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. Humans communicate about objects using language and gesture, fusing information from multiple modalities over time. Existing work has addressed this problem in single modalities, such as natural language or gesture, or fused modalities in non-realtime systems, but a gap remains in creating systems that simultaneously fuse information from language and gesture over time. To address this problem, we define a multimodal Bayes' filter for interpreting referring expressions to objects. Our approach outputs a distribution over the referent object at 14Hz, updating dynamically as it receives new observations of the person's spoken words and gestures. This real-time update enables a robot to dynamically respond with backchannel feedback while a person is still communicating, pointing toward a mathematical framework for human-robot communication as a *joint activity* [?]. Moreover, our approach takes into account rich timing information in the language as words are spoken by processing incremental output from the speech recognition system, traditionally ignored when processing a command as an entire sentence. It quickly adapts when the person refers to a new object. We collected a new dataset of people referring to objects in a tabletop setting and demonstrate that our approach is able to infer the correct object 90%. Additionally, we demonstrate that our approach enables a Baxter robot to provide back-channel responses in real-time.**

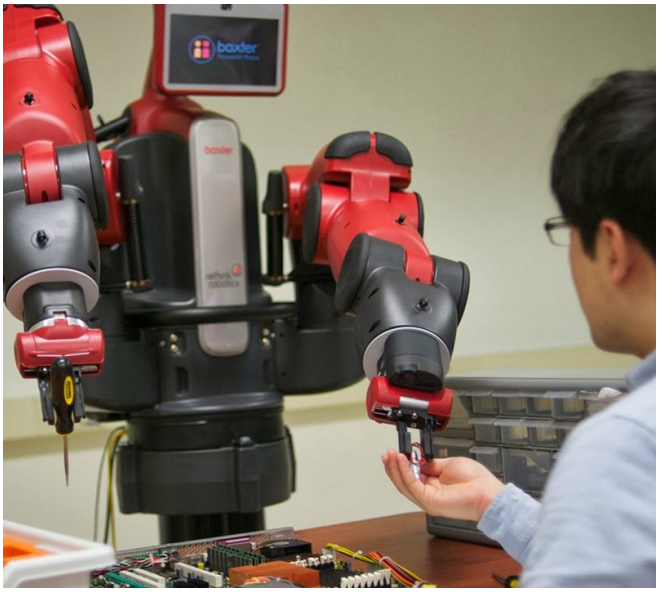


Fig. 1. Robots that collaborate with people need to understand their references to objects in the environment. For example, if a person asks for a tool using language and gesture, the robot needs to interpret the person's reference in order to pick up the correct tool.

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. **?** 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. 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 robot is confused.

Despite the importance of real-time response to multimodal input, existing unimodal models do not integrate information from language and gesture [**???**] , even though people fluidly use language and gesture together. Approaches that fuse information from language and gesture [**?**] 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.

To provide a foundation for these capabilities, we propose a Bayes' filtering approach for interpreting multimodal information from language and gesture [**?**]. 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. Additionally, we demonstrate a robot providing backchannel responses in real-time to a person's language and gesture input.

II. RELATED WORK

? 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 refers to the process of two conversational participants establishing joint understanding about the beliefs of the others[1]. 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 [**????**]. This work does not take into account the continuous nature of natural language input, and requires sentences or at least chunks of words understanding can take place. Our approach, in contrast, incorporates information from each word as it is processed by the speech recognition system, integrating word information over time and fusing it with gesture information. **?** presents a framework for interpreting open-domain references to objects but focuses on interpreting language rather than language combined with gesture. **?** 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 **?** 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" [**??**] 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.

? 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.

POMDP-approaches to dialog **??** have been extended to incorporate gesture and noise models, and our approach is related to these types of belief updates. We are eager to explore enabling a robot to adaptively respond to its estimate of which object a person is referring to, leading to backchannels.

? created a framework enabling a robot to produce gesture. Similarly, **?** described an approach for enabling a robot to generate language by inverting a semantics framework. Our long-term 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 [**?**], 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:

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

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

Algorithm 1 shows pseudocode for our approach.

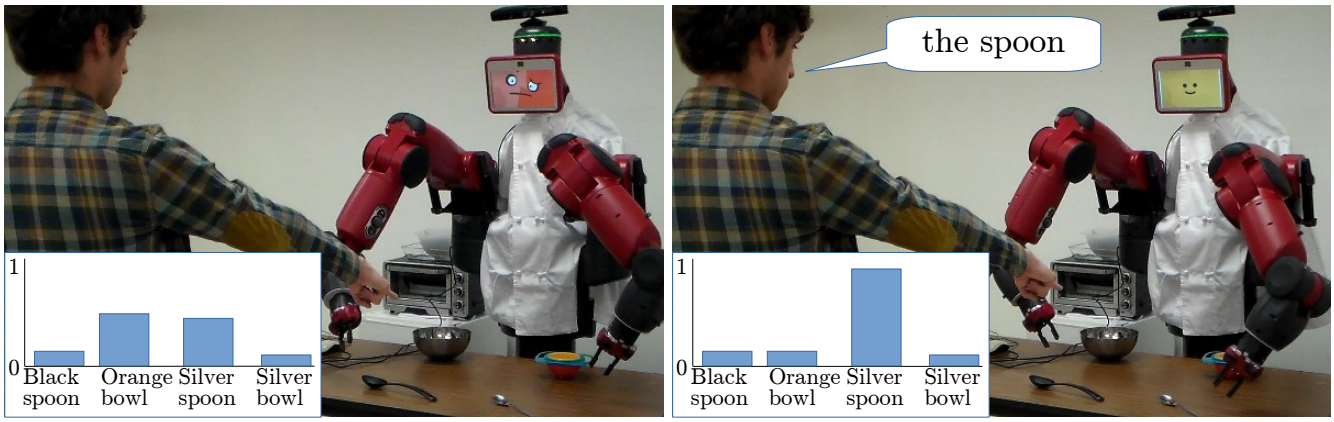
A. Prediction Model

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:

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

ST: move to model parameters and give the value ME: Do you just want this line moved? — In our experiments, c **has a value of 0.005**. 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.

[1]Note that common ground is in dialog is distinct from *symbol grounding* proposed by **?**, which is the problem of mapping from language to aspects of the external world.



(a) Ambiguous gesture.

(b) Clarification with language.

Fig. 2. After an ambiguous gesture, the model has a uniform distribution between two objects (a). The robot responds by indicating confusion. Clarification with language causes a probabilistic update leaving the model highly confident it has inferred the correct object (b). The robot responds by smiling and pointing to the correct object.

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.

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 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

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

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

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.

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

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

To account for continuous gesture and non-continuous speech input, we have both null poses and speech. 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. While gesture remains a continuous input throughout the entire interaction, many gestures have little or no meaning. To allow for these without overloading the model with noise, we also calculate the angle between each arm vector and each foot. If the angle between the arms and a foot is smaller than the angle between the arms and any object, we assume that the user is in a resting pose, and treat that gesture as indicating uniform probability over all states.

D. Model Parameters

We tuned model parameters by hand, using trial and error with several subjects to fine tune them. We considered collecting and annotating a data set to train the model parameters, however with the subjectivity of gesture, we found our initial process both accurate and expedient. We generated the language model by hand, adding to it based on results of our first user studies. We expect that as we add larger sets of objects, a language model trained using data from Amazon Mechanical Turk will be necessary to increase

robustness over a larger set of objects. In our experiments, we had the following parameters: Transition probability was 0.0005. This was determined to give an object that has 100% confidence a 5-10% drop in confidence per second with no input. Standard deviation for the Gaussian used to model probability of gesture was 1.0 radians. We found that this standard deviation allowed for accurate pointing, without skewing the probabilities during an arm swing. For example, if you point at an object behind another object, you must swing your arm to point at the front most object along the way. A standard deviation prevented these probabilities from moving so quickly that rapid arm movements were considered accurate. Epsilon for the language model was set to 0.0001. We found that tuning this had little effect due to the size of our language model. The language model was relatively small, containing hand generated common descriptors for the objects used such as "bowl", "spoon", "metal", "shiny", etc. It also included words that were commonly misinterpreted, such as "bull" when the user was requesting a bowl. Using these descriptors and the specified epsilon, we trained a unigram language 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, and the system initially infers an approximately bimodal distribution between the orange bowl and silver spoon. The robot indicates it has not understood by showing a confused face. This reaction elicits a disambiguating response from the person, who says, "the spoon." The model incorporates information from language and infers the person is referring to the silver spoon. The robot indicates it has understood with a facial expression and by pointing to the correct object. Note that the person's linguistic response was itself ambiguous, but provided complementary information to the person's gesture, leading to overall success at interpreting their intent.

TABLE I

SIMULATION RESULTS

	$\sigma^2 = 0.5$	$\sigma^2 = 1.0$
Language alone	36.5%	37%
Head alone	50.9%	35.8%
Arms alone	62.4%	42.1%
Language and gesture	65.7%	54.1%

Fig. 3. Scene from our dataset.

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 14Hz, including a 30Hz sleep cycle, on an Asus machine with 8 2.4 GHz Intel Cores that is also performing all perceptual and network processing.

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[2].

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, as you can see in the table when we increase the sample variance.

B. Real-World Corpus-Based Results

Our real-world experiments measured our algorithm's performance when a person referred to an object visually and

[2]video reference

TABLE II

REAL-WORLD RESULTS

Random	25%
Language only	32.4% +/- 10%
Gesture only	73.12% +/- 9%
Head only	21.67% +/- 10%
Multimodal (Language and Gesture)	**81.99% +/- 5.5%**
Multimodal (All)	64.84% +/- 8%

TABLE III

REAL-WORLD RESULTS (END OF INTERACTION)

Random	25%
Language only	46.15%
Gesture only	80.0%
Head only	18.46%
Multimodal (Language and Gesture)	**90.77%**
Multimodal (All)	61.54%

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 [**?**]. 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 **??**al 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 showing the percent of the time the estimated most likely object was the true object appear in Table II with 95% confidence intervals. Additionally, we display accuracy at the end of an interaction in III. These results and confidence intervals are the results of 65 trials, where each trial is one object being referenced for some time. Each test subject performed several trials in succession to simulate real world interactivity such as shifting focus from one object to another.

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 pre-specified object models. Additionally we aim to enable the robot to generate back-channel feedback based on its model. **?** created a framework for generating legible gesture, and we anticipate that enabling a robot to respond by pointing as in **?** 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 **?** of language as joint activity.