1) PARTICIPANTS

We had a total number of 81 participants for this second phase survey, with an almost equal distribution of gender (44 male/37 female). The participants from the preliminary survey (Study 1) did not take part in the gesture vocabulary design (Study 2). These participants were students and staff from the University of Ottawa, Canada. The average participant age was between 22 and 26. Age and gender distributions of the participants are shown in Table 4.

TABLE 4. The age/gender distribution of participants.

Gender	Age	Distribution(%)
Female	18 - 21	23
	22 - 25	9
	26 - 30	4
	31 - 40	7
	>40	2
Male	18 - 21	15
	22 - 25	14
	26 - 30	7
	31 - 40	12
	>40	7

For this study, we inquired about video game playing frequency. We predicted that there would be more users with higher playing frequency in the lower age range or that the samples with more affirmative responses would play more often. However, most of the users from the youngest age range (18-21) answered that they played sometimes (12.35%), or never (24.69%). A small portion of participants was observed as very frequent players (1.23%) and those who played rarely (1.23%). The greatest presence was those who never play (6.17%). In both genders, there were users who played often or very often. Females mostly never played, and males seemed to play only sporadically. In summary, most of the participants were not frequent players or did not play very often. We consider this a beneficial feature from our user sample group; if the participants were frequent players, they might be biased to some pre-existing gestures designed by a diverse range of gaming consoles or applications.

2) PROCEDURE

The participants were asked to answer the same questions from the preliminary survey (Study 1), however, instead of having the option of open-ended answers, they answered these questions in a multiple-choice manner. The multiple-choice answers for each question were extracted from the answers of the preliminary (open-ended) survey. As the preliminary survey participants suggested at least 11 different groups of gestures for each command (Table 3), we limited the number of choices to four or five by choosing the most rated gestures, similar to the number of choices given in related studies [10]. Gestures with the highest frequency were selected as the answer choices of this user survey.

Furthermore, the answers were not limited to one-handed gestures, we had choices with two-handed gestures such as clapping. This freedom of choice, shows that the final results were completely user oriented. We also chose not to show any preferences for specific answers. When explaining how to complete the questionnaire, no example was provided so as not to influence participants. The order of options for each question in the questionnaire was set randomly, as to not influence the participant in any way. The complete questionnaire in Study 2 is shown in Appendix.

3) RESULTS

The results were analysed based on the agreement score test and presented as follows. The elicited gestures were evaluated for each referent by computing an agreement score A_r, which represents the level of consensus between participants for a specific referent r. This agreement score was initially introduced by Wobbrock *et al.* [9]. The agreement score A_r for a specific referent r is calculated as follows

$$A_r = \sum_{P_i \subset P_r} \left(\frac{|P_i|}{|P_r|} \right)^2 \tag{1}$$

where P_r is the set of proposed gestures for referent r and P_i is the subset of identical gestures within P_r. The value of A_r ranges in the interval of $[|P_r|^{-1}, 1]$, where $|P_r|^{-1}$ represents no agreement at all and 1 represents perfect agreement. The studied number of proposals is the result of 81 (participants of the second phase) $\times$ 12 (referents) $=$ 972 proposals.

The main comparisons and references in the present study are Vatavu [14], [19] and Wobbrock *et al.* [1]. When analyzing the results, a higher divergence was indicated in the responses compared to previously mentioned studies. This is mainly due to two reasons. First, the number of participants is much larger, around 4 times as large (81) as that in [1], [14], and [19] which was 20. Second, no explanation was provided on the effects of the referents. The elicitation method is based completely on users' preferences and intuitiveness, both to propose the commands and to train them. There is no external influence whatsoever in the whole process.

Although the proposed method is slightly different from those of Vatavu [14], [19] and Wobbrock *et al.* [1], we use their results as a benchmark for the present study. Since we had more participants, it was expected to have more distributed results. However, the results yield towards the opposite of our expectations. The mean agreement for the set was 0.56 compared to the agreement values obtained by Vatavu (0.53) for hand-held motion control within an augmented TV prototype [19] and (0.42) for free-hand TV control [14] as well as those of Wobbrock *et al.* (0.32) for surface computing [1], and Ruiz (0.28) for mobile phone interaction [12]. The agreement rates were observed for each suggested referent and the average agreement rate of the proposed vocabulary is shown in Figure 1. The standard deviation was 0.12 while it was 0.47 in Wobbrock's study [1]

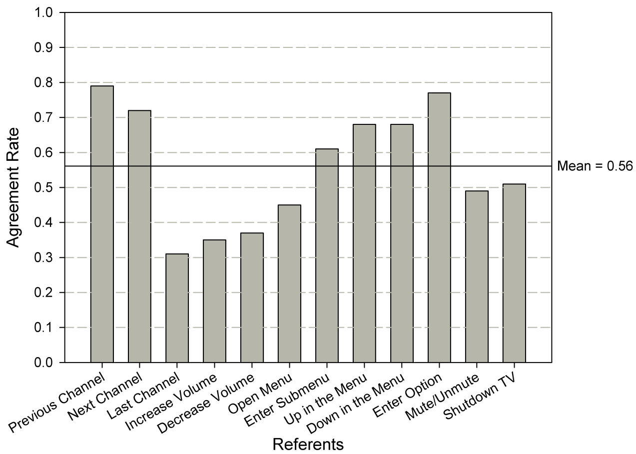


FIGURE 1. **The agreement score rates for user-elicited hand-gesture commands.**

and 0.14 in Vatavu's [18]. The graph shows that the gestures with the highest agreement rate are the ones related to pointing and moving the hand sideways or up/down.

Finally, the proposed interactive hand gesture vocabulary for television and digital display menus navigation is illustrated in Figure 2. It is derived from the answers to questions (Q)(5–16) with the highest percentage, reflecting users' preferences on intuitiveness and comfort. Correlations between different referents can be seen, for example, increase/decrease volume and up/down in menu. Furthermore, similarities to multi-finger touchscreen gestures are identified in referents with linear horizontal/vertical gestures as well as pointing and pushing. However, for referents with a specific button on a touchscreen device such as mute/unmute or shut down, the suggested interactive hand gestures are highly influenced by body/sign language (e.g., hand over the mouth for mute/unmute, goodbye gesture for shut down).

C. STUDY 3: EVALUATION TEST

In this third phase of the study, we focused on the technical evaluation and external user agreement of our proposed interactive hand gesture vocabulary.

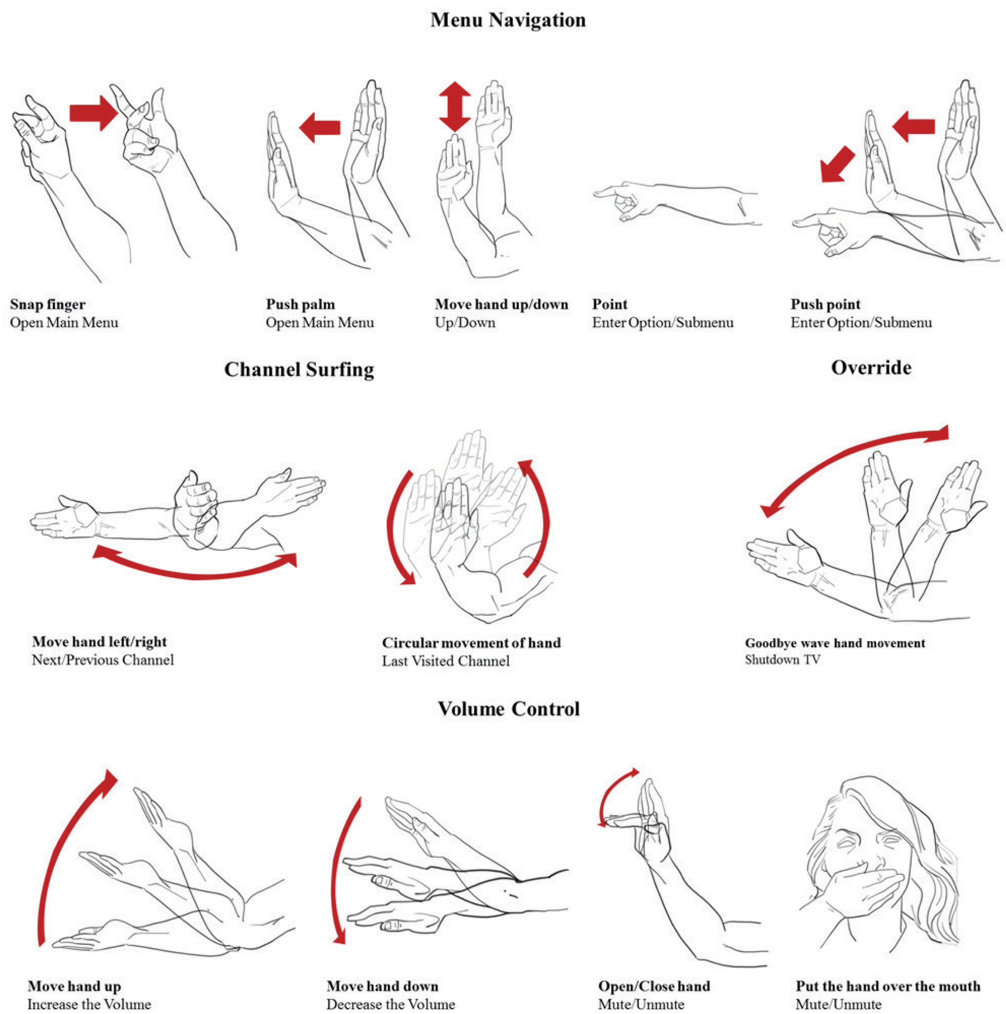


FIGURE 2. **The user-elicited hand-gesture vocabulary for interactive televisions.**

1) PARTICIPANTS

Twenty participants volunteered for this study. Although all of them were university students or staff, they had various backgrounds in engineering, science, management, social science, arts, and linguistics. They were equally distributed based on their gender (10 males and 10 females). They were asked to choose their age range between four options: teenage, 20s, 30s, and 40s or above. The average age range was between 20s and 30s (sd. = 6.07). Moreover, only two (out of 20) either owned or frequently used a Microsoft Kinect sensor. Additionally, two of the participants were left-handed.

2) APPARATUS

To evaluate the proposed gesture vocabulary, we developed a gesture recognition engine. We used dynamic time warping to analyse the captured data [7], which included upper body joint positions, angle of elbow, palm area and dimension ratio, for a preliminary implementation of gesture recognition. Furthermore, for this evaluation experiment, we decided to use the Microsoft Kinect sensor due to its easy-to-use software development kit (SDK) and acceptable accuracy on extracting skeleton and depth data. Table 5 presents the accuracy of the developed engine for each gesture.

TABLE 5. The accuracy of the developed gesture recognition engine (average = 77.03%).

Command	Gesture	Accuracy
Next Channel	Swipe Hand Right to Left	78.57%
Previous Channel	Swipe Hand Left to Right	76.92%
Last Visited Channel	Circular Movement of Hand	66.66%
Turn Up Vol.	Move Hand up	95%
Turn Down Vol.	Move Hand down	90%
Mute	Hand over the Mouth	78.26%
Mute	Close Palm	30.43%
Open Menu	Snap Fingers	31.25%
Open Menu	Push Palm	93.75%
Open/Enter Submenu	Push Point	71.42%
Open/Enter Submenu	Point	93.33%
Up	Move Palm up	91.66%
Down	Move Palm down	84.61%
Shut down TV	Goodbye Wave	96.66%

The developed gesture recognition engine was then embedded into a C# application with three functionalities: teaching, training and interaction. In the teaching phase, videos of recorded gestures were played so that the participant can learn the vocabulary. Then, in the training phase, participants practice the gestures. Finally in the interaction phase, the participants' gestures were recognized and used to control the menu navigation of the smart television. The experimentation room (six metres by five metres) was equipped with the following items: a big-screen TV (63 inches), a comfortable loveseat sofa, a Microsoft Kinect sensor and a Dell desktop computer (OPTIPLEX 760). Figure 3 shows the layout of this room.

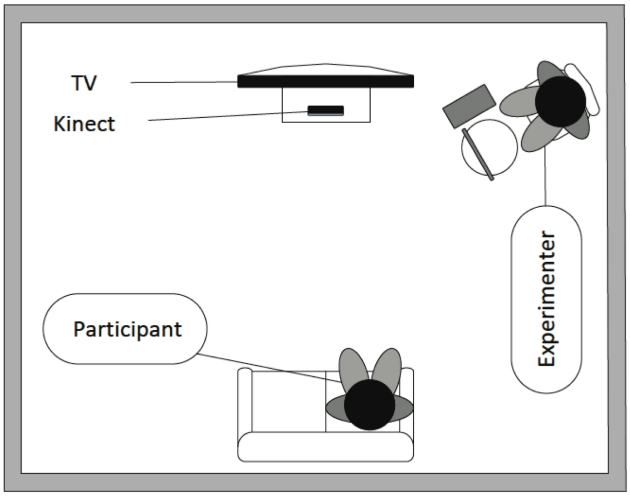


FIGURE 3. The layout of the room for the lab-based experiment.

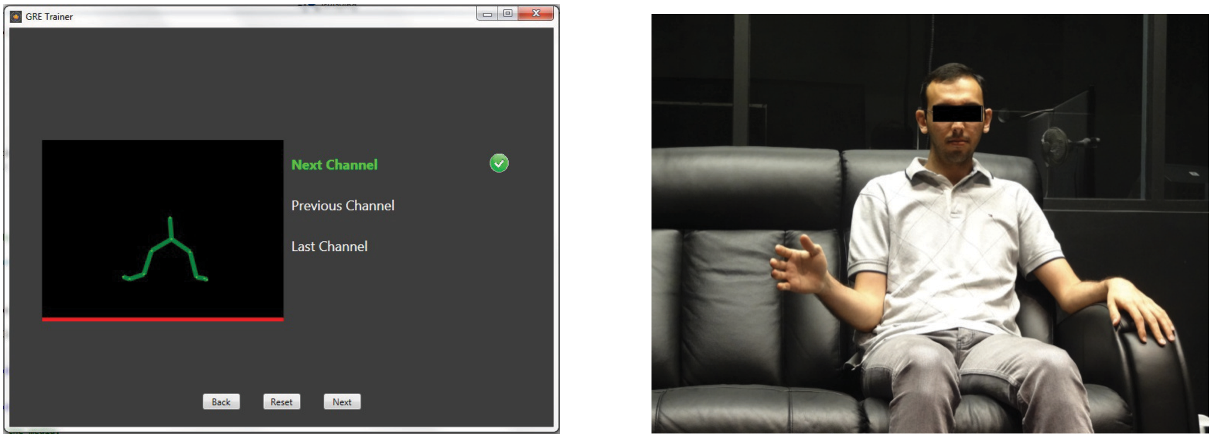
3) PROCEDURE

The participants were asked to come into the room and sit on the sofa. First, the experimenter explained the rights and privacy agreement for the participants. Next, the gesture training step began. The participants initially watched four recorded videos, one for each group of referents. Each video started with the name of the referent's group. Thereafter, the names of each command were shown and followed by the teaching video of that command. Gestures were taught by both audio and video. At the end of each video, the participants were asked to face a screen where all of the presented gestures were listed on the right side and a live skeleton stream from the Kinect sensor played on the left side. Participants could try proposed gestures and imitate them using both movement feedback from the Kinect sensor and the visual indication for correct gesture execution by the gesture recognition engine (Figure 4). Participants could practice gestures a few times. They informed the experimenter when they felt they had learned the gestures, usually taking less than a minute.

After simulating the gestures, participants were asked to complete a questionnaire. They were asked to answer two five-point *Likert*-scale questions. The first question asked if the gestures they had imitated were a good match for the command. The second question asked them to rate the ease of performance of the gesture. In total, they were taught 14 referents for 12 commands (Figure 2), where three commands had two referents. In these circumstances, participants had to answer another question about their preferences on the two available options. This part took 15–20 minutes.

4) RESULTS

Table 6 presents the results of this questionnaire. On the second phase of the user survey (Study 2), "next channel" and "previous channel" had the highest scores. These results of the post-study questionnaire confirmed those of the survey (Appendix). Also, results of the "shut down TV",



(a) Trainer application

(b) Participant

FIGURE 4. **Snapshots of the gesture training session in the evaluation test (Study 3). (a) Shows the participant's skeleton on the left; its corresponding referents are listed on the right side. The skeleton image presents real-time feedback to participants to help them clearly understand the captured movement. When the gesture recognition engine detects a gesture, it switches to a green bold format with a check mark in front of it. (b) Shows a participant learning in the experiment.**

TABLE 6. **The results of the post-study questionnaire.**

Command: Gesture	Good Match			Ease of Performance		
	Median	Mean	Std. dev.	Median	Mean	Std. dev.
Open Menu: Snapping Finger	4	4.2	0.77	4	4.35	0.59
Open Menu: Pushing Palm	3	3.25	1.12	4	4	0.86
Menu Navigation: Up / Down	5	4.55	0.51	4	4.25	0.79
Open Submenu / Enter Option: Pointing	4	3.95	0.76	4	4.2	0.77
Open Submenu / Enter Option: Push Pointing	4	3.65	0.99	4	3.8	0.89
Next / Prev. Channel: Swipe Hand Left/ Right	5	4.6	0.50	4	4.35	0.59
Last Visited Channel: Circular Movement of Hand	4	3.65	1.04	4	3.7	1.03
Increase / Decrease Volume: Moving Up / Down	4.5	4.35	0.81	5	4.5	0.61
Mute: Hand on Mouth	5	4.3	1.03	5	4.4	0.82
Mute: Closing Palm	4	3.85	1.04	4	4.2	0.83
Shut down TV: Goodbye Wave	5	4.55	0.51	5	4.55	0.60

"up", and "down" commands show they are accepted well, while "snapping fingers" for opening the main menu and "increase" or "decrease" had reasonable approval. Moreover, the "putting hand over mouth" gesture achieved a very high score in this test. Two gestures were proposed for the "open submenu/enter option" command; both had a normal distribution. If the weakest options were eliminated in cases where two gestures for the same command exist, it can be indicated that "last visited channel" has the lowest acceptance among all commands and would be the least-used command among the others.

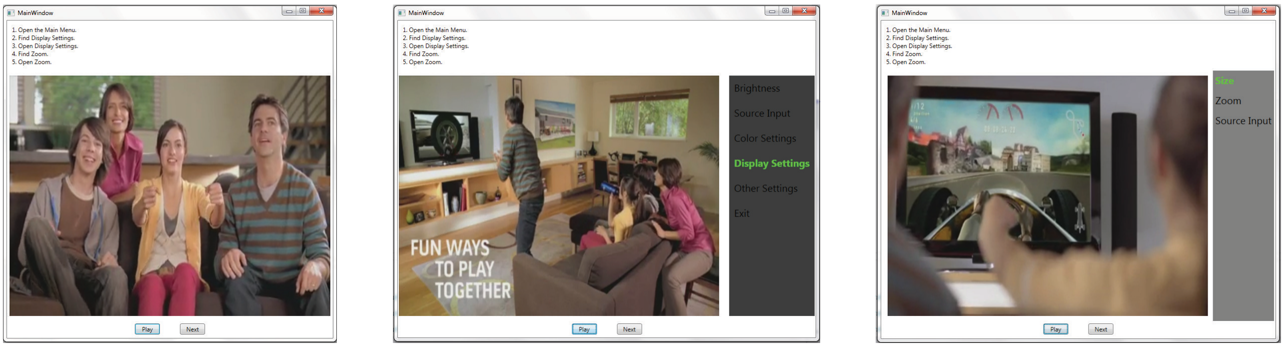
D. STUDY 4: MEMORABILITY TEST

The final phase of our study is a memorability test which was conducted to evaluate the memorability of the proposed gestures and further analyse how intuitive they are. We used the same participants and apparatus as explained in the evaluation test (Study 3).

1) PROCEDURE

The same participants in the evaluation test (Study 3) were asked to return to the experiment room two hours after the evaluation test. They were given four step-by-step scenarios to execute. They had to interact with a developed graphical user interface (GUI) and follow scenarios based on the response from the GUI (Figure 5). The descriptions of scenarios are presented as follows:

- *Testing the Menu Navigation Gestures in Scenario 1:* The participants were asked to open the main menu and navigate through the menu to open the "settings" submenu. They then had to find and open the "zoom" option. In total, they had to perform seven gestures, which covered all of the gestures in the "menu navigation" group.
- *Testing the Channel Surfing Gestures in Scenario 2:* The participants were asked to perform all "channel surfing" gestures with fixed time intervals. They had to follow this action sequence: "next channel", "last visited channel", and "previous channel".
- *Testing the Volume Control Gestures in Scenario 3:* The participants were asked to perform "volume control" gestures in the third scenario. They followed this action sequence: "increase the volume", "decrease the volume", and "mute".
- *Testing the Override Gestures in Scenario 4:* The participants were asked to turn off the TV.



(a) (b) (c)

FIGURE 5. **Snapshots in the memorability test (Study 4). Figures (a), (b), and (c) show three steps of the first scenario where participants are asked to interact with menu widgets. In addition, (a) shows the main GUI layout, which is used in Scenarios 1-4.**

To eliminate error in the gesture recognition engine and reduce the complexity of this part of the experiment, the participants were asked to imitate gestures and explain them verbally while the ''Wizard of Oz'' technique was used. This change assisted the study to focus only on the memorability of the proposed gestures. The experimenter recorded the execution time and number of mistakes for each scenario.

2) RESULTS

In the memorability test, three issues were examined. The first was finding out how fast people could remember and use the gestures. This was achieved by measuring the execution time and gesture accuracy in the scenarios. Figure 6 shows the execution time of each scenario. The first scenario had the widest distribution and was the longest. In this scenario, participants were expected to interact with the designed interface and perform at least seven gestures. The average time for this scenario was 25.55 seconds, while the median was 23.75 seconds where the difference is approximately 2 seconds. This is a reasonable amount of time given that participants had to read and understand the interface for the first time. The last scenario asked participants to shut down the TV. As just one intuitive gesture was needed here (a goodbye wave), it was done quickly. The average time was 1.57 seconds, while the median was only 1.5 seconds. This short response time confirmed that people could remember the proposed gesture and perform it quickly.

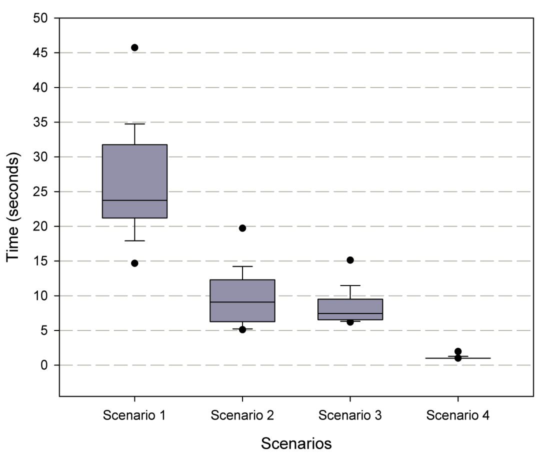


FIGURE 6. **Statistics of the execution in each scenario. The average time to remember and perform a gesture is 3.13 seconds.**

The second was evaluating the performance accuracy. The examiner recorded the total number of mistakes and the names of wrong gestures for each scenario (Table 7). All scenarios had a satisfactory accuracy average, especially the first one, where participants had to perform a number of gestures according to the real-time responses of the system. Furthermore, since the median is 100% for all scenarios, we concluded that more than half of our participants could perform the scenarios completely correctly.

TABLE 7. **The accuracy results of the memorability test. The average of accuracy for all four scenarios is 91.54%.**

Scenario	Median	Average	Std. dev.
Scenario 1	100%	92.48%	0.15
Scenario 2	100%	87.72%	0.23
Scenario 3	100%	96.49%	0.15
Scenario 4	100%	89.47%	0.31

The third issue concerned eliciting the connection between participants' preferences and memories (Table 8). Only three commands (''open menu'', ''open submenu/enter option'', and ''mute'') were considered that had two options in this test (due to their close scores on the second survey's results). In this questionnaire, the participants were asked to choose one preferred gesture for each associated command. Table 8 presents the results of those three questions. Additionally, each gesture that the participants performed during the scenarios was recorded. To open the main menu, ''snapping fingers'' was preferred over ''pushing palm'' by three times. Whereas during the test scenarios, ''pushing palm'' was used slightly more than ''snapping fingers''. The reason behind this difference could be the experience of users upon opening the menus by pushing the menu button. However, user preferences on the two other commands were con-

TABLE 8. The comparison between the available options of three commands.

Command	Gesture	Preferred	Executed
Open Menu	Snapping Finger	15	9
	Pushing Palm	5	11
Open Submenu/ Enter Option	Pointing	13	11
	Push Pointing	7	9
Mute	Hand on Mouth	13	13
	Closing Palm	7	7

firmed by the memorability test as they had almost the same results. Although both proposed gestures for these commands did not have strong advantages over each other, the study indicates that the embodied cognition experience through imitating those gestures may help participants remember the preferred gesture after a time interval.

IV. DISCUSSION

This section presents a brief discussion about the achieved results and confronted challenges. First, the preliminary study is discussed, followed by noted points in gesture vocabulary design. Finally, a discussion on evaluation and memorability tests is given.

A. PRELIMINARY STUDY

Two significant issues relate to the first phase of the user study (Study 1). The first is the issue of size and motivation behind the nominated commands. Q21 in Table 9 confirms the results of Vatavu that people might still prefer to use handheld controllers when available [18]. As a result, we chose a small, frequently used set of commands. While 12 referents were initially selected for this study, two shared the same gesture and thus were merged. By taking a deeper look at the four groups of commands, the need for specific commands such as ''override'' and ''volume control'' became more evident.

The ''menu navigation'' group contained only the fundamental and necessary commands for menu interaction such as opening, navigating, and entering. The ''channel surfing'' group comprised three commands, holding two of the most essential functions, ''next channel'' and ''previous channel'', both of which changed the channel by one unit per gesture. There is no referent that changed the channel for more than one unit per gesture. However, users could open the menu and use the search module or virtual keypad to change the channel for more than one unit. The ''last visited'' channel was added to the vocabulary to help users turn back to their last visited channel without using the menu or widgets.

The second issue was raised by notes from the participants. When asked to suggest gestures for ''next/previous channel'', they usually suggested horizontal movements. They all provided a similar example: turning pages in a book. While this was a good suggestion that accurately showed unconscious ideas and mental models of a communal mind, it raised the issue of culture and language. People from a specific country use different directional indicators that can be polar opposites of those from a different country. We determined that the direction of movement should be adjustable by the users. This challenge was evident in the last steps of this study, when we asked participants to change the channels. A few of them used the opposite gesture, right to left instead of left to right, largely because their native language is written right to left. Moreover, gestures such as putting a hand over the mouth, which was proposed for the ''mute'' command, could potentially have different meanings in different cultures. This issue is a well-known problem in HCI and has been addressed in similar studies [1], [8], [12], [18], [20], [21].

B. GESTURE VOCABULARY DESIGN

Participants of the preliminary study were given open questions, and as a result their suggestions involved many parts of the body including hands, head, chest, eyes, ears, and mouth. As shown in the Appendix, gestures that utilize both hands (e.g., clapping) were not selected. From this, we can infer that one-handed gestures are generally preferred over two-handed gestures. This also confirms similar results from Vatavu [18] and Wobbrock *et al.* [1].

In addition, participants of the preliminary survey had less technical knowledge in their educational background than those in the gesture vocabulary design. ''Turning the head to left/right'' and ''focusing in one direction'' are some suggested gestures in the preliminary study. They are especially good examples to show that participants were not focused on technical aspects. Instead, they gave their suggestions based on instinct and intuition. The participants in the gesture vocabulary design used their knowledge consciously towards selecting among the options. As a result, gestures that might be difficult to detect from a long distance using depth technology (e.g., focusing) or hard to understand (e.g., turning head) were not chosen. It was interesting to note that a majority of participants (67%) identified that they chose answers that felt more intuitive. The results of the external validation and memorability tests verified this answer, even though the participants were completely different.

C. EVALUATION AND MEMORABILITY TESTS

The results of the online questionnaire in Study 2 do not show a unique answer for ''open menu'', ''open submenu/enter option'', and ''mute''. To determine the final gesture for those three referents, the top two answers for each command were selected and taught to the participants in the technical evaluation test (Study 3). Participants were then asked to choose one of them. At the end of this study, each of the three referents had a distinctive answer. Training and imitating a gesture in the technical evaluation may assist participants in clarifying which gesture is more intuitive without being biased by the ease of performance.

The ''mute'' command could be a good example. Initially, in the online questionnaire (Study 2), the ''closing fist''

TABLE 9. The questionnaire of interactive hand gesture vocabulary Q1–22.

Index	Question and Answer Options				
Q1	Select the age range that you are in:				
	< 18 - 21	22 - 25	26 - 30	31 - 40	> 40
Q2	Please select your gender:				
	Male		Female		
Q3	Do you usually play videogames?				
	Almost every day	More than once a week	More than once a month	Sometimes, rarely	Never
Q4	How often do you play videogames in which the game control is made using body movements?				
	Almost every day	More than once a week	More than once a month	Sometimes, rarely	Never
Q5	Your gestures: Next Channel				
	Hand/Arm from left to right/right to left	Head to the left/right	Eyes to the left/right	Hand to the front	
Q6	Your gestures: Previous Channel				
	Hand/Arm from left to right/right to left	Head to the left/right	Eyes to the left/right	Hand to the back	
Q7	Your gestures: Back to the last visited channel				
	Hand/Arm from left to right/right to left	Hand/Arm from top to bottom/from bottom to top	Hand to the back	Circular movements with the hand	
Q8	Your gestures: More volume				
	Hand/Arm from left to right/right to left	Hand/Arm from bottom to top	Thumbs up	Circular movements with the hand	
Q9	Your gestures: Less volume				
	Hand/Arm from left to right/right to left	Hand/Arm from top to bottom	Thumbs down	Circular movements with the hand	
Q10	Your gestures: Open menu				
	Hand to the front	Make a fist with the hand	Clap/Unclap hands	Circular movements with the hand	Snap Fingers
Q11	Your gestures: Menu, enter a submenu				
	Hand/Arm from left to right/right to left	Open/Close the fist	Clap/Unclap hands	Point at the TV	Stop sign
Q12	Your gestures: Menu, up in the menu				
	Hand/Arm from left to right/right to left	Hand/Arm from bottom to top	Thumbs up	Point at the TV	
Q13	Your gestures: Menu, down in the menu				
	Hand/Arm from left to right/right to left	Hand/Arm from top to bottom	Thumbs down	Point at the TV	
Q14	Your gestures: Menu, enter an option				
	Push and point	Fist and point	Yes with the head	Thumbs up	Snap Fingers
Q15	Your gestures: Mute/Unmute				
	Hand/Arm from left to right/right to left	Hands on the ears	Hand on the mouth	Open/Close hand (without bending the fingers)	Make an X with the arms
Q16	Your gestures: Shut down the TV				
	Clap hands	Hands on the eyes	Stop sign	Bye gesture	Make an X with the arms
Q17	Do you prefer accuracy rather than speed (time response)?				
	High	Moderate	Intermediate	Almost nothing	I don't care
Q18	Do you like the idea of a set of recognition gestures instead of conventional commands?				
	High	Moderate	Intermediate	Almost nothing	I don't care
Q19	Would you remember a set of gestures for easy navigation on TV?				
	All of them	Most of them	Half of them	Some of them	None of them
Q20	Would you find it more useful to have one gesture for each option (enter menu, enter volume options, enter channel options...) and repeat the ones for up/down?				
	Yes	No	I don't mind		
Q21	Would you prefer a system controlled by gestures rather han a conventional remote control?				
	Yes	Only a set of choices	Both	No	
Q22	Why do you choose a particular gesture to an associated control command (e.g. Volume Up)				
	It's more intuitive	It reminds me to the smartphone	It's more comfortable	It is based on standards	For no special reason

gesture was slightly ahead of ‘‘putting hand over mouth’’. However, at the end of the last step, ‘‘putting hand over mouth’’ had a higher success rate both on the post-study questionnaire and the memorability test. This indicates that although ‘‘closing fist’’ is easier to perform and might theoretically be a better answer for the mute command, after training and mimicking, "putting hand over mouth" seemed more intuitive to participants.

We should also highlight that describing a gesture without any visual element or imitation may lead the gesture to be an ideal concept rather than a feasible interaction model. When participants were asked to learn and perform these gestures, embodied cognition became involved in the decision and memorization process [22]. We believe that this could be used to explain the differences in the results of the online questionnaire (Study 2) and technical evaluation (Study 3) for the three commands. Moreover, embodied cognition may be the prominent element for the high approval rates of all referents and exceptionally great success rates on the defined scenarios [23]. Finally, although we examined intermediate term memory with duration from minutes to hours in our memorability test [24], most participants in their conversations admitted that they could remember the proposed gestures even after a week and also perform the gesture correctly. This could be considered as a positive feedback for both the right size of the vocabulary set and intuitiveness of proposed referents.

The participants in the technical evaluation (Study 3) said they wanted to be able to perform a continuous interaction with devices. For example, they wanted to change several channels by one swipe gesture, just like scrolling. Generally, this concern was mentioned for gestures with a horizontal or vertical hand movement. We believe this concern is important, but it is more related to the implementation of the gesture vocabulary and not the characteristics of it.

Another important issue is the engagement mechanism, a controversial subject in gesture- and speech-enabled systems. Defining a simple and easy engagement mechanism may not be accurately detectable by the current technology (e.g., direction of eyes). In contrast, defining a mechanism that can be precisely detected by the available sensor technology may not be easy to perform for the users. Advances in technology will help researchers find a solution for this problem that is feasible and user-friendly. For example, the next generation of Microsoft Kinect is more advanced; it can detect fingers more accurately. This could help us reduce the errors in the developed gesture recognition engines and design an acceptable engagement mechanism.

V. CONCLUSION AND FUTURE WORK

In this paper, we presented a study on the elicitation of users' attitudes and preferences towards an interactive hand gesture vocabulary for smart televisions. The study was initiated to propose a gesture vocabulary that is simple, memorable, and intuitive. The first phase of the user survey (preliminary study) was conducted with a set of 49 people to collect ideas and suggestions. The most frequent referents in the first phase formed the choices for the subsequent questionnaire, which had the same questions in the form of multiple choice. The average agreement score of the proposed vocabulary in the second phase of user survey (online questionnaire) exceeded the average score of similar studies. This survey was verified through a technical evaluation and external user agreement tests. It attained high scores on the post-study questionnaire and exceedingly accurate performances on the memorability test. It is shown that although the size of proposed vocabulary is smaller than that in the similar studies, it is fully functional and is able to maintain a high agreement score. Regarding the future work, we are planning to build a gesture-enabled system based on the proposed gesture vocabulary and further study the impacts from culture difference towards gesture preference.

APPENDIX

Table 9 shows the designed questionnaire for the second phase of user survey (Study 2).

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