Gesture Recognition for Humanoid Assisted Interactive Sign Language Tutoring

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***Abstract*— This work is part of an ongoing work for sign language tutoring with imitation based turn-taking and interaction games (iSign) with humanoid robots and children with communication impairments. The paper focuses on the extension of the game, mainly for children with autism. Autism Spectrum Disorder (ASD) involves communication impairments, limited social interaction, and limited imagination. Many such children show interest in robots and find them engaging. Robots can facilitate social interaction between the child and teacher. In this work, a Nao H25 Humanoid robot assisted the human teacher to teach some signs and basic upper torso actions which were observed and imitated by the participants. Kinect camera based system was used to recognize the signs and other actions, and the robot gave visual and audial feedback to the participants based on the performance.**

Keywords-Human-robot interaction; autism; imitation games; sign language

I. INTRODUCTION

Communication is a vital requirement for human life. Language acquisition is an extremely crucial process for brain development and intelligence. Sign Language (SL) is an alternative way of communication for hearing impaired or autistic children who cannot communicate verbally. Sign Language is a visual language that is based on upper body movements (including hands, fingers, arms, upper torso, head and neck) and facial gestures. There are studies on visual recognition of sign language, and sign language tutoring with 2-D visual aids to hearing impaired people [1-6]. Also several robots and robotic hands were utilized to implement sign language [7-8]. In the studies [9-11] visual games are employed for sign language tutoring.

The studies introduced in this paper have been realized as part of an on-going research, which aims to utilize humanoid robots for assisting sign language tutoring due the lack of sufficient educational material. Also in terms of children's sign language education 2-D instructional tools are found to be incompetent. Therefore using humanoid robots as an assistive tool in sign language tutoring for children will be very beneficial. In the proposed system, it is intended that a child-sized humanoid robot is going to perform and recognize various elementary signs (currently basic upper torso gestures and words from sign languages) so as to assist teaching these signs to children with communication problems. 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. We have used imitation based non-verbal interaction games with humanoid robots successfully with children and adults previously in [12-16].

Currently, American Sign Language (ASL) and Turkish Sign Language (TSL) are being implemented and tested within the project.

In the first versions of the game, the robot was telling a short story verbally and through the story for some selected words, the robot was able to express word in the SL among a set of chosen words using hand movements, body and face gestures and having comprehended the word, the child was encouraged to give relevant feedback in SL or visually to the robot (using a colored card visualizing the word), according to the context of the game. The games were demonstrated with more than 100 preschool children with hearing ability and 7 preschool children from Special School for Hearing Impaired Children [17-22] (game demo videos: http://humanoid.ce.itu.edu.tr/).

The current paper summarizes the attempt to extend this study to autistic children as a part of a PhD course entitled as Autism and Computational Aspects, which aims to bring researchers in computer science and robotics with non-engineer experts from psychology, neurology, speech therapy, and autism therapists, to train students who want to work in this field, and for a long term brain storming event on possible computational solutions that can be used within autism therapy (recognition of autism and other related issues were not included in the course schedule due to time limitations). This paper presents one of the projects which are produced as an output of this collaboration, and it is planned to use the system and the game in the collaborative special schools on autism. Autism Spectrum Disorder (ASD) involves communication impairments, limited social interaction, and limited imagination. Researchers are interested in using robots in treating children with ASD [23-27]. Many such children show interest in robots and find them engaging. Robots can facilitate interaction between the child and teacher. 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 game will be based on the visual cards, the cards will be shown to the robot to select among several signs from ASL and basic upper torso motion (hands side, forward, up etc.) Then the robot will perform the sign and wait for the child to imitate. The imitated action will be evaluated using an RGB-D camera (Kinect) and robot will give a motivating comment when the action is imitated with success.

Figure 1 - Some of the cards used in these exercises

II. SIGN RECOGNITION

A. Hidden Markov Model

Every hidden state in Hidden Markov Model (HMM) which models the hand motion is responsible for a specific part of given symbol sequence. In homogeneous hidden Markov models, 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.

The generative models, like HMM, model the common probabilities between observations and states. In distinctive models, the probability distributions of states depend on the observations and it does not model the probability distributions of the observations subject to classes. It is hoped that distinctive models are more efficient in classification. Thus, in order to recognize hand movement, Conditional Random Fields (CRF), which is equivalent to HMM and its kinds were examined [28].

B. Hidden Conditional Random Fields(HCRF)

CRF's do not model the internal dynamics of the class, but inter-class dynamics and because of this constraint it is not suitable for the classification of time series. Therefore Hidden Conditional Random Field (HCRF) [29] and Hidden Dynamic Conditional Random Field (HDCRF) [30] were offered. While HDCRF models both the internal and external dynamics of classes, HCRF only models the internal dynamics and therefore it is more convenient for the isolated hand movement recognition problem.

HCRF's associate the observations with the state transitions instead of learning the state durations. This attribute increases the performance of positive samples, but it also increases the false acceptance rate.

C. Input Output Hidden Markov Models(IOHMM)

Input-Output HMMs as generative and discrete hybrid models show high performance in recognizing hand movements [31]. In IOHMM like HCRF, state transition probability distribution depends on the input sequence that consists of the function of observations [32].

In IOHMM, observations and state transition probabilities are calculated from input sequence using local models. Radial basis functions or multi-layer perceptron's can be used for local models. IOHMM's are more complicated than HMMs and their training requires more samples than HMMs.

D. Hidden Semi-Markov Models(HSMM)

Although HSMMs are similar to the HMMs. HSMMs hidden states produces observation sequence from certain probability distributions instead of producing a single observation [33,34]. HSMM state creates a symbol sequence instead of a single symbol. Fixed-Term Models (FTM) is a kind of HSMM and it determines the exact staying duration at each state with the status of a plug-in counter. FTM solves the problem of the modeling of specific periods, but durations are still independent of each other unless being conditioned to the velocity and dimension.

In order to recognize isolated hand movement, every action class must be modeled from positive samples. When an unclassified hand movement sequence comes, it is evaluated by all defined models in system and class likelihoods are calculated and the class of a model with the highest value is selected as a label. At [35], for evaluating the performance ratio and recognition rate of HMM, IOHMM, HCRF and FTM data set is collected. To ensure the independence of recognition rates from vision modules, a Kinect camera with infrared sensor is used. As a result of the experiments, it was found that performance rates of HCRF and IOHMM are higher than FTMs and HMMs, but they are slow for real time systems. For real time systems, FTMs that shows high performance more than HSMMs are offered.

III. PROPOSED METHOD

In the data collection phase, RGBD camera (Kinect Sensor) starts the input stream and sends every gestural motion data in the form of frame by frame. Different gestural motion data taken from RGBD camera (Kinect Sensor) can have different number of frames. Thus representation of every gesture pattern should be carefully modeled so that recognition process meets the performance criteria for robust recognition.

As a first step, joint spatial coordinates (x,y,z) of skeletal structure for each joint are generated. Then, in order to provide robustness, every frame in the gestural motion data is expressed as a single vector of angle values (Roll, Pitch, Yaw) which is computed from spatial position values (x,y,z) for every joint node of skeletal model. Several image processing and computer vision techniques are used to detect the skeletal model of human successfully using RGBD cameras i.e. Kinect Sensor. Thus the job on image processing in determining a good feature for gesture classification became easier with the availability of Kinect.

There are two main goals for this study. First, one is to represent gesture pattern (Sign Language (SL) word) using a suitable classification algorithm (K-Means). It provides clusters from every spatial motion data coming from the Kinect sensor corresponding to the related centroid of data. The generated probabilistic model (Hidden Markov Model) which is generated as a result of the system accepts this clustered discrete data.

In the second phase, the recognizer cycle is started to provide recognition of this gesture so that recognized gesture patterns (SL words) are adaptively transferred to humanoid robot (Nao). In order to recognize the gesture, it generates a

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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).

IV. INTERACTIVE ISIGN GAME

As stated before, as an outcome of the PhD level course on Autism and Computational Aspects, an imitation game was constructed using Kinect and Nao H25, based on the recommendations of autism therapists. Our main goal was to extent our studies on signing based interaction games with humanoid robots, to autism therapy.

Figure 2 - “up”, and “side” actions.

The sign imitation game is an extension of the sign language game; as an initial step, we used basic upper torso gestures, i.e. opening the arms sides, up, forward, waving hand, etc., in the long run, we plan to use signs from ASL and TSL as well. The aim of the game is to teach the children to recognize and imitate the gestures/signs, within a turn-taking interaction game. The demonstrator will be the robot and the therapist will be able to manually assist the child, when the child fails to imitate the action successfully. Within this game it is possible to locate many of the exercises already being used as a part of the autism therapy.

The game consists of 3 stages. In the first stage the child will learn how to play doing the gestures one by one, the sequence and the quality of the gestures were chosen by the therapist or the child. When they show a picture of the gesture to the robot, the robot does the gesture and waits for the child to repeat the action. Using a Kinect camera we can evaluate child’s actions and send the robot feedback. If the child can repeat the action then robot says “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 “congradulations”). Else the therapist helps the child manually to do the gesture. (The experts told us we should not let the child do the action wrong, because then the action will be learned wrong).

In the second stage, the game is like a sports work out, each action/gesture is repeated several times without the picture display and the therapist get involved less. The child is assumed to learn each action by now.

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.

Figure 3 - Demo setup with participant, Nao robot and Kinect Device (a second Kinect device was also employed for finger detection but not used within the demos)

Figure 4 - Therapists help children in the first stage of the game

The robot will record the success rate of the child and also the experimenter will record the therapist’s corrections and child’s success.

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

V. GAME IMPLEMENTATION

A. Data Collection

Kinect and Microsoft Kinect SDK v1.5 was used to get human joint data from human motion. The human skeletal model of Kinect camera system is used to get 20 different joint data (X, Y, Z coordinates) over the SDK. Only upper torso information (shoulder, elbow, wrist coordinates) is used in this study, to classify the actions. Neck, head, face and fingers were no included within this study, but will be included in the overall project.

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As a start, 6 actions, namely, 3 basic sign language action (ASL and TSL) and 3 basic upper torso actions from 15 university students were recorded with Kinect. For each action, every participant was asked to perform 4 times, of which 2 were used for training the system and 2 were used for testing. 30 frames/sec were recorded by the camera. Discrete HMM was used for sign recognition. The actions to be implemented were selected specially based on the advises of the therapists so that the tests can be also applied to the children with autism or mental disabilities. Also the actions which can be implemented by the Nao robot (due to Kinematic constraints) were selected among these advised actions. In order to avoid boredom, confusion and fatique in children during the tests, number of the actions and the repeats were set to a minimum, as possible.

The actions were introduced to half of the participants (6 participants) using the real physical robot and the simulated robot, and by a real human to the rest of the participants. All of the participants were asked to stay on a special sign on the floor and implement the signs to make sure that they keep the same distance to the Kinect camera during the tests (1.5 mt). The participants were not given any information except the fact that they should follow the robot/human and imitate the actions afterwards, and their actions are recorded with the Kinect camera.

First of all, a classification algorithm was used to enable the usage of discrete observation symbols and states on the motion data captured by Kinect. K-Means method was used to discretize the motion data and classified, then for every motion, in total 6 HMM was trained and the parameters were determined with Baum-Welch algorithm.

Afterwards, the observation sequence was matched to the related action using the 6 different HMM which were trained before, and their probability to produce these observations was calculated using forward algorithm. The action matching the biggest probability was classified with this action. If it was trained with the same model in the training set, then the classification was successful. The complexity of the HMM should be detected according to the data used with the model.

B. Aldebaran(NAO) Tools Used

In this project, the goal is to empower teacher that works with children with ASD and to customize robot behavior to suit the needs of each child. 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.

Aldebaran Robotics offer several software tools for use with the NAO robot. Choregraphe can be used for face detection, face recognition, speech, speech recognition, walking, recognizing special marks and dances, and individual control of the robot's joints. The movements can be performed in sequence or in parallel. Choregraphe needs to be used with a robot proxy, real or simulated.

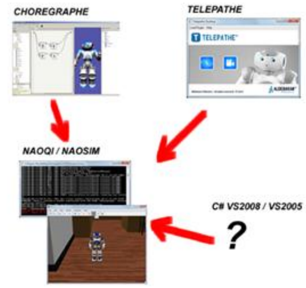

Figure 5 - Interaction of Aldebaran software for the NAO robot. Owners can use various software tools including Visual Studio to develop their own NAO software.

The simulated proxy can be NAOqi or a sophisticated simulator such as NaoSim [36]. NAOqi is a piece of software that simulates the robot for Choreographe and tests it before trying on the actual robot. NAOsim is simulation tool that allows for robot simulation in an apartment having simulated furniture. Whereas NAOqi only simulates the robot, NAOsim simulates an environment with which the robot can interact. Monitor, which was called Telepathe until the current release, allows the user to access the robots memory, see through the robots two cameras and observe the environment as the robot senses it. Also, it is possible to use some of program languages, Python or C++ to program the NAO.

During the implementation phase, different methods for the kinematic modelling of the humanoid robots are available such as [38].

C. Image Recognition

To navigate through the exercises, the instructor used a set of cards with different images. Each image represents a different exercise. This requires image recognition software which was coded using C++ and OpenCV 2.3.1. The algorithms used in this project included SURF feature detection, Bag-of-Words, K-means clustering and support vector machines (SVM).

OpenCV has many algorithms to detect and describe local feature. SURF was chosen for feature extraction and object detection. This is one of the most common methods.

The Bag of words (BoW) approach is more commonly used in natural language processing. When used for image processing, an image and its graphical features are analogous to the document and to the words, respectively. After image representations had been obtained with BoW, SVM supervised learning was used for classification. SVM takes an input array which consists of data and a label. The label represents the class to which data belongs. There are many hyperplanes that could be used to classify the data sets. The best hyperplane is the one that gives the greatest separation or margin between the classes.

The training database consisted of a scanned set of Walt Disney cartoon characters printed on cards. Every card was identified by a number which became the SVM label for that card. Training began by extracting the features from the images and computing image descriptors:

Then, the dictionary of graphical features was determined with K-means clustering as shown below. The result set of BowKmeansTrainer was written to file in YAML format. That improves speed of image recognition. The last step in training was training the SVM. CvSVM, an implementation included in OpenCV was used. The SVM training results were also written in a file to improve performance.

Once training was complete, the cartoon characters printed on the cards can be recognised by simply detecting the features of the images and sending them to the SVM for prediction.

D. Test and Result

6 Hidden Markov Models belonging to 6 signs were trained with 219 training sample and tested with 80 test samples. In this test every class has different state and event counts. The data which belongs to these classes, clustered corresponding to these event and state counts. The confusion matrix showing the tests with these parameters is shown in the Table 1. These state and event counts are the ones which gave the best solution in the test trials. At the tests, 8 state and 10 event were used for “side”, 8 state, 10 event were used for “forward”, 7 state, 9 event were used for “table”, 4 state, 5 event were used for “car”, 4 state, 6 event were used for “up”, 6 state, 9 event were used for “dad”.

The successfully matched classes were located in the diagonal of the table. 54 of the 80 test samples were classified successfully. When the unsuccessful groups were studied, it is observed that this is caused by the groups with similar features (similar actions).

For example “table” was recognised as “forward” 1 times, and “dad” and “up” signs were mislabeled. Another reason for the mislabeled signs, is that, some participants realized some actions wrong (not similar to the human/humanoid teacher), partly or as a whole.

TABLE I. CLASSIFICATION MATRIX

		Predicted classification					
		Araba (Car)	Baba (Dad)	Forward	Masa (Table)	Side	Up
Actual classification	Araba (Car)	13	0	0	1	1	0
	Baba(Dad)	0	11	1	0	1	1
	Forward	0	0	8	0	0	5
	Masa(Table)	3	1	1	7	0	0
	Side	3	1	3	0	6	0
	Up	1	0	2	1	0	9

In the future works, it is planned to improve the system recognition performance using probabilistic machine learning methods such as Hidden Conditional Random Fields, Input-Output Hidden Markov Models and Hidden Semi Markov Models.

There were no statistically significant difference between the performance of the actions imitated from human teacher and humanoid teacher (simulated/physical).

Within the studies, 1 child with normal developments, and 2 children with ASD (all in the age group 6-7) participated, as well as the university students. The children did not stay stable during the recording of data, which makes it very hard to get data. The child with the normal development and one of the children with ASD could finish all the actions, yet not exactly same with the adults. Unfortunately, since they did not stay still and were tired and leave the test before enough data was collected, the Kinect system could not be trained to recognize their actions. We are working on the necessary improvements to get data from children as fast and robust as possible. The system should be fast, and the time for calibration should be as short as possible.

VI. CONCLUSION AND FUTURE WORK

In this paper, we introduced a project on teaching children sign language by means of interaction games with humanoid robots. The extended versions of the studies are also being used with children with autism in teaching non-verbal communication skills, imitation and turn-taking. Several types of media including robots with different embodiment, tablets, and web based applications are being used within the study. The experiments are being conducted with adults, sign language students, children with normal development, hearing impaired children and children with autism. 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.

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