Interpreting Multimodal Referring Expressions in Real Time

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***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. Our approach outputs an estimate of which object the person was referencing several times per second, enabling a robot to dynamically respond with backchannel feedback while a person is still communicating. 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 ingredients and tools, while a robotic factory assistant could deliver a part or a hospital robot could deliver water to a bedridden patient; Figure 1 shows a robot handing a tool to a worker in a factory. 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. Moreover, a human listener responds to these signals as they are given using *backchannels*, for example nodding their head when they understand and looking confused or interrupting to ask a question when they do not. Clark [1996] refers to this continuous dance as *joint activity* and compares language use to playing a duet because of its collaborative nature, where both parties act to establish common ground and reduce uncertainty. Language and gesture co-occur and the relative timing of speech and gesture is critical for accurate understanding.

In contrast, many existing unimodal models that do not integrate information from language and gesture [Matuszek et al., 2014, Tellex et al., 2011, Kollar et al., 2010] , 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. These approaches make it impossible for a robot to provide back-channel feedback, because of the length of time required to interpret the communication and because of the inability to interpret partial utterances.

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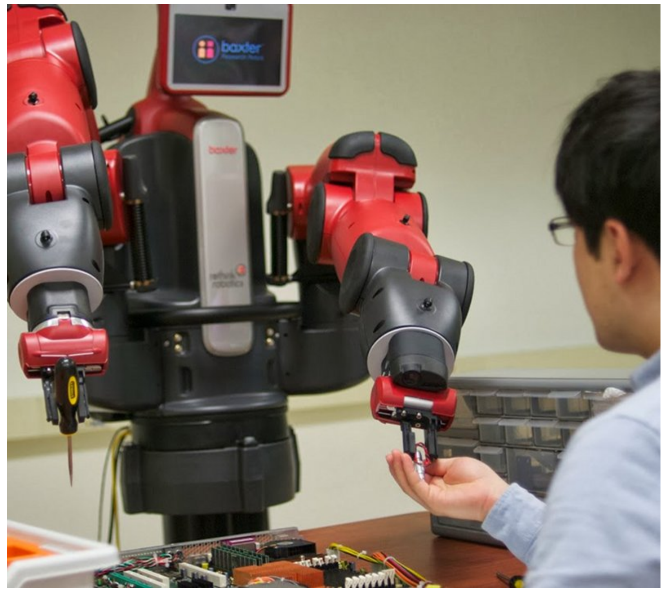


Fig. 1. Robots that collaborate with people need to understand their references to objects in the environment. For example, if a person asks for a tool using language and gesture, the robot needs to interpret the person's reference in order to pick up the correct tool.

Taking into account time is important because it is the foundation of seeing language and conversation as a joint activity embedded in time. 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 could 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 referencing. We describe how this approach can be used to program backchannel responses and demonstrate these responses on a real robot.

II. Related Work

Clark [1996] proposed that conversation is a *joint activity*, a coordinated, collaborative processes akin to playing a duet or performing a waltz. 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 refers to the process of two conversational participants establishing joint understanding about the beliefs of the others. To establish common 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 to iteratively establish common ground as the conversation progresses. Our approach for interpreting language and gesture in real time provides a foundation for producing backchannel feedback with a robot, pointing toward increased robustness as a person and robot iteratively establish common ground and actively communicate to reduce errors.

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] presented a framework for understanding language incrementally in real time dialog but did not use gesture and did not use a corpus-based evaluation. 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

POMDP dialog (Steve Young cites gesture stuff.)

Matthias.

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 participate 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 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:

$$\begin{aligned} p(x_t|z_{0:t}) &= \frac{p(z_t|x_t) \times p(x_t|z_{0:t-1})}{p(z_t|z_{0:t-1})} & (3) \\ &\propto p(z_t|x_t) \times p(x_t|z_{0:t-1}) & (4) \end{aligned}$$

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. This assumption means that the robot's certainty slowly decays over time, in the absence of corroborating information. Our framework integrates past language and gesture information but also quickly adapts to new, conflicting information because it assumes the person has changed objects.

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.

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 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? ME: It's the observed data, so its the probability of seeing the third argument with the given mean and variance ST: So Φ is introduced here without being defined. I'm not sure what it means.**

$$p(l|x_t) \propto \mathcal{N}(\mu_l = 0, \sigma_l, \Phi(l_o, l_v, x_t)) \tag{9}$$
$$p(r|x_t) \propto \mathcal{N}(\mu_r = 0, \sigma_r, \Phi(r_o, r_v, x_t)) \tag{10}$$

If the person's arm is more than a certain angle away from the table, we assume they are referring to none of the objects, and perform an update. As a result, these gestures do not effect the robot's estimate of the objects being referenced.

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

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

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.

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

C. Null Words and Gesture

ST: Broaden this to talk about words and gesture When no words are spoken, we assume a null word which has a uniform distribution over the objects. This effect means that spoken words cause a discrete bump in probability according to the language model, which then decays over time.

D. Training Model Parameters

ST: Miles, can you rewrite this section? I think model parameters are tuned by hand right now, and not learned from data.

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 ourselves 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 evaluate our model.

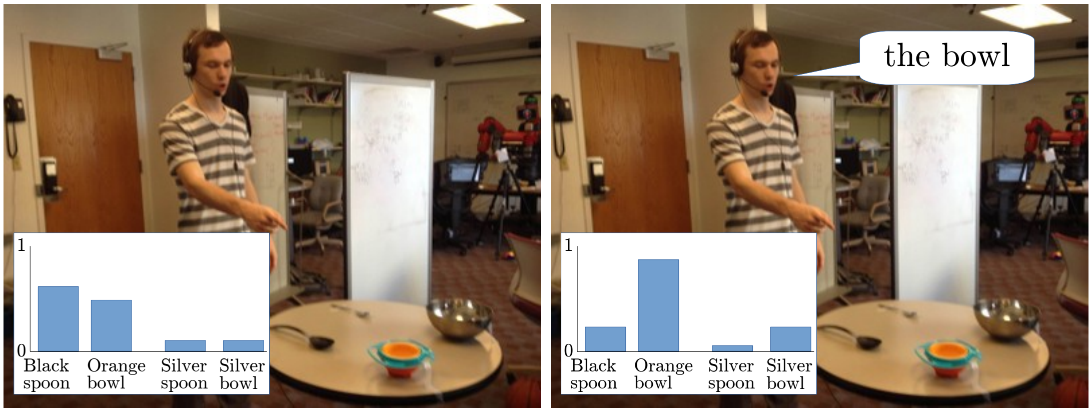
Algorithm 1: Interactive Bayes Filtering Algorithm

Input: $bel(x_{t-1}), z_t$
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

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 demonstrating 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. Our approach runs at 30Hz, continuously outputting an estimate of the object the person is referencing. **ST: Is 30Hz correct?**

IV. EVALUATION

We evaluate our model in simulation, comparing the full model to versions without multimodal information. Addi-



(a) Ambiguous gesture.

(b) Clarification with language.

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

TABLE I
SIMULATION RESULTS

Language alone	36.5%
Head alone	50.9%
Arms alone	62.4%
Language and gesture	65.7%

Fig. 3. Scene from our dataset.

tionally 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 referenced. We generate simulated pointing data for each hand, the face, as well as spoken utterances at each timestep according to the model parameters. We then use these parameters to update the system's estimate of the object being referred to. Table I shows the results. Our accuracy metric is the fraction of time that the robot is pointing at the correct object. We report performance using language alone, gesture alone, and language combined with gesture. 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. While a gesture and language output probabilistically referencing the true object are produced at each time step in simulation, the multimodal accuracy is robust to severe increases in single-modal noise. **ST: Can we create results demonstrating this? For example, a few more columns in table I for different levels of language and gesture noise?ME: Yeah, I can look into it**

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 subject stood in front of a table with four objects placed approximately one foot apart, forming four corners of a square, as shown in Figure 3. We instructed subjects to ask for the indicated object in the most naturally way possible, using whatever combination of gesture and language they felt was appropriate. 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 a single Kinect that was able to capture both the user and the table.

We used the HTML5 Speech Recognition package in conjunction with Google Chrome to recognize speech. This package reports incremental output in real time as recognition proceeds, and we perform a model update each time a new word is perceived. 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.

Results appear in Table II.

ST: We need to add:

- **what the numbers mean. (Is this still % of time that it was correct?)**
- **Table for correctness at the end of the interaction (offset by something, as we talked about**
- **Confidence intervales**
- **Random. I think it's 25%, and if that's right we can just add a row.**

ME: A few things of interest we should note: Head

[1]video reference

TABLE II
REAL-WORLD RESULTS

Language only	35%
Gesture only	75%
Head only	24%
Multimodal (Language and Gesture)	**85%**
Multimodal (All)	65%

results are poor because NITE doesn't perform fine grained head tracking. Arms have a much higher variance based on how much users rely on gestures vs specific language. I don't know how much we get into that, but I've seen 45 - 95% accuracy on gesture, while I've seen 75-98% multimodal, which will be shown once I add the confidence interval to the table, but we might want to discuss

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 interpreting a person's multimodal language and gesture references to objects continuously 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 legible 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. This paper represents steps toward continuous language understanding and the vision presented by Clark [1996] of language as joint activity.

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