Context-responsive ASL Recommendation for Parent-Child Interaction

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ABSTRACT

Parental language input in early childhood plays a critical role in lifelong neuro-cognitive and social development. Deaf and Hard of Hearing (DHH) children are often at risk of language deprivation due to hearing parents' limited knowledge of sign language - the natural language for DHH children at birth. To offer an immersive sign language environment for DHH children, we designed a novel computer-mediated communication technology named Table Top Interactive System (TIPS). It aims to provide context-responsive recommendation of American Sign Language (ASL) in real-time for hearing parents during face-to-face joint play with their DHH children. The system emphasizes supporting parent autonomy by adapting ASL recommendations using parent's speech during play, and minimizes obtrusion for face-to-face interaction through an Augmented Reality (AR) display. This paper describes the design and development of an initial working prototype of TIPS and preliminary results of the system's efficiency regarding system latency and accuracy for ASL recommendation and visualization. Next, we plan to conduct a user study to gather expert and parent feedback about the system design and ASL recommendation strategies for long-term and personalized usage.

CCS CONCEPTS

• **Human-centered computing** → **Human-centered computing**; **Accessibility**.

KEYWORDS

Computer-mediated communication, American Sign Language, Parent-Child Interaction, Augmented Reality

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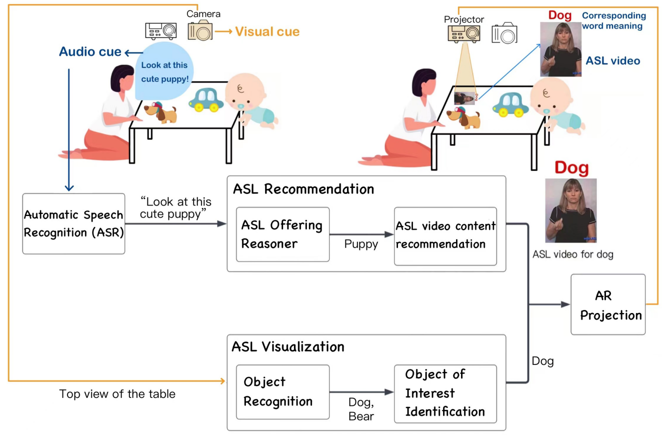
1 INTRODUCTION AND RELATED WORK

More than 90% of DHH children are born to hearing parents [31]. A lack of an immersive sign language environment at home may pose the risk of language deprivation for DHH children [13] [12] [5], leading to long-term effects on a child's ability to acquire a first language [27], cognitive delays [21], and mental health problems [14]. Therefore, there is an increasing emphasis in pediatrics research on parent and family support for sign language during the early stages of child development [18] [17].

Existing research mainly focuses on supporting sign language acquisition for hearing parents and DHH children (e.g., games [3], mobile applications [43], storybooks [25], and avatars [37] [39] [36] [1]). There remains a critical research gap of technologies that support sign language exposure for DHH children through real-time interaction with hearing parents and caregivers [43]. Emerging research on computer-mediated communication sheds light on using Natural Language Processing (NLP) technologies in monitoring parent-child conversation, and providing parents with feedback on communication strategies such as turn taking and praise when interacting with children with language and behavioral difficulties ([19] [16]). A recent system was developed to provide situation-related phrases for immigrant parents during play [22]. This system guides the parent with pre-defined phrases relevant to toys of attention, however, it may hinder parents' autonomy and fluency of play when the recommended phrase lacks correspondence to the momentary play episode. For example, the system may recommend the phrase "car moves" because it's relevant to a car toy, but if the parent says "the car is fast," then the parent may have to yield the play idea to the recommended phrase. Furthermore, visual feedback of communication strategies and language inputs in these systems are often displayed on mobile or tablet devices, which may direct away the parent's attention and impede the fluency of face-to-face interaction [45][40] [19].

To address these challenges, we designed a novel computer-mediated communication technology named TIPS (Tabletop Interactive Play System) (Figure 1). It aims to provide context-responsive recommendation of American Sign Language (ASL) in real-time for hearing parents during face-to-face joint play with their DHH children. The system emphasizes on (1) supporting parent autonomy by recommending ASL in alignment with the semantic contents of the parent's speech during play, and (2) minimizing obtrusion for face-to-face interaction through Augmented Reality (AR) display, which

(a) An illustration of the TIPS setup - the parent (left) and child (right) sit across the table. TIPS monitors the parent's speaking, and projects context-appropriate ASL near the object of interest.



(b) Overview of system pipeline for TIPS system

Figure 1: System Overview of TIPS: Tabletop Interactive Play System

is promising in eliminating attention diversion in face-to-face interaction ([20] [32]). TIPS adopts a projection-based AR display that visualizes the recommended ASL video near the object of interest in a tabletop setting. A recent study demonstrates that the design concept of projection-based AR display is most preferred for ASL visualization during face-to-face interaction as compared to tablets, smart watches, and smart glasses, due to its high glanceability, unobtrusiveness, and visibility of facial gestures (an integral aspect of ASL) [2].

This paper describes the design and development of an initial working prototype of TIPS, which includes two main modules: **vocabulary-based ASL recommendation** and **ASL AR visualization**. A small scale system performance evaluation shows satisfactory efficiency regarding system latency (on average 0.28 seconds) and visualization with a 75% accuracy rate for detecting the correct toy of interest. Next, we plan to conduct a user study to gather expert and parent feedback about the system design and ASL recommendation strategies for long-term and personalized usage.

2 SYSTEM DESIGN

The goal of the **ASL Recommendation Module** (ARM) is to analyze the parents' utterances and provide context-responsive ASL content directly derived from the utterances. ARM consists of three components: **Automatic Speech Recognition**, **ASL Recommendation Reasoner**, and **ASL Video Retrieval**. ARM captures the verbal cues using an ASR system which transcribes the speech into text. Then the "ASL recommendation reasoner" conducts semantic analysis of the text, and extracts the appropriate vocabulary based on pre-defined ASL recommendation strategies.

The current ASL recommendation reasoner focuses on vocabulary-based language input over phrases and sentences. According to usage-based theory, children learn low-scope structures based on individual words or morphemes and gradually develop more complex and abstract linguistic representations [23]. The reasoner prioritizes content words (nouns, main verbs, adjectives, and adverbs) over function words (e.g., that, the). Research shows that content words are more helpful to promote children to engage during interactions [23], and there is a high percentage of content words in young children's expressive vocabulary [10]. The current reasoner serves as a technology probe to allow co-design with key stakeholders about advanced ASL recommendation strategies, and personalized approach to adopt to individual's ASL communication needs (see the "future user study plan" section).

The goal of the **ASL AR Visualization Module** is to dynamically project the recommended ASL video next to the toy of interest. The **"Object of interest identification module"** (TIIM) captures both verbal cues and real-time visual information (top view of tabletop) to determine where to project the ASL content. ARM provides the current context, and TIIM identifies the most relevant toy associated with the parent's utterance. Then, the AR projection module projects the video next to the toy on the table. According to dual-coding learning theory, linking physical objects with appropriate semantic information may improve language acquisition [28].

3 SYSTEM DEVELOPMENT

3.1 ASL Recommendation Module (ARM)

3.1.1 Automatic Speech Recognition Framework. We used the state-of-the-art offline speech recognition framework Wav2vec2 [46] to accomplish the ASR task. This framework is being used in different real-time context-aware application such as valence-arousal estimation [30], mispronunciation detection [34], emotion estimation [29], autism classification [6], and sentiment analysis [26]. The Word Error Rate (WER) of this framework is 1.8/3.3 (in%) [46] on the noisy/clean test sets of Librispeech [33] which is better than other existing ASR system such as Discrete-BERT [15], ContextNet [15], Conformer [11]. Considering the performance in terms of WER and it's practical usage in different context-aware application, we choose this framework for ASR.

3.1.2 ASL Recommendation Reasoner. To suggest vocabulary from the transcribed speech, we used Stanford Dependency Parser [35] to extract content words. To remove function/stop words, we used the NLTK package [4].

3.1.3 ASL Video Retrieval. The ASL Video Retrieval System searches for the selected word's exact or the semantically relevant ASL video content. We used BERT embedding [7] for semantic search because such embeddings are dynamically calculated according to sentence-level context [42]. The difference between static and dynamic embedding is that dynamic embedding can capture the sense [44] of a word in a sentence. For example, the word "fly" can be used in two different senses, as a "bug" or as "moving through the air." BERT will compute different embeddings for "fly" based on the contextual senses in a sentence. For semantic vocabulary search, first, we pre-calculated the embeddings of each word in our ASL dictionary. The algorithm uses cosine similarity to provide the exact or the most relevant ASL video content against the selected word. This design will support parents' diverse semantically relevant linguistic input. For example, a parent addresses a "dog" toy as "puppy" or "doggy." In both cases, our systems provide ASL for "dog."

3.2 ASL Video Databases:

To build an extensive and comprehensive ASL video corpus, we used the open-sourced ASL video data from three university ASL databases: the University of Rochester, Rochester Institute of Technology, and Gallaudet University. In total, we have 6472 number of ASL videos.

3.3 ASL AR Visualization Module

A camera and a projector are requirements to implement projection-based augmented reality 1b, and projector-camera calibration is recommended for the best outcome of AR projection. However, for this study, we only did a camera calibration following the suggestion of system implementation in PATI [9]. To get the exact location of the toy on a table from the top view, the camera-captured image should be transformed into the - "birds-eye-view" image. To calculate this, first we need to apply perspective transformation on the pre-selected four points to calculate the perspective matrix M. Using this matrix, we applied warp transformations on the camera-captured image to obtain a "birds-eye-view" image of the table surface. We chose a projector (Optoma ML1050ST+) with a short throw ratio for better projection because our projector is situated around 3 feet above the table. The other factors in choosing this projector were size, weight, screen width, and brightness.

3.4 The "Object of interest identification module" (TIIM)

To project ASL video content near the toy, the CV module detects the current toy of interest through a multimodal approach based on the verbal cue (parent's input) and visual input (top view image of tabletop). First, to locate the current toys on the table, we choose the YOLO object detection model [24] for its robustness for real-time performance and detecting small objects. We fine-tuned the existing model with 13 toys. The next task is to localize which toy is the most relevantly referred to. We use BERT to calculate the word embedding of the selected word extracted by the ASL offering reasoner and the current-table-top detected toys using the labeled class name. Then, the cosine similarity is calculated to find the most relevantly referred toy against the selected word from the parent's utterance. After the AR module projects the video follows the current toy of interest.

4 PRELIMINARY EVALUATION

We conducted an internal preliminary evaluation with two researchers on the team (both are native English speakers) to evaluate the system's efficiency. We placed five toys on the table first one at a time, then two toys at a time (bus, firetruck, red bus, policeman, girl doll), and asked each speaker to play with these toys for a total of 10 minutes. The pairings of toys were the bus with the firetruck, policeman with firetruck, and girl doll with bus. We limited the amount of instructions given to the evaluators as to not limit their toy play and sentence generation. The only instructions were to not use complex sentences or questions, and that the sentences should either be about only one toy or two toys interacting. We also let the speakers know that the sentences do not have to be directly about the object or mention the object, and that they can use the toy to represent other objects of interest. The total number of sentences collected during the evaluation was 41. The average length of these sentence was 5.225. We calculated the latency of the system using the sentences uttered by the speakers. The system's overall latency is composed of the duration of speech to text, the time that it takes for the ASL recommendation algorithm to select the appropriate word, the retrieval of the corresponding ASL video content from the ASL video dictionary, and the time to visualize ASL video through the projector. ASL recommendation latency refers to the time the system takes to generate the POS (parts of speech) tags from a transcribed sentence, and to suggest an appropriate word from the extracted POS tags. Video retrieval latency refers to the time the system takes to perform the semantic search over the ASL dictionary to retrieve the relevant ASL video content for the selected word. The amount of time from the retrieval of the ASL video content to projector visualization is negligible. That is why we did not consider this latency to calculate the overall system's latency. The average display latency between the finish of the sentence and the appearance of the ASL video was 0.28 seconds (*SD = 0.084*). Based of off [38], [8], and [41] our system qualifies as being instantaneous due to being under 300 milliseconds. Our system also showed 75% accuracy rate of identification of toy of interest. TIPS captures the audio and video stream simultaneously. If the "Object of interest identification module" (TIIM) displays the retrieved ASL video content that matches with the intended object that the parent refers to, we consider that our system successfully identified the toy of interest. We calculated this by dividing the total number of successful identification of toy of interest by the total number of identification attempts.

5 FUTURE USER STUDY PLAN

We are currently working on improving the system's performance. We plan to conduct a larger scale usability study to evaluate the efficiency of the improved system in terms of display latency, accuracy rate of identification of toy of interest, and precision of ASL video projection. We will then conduct two consecutive user studies. The first study is a co-design study with key stakeholders (language acquisition researcher, ASL educator, early childhood educator and hearing parents with DHH children, novice ASL learners, and DHH individuals). This study aims to gather feedback on the current system and brainstorm ASL recommendation strategies for long-term and personalized usage. The second study will be with hearing parents and DHH children. This study aims to evaluate the effectiveness of the working prototype in supporting hearing parents to deliver context-responsive ASL on the fly during joint play with DHH children.

6 CONCLUSION

In this research, we developed a working prototype of the TIPS system to improve sign language exposure for DHH children, through recommending hearing parents context-responsive ASL during joint play. TIPS adopts a speech-driven approach to support the autonomy of the parent by selecting a video of the ASL they wish to sign in line with an ongoing play episode, and by implementing the projection-based AR display to minimize obtrusion during face-to-face interactions. Results of a small scale usability evaluation demonstrate satisfactory system efficiency. We discussed the plan for future studies to iterate the system development and conduct quantitative evaluation of the effectiveness of TIPS in augmenting hearing parents' communication in ASL with their DHH children.

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