Using On-Line Conditional Random Fields to Determine Human Intent for Peer-To-Peer Human Robot Teaming

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Peer-to-Peer Human-Robot Teaming

We want Human-Robot teams where humans and robots ... 

▶ work together as partners.  
▶ work together in a way that human-only teams work together. 
  ▶ No explicit commands. (i.e. Go there, do this) 
  ▶ Work using implicit communication and coordination.
Test Domain

We use a *site clearing* and *box pushing* domain common in multi-robot system research. However, with a twist!

- Boxes first begin in random positions
- Push the boxes into one of three goal positions:
  1. Into a line
  2. To the walls
  3. Into Groups (of like colored boxes)
- When done, pick a new goal

![Diagram with three goals: To Line, To Wall, To Groups]
Example Sequence

Using On-Line Conditional Random Fields (CRFs) to Determine Human Intent for Peer-To-Peer Human Robot Teaming
Our Classifier

So what we want is a classifier that:

- can determine the human’s goal, as quickly as possible.
- runs “on-line” as the human is working.

So that (in future work)

- the robot(s) knows the human’s goal.
- the robot(s) can come help the human complete his/her task.
### For Example...

presvid/two-humans.m4v
Outline

Introduction

Related Work

Approach

Evaluation

Conclusions & Future Work

References

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Related Works

- **Sliding Autonomy** [Dias et al., 2008, Marble et al., 2004]
  - Common for “Peer-to-Peer” Teaming
  - Human is not in the same workspace
  - Human is used when robot doesn’t know what to do

- **Shared Workspace Interaction** [Hoffman and Breazeal, 2004]
  - Human and robot work in same workspace
  - Focuses on very social interaction, talking, gestures, etc.

- **Activity Recognition of Robots** [Vail et al., 2007]
  - Determines the role of a robot using two-dimensional positioning data
  - Does not work “on-line” labels data after the fact.
Outline

Introduction

Related Work

Approach

Evaluation

Conclusions & Future Work

References
Architecture

- Input: Vector of features (to be defined) twice per second
- Output: Classification Label associated with each input vector.
Use Conditional Random Fields

- Undirected Graphical Model
- Models the conditional Probability of $P(Y|X)$ for every label given the observation.

HMM-Like CRF Model

- Single feature for each state-state pair $(y', y)$ and state-observation pair $(y, x)$ in the data set used to train CRF.

Compared to a Hidden Markov Model:

- No effort wasted on modeling the observations
- Also no unwarranted independence assumptions
Three different sets of Features

- $f_{\text{simple}}(t, S)$: Simple Features
- $f_{\Delta}(t, w, S)$: $\Delta$ Features
- $f_{\text{Indicator}}(t, S)$: Indicator Features
Simple Features

- $f_1(S[t]) = \text{Error To Line Fit}$
- $f_2(S[t]) = \text{Average distance to nearest wall}$
- $f_3(S[t]) = \text{Average distance to the centroid of like-colored boxes}$

Figure: Error to Line Fit
Features

- 1:1 Mapping of Simple Features
- Difference of each Simple feature over a time window
- Captures which feature is changing the most

\[ f_{\Delta}(t, w, S) = \{ f_i(S[t]) - f_i(S[t - w]) \}, \forall f_i \in f_{\text{simple}} \]
Indicator Features

Binary 0/1 feature indicate if a certain condition is met:

- $f_4(S, b) = I(b \text{ boxes within } S \text{ are within threshold of each other})$
- $f_5(B_p) = I(p^{th} \text{ last moved box was moved to within threshold of the wall})$
- $f_6(S, B_p) = I(p^{th} \text{ last moved box was moved within threshold } \epsilon_{\text{group}} \text{ of like-colored boxes in } S)$
- $f_7(\{B_p, B_{p-1}, \ldots, B_{p-b}\}) = I(\text{Last } b \text{ moved boxes were pushed within threshold of a line})$

Figure: Indicator Feature: Within Threshold
Outline

Introduction

Related Work

Approach

Evaluation

Conclusions & Future Work

References
Dataset

Our data comes from two datasets:

- **Simulated Environment**
  - Human moves boxes in a computer window by dragging them with the mouse

- **Real World Environment**
  - Human moves actual boxes tracked with overhead camera system using ARToolKitPlus.
Simulated Environment

Figure: The Simulated Environment
Real World Environment

presvid/realworld.mpeg
Metrics

- **Accuracy**
- **Time To Correct Classification (TTCC)**
  - the time required after a goal change to successfully steadily classify the humans goal.
  - i.e. If correct classification occurred at 3 and then incorrect until 5 seconds, and stays correct onward, the TTCC would be 5 seconds.

Example:

<table>
<thead>
<tr>
<th>Time:</th>
<th>-2</th>
<th>-1</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual:</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Classified:</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

Results in a TTCC of 3, even though a correct classification occurs at time 1.
Comparisons

Simulated Environment
- CRF
- Decision Tree

Real World Environment
- CRF
- Decision Tree
- Human Classification
Real World Environment: Human Classification

- 5 Test Subjects
- Could see tracker results (not the video)
- Average Accuracy: 72.2%
- Average TTCC: 11.6 Seconds

Table: Results of human classification of the Physical experiments, in terms of Accuracy and Time to Correct Classification (TTCC)

<table>
<thead>
<tr>
<th>Subject</th>
<th>Avg. Accuracy</th>
<th>Accuracy SD</th>
<th>Avg. TTCC</th>
<th>TTCC SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.66</td>
<td>0.047</td>
<td>14.5</td>
<td>6.46</td>
</tr>
<tr>
<td>B</td>
<td>0.76</td>
<td>0.043</td>
<td>9.5</td>
<td>4.79</td>
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<tr>
<td>C</td>
<td>0.72</td>
<td>0.095</td>
<td>12</td>
<td>8.74</td>
</tr>
<tr>
<td>D</td>
<td>0.71</td>
<td>0.047</td>
<td>12.5</td>
<td>10.10</td>
</tr>
<tr>
<td>E</td>
<td>0.76</td>
<td>0.043</td>
<td>9.5</td>
<td>4.08</td>
</tr>
</tbody>
</table>
Accuracy: Decision Tree

Decision Tree Classification Accuracies for Simulated Environment data

Decision Tree Classification Accuracies for Physical Environment data

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TTCC: Decision Tree

**Decision Tree - Simulated Environment Data**

- Simple + Δ Features
- Δ Features
- Simple + Δ + Indicator Features
- Δ + Indicator Features
- Human Classification

**Decision Tree - Physical Environment Data**

- Simple + Δ Features
- Δ Features
- Simple + Δ + Indicator Features
- Δ + Indicator Features
- Human Classification

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Simulated Environment: CRF

- With Full Sequence, almost 90% accuracy on average.
- With On-Line Classification, about 75% accuracy.
- Models with Indicator features outperform Simple + Δ model for \( w > 6 \)

![Graphs showing classification accuracies for Simulated data with full sequence and on-line classification.](image-url)
Simulated Environment: TTCC

- TTCC Much lower for CRF then for Decision Tree.
- Decision tree classifications much “noisier”
Real World Environment: CRF

- CRF can do much better when it can see the full sequence
- With On-Line Classification, Indicator features seem to not improve performance
Real World Environment: TTCC

- CRF performs with a much lower TTCC.
- CRF performs closely to Human's TTCC.
Timing Diagrams

CRF Classifications Simple and $\Delta$ Features $w = 1s$

Decision Tree Classifications $w = 6s$

CRF Classifications All Features $w = 1s$

Human Subject D

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Introduction

Related Work

Approach

Evaluation

Conclusions & Future Work

References
Conclusions

For Simulated Environment:

▶ Simple + Δ + Indicator features perform the best
▶ CRF outperforms Decision tree in terms of TTCC, but not accuracy

For the Real World Environment:

▶ Simple + Δ performs same as Simple + Δ + Indicator Features.
▶ CRF outperforms Decision Trees with respect to TTCC.
▶ CRF Performs ”closely” to Human classification.
Future Work

- From using this work, have the robot(s) respond and be helpful to the human, like a second human would be.
- We are looking at how human-human teams work together to solve this task as training data to train a robot to work in place of the ”helper” human.
- Hope to improve Indicator features by doing better tracking of human.
Box Pushing

P2P-Robot-Right-2x.mpeg
Outline

Introduction

Related Work

Approach

Evaluation

Conclusions & Future Work

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