Interpreting Multimodal Referring Expressions in Real Time

Miles Eldon[1] and Stefanie Tellex[1]

***Abstract*— Robots that collaborate with humans must be able to identify objects used for shared tasks, for example tools such as a knife for assistance at cooking, or parts such as a screw on a factory floor. Existing work has addressed this problem in single modalities, such as natural language or gesture, but a gap remains in creating real-time multimodal systems that simultaneously fuse information from language and gesture in a principled mathematical framework. We define a multimodal Bayes' filter for interpreting referring expressions to objects using language and gesture in real time. We collected a new RGB-D and audio dataset of people referring to objects in a tabletop setting and demonstrate that our approach successfully integrates information from language and gesture in real time to quickly and accurately identify objects continuously.**

I. INTRODUCTION

In order for humans and robots to collaborate in complex tasks, robots must be able to understand people's references to objects in the external world. For example, a robotic cooking assistant might fetch incredients and tools To refer to objects, people use a combination of language, gesture, and body language such as eye gaze and looking. People provide these signals continuously, and a person's reference can quickly change based on new information about the domain. For example, Figure 1 shows a robot handing a tool to a human collaborator for a manufacturing task; in order to infer the correct tool to deliver, the robot must interpret a person's language and gesture over time.

Most existing approaches for interpreting language and gesture rely on unimodal models that do not integrate the two information sources, even though people fluidly use language and gesture together. Approaches that fuse information from language and gesture [Matuszek et al., 2014] do not take into account that information appears to the system over a period of time. Taking into account time is important because it is the foundation of seeing language and conversation as a *joint activity* [Clark, 1996] embedded in time. Language and gesture co-occur and the relative timing of speech and gesture is critical for accurate understanding. Furthermore, responding quickly to a person's input makes interaction more fluid and enables a robot to provide back-channel feedback based on its ability to understand: when it is confident, it can indicate that it is confident, and when it is unsure, it can indicate that. This backchannel feedback elicit appropriate responses from the person: they will move to the next task when the robot understands, or provide more information to disambiguate when the person is confused.

To provide a foundation for these capabilities, we propose a Bayes' filtering approach for interpreting multimodal information from language and gesture [Thrun et al., 2008]. Our framework relies on a factored observation probability that fuses information from language, hand gestures, and head gestures in real time to continuously estimate the object a person is referring to in the real world. We demonstrate our model in simulation, as well as providing quantitative results on a real-world RGB-D corpus of people referring to objects in the environment. These results demonstrate that our approach quickly and accurately fuses multimodal information in real time to continuously estimate the object a person is referring to.

[1]Computer Science Department, Brown University

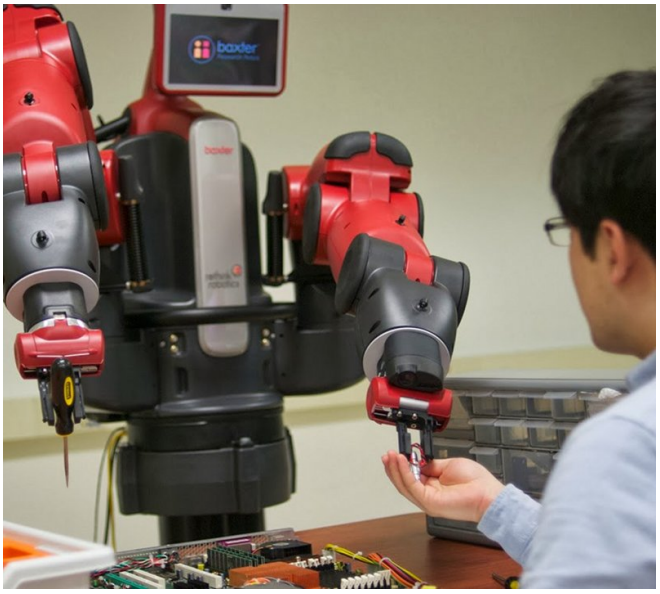


Fig. 1. Robots that collaborate with people need to understand their references to objects in the environment. For example, if a person asks for a tool using language and gesture, the robot needs to interpret the person's reference in order to pick up the correct tool.

II. RELATED WORK

Clark [1996] proposed that conversation is a *joint activity*, a coordinated, collaborative processess akin to playing a duet or performing a walz. The two participants must establish *common ground*. Common ground in dialog is distinct from symbol grounding [Harnad, 1990], which is the problem of mapping from language to aspects of the external world. Common ground, in a dialog sense, refers to the process of two conversational participants establishing joint understanding about the beliefs of the others. To establish commond ground, people use *backchannel* feedback, such as head nods, looks of confusion, as well as explicit request for clarification such as asking a question. These mechanisms enable the participants in a conversation to engage in a feedback loop

A large body of work focuses on language understanding for robots [MacMahon et al., 2006, Dzifcak et al., 2009, Kollar et al., 2010, Matuszek et al., 2012]. This work does not take into account the continuous nature of natural language input. Guadarrama et al. [2014] presents a framework for interpreting open-domain references to objects but focuses on interpreting language rather than language combined with gesture. Cantrell et al. [2010] presnted a framework for understanding language incrementally in real time dialog but did not use gesture and did not use a corpus-based evaluation of the approach. Our approach is related to Holladay et al. [2014] but focuses on interpreting a person's gestures rather than enabling a robot to generate pointing gestures.

Many existing approaches for interpreting gesture rely on fixed vocabularies of gesture, such as "stop" or "follow" [Waldherr et al., 2000, Marge et al., 2011] without a principled way for fusing information from language and gesture. Our work unifies language and gesture interpretation into a single mathematical framework, and focuses on parameterized gestures such as pointing.

Matuszek et al. [2014] presented a multimodal framework for interpreting unscripted references to tabletop objects using language and gesture. Our approach similarly focuses on tabletop objects but uses language, gesture, and head pose, and integrates these disparate data sources continuously over time using a Bayes' filtering framework. This approach enables the robot to continuously process new information and produce an estimate that converges over time to the correct object as new information is observed from the person.

LP and ICMI stuff

Dragan and Srinivasa [2013] created a framework enabling a robot to produce gesture. Similarly, Tellex et al. [2014] described an approach for enabling a robot to generate language by inverting a semantics framework. Our long-germ aim is that by combining these types of generation approaches with real-time understanding, the robot will produce back-channel feedback that closes the loop of dialog and enable it to pariticpate in dialog as a joint activity.

III. TECHNICAL APPROACH

Our aim is to estimate a distribution over the object that a person is referring to given language and gesture inputs. We frame the problem as a Bayes' filter [Thrun et al., 2008], where the hidden state, $\mathcal{X}$, is the set of m objects in the scene that the person is currently referencing. The robot observes the person's actions and speech, $\mathcal{Z}$, and at each time step estimates a distribution over $\mathcal{X}$:

$$p(x_t|z_0 \dots z_{0:t}) \tag{1}$$

To estimate this distribution, we take a Bayes' filtering approach and alternate performing a time update and a measurement update. The time update updates the belief that the user is referring to a specific subset of objects given previous information:

$$p(x_t|z_{0:t-1}) = \int p(x_t|x_{t-1}) \times p(x_{t-1}|z_{0:t-1}) \mathrm{d}x_{t-1} \tag{2}$$

The measurement update combines the previous belief with the newest observation to update each belief state:

$$p(x_t|z_{0:t}) = \frac{p(z_t|x_t) \times p(x_t|z_{0:t-1})}{p(z_t|z_{0:t-1})} \tag{3}$$

$$\propto p(z_t|x_t) \times p(x_t|z_{0:t-1}) \tag{4}$$

Algorithm 1 shows pseudocode for our approach.

A. Prediction Model

We assume that a person is likely to continue referring to the same object, but at each timestep has a small probability, c, of transitioning to a different object:

$$p(x_t|x_{t-1}) = \begin{cases} 1-c & \text{if } x_t = x_{t-1} \\ c & \text{otherwise} \end{cases} \tag{5}$$

In our experiments, c has a value of XXX.

B. Observation Model

We assume access to an observation model of the form:

$$p(z_t|x_t) \tag{6}$$

Observations consist of a tuple consisting of a person's actions, $\langle l, r, h, s \rangle$ where:

- l represents the observed origin (l_o) and vector (l_v) for the left arm.
- r represents the observed origin (r_o) and vector (r_v) for the right arm .
- h represents the observed origin (h_o) and vector (h_v) for head.
- s represents the observed speech from the user, consisting of a list of words. Duo to the nature of current methods of speech recognition, we maintain all recognized speech from the previous XXX seconds as the current speech input. **ME: Should we look into discounting speech based on proximity to current time?**

Formally, we have:

$$p(z_t|x_t) = p(l, r, h, s|x_t) \tag{7}$$

We factor assuming that each modality is independent of the others given the state (the true object that the person is referencing):

$$p(z_t|x_t) = p(l|x_t) \times p(r|x_t) \times p(h|x_t) \times p(s|x_t) \tag{8}$$

The following sections describe how we model each type of input from the person.

Gesture. We model pointing gestures as a vector through three dimensional space. We calculate the angle between the gesture vector and the vector from the gesture origin to the mean of each cluster, and then use the PDF of a Gaussian ($\mathcal{N}$) with trained variance (σ) to determine the weight that should be assigned to that object. We define a function $\mathrm{A}(o, p_1, p_2)$ as the angle between the two points, p_1

and p_2 with the given origin, o. Then **ST: I'm confused – what is the third parameter to the Gaussian?**

$$p(l|x_t) \propto \mathcal{N}(\mu_l = 0, \sigma_l, \Phi(l_o, l_v, x_t)) \quad (9)$$

$$p(r|x_t) \propto \mathcal{N}(\mu_r = 0, \sigma_r, \Phi(r_o, r_v, x_t)) \quad (10)$$

Head Pose. Head pose is modeled in the same manner as arm gestures.

$$p(h|x_t) \propto \mathcal{N}(\mu_h = 0, \sigma_h, \Phi(h_o, h_v, x_t)) \quad (11)$$

Speech. We model speech as a bag of words. We take the words in a given speech input and count how many words in this text match descriptors (denoted x_d) of specific objects.

$$p(s|x_t) = \prod_{w \in s} p(w|x_t) \quad (12)$$

C. Training Model Parameters

We train model parameters by fitting each factor to an annotated training corpus. We collected a dataset of people referring to an object, including language and gesture. We instrumented human annotators with a microphone and initialized the gesture tracker. Then we instructed them to refer to an object which we indicated with a laser pointer; using a laser pointed meant that we avoided using language and gesture ourselfs to refer to the object. We periodically changed the object to refer to, to simulate a dialog where the person periodically refers to different objects. For example, the robot could be acting as a cooking assistant and retrieving different ingredients, or in a hospital fetching water, a phone, or a book for a patient recovering from surgery, who is unable to get out of bed. We used this real-world dataset to train and evalaute our model.

Figure 2 shows an example of the system's execution. The person's gesture is ambiguous, but information from language, that is itself ambiguous (because there are two bowls in the scene, enables the system to infer the correct object. Although in this example we are demonstarting the approach at two specific timesteps, the system is updating its distribution continuously, enabling it to fuse language and gesture as it occurs and quickly updating in response to new input from the person, verbal or nonverbal.

Algorithm 1: Interactive Bayes Filtering Algorithm

Input: $bel(x_{t-1}), u_t, z_t$ **ME: What is u_t?**

Output: $bel(x_t)$

for x_t **do**

$\bar{bel}(x_t) = \prod_{x_{t-1}} p(x_t|x_{t-1}) * bel(x_{t-1})$

if not is_null_gesture(l)

$\bar{bel}(x_t) = p(l|x_t) * \bar{bel}(x_t)$

if not is_null_gesture(r)

$\bar{bel}(x_t) = p(r|x_t) * \bar{bel}(x_t)$

if not is_null_gesture(h)

$\bar{bel}(x_t) = p(h|x_t) * \bar{bel}(x_t)$

for $w \in s$ **do**

$\bar{bel}(x_t) = p(w|x_t) * \bar{bel}(x_t)$

end

$bel(x_t) = \bar{bel}(x_t)$

end

ME: if speech: do stuff else 1. A cartoon of how this works, display multinomial over objects ST: Miles – can you fill in the algorithm? We shouldn't just reproduce a simple Bayes' filter; it should get into what specific things we had to do to make it work with multimodal input. In particular, I think the belief updates should include the gaussians and show how the parameters are changing in response to new information.

IV. EVALUATION

We evaluate our model in simulation, comparing the full model to versions without multimodal information. Additionally we assessed its performance on an RGB-D audio and video corpus of people referring to objects. Finally we created an end-to-end robotic demonstration, demonstrated in the video attachment to our paper, and available online[1].

A. Simulation Results

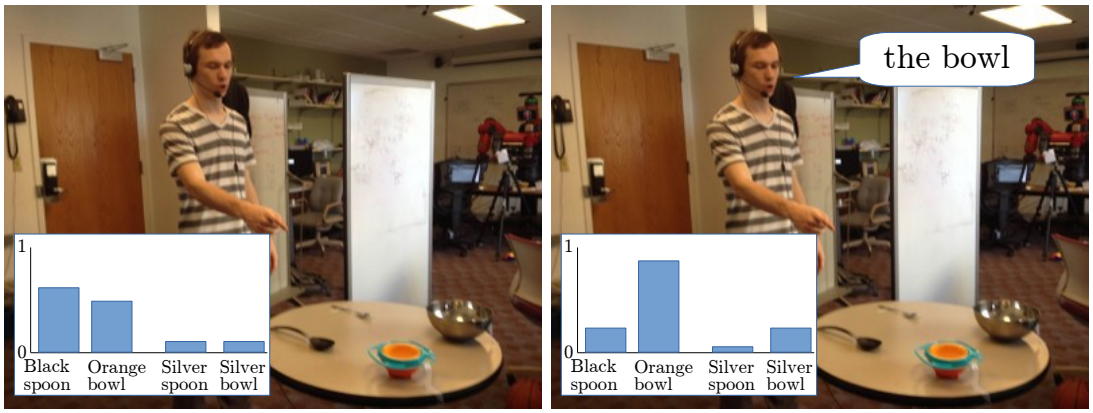
We evaluated our approach in simulation by generating data from the model and assessing its accuracy at estimating the object being referred to. We generate simulated pointing data for each hand, the face, as well as spoken utterences at each timestep according to the model parameters. We then use these paramters to update the system's estimate of the object being referred to. This evaluation demonstrates that our approach successfully fuses multimodal information. We report performance using language alone, gesture alone, and language combined with gesture. Our accuracy metric is the fraction of time that the robot is pointing at the correct object. Table I shows the results. These results demonstrate that the system is successfully able to fuse multi-modal information to achieve higher accuracy than each modality alone, but do not show performance in the real world.

TABLE I
SIMULATION RESULTS

Language alone	XX
Gesture alone	XX
Language and gesture	XX

[1]video reference

Fig. 3. Scene from our dataset.



(a) Ambiguous gesture.

(b) Clarification with language.

Fig. 2. After an ambiguous gesture, the model has a uniform distribution between two objects. Clarification with language causes a probabilistic update leaving the model highly confident it has inferred the correct object.

TABLE II

REAL-WORLD RESULTS

Language only	XX
Gesture only	XX
Head only	XX
Multimodal	XX

B. Real-World Corpus-Based Results

Our real-world experiments measured our algorithm's performance when a person referred to an object visually and with gesture. The person was seated roughly five feet from a table which had several objects, as shown in Figure 3. We instructed them to refer to the object as if they were talking to another person, using language and gesture. We indicted the object to refer to using a laser pointer, and we periodically shifted to a different object on a predetermined schedule. They wore a microphone to pick up high-quality audio, and we tracked their body pose using the NITE tracker [ope, 2014]. We used two Kinects: one pointed outward at the person, and one pointed down to recognize objects on the table.

We used the Google Voice Recognition package to recognize speech. This package reports incremental output in real time as recognition proceeds. Our training procedure works on actual speech recognition results rather than transcript speech, enabling the algorithm to adapt to the errors produced by the recognizer: if it returns "cake" instead of "cup," our language model will correctly associate the word "cake" with the "cup" object.

C. Robotic Demonstration

Because our approach enables a robot to quickly and constantly monitor a person's references to an object, a robot can respond to these estimates in real time. We demonstrate this behavior by enabling Baxter to demonstrate its certainty about what object is being referenced, this eliciting more feedback from the person. When the robot is very unsure, its arm moves back and forth between the candidate objects. When it is sure, then it moves with more precision. The video shows this behavior, as a person provides more information about what object is being referred to by the person.

V. CONCLUSION

We have demonstrated a Bayes' filtering approach to interperting a person's multimodal language and gesture references to objects continoulsly in real time. Our approach enables a robot to understand a person's references to objects in the real world.

In the future we plan to expand our language model to incorporate models of compositional semantics and lower-level visual features so that the robot is not limited to prespecified object models. Additionally we aim to enable the robot to generate back-channel feedback based on its model. Dragan and Srinivasa [2013] created a framework for generating legibile gesture, and we anticipate that enabling a robot to respond by pointing as in Holladay et al. [2014] when it is sure and reflecting its confusing when it is unsure. Closing the loop will enable the human-robot dyad to increase efficiency and enable the robot to accurately infer the human's intent, naturally eliciting more information when it is confused and indicating that it has understood when it is sure.

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