iSign: An Architecture for Humanoid Assisted Sign Language Tutoring

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Abstract. This paper investigates the role of interaction and communication kinesics in human-robot interaction. It is based on a project on Sign Language (SL) tutoring through interaction games with humanoid robots. The aim of the study is to design a computational framework, which enables to motivate the children with communication problems (i.e., ASD and hearing impairments) to understand and imitate the signs implemented by the robot using the basic upper torso gestures and sound in a turn-taking manner. This framework consists of modular computational components to endow the robot the capability of perceiving the actions of the children, carrying out a game or storytelling task and tutoring the children in any desired mode, i.e., supervised and semi-supervised. Visual (colored cards), vocal (storytelling, music), touch (using tactile sensors on the robot to communicate), and motion (recognition and implementation of gestures including signs) based cues are proposed to be used for a multimodal communication between the robot, child and therapist/parent. We present an empirical and exploratory study investigating the effect of basic non-verbal gestures consisting of hand movements, body and face gestures expressed by a humanoid robot, and having comprehended the word, the child will give relevant feedback in SL or visually to the robot, according to the context of the game.

Keywords: Humanoid Robots, Interaction games, Non-verbal communication, Sign Language.

1 Introduction

Sign Language (SL) is a visual language that is an essential way of communication for hearing impaired people. SL is composed of upper body (including arms, hands and fingers) head, and face gestures. Since language acquisition is very important for brain development and intelligence, hearing impaired children have

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to learn this language as their native language even before they learn written language on condition that their parents are hearing impaired as well. Given that, existence of sufficient native sign language materials is of great importance for the training of children with communication impairments.

Several computational solutions have been developed for the hearing-impaired people so far [1]. Among these studies, CopyCat is a vision-based interactive game to help in teaching American Sign Language [2]. The ICICLE (Interactive Computer Identification and Correction of Language Errors) project [3], aimed to establish an instructive system for the hearing-impaired children in order to provide them with individual lectures and guidelines by computer-aided commands. A comprehensive research is being held in Turkey for teaching Turkish Sign Language (TSL) and recognition of sign language performed by people through videos [4,5].

Various studies have been carried out for the recognition of different sign languages via face, hand, upper torso and finger actions. Staner et al [6], presents a system that recognizes 40 words in American Sign Language, with 90% precision. Another study states 80% success rate for recognizing 95 words taken from the Australian Sign language [7]. [8] describes a system based on the Japanese Sign Language, where, a total of 52 words, 42 of which are represented by the finger-alphabet, are identified. In another study, 19 words from American Sign Language are recognized by utilizing Hidden Markov Models (HMM) [9]. These words are expressed by the movements of the head and the two hands. The participant wears two different colored gloves so that the hands can be identified by the system. A success rate of 99% has been reported for the recognition of words expressed solely by hands and a success rate of 85% is achieved for the classification of words performed both by hands and the head. Various other studies on sign languages such as the recognition of hand shapes and movements or the classification of facial gestures have been carried out by the same research group in order to analyze and help teach sign languages [10,11]. Moni and Ali used a Matrox camera to recognize words expressed by hands in Bahasa Melayu Sign Language [12]. HMM and variations are used widely for hand gesture recognition. Comparison of the performances of several HMM variations were presented in [13], discarding their speed.

Since 1977, robotic devices including robotic hands that are able to spell words by utilizing the manual alphabet have been constructed to assist hearing-impaired individuals [14,15]. A study on the humanoid robot called Dinsow, which recognizes Thai sign language with the aid of its cameras to help hearing impaired people, is presented in [16]. Several studies on different sign languages via avatars are presented in [17,18]. Many cutting edge humanoid robots including ASIMO and HUBO demonstrated words from sign language with their hands and arms [19,20].

Our long-term project aims to utilize socially interactive humanoid robots to assist sign language tutoring for children due to the incompetency of 2-D instructional tools developed for this goal and the lack of sufficient educational material. In our proposed system, it is intended that a child-sized humanoid robot should perform and recognize various elementary sign language words in order to assist teaching these words to participants, especially children with communication disabilities. This will be achieved through interaction games based on non-verbal communication, turn-taking and imitation that are designed specifically for robot and child to play together. There are several successful user studies on non-verbal communication through imitation based interaction games with humanoid robots and human participants [21,22]. A specially designed non-verbal interaction game based on drumming entitled as *drum-mate* with gestures provided by the robot to motivate successful turn-taking and interaction were studied in [22]-[24].

Within the framework of this sign language project, first several surveys have been carried out to evaluate the success of robot tutors within the video based studies. A subset of sign language words, which can be implemented by the Nao H25 robot were chosen, and for each word selected, a video which displays the robot performing the sign language expression has been prepared. The corresponding videos of sign language representations by human teachers are available within the TSL tutoring software [25]. For the test study, following the demonstration of the robot's and human teacher's performances of several selected words from TSL by videos, participants have been asked to give feedback via written questionnaires regarding the success of the robot's performance in matching to the correct human implementation. The survey was applied to several groups of participants of different age groups and test environments, such as class studies with adult participants, who were not familiar with sign language, adults who knew sign language, teenagers and preschool children having the test as a web based game [26,27].

Our main research interest was using the physical robot within *interactive games*. As a preliminary step, we designed a tale-telling based interaction game with Nao robot. In one study, the robot verbally told a story including some words in sign language (words were selected from the ones tested in the previous video-based study [26]). The children were asked to assist the robot by showing the color flashcards matching the signs. The performance of the children was evaluated through the play cards they filled after the tests, demonstrating if they have learned the sign language words or not. This study was tested on 106 preschool children with normal development and 6 preschool children with hearing disability [28,29].

This interactive story based study was extended with basic upper torso moves and action recognition mechanism to give relevant action feedback to children, as well as the feedback system with flashcards. In this game, the child was able to actively communicate with the robot by realizing the signs. This game was evaluated by several therapists and children with autism [30]-[32].

The aim of this paper is not to propose one single game for all children, but rather than that develop a multi-modal interactive platform, which enables the therapists/teachers/parents to design different games with different scenarios using different modules available in the platform. Every child/participant has different needs and different level of learning capability from different modalities, therefore enriching the system with these inputs and outputs is vital for improvement of the learning and imitation performance and motivation of the children.

In order to achieve this aim, we prepared different scenarios to test the tutoring of same words in different contexts based on the same architecture, which will be described in details in the following subsections. Also different parameters, i.e., number of words taught in one test setup, are evaluated in this concept. We presented two example studies from this framework. In the first one, a story-telling based interaction game scenario is used to teach selected words from TSL. First 5 words are tested with preschool children. Then 10 words including the first 5 are tested with adults. We also included abstract words (i.e., "very", and "nice") as well as simple daily words (i.e., "car", and "table"). Usign a story-telling concept enables the experimenter/therapist to use the words within sentences to teach the semantics of abstract words as well. In this game, the interaction is achieved through colored flashcards. In the second game, action recognition is included to motivate the child to be an active learner. Unlike the first game, this second game focuses on teaching the imitation of the signs, and turn-taking, rather than the semantics. This game is designed especially for children with autism.

The rest of the article is organized as follows: In Section 2, we discuss the motivation behind this study and the research questions. Section 3 describes the proposed system and briefly summarizes the computational architecture of the sign language project. Section 4 investigates robot perception in detail. In Section 5, we explain sign selection procedure of the robot, while Section 6 elaborates the imitation-based motion generation scheme. In Section 7, we investigate two gaming modes: story telling interaction game and sign imitation game within the framework of game coordination module. Conducted experiments and consecutive results are presented in Section 8. The last section gives a conclusion and future work.

2 Motivation and Research Questions

The main contribution of the *Robotic Sign Language Tutor* project is to design an assistive and social robotic system for children with communication impairments to be used with/by the human therapist/tutor/parent as a part of Turkish Sign Language tutoring. In the project, humanoid robot is employed as a teacher/peer in order to improve their interaction ability.

In the previous studies within the project participants' subjective and objective evaluations through different test setups were tested [26]-[28] as such:

- Test environment:
  - Classroom, web-based and social media (Facebook)-based
- Demonstrators/tutors:
  - Human tutors
    - Virtual (video of the human) or physical

    (note: human avatar will not be tested within the scope of this project)

  - Robot platforms
    * Virtual (avatar) robot, video of the physical robot, physical robot
- Participants
  - Preschool children, primary school children, teenagers, university students, adults
  - People, who are not familiar with sign language and people with sign language acquaintances
  - People without hearing impairment, and people with different levels of hearing impairment

In [26] the signs were taught directly to the participants (without the games). The study showed that children had difficulty recognizing the signs from the virtually embodied robot (or graphics generator), and lose motivation if the signs were taught directly in class studies/online studies instead of interaction games. Based on the findings of our previous studies in the sign language tutor project, we made several hypotheses, tested and verified them:

- H1: Participants, especially children's performance improves with the asistance of the **physically embodied** robot.
- H2: Children's performance and motivation improves if the signs are taught within **interaction games** with the robot
- H3: **Imitation based turn-taking** interaction games with robot for sign language tutoring, also improves imitation, turn-taking, communication, sensory-motor and interaction skills for children, i.e., for children having hearing impairement and autism.

In this paper, we come up with two additional hypotheses to be tested:

- H4: **The number of words** taught in one test can affect the performance. In [33], 15 words are taught in one scenario, and this decreased the performance. In [34], using 10 words in both Nao and R3 robots resulted in a better performance. In [28] 5 words were taught in the game, and the results are quite successfull. In this study we aimed to test 5 words and 10 words in the same concept , to see if the performances decrease with the increasing number of words.
- H5: It is easily possible to teach **abstract sign language words** within a story-telling based concept. To test this, we use colored flashcards to teach the signs but had difficulty in teaching abstract words, i.e., "nice", and "very". In this study we added these words to a child story we created and aimed to teach both the imitaiton and semantics of these words within this story based framework.

3 System Overview

To the best of our knowledge, this is the first project on the usage of humanoid robots in both producing and recognizing gestures for sign language tutoring

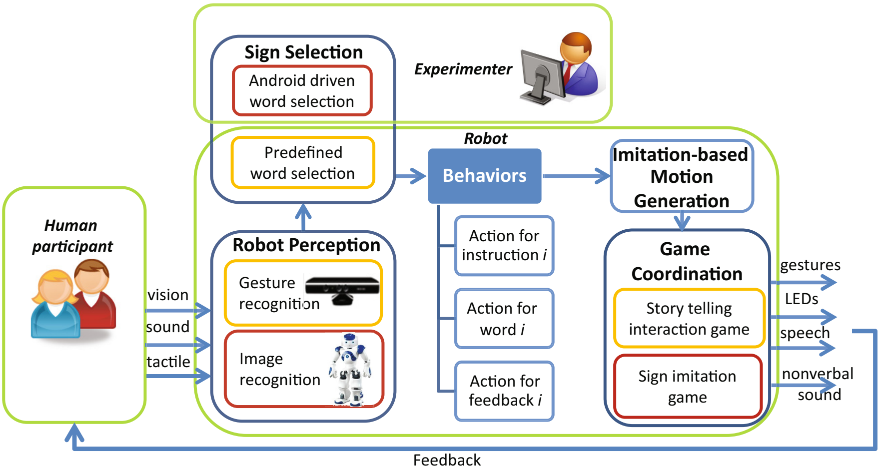


Fig. 1. Interactive game model of the project

within interaction games. In Fig. 1, the computational architecture of the whole *sign language project* is presented.

We present the overall system by partitioning it to its subsystems and introduce some modules of mutually exclusive possibilities to achieve an adaptive setup for the optimal sign language learning experience of the students. These modules can be selected based on the physical conditions of the learning room as well as physical and cognitive capabilities of the students.

In this research, the subsystems of special interest are 1. Robot perception, 2. Sign selection, 3. Motion generation, and 4. Game coordination:

1. We introduce two different modules to recognize the response of the student: camera based recognition of shown cards; and recognition of the signs directly from human motions.
2. The robot selects the signs in two modes: The supervised selection is performed using an interface developed on an Android-based device. In this mode, the experimenter is provided a set of motions to choose from and alter the scenario of the game instantly. In the second mode, the robot behaves according to a predefined scenario dictated by a hard-coded sequence of the motions and responses.
3. We propose to use a human inspired imitation of signs on robot platforms to generate motions.
4. The game coordination regulates the pattern of the outputs of the robot. Two interaction games with the robot were designed. The first game is based on story-telling. Children passively learn the signs from the robot and give feedback with colored flashcards. In the second game, the child can also actively communicate with the robot using the signs/upper torso gestures, as well as the cards therefore two modalities of feedback were employed

within the game. Also music is used to make the setup similar to the regular therapies used within autism.

In the following sections, we will describe all modules used in our long-term sign language tutor project in detail.

4 Robot Perception

The following two modules are used to generate the necessary features to be sent to the sign selection module in our proposed architecture. Visual, auditory and tactile cues coming from the students are observed.

4.1 Card Recognition

Hand gesture recognition has an important role in the problem of natural human-computer interaction. However, the effects of lighting conditions on vision, to access a third dimension requiring more than one camera and a particular arrangement of cameras prevented the spread of hand movement recognition. Camera based recognition of shown cards is also motivated by the fact that the physical and cognitive capabilities of the students can differ for every individual. Thus, just selecting a card and bringing it to the view angle of the robot's camera can be preferred by the student, as well as by the tutor occasionaly.

Technical implementation of the procedure to recognize the cards relies on the vision recognition module[1] of Nao developed by Aldebaran robotics. We also enhanced this module by using an image recognition software, which is implemented to recognize the flashcards within the game. OpenCV [2] is used for the technical implementation of this module. SURF was chosen for feature extraction and object detection. After image representations had been obtained with the Bag of Words (BoW) approach, SVM supervised learning was used for classification [30].

4.2 Gesture Recognition

In this section, we describe a method for capturing and recognizing Sign Language gestures performed using hands, arms and torso. Recently, development of cheap sensors that can detect depth with the method of infrared lasers has allowed the researchers to solve hand motion tracking and recognition problems regardless of the lighting conditions as opposed to Sec. 4.1. The upper body pose of the human participant is detected by a motion sensing input device sensor over time. With the captured upper body pose, we perform a vision based gesture recognition task that involves pose estimation and classification tasks [30,31,32]. This system is described below in Fig. 2.

[1] `http://www.aldebaran-robotics.com/documentation/naoqi/vision/alvisionrecognition.html`

[2] opencv.org

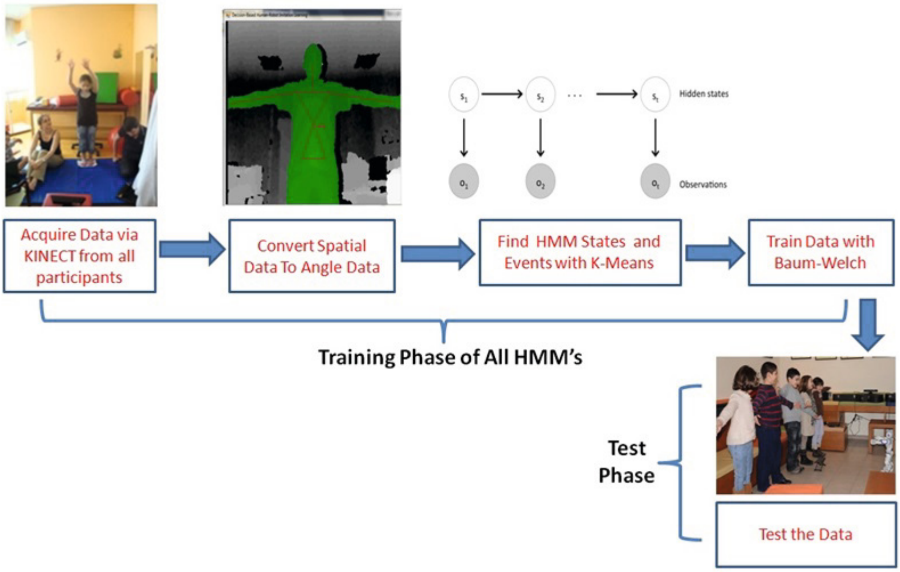


Fig. 2. Overview of the gesture recognition system

Our motion sensor, Kinect, provides the spatial data of 20 different joints of the human body. From these joints, only the spatial data (x, y, z) of 10 joints in the upper body (3 joints for left shoulder, 1 joint for left elbow, 1 joint for left wrist, 3 joints for right shoulder, 1 joint for right elbow, 1 joint for right wrist) are used. The coordinates of human body parts obtained from the *human pose detection* module yields 3D coordinates of the joints with respect to the camera. While the obtained coordinates give an accurate description of the users pose in the sign space, any translation effect caused by a change of the user's position prevents robust gesture recognition. For that reason, it is more convenient to use the data converted into angle values (Roll, Pitch, Yaw) for giving better results, instead of using spatial data obtained by Kinect. Therefore, 10 angle values in exchange for 10 joint values are acquired. To avoid any problems arising from varying frame lengths due to performing the gestures in different speeds, we propose to train a Hidden Markov Model (HMM)-based recognition system as shown in Fig. 2.

Firstly, the angular data regarding a particular training motion from different people are gathered and stored. This data collection procedure is repeated for all training motions corresponding to the gestures. The next step is creating a single HMM for every gesture. We used discrete HMMs for sign recognition. Every hidden state in HMM, which models the hand motion, is responsible for a specific part of given symbol sequence. In homogeneous HMMs, the durations of segments are modeled with geometric distribution. These durations for every state are independent from each other. This constraint becomes important while types of hand movement and the number of different user increase.

In HMMs [35], there are states and events that can be coming up in every state. In order to determine the states and events of the HMM model for every gesture automatically and eliminate the necessity of human-based annotation, Customized K-Means Algorithm [36] is used. In an HMM-based recognition system, the number of states and events need to be specified before creating an HMM model, which is the same as the number of clusters of the K-Means algorithm. Thus, the centroid of the every cluster represents the states. The biggest difference between normal K-Means and Customized K-Means algorithm is that every time executing Customized K-Means algorithm on the same data file, it creates the same clusters. However, normal K-Means creates different clusters every time and the centroids represent the events in the model.

After finding the states and events needed for HMM, system begins the training phase using Baum-Welch Algorithm. In the Baum-Welch algorithm, the parameters of the HMM algorithm, which are the start probabilities (π), transition probabilities (a), and the emission probabilities (b), are recalculated until they do not change anymore. Since there are many probability multiplication in the formulas, underflow is inevitable in the results. To prevent this unwanted event, scaling is applied to the probabilities, which involves usage of loglikelihoods of the probabilities. Finally, an HMM model is created for all the gestures.

In the test phase, the recognizer cycle is started to provide recognition of this gesture so that recognized gesture patterns (SL words) are adaptively transferred to the humanoid robot. In order to recognize the gesture, it generates a dynamic model for every distinct behavior (gesture). According to the clustered data coming from the K-Means algorithm, it determines hidden states (node) and observable variables (output labels). In the training section, data as a target vector (a collection of observation sequences) seeds into recognizer cycle to perform supervised training algorithm (e.g., Baum-Welch). Finally, recognizer model throws a unique distinct behavior as a label (related SL word/ gesture).

5 Sign Selection

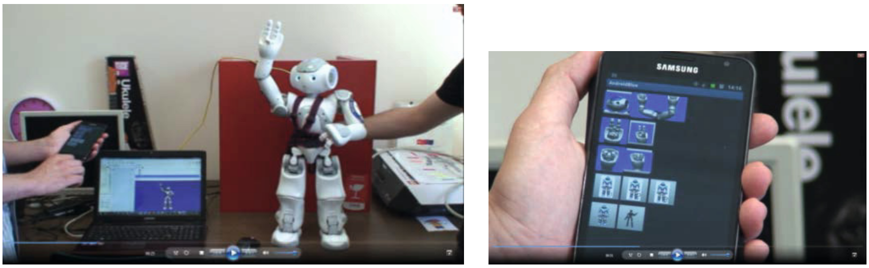
5.1 Predefined Sequence of Actions

Making a robot follow a fixed pattern of actions is mostly desired by the tutors. Such a study can be found in [28]. The robot implements a story-telling activity, both verbally and with sign actions within the predefined order. The feedback is gived using flashcards, which enables the robot to continue its predefined order of actions. In [33] and [34] the order is defined and initiated by the flashcards. The tactiles of the robot are used to start the game and in some experiments enable the robot to dance, to motivate and entertain the participants between the tests.

5.2 Android-Based Robot Control

Robot's tactile sensors, colored cards, motional or vocal cues were employed to initiate robot's actions and communicate with the robot. As suggested by the experts in autism therapy, designing individual games for each child is essential, since every child has different needs. The therapists need to form different schedules for each child, set the difficulty levels of the games and, choose gestures and parameters individually. Therefore, the same game with fixed parameters and actions for every child is not usable in the long term. To overcome this, we introduced a user-friendly interface for our games, to be used by the therapists, and care takers to form individual game patterns for each child, from the database of predefined action patterns and behavior sets. The therapists do not need to be experts in robotics or have programing skills but need an easy way to access the robot and game parameters, and change them without causing any damage to the robot or any harmful action for the children.

Smart phones and tablets are widely used in households, and schools, as well as in special schools as a part of therapy. We develop mobile applications compatible with these devices to be used within our system. The behavior patterns, developed for SL tutoring and autism game, are carried to Android-based smart phones to be used in therapies. By this means, the smart phone, or tablet which is already in use daily, is converted to a powerful tool to control and communicate with the robot (Fig. 3). Currently, our system is implemented on Android based smart phones, but we are working on the integration of the system to iOS devices [31].



(a) Robotic environment (b) Handheld device

Fig. 3. Android based robot control system [31]

In this client-server system, on the client side, which is an Android smart phone, when the user clicks an icon of the selected behavior, the server gets which behavior/action is chosen. Once the server gets this data, it responds as intended, and sends the data to the operating system of the robot (Naoqi for Nao). As the behavior is shown on the simulator, it is also implemented on the physical robot at the same time. On the other side, Naoqi sends back a message to the server which acknowledges that the data is received and the behavior is implemented, and this information is sent to the Android device by the server. On the Android device toastmessage is printed to the screen, which shows that the system works with success [31]. The steps of the system are displayed as such (Fig. 4):

1. Request for input
2. Response
3. Transmitting data to simulation
4. Transmitting from simulation to Nao
5. Acknowledgement
6. Acknowledgement
7. Output

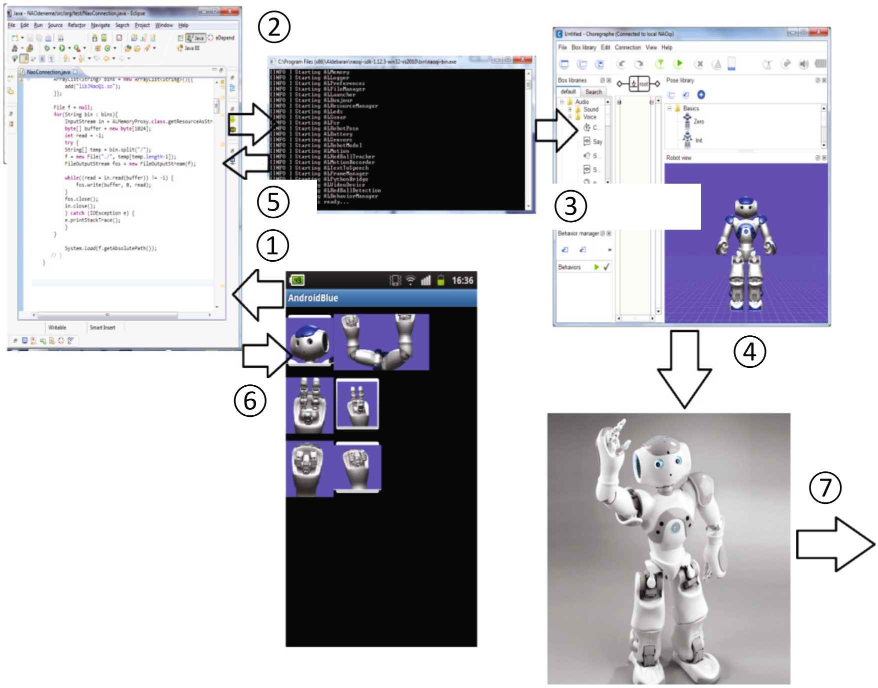


Fig. 4. Client-server system implementation [31]

6 Imitation-Based Motion Generation

This section summarizes our efforts to transfer the sign language actions of human teacher to robot by making use of motion recognition sensor [37]. This approach will decrease the time and effort to model and implement the SL words on robot, which is otherwise done manually. Since the Nao skeletal model and human skeletal model do not match due to the number of joints and limb lengths, this transfer can not be done directly. For simple actions such as putting the arms forward, down, and sides the problem is less visible, but for more complex actions, the human joint values can be lost, or mismatched, therefore may not be interpreted on the robot perfectly. The ultimate aim is to translate the human action to the robot with the minimum information loss, maximum safety, and robustness.

This module is used to model and implement different sign language gestures using two probabilistic methods, Gaussian Mixture Model (GMM) and Gaussian Mixture Regression (GMR) [38]. The results from these models are performed on a humanoid robot. Using the first method (GMM), important features of the gestures are extracted. Secondly, generalized trajectory was retrieved by GMR. Finally, the reproduction of the gesture trajectory is implemented on virtual Nao humanoid robot using the Choregraphe simulation environment and tested whether humanoid robot is imitating the gestures well according to human gestures. Proposed learning model is illustrated at Figure 5.

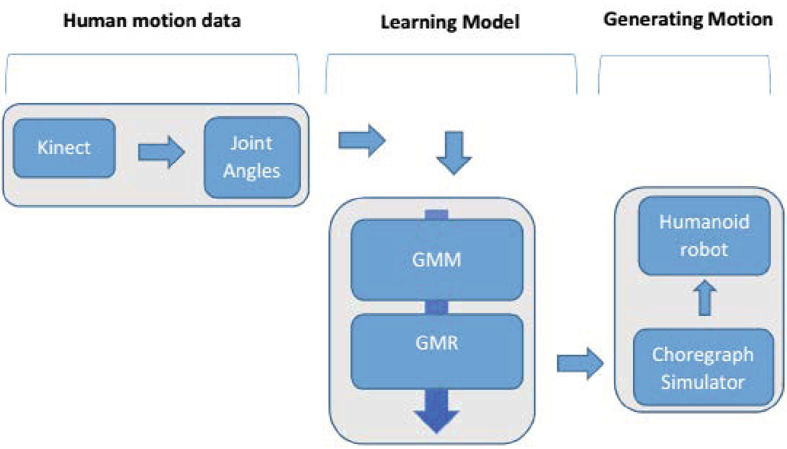


Fig. 5. Motion generation model

The main challenge in determining Gaussian mixture regression function is the estimation of the density of mixture. While you are converging to local optima using the maximum likelihood estimation, the number of components, defining the complexity of model, should be selected properly. Optimum number of components, namely number of component of regression function will not be known initially. It should be determined according to the data originally worked on [39]. For each gesture optimum number of mixture density of gaussian mixture regression function is determined as plotting dataset and making different trials.

7 Game Coordination

7.1 Coordination for Story Telling Interaction Game

In this gaming mode, the robot is telling an interactive story verbally, and implementing some of the words of the story using TSL signs without pronouncing the word verbally. The participating children are encouraged to assist the robot using special flashcards illustrating the signs of TSL in the story. A test including the signs in the story follows the story telling as well, to evaluate the children's learning performances within the game. Story telling robots were used in the literature before to model human-like gaze behaviour [40]. As stated in [23], this gaming mode allows us to observe a positive effect of the physical embodiment of the robot within a social interaction context, on the performance, and interaction of the children [28], compared to the video based studies [26].

The detailed game flow is displayed in Table 1. The game consists of two phases. In the first phase the robot tells a short story verbally. The children can also follow the story from the story cards which include the written story. Some of the words in the story were displayed by colored pictures. We have colored flashcards of same pictures. Whenever the robot reaches these points in the story, it implements the sign of these pictures, without any verbal clue and waits for a response from the participant (child). The participant is expected to show the matching flash card of this sign (if they do not know sign language, experimenter helps them with finding the matching card). This phase is the learning phase. If the flashcard was not the one that the robot expected to see, the robot's eyes turn from green to red, then they become green again, and robot waits for the child to guess again and give the right answer. In case the flash card is correct, the robot says the name of the flash card and continues the story until the next sign is done, or the story finishes.

We designed a story which is simple, and easy to understand and remember, yet interesting for preschool children. Also the story was specially arranged so that every special word appears exactly twice in the story, mostly at the beginning of the sentence (these make it easier to detect signs from the story it is required in our parallel study, which includes detection of sign language by the robot, as well). No more than two signs were used per sentence. At the time of the design, Nao did not have Turkish text-to-speech feature (by 2013 Nao robots have Turkish text-to-speech, and Turkish speech recognition support), we were unable to find a natural sounding Turkish text-to-speech program that is suitable with the robot's childlike appearance, hence we asked a 6 years old child to read the story loudly and use her voice on the robot. Hearing the story from a child's voice had a very positive effect on the children [28].

After the story is demonstrated by the robot, the experimenters explain the children that the robot would play a game with the children. In this second phase, the robot repeats the signs/gestures introduced in the first phase in a random order without any verbal clue. After each sign is repeated twice by the robot, the robot waits for the child to answer the question and continues with the next word. The child answers each question by putting the relevant colored

Table 1. Game flow chart

Order of action	*Reason*	*Actor*	*Action*	*Implementation*
1	Motivating and giving feedback to the participants verbally	Robot	Verbal story telling	Audio playing/text-to-speech
2	Teaching the implementation of the signs to the children	Robot	Non-verbal Sign implementation	Manual implementation of the selected signs on the Robot (action implementation module)
3	Child is motivated to follow the story from the story card, match the implemented gesture with the colored flashcard and gives visual feedback to the robot	Child	Choosing and showing the related Flashcard to robot	Paper based colored unique flashcards are used for each gesture.
4	Feedback to child	Robot	If the card is correctly matched to the implemented sign, eyes change to green color, and robot verbally says the word (name of the sign), else eyes become red, and robot waits for the correct card, until the correct card is shown. Robot continues to tell the story verbally until the next sign (action 1).	The robot is trained with the colored flash cards before, and can recognize them (vision recognition module). Feedback is given with LEDs in the eyes, name of the word is displayed by audio/text-to-speech,
5	Testing	Robot	After the story is finished, The robot verbally tells the child they will do a test now, and implements every action twice, without verbal cue. It waits shortly between the actions to let the child answer the question	Audio playing, and gesture implementation
6	Testing	Child	Child is motivated to put the colored sticker with the picture of the sign currently implemented to the selected place in the story card, he/she used to follow the story.	

(a) A child listens to the robot's story [28]

(b) Child interactively play with robot to complete the story [28]

Fig. 6. Screenshots from the story telling game

sticker of the implemented sign to the boxes placed on the story cards. The pictures on the stickers are exactly the same with the pictures used for each colored flashcard, only smaller in size.

In this stage, the robot realizes the signs one by one and the children are asked to put the sticker of the relevant word to their story cards. There are also slots for their names and picture of a boy and a girl which they can choose according to their gender for demographic information. Since most of the preschool children do not know how to read and write we have to simplify the questionnaire and test instructions as much as possible.

7.2 Coordination for Sign Imitation Game

Autism Spectrum Disorder (ASD) involves communication impairments, limited social interaction, and limited imagination. Researchers are interested in using robots in treating children with ASD [41]-[46]. Many children with ASD show interest in robots and find them engaging. Robots can act as a social tool for interaction between the child and teacher, and robot based interaction games play an important role in encouraging the children to carry the interaction skills they gain from the dyadic interaction with the robot to the interaction with their environment. Every child with autism has different needs. Robot behavior needs to be changed to accommodate individual children's needs and as each individual child makes progress.

The sign imitation game is an extention of the story telling game described in Sec. 7.1; it involves signs from American Sing Language (ASL) and TSL, and basic upper torso gestures, i.e., opening the arms sides, up, forward, waving hand, etc., as well. The basic upper torso gestures will act as a preliminary step to eliminate the bias when the children interact with the robot for the first time. This game was developed to teach the children to recognize and imitate the gestures/signs, within a turn-taking interaction game [30,31]. The robot will act as a demonstrator and the therapist will be able to manually assist the child, when the child fails to imitate the action demonstrated by the robot successfully.

Within this game it is possible to locate many of the tasks and exercises, which are already being used as a part of the autism therapy.

The game consists of three stages. In the first stage, the children will learn how to imitate the gestures one by one, the sequence and the quantity of the gestures were chosen by the therapist or the child. The robot's actions are initiated by the therapist/children using colored flashcards of the signs/gestures. When they show the flashcard with the picture of the selected gesture to the robot, the robot realizes the gesture and waits for the child to repeat the action. Using a RGB-D (Kinect) camera based system (as described in Sec. 4.2), child's actions are recognized, and evaluated. The system returns a feedback about how good the imitation is, to the robot. If the actual action matches the observed action of the robot, so as to say, if the child can repeat the action successfully, the robot gives a verbal feedback to the child, such as *you did the action good* (The experts suggested us that we have to praise the action of the child, it is not enough to say *its good* or *congratulations*), and action feedback with the green colored eye LEDs. Also robot nods the head in a positive manner. These feedback gestures, which are interpreted as praising and positive gestures in our culture, are suggested by the experts and are also used in the daily therapy routine of the children.

If the child fails to imitate the action, the robot asks the child to repeat the action and the above procedure is repeated. Through this stage, whenever child performs the wrong action, the therapist helps the child manually to correct the gesture. The experts we worked with in this experiment suggested this approach, which will not let the child complete the action wrong, but support the child to learn it correctly, otherwise the action will be learned wrong.

In the second stage, the game is like a sports work out, each action/gesture is repeated one after another several times without the need to initiate every action with flashcards and the therapist gets involved less (but still asists the child when the child fails to imitate or needs help).

In the third stage, we turned the game into a musical play. Robot sings a song related to the actions, and do the actions one by one; and the child is expected to repeat the sequence of actions in a rhytmic way like a dance (Fig. 7).

The robot will record the success rate of the child's imitation (from the feedback of the Kinect-based sign recognition system) and also the experimenter will record the therapist's corrections and the number of gestures completed by the child without the therapist's intervention. Also it is important to note how long the child plays, and which activities encourage the child to play more. The success rate related to each gesture also gives a good feedback to the researcher.

These games were usually played with the therapist, or the video of the therapist, or another autistic child as in Fig. 8. The robot will act as a play mate in these games.

The game was demonstrated for the therapists working in ASD, and positive feedback was achieved [26]. We also demonstrated a limited version of the game (only the first stage) in a special school for children with ASD using 4 children of 6-8 years old. One child attended the game with the asistance of her therapist.

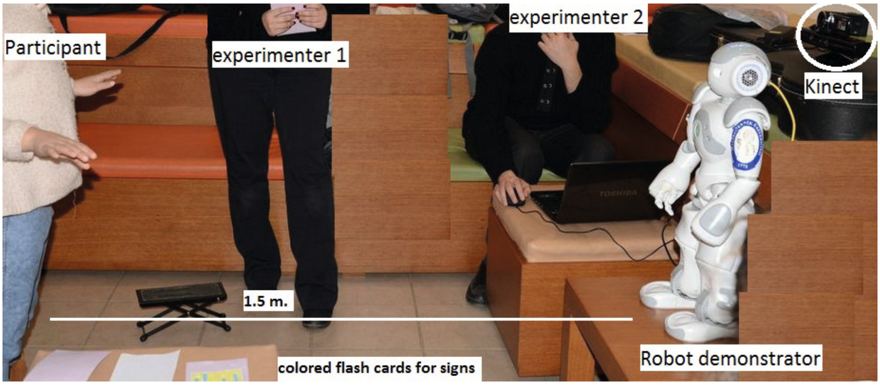


Fig. 7. Sign imitation game setup [26]

(a) Gesture for touching the ears

(b) Gesture for leaning forward

Fig. 8. Therapists help children in the first stage of the game [31]

She was happy and got motivated with the game. The actions in the game were demonstrated to the children by the therapists. We plan to test all the three stages of the game with children, in a collaborative special school for ASD to verify the hypothesis H3 in the short term.

8 Experiments on Story Telling Interaction Game

The main aim of this study is to study the effect of interaction game context in the physical robot assisted sign language tutoring. Therefore, an interactive turn-taking game based on story telling using both words and signs from TSL is designed and implemented. The game is based on the same set of 5 TSL words used in the video based studies in [26], and was implemented on physically embodied Nao H25 robot. Then the story is extended with additional 5 words, and the new 10-word story is also tested within the same test setup. These games enable us to study the effect of using a physical robot within the project and interaction game context as well.

8.1 Participants

The 5-word story telling game was first tested with 106 preschool children (6 years old) within the nursery of our university. The experiment took place in the big atrium of the nursery as a demo event rather than a strictly controlled laboratory experiment due to the restrictions and limitations caused by the age and quantity of the children. None of the children who attended the demo session were hearing impaired and they were not familiar with any sign language. This work is one of the biggest robotic events in the world with this age group to the best of our knowledge. Our previous robotic experiment based on interaction games with a drumming robot included 68 primary school children of 7-11 age group in UK [23]. Then the game was demonstrated in a pilot preschool class in a special school for hearing impaired children with 6 children of age group 6-8. In the second phase of our project, 22 university students from Istanbul Technical University, Computer Engineering Department (age average 26.32) attended both 5-word and 10-word tests.

8.2 Robot Platform

The H-25 Nao robots is be used for this research in the user-studies, as they have hands and fingers to implement most of the sign language words, and appropriate to use in interactive children games due to its expressive face, small size, compact shape and toy-like appearance. The Nao robot, which has a height of 0.57 m. and a weight of 4.5 kg., is a system with 21-25 degrees of freedom, 500 MHz processor, two cameras, sonar sensors and force-sensitive resistors [47]. Aldebaran Robotics offer several software tools for use with the NAO robot, such as Choregraphe for face detection, face recognition, speech, speech recognition, walking, recognizing special marks and dances, and individual control of the robot's joints. Choregraphe needs to be used with a robot proxy, real or simulated. The simulated proxy can be NAOqi or a sophisticated simulator such as NaoSim [48].

A subset of the most appropriate words from ASL and TSL that can be demonstrated by a Nao H25 robot have been chosen for the experiments. The physical limitations of the Nao robot makes it hard to implement some of the words. One of the reasons for this is the fact that the Nao robot has only 3 dependent fingers while most of the words from the i.e., TSL are performed by using 5 fingers (mostly independent, i.e one pointing a part of the face and other 4 are curled). Our current experiments are duplicated on a humanoid platform with 5 fingers and more DOF on the arms (a modified R3) to overcome these limitations [34].

8.3 Game Setup

The children were sitting around the robot and the robot was placed on a small table. Robot was assisted by two researchers, and the children who were directly playing with the robot were assisted by an additional researcher(Fig. 9). The other children watching the event were assisted by their own classroom teachers. We prepared special survey papers with the story where the special words were shown with flashcard pictures. Visual directions and instructions were chosen so that even if the children can not read and write they can still follow the study and express their written feedback.

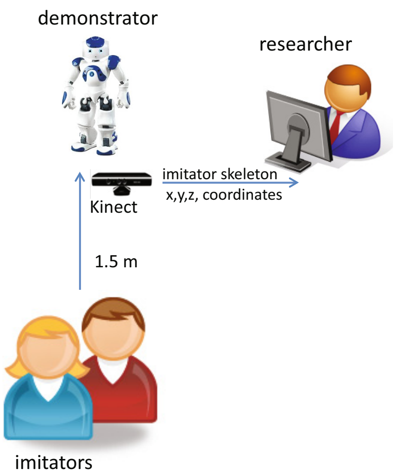


Fig. 9. Interaction game test setup

8.4 Tests and Results

First we had a demo with one of the experimenters. Then one of the children was chosen to play with the robot (Fig. 6(a)). The robot starts telling a short story. Whenever the robot does the sign, the child was expected to hold the relevant flashcard to the robot (Fig. 6(b)). The game continues as described in Sec. 7.1 in details. After these demo sessions we had the test session with all of the students. Due to the high number of students, we could not get more one-to-one sessions with children, and could not get the completed story cards immediately. But the teachers of each class were asked to help children to fill out the cards and return them as soon as possible. We also recorded the robot's telling the story, all the instructions and the test at the end as video. We included the video of the story told by one of the experimenters and several dance videos of the robot, which we promise to show to the children as a reward. We handed them to all classes, and the teachers told us they would show them to children again, in case some children might not see all the details due to crowdedness, and hand out the completed story cards for feedback, afterwards.

The demo and the game was demonstrated with 106 children of 6 years. Due to the high number of children and their small age, one class was chosen as pilot class and the detailed results of that class was reported by their teachers. The report suggested that, out of 20 children who attended the event, 18 children (9 boys and 9 girls) completed the play cards with 100% success, and the other two children had 80% success. The children showed much interest and were successful compared to their age group in terms of similar skills. Moreover the children liked the event, and although none of them knew sign language before they started to imitate signs after the robot. Although both girls and boys showed same success, the teachers reported that boys were more interested on the robot. They even asked to take the play cards to their homes to show to their parents. The teachers and the school gave promising and positive feedback and asked if they can use the videos and video based tests in other age groups and the following semesters as a part of their activity schedule [28].

The reader should note that, although the success rate is quite high, the test was not so trivial. The children attending the story-telling game were asked same signs as the adults including the sign language professionals, preschool children of same age group and teenagers, where teenagers, and children in these web-based studies showed a poor performance compared to the adults [26]. In comparison to these web-based studies, the high success rate of this study is an important step to verify the hypothesis H1 (Fig. 10). Moreover, in this experiment we saw that if the words are taught within a relevant story/context than their identification /recognition increases. This is a very important gain for us, which verifies the hypothesis H2.

In this game, verbal storytelling as well as visual and sign cues are used because the linguists, who are experts especially in TSL reported that children have different levels of hearing, some children could not hear anything, whereas some children had cochlear implant and could have limited hearing. Therefore, it will be convenient to give verbal support as well as signs and colored pictures, so

Fig. 10. The game was also performed in public demos within Robocup (obtained from press)

that the child can learn verbal communication, too. We have also demonstrated the game in a pilot preschool class in TIV (Turkish Hearing impaired Foundation) special school with 6 children of age group 6-8 and got positive feedback. Hearing impaired children were very engaged and motivated with the robot and the game and were managed to understand and answer most of the questions correct (appx. 70%). They were so excited that they could not wait until the end of the test, and wanted to play with the robot, and asked questions about the robot, therefore the written tests for feedback could not be completed. But as a preliminary work, the comments and positive attitude towards the play cards and robot were very promising.

In the second phase of our project, this 5-word story telling test is extended to a 10-word test keeping the same test setup in order to verify H4. At first, 6 people took the original 5-word test only, which will be called Experiment 1 (Exp.1). In Exp.2., other set of participants consisting of 16 people coming from the same educational background and age group took the test with 10 words, which includes the first 5 words implicitly. The profiles of the test subject participating in Exp.1 and Exp.2 are given in Tables 2 and 3.

Table 2. Exp.1: Profiles of the participants and their score

Gender	**Total Number**	**Full score**	**Prior experience on Sign Language**	**Prior experience on Robots**
Women	3+4	5	0	1
Men	13+2	11	3	0

Table 3. Exp.2: Profiles of the participants and their score

Gender	Total Number	Full score	Prior experience on Sign Language	Prior experience on Robots
Women	3	2	0	1
Men	13	9	2	0

The words used in the sign set and the corresponding scores are presented in Tables 4 and 5.

Table 4. Exp.1: Word set and success rates

Turkish Word	English Meaning	Referred in the Text as	Correct	Wrong	Empty
Masa	Table	Word 2	20	1	1
Üç	Three	Word 4	21	0	1
Araba	Car	Word 5	21	0	1
Arkadaş	Friend	Word 7	17	4	1
Baba	Dad	Word 9	22	0	0

The results of the Exp.2 were similar for the first 5 words (Exp.1), which are common in both tests, yet as the number of words increase, the number of overall mislabelling increases due to the similarity of the generation of some of the words (Fig. 11 and 12). Several people mislabelled same words such as"friend". One test subject out of six (the 5-word test group) got 2 mistakes in 5-words test. Others had 100% success rate in this group.

8.5 Discussion

The results show the success of the system with the Nao humanoid robot. The important fact is that, the participants had no difficulty in remembering even the abstract concepts when used in a text/story. This will be helpful in teaching abstract concepts to especially children using sign language, where it is difficult to teach via illustrations or physical examples (Hypothesis H5). For example, to teach an apple showing the picture of an apple or a real apple vs. to teach "nice", "accept", or "very". The reader should note that the usage of another robot platform with more physical capabilities such as having five fingers and longer limbs to demonstrate the actions in more detail will increase the success rate even more [34]. Figures 13 and 14 illustrate the improved capability of R3 robot in sign generation compared to Nao in one of the common words used in this study and [34].

Table 5. Exp.2: Word set and success rates

Turkish Word	English Meaning	Referred in the Text as	Correct	Wrong	Empty
Ev	House	Word 1	16	0	0
Masa	Table	Word 2	14	1	1
Güzel	Nice	Word 3	15	1	0
Üç	Three	Word 4	16	0	0
Araba	Car	Word 5	16	0	0
Çok	Very	Word 6	14	1	1
Arkadaş	Friend	Word 7	11	4	1
Küçük	Little	Word 8	15	1	0
Baba	Dad	Word 9	16	0	0
Kabul etmek	Accept	Word 10	16	0	0

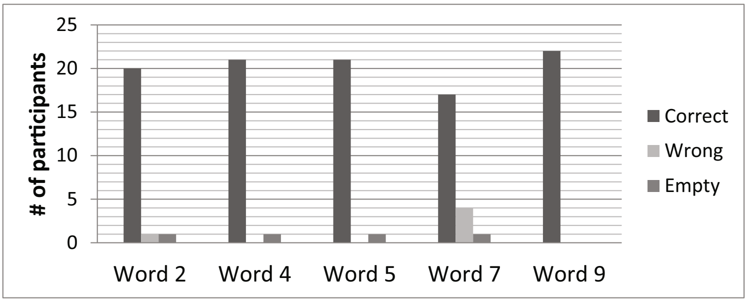


Fig. 11. Exp.1: Interaction game results

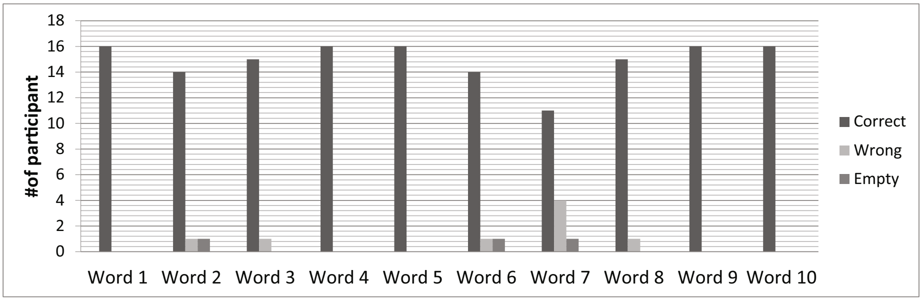


Fig. 12. Exp.2: Interaction game results

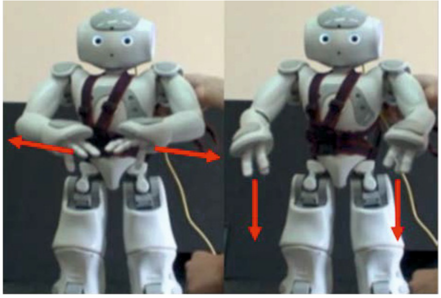


Fig. 13. Nao performing the “Table” sign: 87.5% succes rate achieved on 16 participants

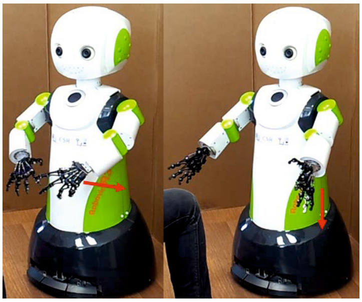


Fig. 14. R3 performing the “Table” sign. 98% succes rate achieved on 21 participants

For adults with no hearing disability, we use written texts and verbal instructions, in the games. For children especially with hearing difficulties or ASD, the instructions and some of the feedback in the game are given using flash cards. The words and their illustrations are presented with the flashcards in the games with children. We are careful about not using signs or any clue related to the signs in the illustrations (unless the sign is iconic itself like “throwing”, or “me”). Therefore we tried to eliminate the participants getting extra clue about the action of the sign from the illustration. These cards are specially used for children of small age groups who can not read and get benefit from written instructions. Also this gives the children a non-verbal way to communicate with the robot (robot “understands” the message given by the cards). The cards are taken from a child game which aimed to teach preschool children words in written language, and especially in the early stage of the learning phase, it also encourages and motivates the children in the game.

In a pilot study conducted by Kose et al. in 2014 (unpublished data), 29 hearing impaired primary school students were tested using Nao robot in a classroom based study. The word-based game was used in the study, and the evaluations were taken by paper based tests including both written and visual instructions used in the previous studies with hearing children. The children were asked 10 words similar in the tests conducted with the university students, and the success rate of recognizing the signs performed by the robot was in the range of 88%-100%. These results were similar to the results obtained in this paper. Furthermore, the children were eager to work with the robot; they asked their teachers to keep the robot in their school as part of their daily education. Several teachers, who are experts in Turkish Sign Language attended the session, and helped the students, who needed further instructions by communicating in sign language (i.e., “the robot will repeat every word twice, if you do not understand a word, please continue with the following question”, etc.). The study will be repeated with student groups of 1-2 with different word sets, in the long term.

9 Conclusion and Future Work

In this paper, we developed a multi-modal interactive platform, which enables the therapists/teachers/parents to design different games with different scenarios using different modules available in the platform for teaching children sign language by means of interaction games with humanoid robots. We also introduced several studies from our long-term project. The first study is a tale-telling Nao Humanoid robot with both verbal and sign language, with visual feedbacks from the child. From the studies with children we verified our hypotheses on motivating and increasing the performance of children learning sign language within interaction games with robots. We showed that the number of words taught in one session can be up to 10 words without losing the accuracy of the teaching process. We also demonstrated that it is easily possible to teach abstract sign language words within a story-telling based scenario.

The main aim of this interdisciplinary study is to build a bridge between the technical know-how and robotic hardware with the know-how from different disciplines to produce useful solutions for children with communication problems. Moreover we would like to increase the awareness among families and public.

NAO H-25 humanoid robot is used during the field studies, since it is a small size humanoid robot which is suitable to implement basic signs in the ASL and TSL, robust and safe to work with children. For further studies a bigger size humanoid robot platform with 5 fingers and more DOF on arms will be used within the project. The extended version of this study is another multi-modal interaction game, which includes action recognition feedback, and also being used with children with autism in teaching non-verbal communication skills, imitation and turn-taking.

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