Conversational Strategies for Robustly Managing Dialog in Public Spaces

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Abstract

Open environments present an attention management challenge for conversational systems. We describe a kiosk system (based on Ravenclaw–Olympus) that uses simple auditory and visual information to interpret human presence and manage the system’s attention. The system robustly differentiates intended interactions from unintended ones at an accuracy of 93% and provides similar task completion rates in both a quiet room and a public space.

1 Introduction

Dialog systems designers try to minimize disruptive influences by introducing physical and behavioral constraints to create predictable environments. This includes using a closed-talking microphone or limiting interaction to one user at a time. But such constraints are difficult to apply in public environments such as kiosks (Bohus and Horvitz, 2010; Foster et al., 2012; Nakashima et al., 2014), in-car assistants (Kun et al., 2007; Hofmann et al., 2013; Misu et al., 2013) or on mobile robots (Haasch et al., 2004; Sabanovic et al., 2006; Kollar et al., 2012). To implement dialog systems that operate in public spaces, we have to relax some of these constraints and deal with additional challenges. For example, the system needs to select the correct interlocutor, who may be only one of several possible ones in the vicinity, then determine whether they are initiating the process of engaging with the system.

In this paper we focus on the problems of identifying a potential interlocutor in the environment, engaging them in conversation and providing suitable channel-maintenance cues (Bruce et al., 2002; Fukuda et al., 2002; Al Moubayed and Skantze, 2011). We address these problems in the context of a simple application, a kiosk agent that accepts tasks such as taking a message to a named recipient. To evaluate the effectiveness of our approach we compared the system’s ability to manage conversations in a quiet room and in a public area.

The remainder of this paper is organized as follows: we first describe the system architecture, then present the evaluation setup and the results, then review related work and finally conclude with an analysis of the study.

2 System Architecture

Figure 1 shows the architecture; it incorporates Ravenclaw/Olympus (Bohus et al., 2007) standard components (in white), new components (in black) and modified ones (shaded). In the system pipeline, the Audio Server receives audio from a microphone, endpoints it and sends it to the ASR.
The subjects were told that they would interact with a virtual agent displayed on a screen. Their task for the awareness experiment was to make the agent aware that they wished to interact. For the end-to-end system performance, the task was to instruct the agent to send a message to a named recipient.

3.1 Situated Awareness

We define situated awareness as correctly engaging the intended interlocutor (i.e., verbally acknowledge the user’s presence) under two conditions. When the user is positioned (i) inside the visual range of the Kinect at LOC-0 in Figure 3(a); and (ii) outside the visual range of the Kinect at LOC-1 in Figure 3(a). We used the effective range of the camera’s documented horizontal field of view (57°); hereafter referred as its cone-of-awareness.

We conducted the awareness experiment in a public space, a lounge at a hub connecting multiple corridors. The area has tables and seating, self-serve coffee, a microwave oven, etc. The experiment was conducted during regular hours, between 10am to 6pm on weekdays. During these times we observed occupants discussing projects, preparing food, making coffee, etc. No direct attempt was made to influence their behavior and we believe that they made no attempt to accommodate our activities. Accordingly, the natural sound level in the room varied in unpredictable ways. To supplement naturally-occurring sounds, we played audio of a conversation between two humans, an extract from the SwitchBoard corpus (Graff et al., 2001). It was played using a loudspeaker placed at LOC-2 in Figure 3(a). The locations (0, 1, and 2) are all 1.5m from the Kinect, which we deemed to be a comfortable distance for the subjects. LOC-1 and LOC-2 are 70° to the left and right of the Kinect, outside its cone.

To detect the presence of an intended user, we build an awareness model that uses three sensory streams viz., voice activity, skeleton, and sound source azimuth. This model relies on the coincidence of azimuth angle and the skeleton angle (along with voice activity) to determine the presence of an intended user. We compare the pro-
Figure 3: (a) Plan of Public Space (lounge); (b) Plan of Quiet Room (lab). Dark circled markers indicate locations (LOC-0, LOC-1, LOC-2), discussed in the text.

| Condition         | Voice | +Skeleton | +Azimuth |
|-------------------|-------|-----------|----------|
| Outside the cone  | 28%   | —         | 93%      |
| Inside the cone   | —     | 25%       | 93%      |

Table 1: Accuracy for the Awareness Detection

We propose model with two baselines: (1) conventional voice-activity-detection (VAD): once speech is detected the system responds as if a conversation is initiated and (2) based on skeleton plus VAD: once the skeleton appears in front of the Kinect and a voice is heard, the system engages in conversation.

Table 1 shows the combination of sensory streams we used under two conditions. For the outside-the-cone condition, the participants stand in LOC-1 as shown in Figure 3(a) and follow the instructions from the agent. Initially, the subject’s skeleton is invisible to the agent; however the subject is audible to the agent. Therefore, in certain combinations of sensors (e.g., voice + skeleton model and voice + skeleton + azimuth model) the system attempts to guide them to move in front of it, i.e. to LOC-0, an ideal position for interacting with the system. For inside-the-cone condition, subjects stand at LOC-0 where the agent can sense their skeleton.

When user stands at LOC-1 i.e., outside-the-cone voice + skeleton model and voice + skeleton + azimuth models are functionally the same since the source of distraction has no skeleton in the cone. When user stands at LOC-0, i.e., inside-the-cone voice alone is the same as voice + skeleton model since the agent always sees a skeleton in front of it. Therefore, this variant was not used.

We treated awareness detection as a binary decision. An utterance is classified either as “intended” or “unintended”. We manually labeled the utterances whether they were directed at the system (“intended”), “unintended” otherwise. Accuracy on “intended” speech is reported in the Table 1. Within each condition, the order of the experiments with different awareness strategies was randomized.

We observe that the voice + skeleton + azimuth model proves to be robust in the public space. Its performance is significantly better, $t(38) = 8.1$, $p \approx 0.001$, compared to the other baselines in both conditions. This result agrees with previous research (Haasch et al., 2004; Bohus and Horvitz, 2009) showing that a fusion of multimodal features improves performance over a unimodal approach. Our result indicates that a simple heuristic approach, using minimal visual and audio features, provides usable attention management in open environments. This approach helped the system handle a complex interaction scenario such as out-of-cone speech directed to the system. If the speaker is out of range but is producing possibly system-directed utterances, system urges them to step to the front. We believe it can be extended to other complex cases by introducing additional logic.

### 3.2 End-to-End System Performance

To investigate the effect of the environment, we compare the system’s performance in public space and quiet room. The average noise level in the quiet room is about 47dB(A) with computers as
the primary source of noise. The background sound level in the public space was 46dB; other natural sources ranged up to 57dB. The audio distractor measured 57dB. The same ASR acoustic models and processing parameters were used in both environments. The participant stood at LOC-0 in Figure 3(a) during the public space experiment and Figure 3(b) during the quiet room experiment. In both experiments, LOC-0 is 1.5m away from the system. We used the voice + skeleton + azimuth model to discriminate user speech from distractions in the environment.

We gave each participant a randomized series of message-sending tasks, e.g. “send a message to ⟨person⟩ who is in room ⟨number⟩”. Subjects had a maximum of 3 minutes to complete; each task required 7 turns. The number of tasks completed (over the group) is reported in terms of task “success-ratio”. Table 2 shows the success-ratio of the task, the average number of turns needed to complete the task, and the system’s per-utterance concept accuracy (Boros et al., 1996). There were no statistically significant differences between quiet room and public space, (t(38) < 2, p > 0.5, on any metric). We conclude that the channel maintenance technique we tested was equally effective in both environments.

Table 2: Public Space vs Quiet Room Performance

| Metric       | Public Space | Quiet Room |
|--------------|--------------|------------|
| Success Ratio| 15/20        | 16/20      |
| Avg # Turns  | 14.2         | 16.4       |
| Concept Acc  | 67%          | 68%        |

4 Related Work

The problem of deploying social agents in public spaces has been of enduring interest; (Bohus and Horvitz, 2010) list engagement as a challenge for a physically situated agent in open-world interactions. But the problem was noted earlier and solutions were proposed; e.g. a “push-to-talk” protocol to signal the onset of intended user speech (Stent et al., 1999). (Sharp et al., 1997; Hieronymus et al., 2006) described the use of attention phrase as a required prefix to each user input. Although explicit actions are effective, they need to be learned by users. This may not be practical for systems in public areas engaged by casual users.

A more robust approach involves fusing several sources of information such as audio, gaze and pose (Horvitz et al., 2003; Bohus and Horvitz, 2009) (Hosoya et al., 2009; Nakano and Ishii, 2010). Previous works have shown that fusion of different sensory information can improve attention management. The drawback of such approaches is in the complexity of the sensor equipment. Our work attempts to create the relevant capabilities using a simple sensing device and relying on explicitly modeled conversational strategies. Others are also using the Microsoft Kinect device for research in dialog. For example, (Skantze and Al Moubayed, 2012) and (Foster et al., 2012) presented a multiparty interaction systems that use Kinect for face tracking and skeleton tracking combined with speech recognition.

In our current work, we show that situational awareness can be integrated into an existing dialog framework, Ravenclaw–Olympus, that was not originally designed with this functionality in mind. The source code of the framework presented in this work is publicly available for download 1 and the acoustic models that have been adapted to the Kinect audio channel 2.

5 Conclusion

We found that a conventional spoken dialog system can be adapted to a public space with minimal modifications to accommodate additional information sources. Investigating the effectiveness of different awareness strategies, we found that a simple heuristic approach that uses a combination of sensory streams viz., voice, skeleton and azimuth, can reliably identify the likely interlocutor. End-to-end system performance in a public space is similar to that observed in a quiet room, indicating that, at least under the conditions we created, usable performance can be achieved. This is a useful finding. We believe that on this level, channel maintenance is a matter of articulating a model that specifies appropriate behavior in different states defined by a small number of discrete features (presence, absence, coincidence). We conjecture that such a framework is likely to be extensible to more complex situations, for example ones involving multiple humans in the environment.

1http://trac.speech.cs.cmu.edu/repos/olympus/tags/KinectOly2.0/
2http://trac.speech.cs.cmu.edu/repos/olympus/tags/KinectOly2.0/Resources/DecoderConfig/AcousticModels/Semi_Kinect.cd_semi_5000/
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