Personalized Gestural Interaction Applied in a Gesture Interactive Game-based Approach for People with Disabilities

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ABSTRACT

Technology can support people with disabilities to participate in social and economic life. Using relevant Human-Computer Interaction, as obtained through Intelligent User Interfaces, people with motor and speech impairments may be able to communicate in different ways. Augmentative and Alternative Communication supported by Computer Vision systems can benefit from the recognition of users' remaining functional motions as an alternative interaction design approach. Based on a methodology in which gestures and their meanings are created and configured by users and their caregivers, we developed a Computer Vision system, named PGCA, that employs machine learning techniques to create personalized gestural interaction as an Assistive Technology resource for communication purposes. Using a low-cost approach, PGCA has been experienced with students with motor and speech impairments to create personalized gesture datasets and to identify improvements for the system. This paper presents an experiment carried with the target audience using a game-based approach where three students used PGCA to interact with communication boards and to play a game. The system was evaluated by special education professionals using the System Usability Scale and was considered suitable for its purpose. Results from the experiment suggest the technical feasibility for the methodology and for the system, also adding knowledge about the interaction process of disabled people with a game.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**; • **Social and professional topics → People with disabilities**; • **Computing methodologies → Motion capture**.

KEYWORDS

Assistive Technology, Augmentative and Alternative Communication, Gestural Interaction, Machine Learning, Game.

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1 INTRODUCTION

Using computers as a communication tool is trivial for daily activities. However, the use of computing systems by people with motor difficulties is particularly challenging. Often, people with speech disabilities also have associated motor limitations, which further results in barriers to interact with others and the environment [6]. Assistive Technology knowledge area, through specific resources, services, strategies, and practices, can support people with functional losses from disabilities or due to aging actively participate in society and to become or remain autonomous.

For people who are partially unable to move or control their limbs and cannot rely on verbal communication because of a disability, specific technologies such as gesture recognition or brain-computer interface may be required to enable interaction with Augmentative and Alternative Communication (AAC) systems, as proposed by Tu et al.[50], Ma et al. [33], and Gomez-Donoso et al. [21]. Research in Intelligent User Interfaces describes a broad class of system types that apply Artificial Intelligence techniques to different aspects of Human-Computer Interaction [51], focusing on interfaces that require intelligent technologies to bring them to fruition [41]. These include natural language techniques in interfaces, interfaces for intelligent learning systems, new methods for recognizing gestures and attention, among others [41].

A gesture is a nonverbal communication with the hand, finger, head, face, or other body parts. People with motor disabilities may have different or fewer possibilities for gestures. However, they may still be able to activate different muscles, even with limitations on the strength or duration. Interaction based on gesture recognition has the potential to consider particularities of each user when performing movements, being considered "natural" and even intuitive because humans learn to use gestures since childhood [14]. Although gestural interaction solutions have become popular, their application to support AAC still requires technology assessment experiments and examples to demonstrate their technical feasibility. Moreover, it is also necessary to develop low-cost computing solutions to meet the diversity of people in their capabilities and physical, cognitive, social and economic limitations.

In the context of computer games, many individuals with disabilities are still finding themselves excluded from full participation. Players with disabilities need to use Assistive Technology features to play accessible games, and it is not "just playing a game" (which is fun and provides learning benefits) but a question of inclusion into real life [39]. To contribute in this direction, we developed a Computer Vision system, named PGCA (Personal Gesture Communication Assistant), that allows to create personalized gestural interaction for communication purposes including a gesture interactive game-based approach. The system is based on a methodology to support AAC [7] in which gestures and their meanings are created and configured by users and their caregivers. The system was evaluated in previous experiments with HCI experts [7] and with the target audience [8], and learned lessons informed the system redesign for its new version. This paper builds on the results from our previous work, presenting results and perceptions from an experiment carried out with students with motor and speech impairments, analyzing the personalized gestural interaction provided by the developed system to interact with communication boards and to play a simple game. Perceptions obtained by comparing results of this experiment with results from a previous experiment with the same students are also presented.

2 RELATED WORK

Gesture-based interfaces have become an effective control modality within the Human-Computer Interaction realm to assist individuals with motor impairments to use technologies for daily living and entertainment [27]. History of studies over the past 30 years reported by Bhuiyan and Picking [10] suggests that gesture-controlled interfaces now offer realistic and accessible opportunities, which may be appropriate for older or disabled people.

Jacob [25] was one of the first to introduce appearance-based interaction techniques into real-time applications for people with disabilities. Since then, several studies focused on developing Assistive Technology solutions based on recognition of body movements investigate new interaction possibilities. Hand gestures have been widely explored as a viable alternative for the Human-Computer Interaction of people with disabilities and differences in their capacities. Examples are the works of Morrison and McKenna [35], Dehankar et al. [17], and Haria et al. [23], aiming to gestural interaction. Recognition of gestures for communication purposes, such as Schaeffer gestures [46], was developed by Gomez and Cazorla [20] and Oprea et al. [38]. Currently, there are also systems capable of recognizing facial expressions [42] [24], body expressions [44], head [37], nose [48] [34], foot [52], mouth, and tongue [31] [5] [36] movements to offer new possibilities and forms of interaction with and via computing systems.

Affordable motion-based input devices have been used in therapy to help people to recover lost range of motion and motor control [3]. Interacting with gaming technologies can benefit users with motor impairments as games have shown to be useful in providing environments in which users can practice repetitive, functionally meaningful movements, and in inducing neuroplasticity [9].

Games have been proposed to users with motor impairments, as Foletto et al. [19] who presented a serious game to help in rehabilitation and therapy for Parkinson's disease patients. Lopez et al. [2] proposed GNomon, a framework that provides specific functionalities for creating accessible digital games for children with severe motor disabilities, which interact with electronic devices via a single switch only. Studies of Jiang et al. [26, 27] converted a gesture-based interface designed for people without disabilities into an interface usable by individuals with motor impairments. In [27], an experiment was conducted with subjects with quadriplegia using gesture recognition to complete a PAC-MAN game.

The study of Camara-Machado et al. [12] analyzes the effects of Xbox 360 Kinect games employed as physical rehabilitation for children with cerebral palsy. Other objectives included testing the applicability of interactive games as tools for the rehabilitation and investigate the contributions of interactive games to physical development. Altanis et al. [4] carried an empirical study to investigate the effectiveness of using Kinect for the rehabilitation of children with dyspraxia and motor impairments. They based their research on a game called Uni_Paca_Girl, in which players are asked to make movements by driving a girl along related paths.

Games are more appealing than traditional treatment methods and may lead to greater motivation and social interaction among patients, which in turn may influence positively the long-term success of rehabilitation programs [13]. We believe this motivation and engagement also occur in games designed for other purposes when supported by adequate Assistive Technology resources.

For people who have, besides communication disorders, motor difficulties, using AAC systems is a challenge that demands different approaches. Existing AAC computational solutions tend to be employed and focused on specific situations working with predefined gesture sets or tracking a particular body region, offering little flexibility and adaptability that are essential features for accessibility. Existing studies provide little or no detail on difficulties encountered when creating the gesture datasets, possibly because they use existing datasets, or datasets created with gestures performed by people without disabilities [8]. In this context, the contribution of our study supports dataset creation process for gestural interaction, taking into account the abilities and limitations of users when performing movements, and providing support to other people to recognize these movements.

3 RESEARCH APPROACH

The research problem investigated in this paper is understood from a Human-Computer Interaction problem-solving perspective as described by Oulasvirta and Hornbæk [40]. These authors have elaborated Larry Laudan's concept of problem-solving ability as a universal criterion for determining the progress of solutions: rather than asking whether the research is 'valid' or follows the 'right' approach, it encourages researchers to ask themselves how their solutions are advancing and their ability to solve major problems in the human use of computers. From this perspective, the main research problems in HCI fall into three main categories: empirical, conceptual, and constructive.

We treat our research problem as having characteristics of both empirical and constructive nature. Empirical, to test and describe the effect of a methodology designed to support AAC based on personalized gestural interaction. And Constructive because it aggregates information on the understanding of the use of an AAC computer system and a gesture interactive game-based approach by people with motor and speech impairments. Our research approach was designed to explore low-cost and adaptable alternatives, considering needs and challenges reported by special education teachers and family members of people with motor disabilities. In this context, we invited students with motor and speech difficulties, assisted by special education professionals, to create datasets of personalized gestures used to interact with an AAC system, using communication boards and playing a game.

We employ gestures captured through a webcam, as it is easily accessible to computer users. The PGCA system captures movements performed in front of the camera and represents them as Optical Flow-based Motion History Image (OF-MHI). Motion History Image (MHI) converts the 3D space-time information from a video sequence into a single 2D intensity image [49], including information of time and space and reflecting movements order. The Lucas Kanade's optical flow (OF) [32] was used to aggregate velocity information to MHI, as already used in studies of [49] and [18].

Using machine learning techniques, two classifiers were evaluated to recognize the movements performed (gestures): one based on Support Vector Machine (SVM-based classifier) and the other based on Convolutional Neural Network (CNN-based classifier). The SVM-based classifier uses the "one-versus-all" method to address problems of multiple classes, and the feature descriptor Histogram of Oriented Gradient (HOG). The CNN-based classifier employs transfer learning using the TensorFlow [1] Inception V3 [47], trained initially on ImageNet dataset [45], retraining Inception's final layer with new categories according to labels and gestures generated by users. For interaction tests, the SVM-based classifier was used because it presented slightly better results than the CNN-based classifier in a previous experiment. Even so, posteriorly, the CNN-based classifier also was evaluated. For the implementation, it was used the programming language C++ and QT platform. The CNN-based classifier was implemented using programming language Python embedded in the C++ application.

Figure 1 shows screens of the developed system: (A) the Caregiver Area, where datasets are created and the system is trained to gesture recognition; (B) User area where gesture recognition is used for communication, interaction with communication boards[1], and customizing functionalities; (C) Communication boards area where the caregiver can generate customized boards using images.

3.1 Participants

The first author of this paper visited four schools, linked to co-participating institutions, where she met students with motor and speech impairments. Among these students, a group of seven students was selected to participate in a previous experiment aiming to create datasets with personalized gestures. The group was selected based on interview results and recommendations from teachers as it was required the student to have at least a basic level of comprehension capacity and conditions to carry out voluntary movements.

This paper describes a new experiment carried for data collection. Considering the difficulties and learned lessons from the first data collection, for the present experiment only those students who showed good comprehension skills (i.e., able to understand tasks and consciously execute them) and interest in participating in the task were selected. From the seven students selected previously, one was not authorized by the family, two were unable to generate datasets in the first data collection (for different reasons), and one student showed quite a difficulty in understanding the requested tasks. Therefore, for the experiment described in this paper, three students with motor and speech impairments were invited to participate. All students are characterized as people with cerebral palsy, with different levels of disabilities and needs, as presented in Table 1. Families gave their informed consent to students to participate in the study, whose ethical approval was obtained from the local research ethics committee.

[1]Images from ARASAAC portal [43].

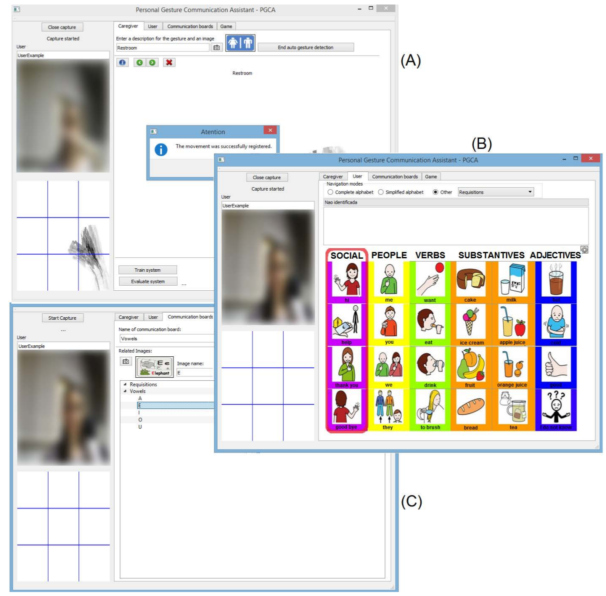


Figure 1: (A) Caregiver Area; (B) User Area; (C) Communication boards Area.

Table 1: Characteristics of students with special needs selected to participate in the experiment

Stud.	Sex*	Age	Medical report
A	M	18 years old	Cerebral palsy due to sequels during labor.
B	M	38 years old	Quadriplegia with athetosis component, bilateral sensorineural hearing loss.
C	F	20 years old	Pseudobulbar palsy. Generalized hypotonia and hyperreflexia.

*Sex: M - Male; F- Female.

3.2 Apparatus

The materials used for the experiment were a laptop with 8GB of RAM and a Camera Hp 1080 Auto Focus attached to a tripod positioned above the laptop screen.

3.3 Procedure

The present experiment was conducted with the target audience aiming to validate the data obtained in a previous experiment and evaluate the system after implementing the following improvements: i. possibility of reproducing via synthesizer voice messages presented by the system; ii. inclusion of distinctive color borders to make the current system status more visible; iii. inclusion of help buttons to describe key system features; iv. inclusion of an interactive gesture-based game approach. The main aim of this experiment was to analyze in a standardized way the system's accuracy in gesture recognition and the effort required for each user to achieve the same goal, each using the gestures he/she can perform.

Some student families were contacted personally by school principals, and others by the first author of this paper. Each student who participated in the experiment was accompanied by a teacher who played the "caregiver user" role in the system, informing and labeling gestures that the student usually uses to communicate. Before starting the experiment, a short training session was carried with each student and teacher, where the first author of this paper explained the operation of the system and the intended tasks. The tasks performed during the experiment were: i. creating the dataset by capturing gestures for training the system; ii. training and evaluating the system; iii. using the system to recognize gestures; iv. using gestures to play a game, whose goal is to move a turtle until it reaches the sea; v. using the system to select options in a communication board. Finally, participant professionals evaluated the system usability.

4 GAME IMPLEMENTATION

The Game Area was included in the system after an experiment with the target audience, as it was observed that some students were not sufficiently motivated to perform the proposed tasks. Thus, a gesture interactive game-based approach was designed to allow analyzing in a standardized way the system accuracy on gesture recognition and the effort required for each user to reach the same goal, each one using the gestures s/he is capable to perform.

Two students participating in an previous experiment use only "Yes" and "No" gestures for communication, therefore, a simple game was designed to require a small number of gestures. Thus, the turtle, which is the main character of the game, can be moved in four directions, but with only one or two directions it is possible to achieve the goal of the game. Using gestures, users must avoid obstacles in the sand (a shell and two crabs) and lead the turtle to the upper region of the image, where is the sea. Passing through any of the obstacles does not prevent the turtle from moving; it only presents a different sound and image. There are no scores or time constraints of any kind because the game has been designed mainly to encourage users to perform repeated gestures, not to compete with each other or with a computer.

Figure 2 (A) shows the Game Area and the turtle's initial state positioned on the beach. Figure 2 (B) shows an example of the turtle state change during gameplay, where the upward motion was recognized and caused the turtle to encounter the crab obstacle. The green border indicates that a gesture has been completed and recognized by the system. The Game Area is available for use after system training had been performed for the created dataset.

At the top of the Game Area there are selection lists with gestures (used to train the system) that can be related to the up, down, right, and left scroll movements. To start the game, the system capture must be enabled ("Start Capture" button). By clicking the "Start Game" button, the turtle is positioned in the lower-left corner of the screen(Figure 2 - A).

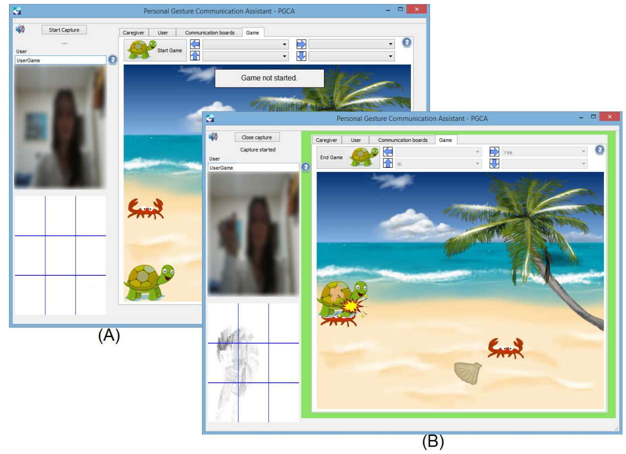
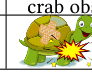
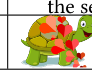


Figure 2: (A) Game home screen; (B) Example of game usage.

Table 2 presents the turtle in its normal state, in its state after touching the shell, or one of the crabs, and after reaching the goal of the game. Each change in turtle status gives a distinctive sound. A "Jump" sound is played when a gesture associated with some movement is recognized. Figure 3 shows the image presented to the user in the beach landscape after completing the game. An "Applause" sound is played.

Table 2: Turtle state changes during game play.

State A Normal	**State B** Touching shell obstacle	**State C** Touching crab obstacle	**State D** Reaching the sea
			

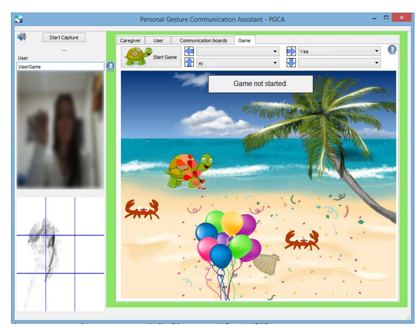


Figure 3: Game screen after user reaching the goal.

In the upper left corner of the screen, there is a "Speaker" icon, which, when activated, enables a speech synthesizer to reproduce all messages presented textually by the system, aiming to facilitate the understanding by non-literate users. The system has buttons characterized by the "?" icon related to helping function. In the Game Area case, the icon is located in the upper right corner of the screen, and when clicked presents a message to the user explaining the game's objectives and interaction form.

The images used in the game were obtained by searching on the Internet for free content. The turtle image was obtained from Commons_Wikimedia [15] (free media repository), and the beach background image (already with the shell and one of the crabs) was obtained from OpenGameArt [16] (a community of game developers with free contents available). The other images used to make modifications on originals were obtained by searching for images marked for reuse on Google Images site [22].

5 DATA COLLECTION AND PERSONALIZED GESTURAL INTERACTION

Datasets with personalized gestures performed by three students with motor and speech impairments were created in two experiments. In the previous experiment, datasets were created in one session, and interaction tests in a second session. In the present experiment, described in this paper, a single session was sufficient, and each dataset contained fifteen original samples by class. For data collection, the Caregiver area was used, where gestures are related to classes labeled with words that will be used for communication or configuration purposes (e.g., Hi, Bye, Restroom, Food, Water, Confirm, Undo) and are relevant to users and their caregiver. Through an image-matching algorithm, the system allows recording only samples valid for each gesture and to discard erroneous samples (OF-MHI very distinct) generated, for example, from some involuntary movement by the user. The algorithm suggests that the gesture was not performed similarly sufficiently to the first one (considered as the base) and the caregiver decides if the sample will be kept or discarded. The researcher who accompanied the experiment assisted the caregiver in this step by filtering the generated samples.

After completing the dataset generation, caregivers can start the system training, which will automatically perform the dataset expansion processes (using Data Augmentation) and train the system to recognize gestures using the SVM-based classifier by default. Following, caregivers can test the system to evaluate classifier's accuracy on gesture recognition. If accuracy test produces acceptable results (ideally above 90%), the model can be used for gesture recognition. If the test indicates poor performance, a description of the captured gestures is presented to caregivers, containing the hit rate for each gesture. This information allows caregivers to perform a new data collection or to remove from dataset gestures with low hit rate. In this experiment, the system was configured to use the "Zoom in" option, which allows for tracking in more detail for facial movements.

To perform the interaction test in the same session in which the dataset was created, the system was evaluated using the Holdout method [28], because it is faster, and also for providing a good perception of system performance on gesture recognition. Thus, two models for gesture recognition were generated: 1) for the system evaluation step where the dataset generated was split into two subsets, with 2/3 of the data to the training set and 1/3 of the data to test set; 2) for the user interaction with the system step where a model was trained using all available samples in the dataset. In both models, the number of training data is expanded by Data Augmentation, where additional samples were created from existing data, creating eight variations by rotating and scaling the original image. Later (because it takes longer to execute), the K-fold Cross-validation method was used, considering ten folds, separating 90% of data for training and 10% for the test, to generate a more accurate overall estimate about the system's ability to recognize captured gestures. Details of the experiment execution with each student are presented below.

5.1 Student A

Student A is enrolled in a specific educational institution for students with special needs (Parents and Friends Association of the Exceptional - APAE). This student uses only two head gestures in the school environment to communicate with his/her classmates and teachers, which refer to "Yes" (moving the head backward) and "No" (moving head to both sides); dataset created was composed of two classes, with fifteen samples by class. Because this student has difficulty keeping his neck erect, in the previous experiment he used a pillow to support his neck. For the present experiment, teacher warned the student's physical mobility worsened a little and the previously used pillow no longer helps. Thus, the student has been using as support in wheelchair a roll of tissue, but even so, during the experiment, it was necessary to adjust the student posture several times. Possibly due to the described situation, samples captured in the previous and present experiments for the same gestures present significant differences. Figure 4 (A) shows examples of samples generated by Student A to compose the dataset in both experiments.

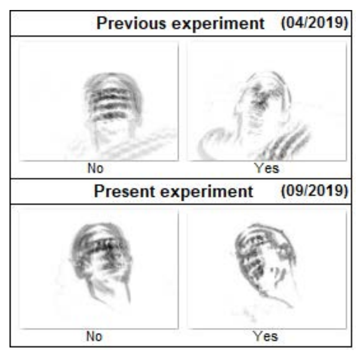


Figure 4: Examples of gesture samples of Student A.

After training, the system was evaluated using the Holdout approach, showing 80% accuracy on gesture recognition. The first step of interaction with the interface test was referring to the recognition of gestures for which the system has been trained. Using the User Area: the "No" gesture was correctly identified by the system in all attempts performed voluntarily by the student, but the "Yes" gesture has not been recognized a few times, mainly because student has difficulty to back to the original position after moving the head back. Sometimes, student ended up lowering the head to view the interface response, generating a movement representation similar to the "No" gesture. Subsequently, the Game Area was used, configuring the "Yes" class to move turtle right and "No" class to move turtle up. After some unsuccessful attempts, the first author of this paper demonstrated how to play, using her dataset. Then the student understood the operation of the game and managed to achieve the goal. Subsequently, the system was configured by associating the "Yes" class with the system "confirm" option, allowing the student to test the image selection on the communication boards available in the User Area. Figure 5 shows an example of an interaction test with a communication board with pictures as performed by each student.

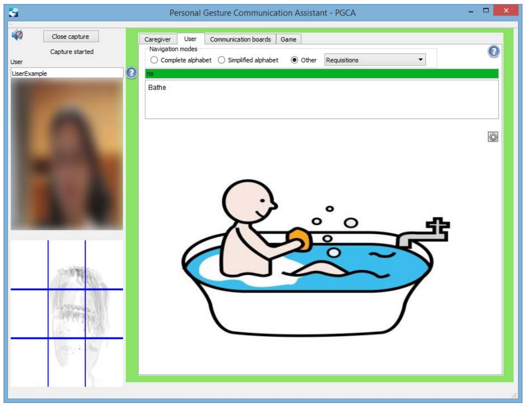


Figure 5: Example of picture selection on the communication board using a head gesture (image from [43]).

Figure 6 presents the student interacting with the system interface, playing the game. Data collection process for composing the dataset in the present experiment took over ten minutes to complete.

Figure 6: Student A interacting with the system interface, playing the game.

5.2 Student B

Enrolled on an inclusive school where students with special needs can also attend regular classes (State Center for Basic Education for Youth and Adults), student B presents motor and speech impairment and severe hearing loss, using hand and head gestures for communication. For the experiment, he was accompanied by his LIBRAS (Brazilian sign language) interpreter and his caregiver. He uses some gestures of LIBRAS and home signs, but because of motor impairment in the hands, not all LIBRAS interpreters can understand his intentions. The dataset created by this student has seven classes, referring to motion-based gestures commonly used by the student in the school environment. Figure 7 shows examples of samples generated by Student B for composing his dataset in the experiments. In the present experiment, the student presented some difficulty to perform wider movements and to raise his arms. LIBRAS interpreter highlighted the student has exhibited considerable weakness and diminished motor skills.

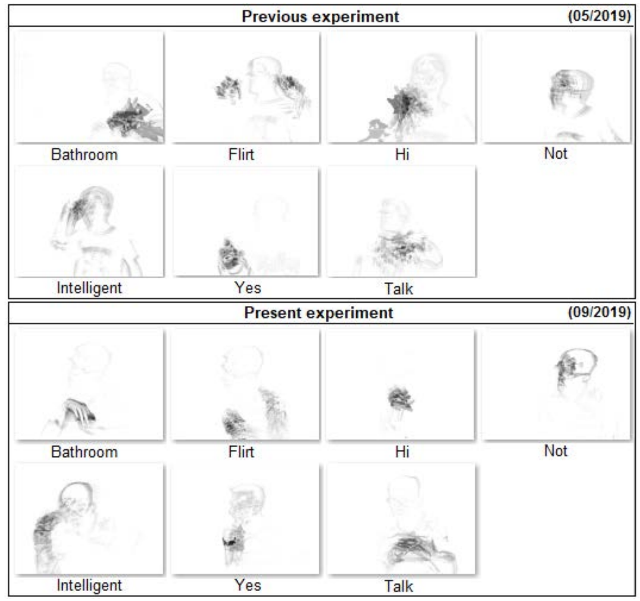


Figure 7: Examples of gesture samples of Student B.

After training, the system was evaluated using the Holdout approach, showing 74% accuracy on gesture recognition. During the interaction test, some gestures were easily recognized by the system, such as "Hi", "Conversation", "Flirt", "Yes" however, other gestures ("No", "Intelligent", "Bathroom") had to be performed several times before being recognized by the system. We observe some tiredness and difficulty of the user to perform the same gestures he did when creating the dataset. Subsequently, the system was configured by associating the "Yes" class with the system "confirm" option, allowing the student to test image selection on the communication boards available in the User Area. In the following, the Game Area was used, configuring the "Hi" class to move turtle right and "Yes" class to move turtle up. The researcher who carried out the experiment explained to the student how to play the game, using gestures and the help of the LIBRAS interpreter. As the student made some attempts and the turtle did not move, the researcher reproduced the gesture that was being performed by the student, causing the turtle to move. From then, the student began to use his movements until he could reach the goal of the game. During the interaction, the student moved in different ways, and different gestures were recognized by the system.

Figure 8 presents the student interacting with the system interface after completing the game objective. Data collection process for composing the dataset of Student B in the present experiment took over thirty minutes to complete.

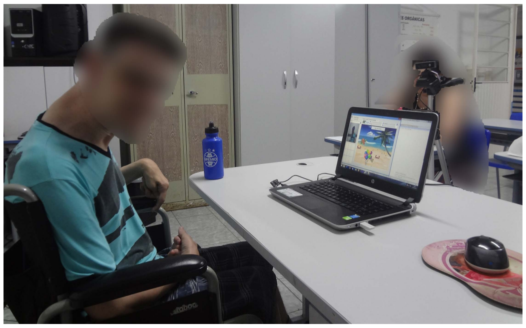


Figure 8: Student B after interacting with the system interface and completing the game objective.

5.3 Student C

Student C is also enrolled in an inclusive school (State College - Elementary and Middle Education) and uses head gestures and facial expressions to expose communication intentions in the school environment. The gesture referring to "Yes" is performed by raising eyebrows, however, as the student moves his head a lot, the system was not able to register this movement of this facial expression correctly. To create a dataset for this student to interact with the system, we chose to capture the movement referring to "No" (moving the head to both sides), and the movement referring to "Hand" (moving his right arm, despite presenting many spastic movements). Figure 9 shows examples of samples generated by Student C to compose the dataset for the previous and present experiments.

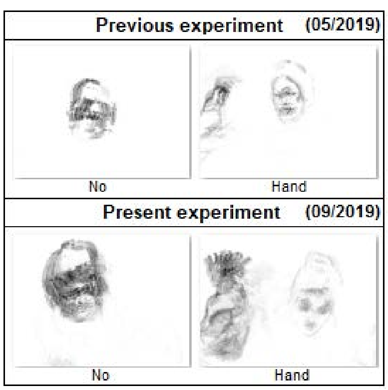


Figure 9: Examples of gesture samples of Student C.

After training, the system was evaluated using the Holdout approach, showing 100% accuracy on gesture recognition. The system correctly identified the two gestures in the interaction test. Eventually, the student presented a significant change in posture, which made it difficult for the system to recognize some movements. In the following, the Game Area was used configuring the "No" class to move turtle right and "Hand" class to move turtle up. The first author explained how to play the game and the student played using his own gestures, presenting no perceived difficulty to understanding its operation. However, physical limitations were observed as performing right arm movements required visible effort from the student. Subsequently, the system was configured associating the "No" class with the "next" option, and "Hand" class with the system "confirm" option. The student managed to use the "No" gesture to navigate between pictures on a communication board, and the "Hand" gesture to select desired pictures.

Figure 10 presents student C interacting with the system interface, playing the game. Data collection process for composing the dataset for the present experiment took over seven minutes to complete.

Figure 10: Student C interacting with the system interface to play the game.

6 RESULTS

The experiment reported in this paper was performed to evaluate the system developed, and the methodology used as the basis for its development. Previous experiments [7, 8] have shown the viability to train a system to recognize personalized gestures performed by users, including the ones with motor and speech impairments, and then use these gestures for gestural interaction with an AAC system. The present experiment focused on the following three aspects: i. classifier performance to recognize personalized gestures; ii. effort required for users to play the game; and iii. system usability.

Table 3 shows the time spent to training and testing steps, considering the Holdout and K-Fold methods, by the SVM-based and the CNN-based classifiers. K-fold Cross-Validation method were used to evaluate the performance of classifiers to recognize gesture from datasets. After running tests on all folds, overall accuracy, Cohen's Kappa (a statistical measure of inter-rater agreement), standard deviation, variance, and False positives were calculated as presented in Table 4. Classifiers considered valid decisions when having 50% certainty or more of a sample belonging to a particular class (confidence level). Typically, a perfect classification would produce zero variance and zero standard deviation, and one for accuracy and kappa value. According to Landis and Koch criteria [29], for the interpretation of kappa value: 0.0 to 0.2 = slight agreement, 0.2 to 0.4 = fair agreement, 0.4 to 0.6 = moderate agreement, 0.6 to 0.8 = substantial agreement, and 0.8 to 1.0 = almost perfect agreement. For gesture-based interfaces, precision (high true positives and low false positive rates) has to be assured while maintaining a natural feeling of interpersonal communication [30].

To evaluate the effort required for users to play the game, the time needed for each user to accomplish the task and the number of gestures performed were recorded. Tables 5, 6, and 7 show the

Table 3: Approximate run time spent by classifiers to training and testing steps using Holdout and K-Fold methods.

Student	SVM-based classifier				CNN-based classifier			
	Holdout		K-Fold		Holdout		K-Fold	
	Train	Test	Train	Test	Train	Test	Train	Test
A	45s	6s	5m	16s	29m	58s	5h	3m
B	8m	7s	56m	26s	29m	5m	12h	9m
C	34s	4s	4m	4s	34m	51s	5h	3m

s: seconds; m: minutes; h: hours.

Table 4: Classifiers performance using K-Fold cross-validation in the experiments: Accuracy, Cohen's Kappa, Standard deviation, Variance, and False positives.

	Classifier	Method	Student dataset		
			A	B	C
Previous Exper.	SVM-based	Accuracy	1	0.87	1
		Cohen k	1	0.85	1
		Std. Dev.	0	0.080	0
		Variance	0	0.007	0
		False pos.	0	0.002	0
	CNN-based	Accuracy	0.97	0.82	1
		Cohen k	0.94	0.79	1
		Std. Dev.	0.030	0.147	0
		Variance	0.001	0.024	0
		False pos.	0.002	0.011	0
Present Exper.	SVM-based	Accuracy	0.87	0.89	1
		Cohen k	0.73	0.87	1
		Std. Dev.	0.200	0.136	0
		Variance	0.044	0.020	0
		False pos.	0.004	0.006	0
	CNN-based	Accuracy	0.90	0.69	0.92
		Cohen k	0.80	0.64	0.92
		Std. Dev.	0.160	0.153	0.200
		Variance	0.028	0.026	0.044
		False pos.	0.004	0.018	0.002

game progress and gesture recognition registered during students interaction with the game, considering the better performance interaction for each student. During interaction in the Game Area, time spent for the system to recognize each gesture varied strongly as it depends on the variations and limitations of each user in performing movements. However, records stored in the log file show some gestures were identified in less than two seconds, suggesting the effectiveness of the interface to provide a natural gestural interaction.

Table 5: Gestures recognized by the system and actions triggered during game interaction of Student A.

Gesture	Moving Turtle	Time (h:m:s:ms)	Turtle State	Sound	Game
Yes	To Right	08:29:34:295	A	Jump	In progress
No	To Up	08:29:48:646	A	Jump	In progress
No	To Up	08:30:00:701	A	Jump	In progress
No	To Up	08:30:03:942	C	Snap	In progress
*	-	08:29:57:163	C	-	In progress
No	To Up	08:30:08:900	C	Snap	In progress
No	To Up	08:30:13:077	D	Applause	Completed

* Unidentified gesture. Time spent: 00:00:38:782

Performance measures were complemented by self-reports collected using a standardized usability assessment. To better understand the perception of the professionals who followed the execution of the experiment, participants (teachers and companions, caregivers, LIBRAS interpreter) completed a system usability evaluation questionnaire, where they gave their opinion about the system and the possibility of using it. The System Usability Scale (SUS) [11] was employed for being quick and simple.

Table 6: Gestures recognized by the system and actions triggered during game interaction of Student B.

Gesture	Moving Turtle	Time (h:m:s:ms)	Turtle State	Sound	Game
*	-	14:28:20:050	A	-	In progress
Talk	To Right	14:28:30:236	A	Jump	In progress
*	-	14:28:31:947	A	-	In progress
*	-	14:28:32:934	A	-	In progress
*	-	14:28:34:672	A	-	In progress
*	-	14:28:36:197	A	-	In progress
Flirt	-	14:28:38:178	A	-	In progress
*	-	14:28:40:671	A	-	In progress
Flirt	-	14:28:42:120	A	-	In progress
*	-	14:28:43:921	A	-	In progress
Flirt	-	14:28:45:381	A	-	In progress
Yes	To Up	14:28:48:481	A	Jump	In progress
Flirt	-	14:28:52:521	A	-	In progress
Flirt	-	14:28:54:394	A	-	In progress
Flirt	-	14:28:55:923	A	-	In progress
Yes	To Up	14:29:00:924	A	Jump	In progress
No	-	14:29:02:013	A	-	In progress
Yes	To Up	14:29:04:549	C	Snap	In progress
*	-	14:29:06:958	C	-	In progress
Yes	To Up	14:29:09:471	C	Snap	In progress
Yes	To Up	14:29:11:454	D	Applause	Completed

* Unidentified gesture. Time spent: 00:00:51:404

Table 7: Gestures recognized by the system and actions triggered during game interaction of Student C.

Gesture	Moving Turtle	Time (h:m:s:ms)	Turtle State	Sound	Game
Hand	To Up	08:18:07:324	A	Jump	In progress
Hand	To Up	08:18:13:969	A	Jump	In progress
Hand	To Up	08:18:22:322	C	Snap	In progress
Hand	To Up	08:18:26:228	C	Snap	In progress
Hand	To Up	08:18:29:653	D	Applause	Completed

Time spent: 00:00:22:329

The SUS model questionnaire has ten questions to measure system usability, where odd questions are framed in a positive form, and even questions in a negative form. Each question should be rated between 1 and 5 (Likert-type scale, where Strongly agree = 5 and Strongly disagree = 1), and the total score of each participant is multiplied with 2.5 to get the score range between 0 to 100. Finally, the average score of all the participants is considered. The total scores are classified as follows: (a) 0 to 64 = Not Acceptable, (b) 65 to 84 = Acceptable and (c) 85 to 100 = Highly Acceptable. Figure 11 presents the SUS questionnaire used to evaluate the usability of the PGCA system. Figure 12 (A) demonstrates the SUS score by five participants and Figure 12 (B) the overall score (for ten questions) for each participant. Odd questions have high values, and even questions have low values. The average SUS score of all the participants was 81, which is acceptable as suggested in SUS description [11].

Two comments written by teachers in SUS questionnaire show their interest to use the system in the school environment: (i) "Very interesting, I would like if in the future results are good to use to work with students at school. If the program meets its goals"; (ii) "I see the application would contribute significantly in the teaching-learning process, being a low-cost tool for people who use this type of resource and extremely important for professionals working with this audience facilitating content adaptations".

	SYSTEM USABILITY SCALE	Strongly disagree 1	2	3	4	Strongly agree 5
Q1	I would like to use this app often.	O	O	O	O	O
Q2	I found the app unnecessarily difficult to use.	O	O	O	O	O
Q3	I found the application very simple to use.	O	O	O	O	O
Q4	I thought I would need technical support to use the app.	O	O	O	O	O
Q5	I found the various features of the application well integrated.	O	O	O	O	O
Q6	I thought there were inconsistencies in the application.	O	O	O	O	O
Q7	I imagine most people quickly learn to use the app.	O	O	O	O	O
Q8	I thought the app was not trivial to use.	O	O	O	O	O
Q9	I felt very confident using the app.	O	O	O	O	O
Q10	I need to learn a lot before I can use this app.	O	O	O	O	O

Figure 11: SUS questionnaire used to evaluate PGCA.

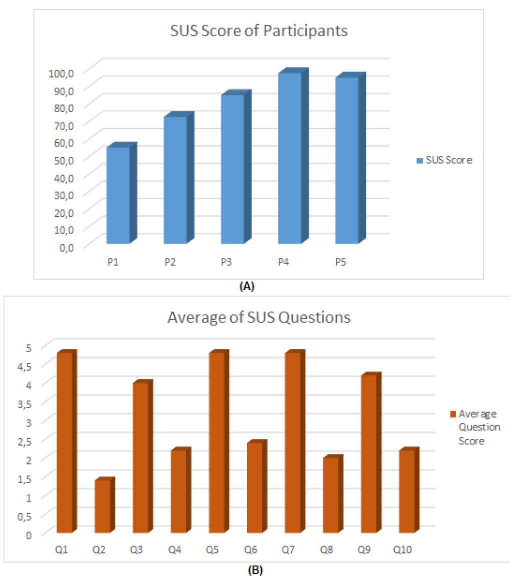


Figure 12: SUS score: (A) Participants (P1 to P5) overall score; (B) Average values for questions (Q1 to Q10).

7 DISCUSSION

Experiments carried out with the target audience allowed us to observe the technical feasibility of the PGCA system and also of the methodology used as a basis for its development. Results suggested it is possible to train a system using low-cost devices and a small number of samples generated by people with motor and speech disabilities, and to use such samples to support AAC using personalized gestural interaction.

System performance on gesture recognition was considered satisfactory in both experiments as the average accuracy for all datasets was close to or greater than 0.9, mainly using the SVM-based classifier. Low standard deviation and variance were observed, and kappa values indicated substantial agreement. Both classifiers evaluated presented satisfactory results. SVM-based classifier performed better on gesture recognition and on run time faster for test and training steps, being an efficient choice. By continuing using the system, caregivers would be able to capture a more significant number of samples before training the system, possibly getting even better results.

Regarding the effort required for students to play the game and achieve its goal, we observed significant differences in the interaction of each student. Students A and C have performed only two interactive gestures, and despite not having a constant posture, they are less likely to accomplish very different gestures, which possibly facilitated to drive the turtle to the sea quickly, using few movements. Student B, on the other hand, for being able to performs several hand gestures ended up moving more when playing, even with difficulties, resulting in unnecessary gestures recognition by the system, such as the "No" (performed with the head) and "Flirt" gesture (performed with both hands) rather than "Hi" and "Yes" gestures (performed with the right hand only). Nevertheless, we believe frequent use can also helps to improve results presented by the system.

Our motivation for choosing a game approach was to increase students engagement to use the system. Attempts to take the turtle to the sea allowed the system to capture a large number of gesture samples quickly. However, by realizing that touching a crab or shell had no damage at all, students did not worry about avoiding obstacles to reach the goal more quickly. A penalty when hitting obstacles could encourage students to follow a more suitable path for the turtle to reach the sea. Even so, we observed students' contentment in achieving the goal, as well as future possibilities inspired by more natural and playful interaction strategies.

Observed situations and learned lessons from the previous experiment carried with the target audience motivated design changes in the system interface and in conducting the present experiment. For the previous experiment, a laptop webcam was used but users presented involuntary movements during the interaction with the system, leaning legs or arms on the table where the computer and camera were arranged, generating samples with information about the back of the room, considered as noises. For the present experiment, an external webcam was used, supported on a tripod, maintaining a position next to the notebook webcam. This change proved useful since no noisy samples were observed. Also, the number of samples captured for each gesture was standardized (fifteen original samples), to allow a better evaluation of the system performance on gesture recognition in different datasets.

The PGCA usability was considered suitable according to the evaluation of the special education professionals. However, two of three students participating in the present experiment showed a reduction in their motor skills since the previous experiment, carried about four months earlier. Unfortunately, as reported by special education professionals, this situation is quite common. It reinforces our perception that Assistive Technology resources need to be flexible and easily adaptable. Possibly, if there were continuous use of the system since the previous experiment performed, the system's performance on gesture recognition would gradually decline, requiring the creation of a new dataset, since the way the gestures are performed currently by students is already quite distinct.

At each gesture performed for interaction with the AAC system, an OF-MHI image and a text file containing the system predicted class and its confidence level are created. This information could be used in a more autonomous version of the system, in the future, to reload the dataset with new samples, whose classification has shown a high confidence level. It could be valuable towards a movement from customization to personification, as the system could identify, for example, that over time a particular gesture has been executed very differently from its original execution when the system was trained. And by reaching a very significant level of difference, the system could suggest a retrain using newer samples. After a long period of system use, a larger number of new samples could be generated, making it viable training from scratch a deep network like CNN, and then to analyze if the system could deliver better results with this technology compared to using Transfer Learning.

The principal of one of the schools highlighted potential of the system as a tool to assist physical therapy work, as by performing the same gesture over and over, it encourages movements that may be beneficial for the motor-disabled user. For example, in the case of the student who can perform movements with the right arm but was not used to it for communication purposes, the necessary training could be obtained through stimuli to interact with the system, either through communication boards or playing games. Future research can address further interaction possibilities via the system and embedded games.

8 LIMITATIONS

The number of students who participated in the experiment was lower than expected because, in the first contact with the schools, several students were presented as possible candidates (i.e., students with motor and speech impairments). However, as the researcher became better acquainted with these students, it was found out the majority of students also has cognitive limitations that compromise their intentional interaction. Even in situations where there are similar diagnoses (e.g., people with cerebral palsy), teachers themselves have doubts about the level of understanding each student effectively has. Then, many students initially considered as potential participants were not selected, because it was imperative the student to be able to understand both to accept taking part in the experiment and to benefit from the intentional use of the system.

We are aware that small number of participants means that comparison is based on limited data, but we believe results allow drawing conclusions and learned lessons. We consider results can be generalizable for other people who have motor and speech impairments, as long as they have comprehension skills and sufficient motor skills to perform at least one intentional movement. By observing the students' daily life, to evaluate the effectiveness of the tool as a support for communication, constant training and follow-up would be necessary, making several data collections to generate an increasingly complete dataset with each user's motor skills.

The system developed in its current version may not yield satisfactory results for the recognition of complex signal languages, composed by a large number of gestures with few variations between them. However, the methodology was used as a basis could be employed to develop other approaches, taking into account different training and recognition strategies, and the characteristics of the gestures employed in communication by the intended audience.

9 CONCLUSION

This paper presents results from an experiment carried out with students with cerebral palsy using a Computer Vision system (PGCA) to overcome motor and speech disabilities. Developed by the authors, the system allows to create personalized gestural interaction for communication purposes. PGCA is based on a methodology to support AAC in which gestures and their meanings are created and configured by users and their caregivers. The personalized gestural interaction was used by the target audience to interact with communication boards of pictures and to play a digital game. System usability was evaluated by special education professionals and was considered suitable according to SUS scale. Two classifiers were evaluated to gesture recognition: SVM-based classifier and CNN-based classifier. Both classifiers presented satisfactory results, but SVM-based classifier proved to be more appropriate for having a better performance on gesture recognition and quick execution.

From our perception, a game-based approach promoted motivation for students to participate in the experiment, and it could be explored in the future for other system usage situations. Results point out to the technical feasibility of the methodology employed and the developed system, although some system limitations and users difficulties were observed. A more extended usage period is necessary to evaluate the system effectiveness as an Assistive Technology resource. Thus, new experiments with the target audience is essential to evaluate the system potential to support AAC. As the comprehension capacity and motor skill of users may vary significantly, future work include investigation a personified approach focused on user individualities, being able to learn and represent the user by going beyond system interface adaptation and personalization.

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REFERENCES

[1] Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, et al. 2016. Tensorflow: a system for large-scale machine learning.. In *OSDI*, Vol. 16. 265–283.

[2] Sebastian Aced Lopez, Fulvio Corno, and Luigi De Russis. 2015. Gnomon: Enabling dynamic one-switch games for children with severe motor disabilities. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems.* ACM, 995–1000.

[3] Gazihan Alankus, Rachel Proffitt, Caitlin Kelleher, and Jack Engsberg. 2011. Stroke therapy through motion-based games: a case study. *ACM Transactions on Accessible Computing (TACCESS)* 4, 1 (2011), 3.

[4] Giannis Altanis, Michalis Boloudakis, Symeon Retalis, and Nikos Nikou. 2013. Children with motor impairments play a kinect learning game: first findings from a pilot case in an authentic classroom environment. *J Interact Design Architect* 19 (2013), 91–104.

[5] Natasha Alves, Stefanie Blain, Tiago Falk, Brian Leung, Negar Memarian, and Tom Chau. 2016. Access Technologies for Children and Youth with Severe Motor Disabilities. *Paediatric Rehabilitation Engineering: From Disability to Possibility* (2016), 45.

[6] Rúbia Eliza de Oliveira Schultz Ascari, Roberto Pereira, and Luciano Silva. 2018. Mobile Interaction for Augmentative and Alternative Communication: a Systematic Mapping. *SBC Journal on 3D Interactive Systems* 9, 2 (2018), 105–118.

[7] Rúbia Eliza de Oliveira Schultz Ascari, Roberto Pereira, and Luciano Silva. 2018. Towards a Methodology to Support Augmentative and Alternative Communication by means of Personalized Gestural Interaction. In *Proceedings of the 17th Brazilian Symposium on Human Factors in Computing Systems.* ACM, 1–12.

[8] Rúbia Eliza de Oliveira Schultz Ascari, Roberto Pereira, and Luciano Silva. 2019. Personalized Interactive Gesture Recognition Assistive Technology. *Proceedings*

of the 18th Brazilian Symposium on Human Factors in Computing Systems (2019), 1–12.
[9] N Barrett, I Swain, Christos Gatzidis, and Choukri Mecheraoui. 2016. The use and effect of video game design theory in the creation of game-based systems for upper limb stroke rehabilitation. *Journal of Rehabilitation and Assistive Technologies Engineering* 3 (2016), 2055668316643644.
[10] Moniruzzaman Bhuiyan and Rich Picking. 2011. A gesture controlled user interface for inclusive design and evaluative study of its usability. *Journal of software engineering and applications* 4, 09 (2011), 513.
[11] John Brooke. 1996. SUS-A quick and dirty usability scale. *Usability evaluation in industry* 189, 194 (1996), 4–7.
[12] Fabiana Rita Camara Machado, Priscilla Pereira Antunes, Jandara De Moura Souza, Antônio Cardoso Dos Santos, Daniela Centenaro Levandowski, and Alcyr Alves De Oliveira. 2017. Motor improvement using motion sensing game devices for cerebral palsy rehabilitation. *Journal of motor behavior* 49, 3 (2017), 273–280.
[13] Yao-Jen Chang, Wen-Ying Han, and Yu-Chi Tsai. 2013. A Kinect-based upper limb rehabilitation system to assist people with cerebral palsy. *Research in developmental disabilities* 34, 11 (2013), 3654–3659.
[14] Weiqin Chen. 2013. Gesture-based applications for elderly people. In *International Conference on Human-Computer Interaction*. Springer, 186–195.
[15] Wikimedia Commons. [n.d.]. CommonsWikimedia. ([n. d.]). https://commons.wikimedia.org/wiki/File:Turtle_clip_art.svg
[16] Sky Box-Sunny Day. 2015. OpenGameArt. org. *The Chayed-KIIRA* (2015). https://opengameart.org
[17] Archana Vilas Dehankar, Sanjeev Jain, and Vilas M. Thakare. 2017. Using AEPI method for hand gesture recognition in varying background and blurred images. In *Electronics, Communication and Aerospace Technology (ICECA), 2017 International conference of*, Vol. 1. IEEE, 404–409.
[18] Xijian Fan and Tardi Tjahjadi. 2017. A dynamic framework based on local Zernike moment and motion history image for facial expression recognition. *Pattern Recognition* 64 (2017), 399–406.
[19] Antônio Augusto Foletto, Marcos Cordeiro d'Ornellas, and Ana Lucia Cervi Prado. 2018. Serious Games for Parkinson's Disease Fine Motor Skills Rehabilitation Using Natural Interfaces. In *MEDINFO 2017: Precision Healthcare Through Informatics: Proceedings of the 16th World Congress on Medical and Health Informatics*, Vol. 245. IOS Press, 74.
[20] Francisco Gomez-Donoso and Miguel Cazorla. 2015. Recognizing Schaeffer's gestures for robot interaction. *Advances in Artificial Intelligence, CAEPIA* (2015).
[21] Francisco Gomez-Donoso, Miguel Cazorla, Alberto Garcia-Garcia, and Jose Garcia-Rodriguez. 2016. Automatic Schaeffer's gestures recognition system. *Expert Systems* 33, 5 (2016), 480–488.
[22] Google. 2019. Google Image. http://images.google.com.
[23] Aashni Haria, Archanasri Subramanian, Nivedhitha Asokkumar, Shristi Poddar, and Jyothi S Nayak. 2017. Hand gesture recognition for human computer interaction. *Procedia Computer Science* 115 (2017), 367–374.
[24] Chaudhary Muhammad Aqdus Ilyas, Mohammad A Haque, Matthias Rehm, Kamal Nasrollahi, and Thomas B Moeslund. 2017. Facial Expression Recognition for Traumatic Brain Injured Patients. In *International Conference on Computer Vision Theory and Applications*. SCITEPRESS Digital Library.
[25] Robert J. K. Jacob. 1991. The use of eye movements in human-computer interaction techniques: what you look at is what you get. *ACM Transactions on Information Systems (TOIS)* 9, 2 (1991), 152–169.
[26] Hairong Jiang, Bradley S Duerstock, and Juan P Wachs. 2014. An analytic approach to decipher usable gestures for quadriplegic users. In *2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 3912–3917.
[27] Hairong Jiang, Bradley S Duerstock, and Juan P Wachs. 2016. Variability analysis on gestures for people with quadriplegia. *IEEE transactions on cybernetics* 48, 1 (2016), 346–356.
[28] Ron Kohavi et al. 1995. A study of cross-validation and bootstrap for accuracy estimation and model selection. In *Ijcai*, Vol. 14. Montreal, Canada, 1137–1145.
[29] J Richard Landis and Gary G Koch. 1977. The measurement of observer agreement for categorical data. *biometrics* (1977), 159–174.
[30] Marco Leo, G Medioni, M Trivedi, Takeo Kanade, and Giovanni Maria Farinella. 2017. Computer vision for assistive technologies. *Computer Vision and Image Understanding* 154 (2017), 1–15.
[31] Li Liu, Shuo Niu, Jingjing Ren, and Jingyuan Zhang. 2012. Tongible: a non-contact tongue-based interaction technique. In *Proceedings of the 14th international ACM SIGACCESS conference on Computers and accessibility*. ACM, 233–234.
[32] Bruce D Lucas and Takeo Kanade. 1981. An iterative image registration technique with an application to stereo vision. In *Proceedings of the 7th International Joint Conference on Artificial Intelligence*. Vancouver, BC, Canada.
[33] Xinyao Ma, Zhaolin Yao, Yijun Wang, Weihua Pei, and Hongda Chen. 2018. Combining Brain-Computer Interface and Eye Tracking for High-Speed Text Entry in Virtual Reality. In *23rd International Conference on Intelligent User Interfaces*. ACM, 263–267.
[34] Cristina Manresa-Yee, Pere Ponsa, Javier Varona, and Francisco J Perales. 2010. User experience to improve the usability of a vision-based interface. *Interacting with Computers* 22, 6 (2010), 594–605.
[35] Kenny Morrison and Stephen J McKenna. 2002. Contact-free recognition of user-defined gestures as a means of computer access for the physically disabled. In *Workshop on Universal Access and Assistive Technology*. 99–103.
[36] Shuo Niu, Li Liu, and D Scott McCrickard. 2018. Tongue-able interfaces: Prototyping and evaluating camera based tongue gesture input system. *Smart Health* (2018).
[37] Ryan O'Grady, Charles J Cohen, Glenn Beach, and Gary Moody. 2004. NaviGaze: enabling access to digital media for the profoundly disabled. In *Information Theory, 2004. ISIT 2004. Proceedings. International Symposium on*. IEEE, 211–216.
[38] S Oprea, A Garcia-Garcia, J Garcia-Rodriguez, S Orts-Escolano, and M Cazorla. 2017. A recurrent neural network based Schaeffer gesture recognition system. In *Neural Networks (IJCNN), 2017 International Joint Conference on*. IEEE, 425–431.
[39] Roland Ossmann, Dominique Archambault, and Klaus Miesenberger. 2008. Accessibility issues in game-like interfaces. In *International Conference on Computers for Handicapped Persons*. Springer, 601–604.
[40] Antti Oulasvirta and Kasper Hornbæk. 2016. HCI research as problem-solving. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 4956–4967.
[41] Cécile Paris and Candace L Sidner. 2007. Introduction to the KBS special issue on intelligent user interfaces. *Knowledge-Based Systems* 20, 6 (2007), 509–510.
[42] Thiago Pradi, Luciano Silva, Olga R. P. Bellon, and Gustavo M. S. Dória. 2016. Ferramentas de computação visual para apoio ao treinamento de expressões faciais por autistas: uma revisão de literatura. *43o Seminário Integrado de Software e Hardware (SEMISH)* (2016).
[43] Jose Rodrigo and David Corral. 2013. ARASAAC: Aragonese portal of augmentative and alternative communication. Software, tools and materials for communication and inclusion. *Informática na Educação: teoria & prática* 16, 2 (2013).
[44] Cristhian Rosales, Luis Jácome, Jorge Carrión, Carlos Jaramillo, and Mario Palma. 2017. Computer vision for detection of body expressions of children with cerebral palsy. In *Ecuador Technical Chapters Meeting (ETCM), 2017 IEEE*. IEEE, 1–6.
[45] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. 2015. Imagenet large scale visual recognition challenge. *International Journal of Computer Vision* 115, 3 (2015), 211–252.
[46] Benson Schaeffer, Arlene Musil, and George Kollinzas. 1985. *Total communication: A signed speech program for nonverbal children*. Research.
[47] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. 2016. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2818–2826.
[48] Kentaro Toyama. 1998. Look, ma-no hands! hands-free cursor control with real-time 3d face tracking. *PUI98* (1998).
[49] Du-Ming Tsai, Wei-Yao Chiu, and Men-Han Lee. 2015. Optical flow-motion history image (OF-MHI) for action recognition. *Signal, Image and Video Processing* 9, 8 (2015), 1897–1906.
[50] Jilin Tu, Hai Tao, and Thomas Huang. 2007. Face as mouse through visual face tracking. *Computer Vision and Image Understanding* 108, 1-2 (2007), 35–40.
[51] Scott D Wood, Jack Zaientz, Jonathon Beard, Richard Frederiksen, Sean Lisse, Jacob Crossman, and Marcus Huber. 2004. *An intelligent interface-agent framework for supervisory command and control*. Technical Report. Soar Technology INc Ann Arbor Mi.
[52] Ikushi Yoda, Kazuyuki Ito, and Tsuyoshi Nakayama. 2017. Modular Gesture Interface for People with Severe Motor Dysfunction: Foot Recognition. *Studies in health technology and informatics* 242 (2017), 725–732.