AN ARCHITECTURE FOR UNDERSTANDING INTENT USING A NOVEL HIDDEN MARKOV FORMULATION

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Understanding intent is an important aspect of communication among people and is an essential component of the human cognitive system. This capability is particularly relevant for situations that involve collaboration among multiple agents or detection of situations that can pose a particular threat. In this paper, we propose an approach that allows a physical robot to detect intentions of others based on experience acquired through its own sensory-motor capabilities, then using this experience while taking the perspective of the agent whose intent should be recognized. Our method uses a novel formulation of Hidden Markov Models (HMMs) designed to model a robot's experience and interaction with the world when performing various actions. The robot's capability to observe and analyze the current scene employs a novel vision-based technique for target detection and tracking, using a non-parametric recursive modeling approach. We validate this architecture with a physically embedded robot, detecting the intent of several people performing various activities.

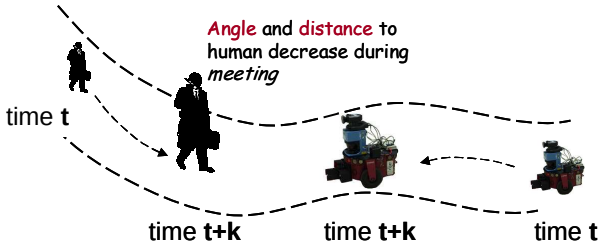
1 Introduction

The ability to understand the intent of others is critical for the success of communication and collaboration between people. In our daily interactions we rely heavily on this skill, which allows us to "read" other people's minds. While people are very good at recognizing intentions, endowing a robot with similar skills is a more complex problem, which has not been sufficiently addressed in the field. If robots are to become effective collaborators in human environments, their cognitive skills must include mechanisms for inferring intent, which allow them to understand and communicate with people at or close to their level. In this paper, we propose a method that targets the development of such capabilities.

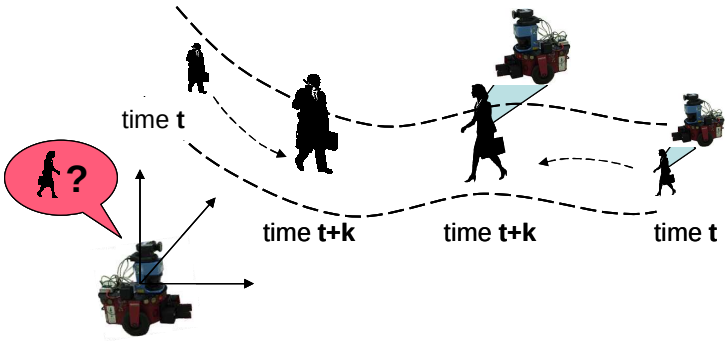
The general principle of understanding intentions that we propose in this work is inspired from psychological evidence of a Theory of Mind [1], which states that people have a mechanism for representing, predicting and interpreting each other's actions. This mechanism, based on taking the perspective of others [2], gives people the ability to infer the intentions and goals that underlie action [3][4]. We base our work on these findings and we take an approach that uses the observer's own learned experience to detect the intentions of the agent or agents it observes.

Humans are continuously exposed to sensory information that reflects their actions and interactions with the world while performing certain activities. We propose to use this experience to infer the intent of others, by taking their perspective and observing

their interactions with the world. When matched with own past experiences, these sensory observations become indicative of what our intentions would be in the same situation. We propose to model the interactions with the world using a novel formulation of Hidden Markov Models (HMMs), adapted to suit our needs. The distinguishing feature in our HMMs is that they model not only transitions between discrete states, but also the way in which parameters encoding the goals of an activity *change* during its performance. The goals are represented as abstracted environmental states, such as *distance-to-object* or *angle-to-goal*. This novel formulation of the HMM representation allows for recognition of the agents' intent well before the underlying actions are finalized. In our models, the *goals' changes* represent the *visible, observable states*, while the *hidden states* encode the *intentional goals* of the observable agents.



(a) **Activity modeling** from experience (as HMM)



(b) **Intent recognition** from own learned experience and perspective taking

Figure 1. The two stages of the architecture.

Our approach has two main stages: *activity modeling* and *intent recognition*. During the first stage the robot learns corresponding HMMs for each activity it should later recognize, from its own experiences of performing these activities. For example (Figure 1(a)), the agent observes that during a *meeting* activity the *distance* and *angle* between its heading and the direction of a person decrease as the two agents are approaching.

During the intent recognition phase (Figure 1(b)), the robot, now an observer, is equipped with the trained HMMs and monitors other agent(s)' performance by evaluating the changes of the same goal parameters, from the perspective of the observed agents.

A significant advantage of our work is that unlike typical approaches to HMMs, which are restricted to be used in the same (training) environment, our models are general and can be transferred to different domains. Even if trained in different

environments, our HMMs encode features of the activities that are identical irrespective of the domain. For example, a meeting between two agents will always be characterized by the agents approaching each other, irrespective of the place, the agents or the specifics of their goals.

The remainder of the paper is structured as follows: Section 2 summarizes related work in activity modeling and recognition, and inferring intent. Section 3 presents our novel architecture for understanding intent using HMMs and Section 4 describes the visual capabilities we developed for this work. Section 5 describes our results, and Section 6 gives a discussion of the approach and directions for future work. Section 7 summarizes our paper.

2 Related Work

HMMs are a powerful tool for modeling processes that involve temporal sequences, and have been successfully used in applications involving speech and sound. Recently, HMMs have been used for activity understanding, showing a significant potential for their use in activity modeling and inferring intent. In particular, the HMM approach has been used mostly in manipulation tasks, which lend themselves naturally to segmentation in relevant task stages, with clear discrete end-states (e.g., *object-on-table, object-in-hand,* etc.). Representative examples include learning to use a spatula and a pan [5], learning peg-in-the-hole assembly tasks [6], learning trajectory of a 7-DOF robotic arm [7], and sequences of trajectories [8]. In such training scenarios, the robot learns the transition probabilities between these states by observing the demonstration of the task performed by a human. The discrete states are linked to robot actions (e.g., *grasp, drop,* etc.), which combined with the learned HMM allow the robot to reproduce the demonstrated task. While some of the existing approaches allude to the potential of using HMMs to learn the user's intentions, these systems fall short of this goal: the approach allows detecting that some goal has been achieved only *after* observing its occurrence. However, for tight collaborative scenarios or for detection of potentially threatening situations, it is of particular importance to detect the intentions *before* the goals of the actions have actually been achieved. In the context of using HMMs for activity recognition, several approaches have addressed the problem of gesture recognition [9], with the purpose of easily controlling the actions of a mobile robot, and robot behavior recognition [10], with application to the robot soccer domain. However, these systems require that an entire sequence of actions be completed before the activity can be recognized.

An application of HMMs that is closer to our work is that of detecting abnormal activity. The methods used to achieve this goal typically rely on detecting inconsistencies between the observed activity and a set of pre-existing activity models [11][12][13]. While this approach is useful in detecting deviations from expected activity patterns, it does not provide information regarding the intent of the observed actions.

Intent recognition has also been addressed from the perspective of intent inference and plan recognition for collaborative dialog [14], but these methods use explicit information such as natural language in order to infer intentional goals. Our robotic domain relies entirely on implicit cues that come from a robot's sensory capabilities, and thus requires different mechanisms for detecting intent.

In robotics, the only existing approach for intent recognition that we are aware of has been proposed by Gray *et. al* [15]. Their solution, which is also based on perspective

taking, uses models of a robot's tasks to infer the goals and intentions of human users. The robot monitors the actions performed by the human from his/her perspective and matches them with high-level goals of its own tasks in order to infer what goals the human is trying to achieve. If the human encounters a problem, the robot is able to help the person finish the task. Thus, the method allows for detecting the intentional meanings of a human's high-level task goals (goal sequences or hierarchies). The difference in our work is that we aim at inferring intentions for lower granularity goals, such as the individual goals from [15], before the person finishes the actions meant to achieve them. Our models look at how an activity's goals are changing as the human executes it, rather than modeling a long task activity sequence.

3 General Architecture for Intent Understanding

3.1 Novel HMM Formulation

Hidden Markov Models have found greatest use in problems that have inherent temporality, to represent processes that have a time-extended evolution. In this framework, a system is represented as a set of N discrete states $\{s_i\}$. At each time step the system can be in any of these states and can transition to another state with probability $P(s_j(t+1)|s_i(t)) = a_{ij}$. Thus, a_{ij} is the probability of being in state s_j at time $t+1$, given that the system was in state s_i at time t.

However, the state of the system at time t is not directly observable. Instead, a set of visible variables (states) $\{v_i\}$, dependent upon the hidden states, is available. For each state s_j, we have a probability of observing a particular visible state v_k, given by $P(v_k(t)|s_j(t)) = b_{jk}$. In the classical HMM learning approach, a structure of the model is given (i.e., number of hidden and visible states, topology of transitions between states), along with a training data set of observations of the visible symbols. From these, the transition probabilities a_{ij} and the b_{jk} probabilities are computed.

The main contribution of our approach consists in choosing a different method for constructing the model. This new HMM formulation models an agent's interaction with the world while performing an activity, through the way in which parameters that encode the goals of the task are changing (e.g., increase, decrease, stay constant, or unknown). This is in contrast with the traditional approaches that solely model transitions between static states. With this representation, the *visible states* encode the changes in task goal parameters and the *hidden states* represent the hidden underlying intent of the performed actions.

The reason for choosing the activity goals as the parameters that are monitored by the HMM is that goals carry intentional meanings, and thus tracking their evolution is essential for detecting and understanding an agent's intent.

3.1.1 Activity Modeling

During this stage, the robot uses its experience of performing various activities to train corresponding HMMs, whose structure is currently designed by hand. The robot is equipped with a basis set of behaviors and controllers [33] that allow it to execute these tasks. We use a schema-based representation of behaviors, similar to that described in [16][34][35]. Examples of activities that we used in this work include *Following*, *Meeting* and *Passing By*. While executing these activities, the robot monitors the changes in the corresponding behaviors' goals. For example, for a *meeting* activity (Figure 2), the *angle* and *distance* to the other person are parameters relevant to the

goal, which could be {*angle* = 0 and *distance* = 1m} (i.e., "face the other person directly at 1m away). The robot's observable symbol alphabet models all possible combinations of changes that can occur: increasing (++), decreasing (--), constant (= =), or unknown (∗). For example, a visible symbol could be v_k = {*distance:* --, *angle:* ++}. The underlying intent of the actions is encoded in the HMMs' hidden states.

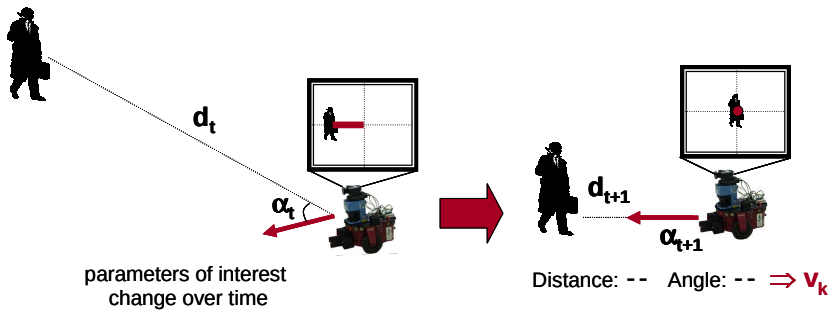


Figure 2. Activity modeling stage:
observable symbols are changes in activity goals.

Repeated execution of a given activity provides the data used to estimate the model transition probabilities a_{ij} and b_{jk} using the Baum-Welch algorithm [17]. As a result of training, the robot has a set of HMMs, one for each activity.

During the training stage, the observed, visible states are computed by the observer from its own perspective. The detection and tracking of other agents or relevant targets use the robot's on-board sensing capabilities such as the camera and the laser rangefinder, as described in Section 4.

3.1.2 Intent Recognition

The recognition problem consists of inferring, for each observed agent, the intent of the actions they most likely perform, from the previously trained HMMs. Toward this end, the robot observer monitors the behavior of all the agents of interest with respect to other agents or locations. The robot also evaluates the observable symbols for all applicable HMMs. During the recognition phase, the system computes these visible symbols in a different manner than during training. Since the observer is now external to the scene, the features need to be computed from the observed agents' perspective rather than from the observer's own point of view. These observations consist of monitoring the same goal parameters that have been used in training the HMM (e.g., change for distance to target, angle, etc.). For example, in Figure 3, in order to detect the intentions of the woman, the robot takes the following steps: (i) obtains agents' positions with respect to itself (values in black in Figure 3), (ii) transfers the coordinate system to monitored agent (the woman), (iii) computes agents' positions from woman's point of view (values in red in Figure 3), and (iv) computes observable symbols in the woman's coordinate system. The woman's heading is computed by integrating her previous positions, which helps determine the orientation of the coordinate system in step (ii).

For each agent and for all HMMs, the robot computes the likelihood that the sequence of observations has been produced by each model, using the Forward Algorithm [18]. To detect the most probable state that represents the intent of an agent we consider the intentional state emitted only by the model with highest probability. For that model, we then use the Viterbi Algorithm [19] to detect the most probable sequence of hidden (intentional) states.

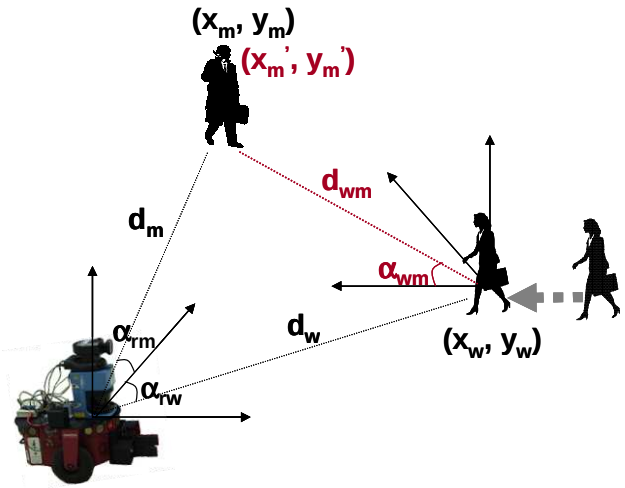


Figure 3. Intent recognition stage: the robot takes the perspective of the monitored agent. $d_{\{m,w,wm\}}$ represent distances, $x_{\{m,w,\,m'\}}$ and $y_{\{m,w,m'\}}$ represent 2D coordinates and $\alpha_{\{rm,rw,wm\}}$ represents the angle displacements w.r.t. the robot and woman.

The standard approach to recognition using an HMM relies on a clear segmentation of the observed activities and on a precise synchronization between observed sequence and the recognizing process. In our work, it cannot be assumed that this segmentation is provided, as agents' underlying behaviors are not known, and can start or change at any time. A related challenge is that the observations come as a continuous stream of measurements, rather than as a fixed sequence. In this situation the probability of a particular model decreases to zero as the length of the sequence grows. To address this problem, we chunk the observation sequences to the most recent *k* observations, similar to [9]. In our work, $k = 30$ has been empirically determined to give good results, and corresponds to a few seconds of video. For more complicated scenarios, a larger chunk size may be necessary.

4 Vision-Based Perceptual Capabilities

We provide a set of vision-based perceptual capabilities for our robotic system that facilitate the modeling and recognition of actions carried out by other agents. Specifically, we are interested in: *detection and tracking* of relevant entities, and *estimation of 3D positions* for the detected entities, with respect to the observer.

As the appearance of these agents is generally not known a priori, the only visual cue that can be used for attracting the robot's attention toward them is image motion. Although it is possible to perform segmentation from an image sequence that contains general motion (both the camera and the objects in the scene may be moving), such approaches – typically based on optical flow estimation [20], [36] – are not very robust and quite time consuming. Therefore, our approach makes significant use of more efficient and reliable techniques traditionally used in real-time surveillance applications, based on background-foreground modeling and segmentation, structured as follows:

- During the *activity modeling stage*, the robot is moving while performing various activities. The appearance models of the other mobile agents, necessary for tracking, are built in a separate, prior process where the static robot observes each agent that will be used for action learning. During this process, the agents are detected through a foreground-background segmentation technique. Once the agent model is learned the robot starts performing the designated scenarios in order to learn different actions/intentions parameters. When the robot starts moving, the background subtraction stage of the process is stopped and the robot uses an enhanced mean-shift tracking method to track the foreground object.
- During the *intent recognition stage*, we assume that the camera is static while the robot observes the actions carried out by the other agents. This allows the use of a foreground-background segmentation technique, in order to build appearance models on-line, and to improve the speed and robustness of the tracker. The stationary assumption is simply used for efficiency reasons. If the robot is moving during the *intent recognition stage* we can use the approach from the *modeling stage*.

4.1 Detection and Tracking

For tracking we use a standard kernel-based approach [21], where the appearance model for each detected region is represented by a histogram-based color distribution. The rest of this section describes our proposed method for background modeling and foreground segmentation, extensively used for the detection of these regions of interest.

The detection is achieved by building a representation of the scene background and comparing the new image frames with this representation. Motivated by the requirements of our application, we focus on building a statistical representation of the scene background that supports reliable and real-time detection of foreground objects in the scene, while adapting automatically to each scene, and being robust to natural scene variations (quasi-stationary backgrounds).

The most commonly used feature in foreground object detection is pixel intensity or color. In video sequences with stationary background, deviations of pixel intensity or color values over time can be modeled by a Gaussian distribution function. A simplistic approach is to compute the average of intensity at each pixel position, find the difference of pixel intensities at each frame with this average and simply threshold the results. Using adaptive filters for modeling gradual changes in the scene illumination is the approach employed in [22], while Kalman filtering is used in [23], and a linear prediction using a Wiener filter is proposed in [24]. Other features such as block features [25] and edge features [26] are also used to model the background.

However, because of inherent changes in the background, such as fluctuations in monitors and fluorescent lights, waving flags and trees, water surfaces, etc. the background may not be completely stationary. In the presence of these types of backgrounds, referred to as quasi-stationary, more complex background modeling techniques are required.

In parametric background modeling methods, the model is assumed to follow a specific distribution whose parameters must be determined. Mixtures of Gaussians are used in [27]; in order to find the parameters that characterize the mixtures of Gaussians, an Expectation Maximization (EM) algorithm is employed, while the adaptation of parameters can be achieved using an incremental version of the EM algorithm. A Bayesian framework that incorporates spectral, spatial and temporal features to

characterize the background appearance is proposed in [28]. In order to model the variations of the background as different states for distinct situations (e.g., sunlight vs. shadow), Hidden Markov Models are used in [29] and [30].

As opposed to this trend, one of the most successful approaches in background modeling [31] proposes a non-parametric model. The background representation is drawn by estimating the probability density function of each pixel, by using a kernel density estimation technique.

The background model. In this work, we use the more general *non-parametric modeling*, which estimates the density directly from the data, without any assumptions about the underlying distribution. This avoids having to choose a specific model (that may be incorrect or too restricting) and estimating its distribution parameters. It also addresses the problem of background multi-modality, leading to significant robustness in the presence of quasi-stationary backgrounds. At the same time, it allows enough generality for handling a wide variety of scenarios without the need to manually fine-tune various parameters for each scene type, as all thresholds used in detection are estimated during model acquisition.

However, the method described in [31] is still dependent on the number of image frames used as samples for estimating the background model. Choosing a small number of frames for the model increases speed, while it does not incorporate enough history for the pixel, resulting in a less accurate model. Increasing the number of frames improves the model accuracy but at the cost of higher memory requirements and slower convergence. This becomes apparent especially in the case of slowly changing backgrounds, where a large number of samples would be needed for accurate modeling. In general, the non-parametric kernel density estimation tends to be memory and time consuming, as for each pixel in each frame the system has to compute the average of all kernels centered at each training sample.

In order to preserve the benefits of non-parametric modeling while addressing its limitations, we propose a *recursive modeling* scheme. Our approach for background modeling employs a recursive formulation, where the background model $\theta_t(x)$ is continuously updated according to equation (1):

$$\tilde{\theta}_t(x) = (1-\beta_t)\cdot\theta_{t-1}(x) + \alpha_t \cdot H_\Delta(x - x_t) \qquad (1)$$

$$\sum_x \theta_t(x) = 1 \qquad (2)$$

The model $\theta_t(x)$ corresponds to a probability density function (distinct for each pixel), defined over the range of possible intensity (or color) values x. After being updated, the model is normalized according to equation (2), so that the function takes values in [0,1], representing the probability for a value x at that pixel to be background. This recursive process takes into consideration the model at the previous image frame, and updates it by using a kernel function (e.g., a Gaussian) $H_\Delta(x)$ centered at the new pixel value x_t.

In order to allow for an effective adaptation to changes in the background, we use a *scheduled learning* approach by introducing the learning rate α_t and forgetting rate β_t as weights for the two components in equation (1). The learning and forgetting rates are adjusted online, depending on the variance observed in the past model values. This schedule makes the adaptive learning process converge faster, without compromising

the stability and memory requirements of the system, while successfully handling both gradual and sudden changes in the background, independently at each pixel.

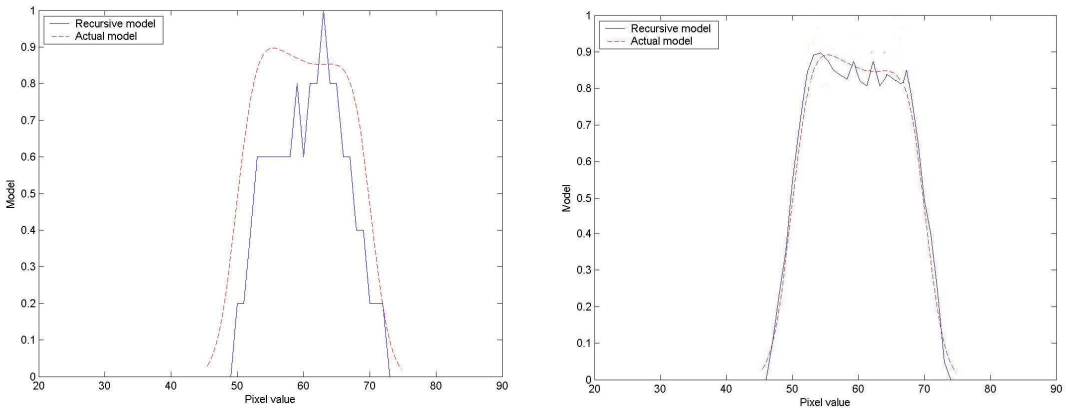


Figure 4. Model evolution after 10 frames (left) and 100 frames (right).

Results. Figure 4 shows the updating process using our proposed recursive modeling

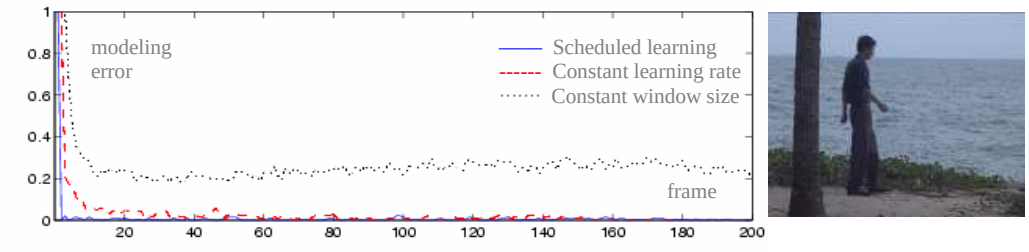


Figure 5. Convergence speed.

technique. It can be seen that the trained model (solid blue line) converges to the actual one (dashed red line) as new samples are introduced. The actual model is the probability density function of a randomly generated sample population and the trained model is generated by using the recursive formula presented in equation (1).

Figure 5 illustrates the convergence speed of our approach with scheduled learning,

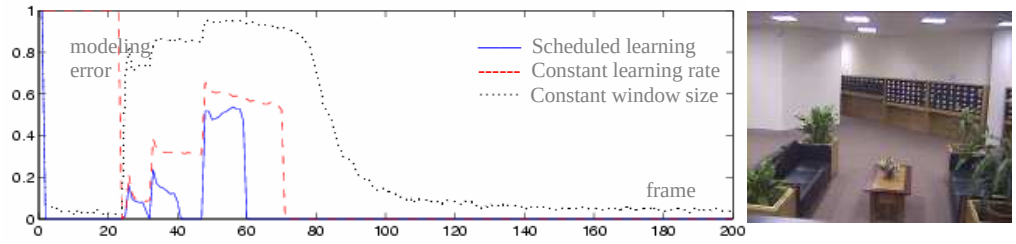
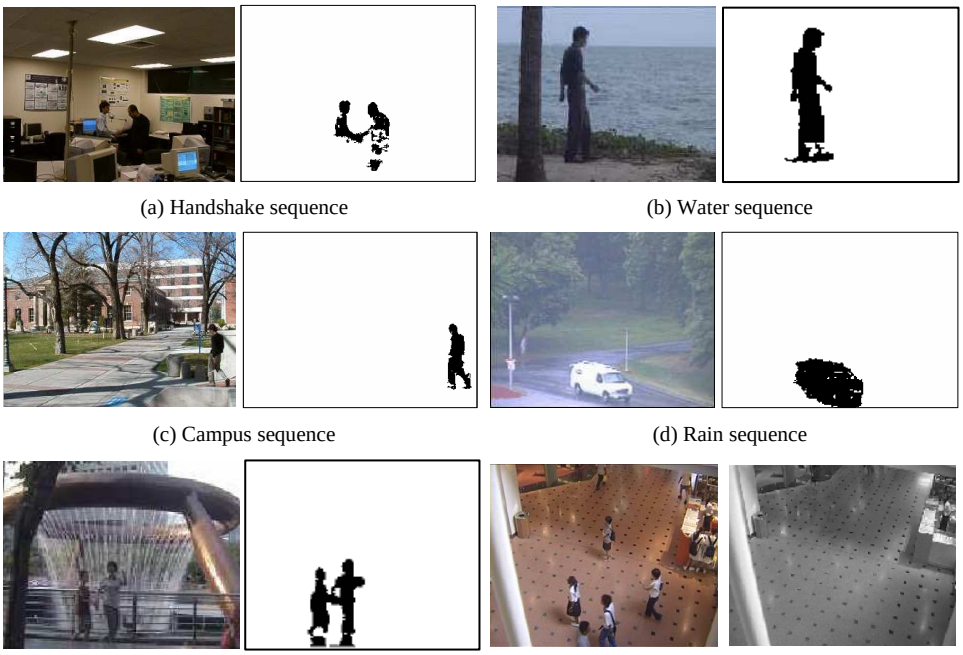


Figure 6. Recovery speed from sudden global changes.

compared to constant learning and kernel density estimation with constant window size.



(a) Handshake sequence (b) Water sequence

(c) Campus sequence (d) Rain sequence

(e) Water fountain sequence (f) Non-empty background (model at 50 frames)

Figure 7. Background modeling and foreground detection in the presence of quasi-stationary backgrounds.

Figure 6 compares the same three approaches in terms of recovery speed after sudden global illumination changes (three different lights switched off in sequence).

Results on several challenging sequences are illustrated in Figure 7, showing that the proposed methodology is robust to noise, gradual illumination changes or natural scene variations, such as local fluctuating intensity values dues to monitor flicker (a), waves (b), moving tree branches (c), rain (d) or water motion (e). The ability to correctly model the background even when there are moving objects in every frame is illustrated in Figure 7(f).

Quantitative estimation. The performance of our method is evaluated quantitatively

Video Sequence	MR	LB	CAM	SW	WS	FT	**Avg**
Proposed approach	0.92	0.87	0.75	0.72	0.89	0.87	**0.84**
Statistic modeling [28]	0.91	0.71	0.69	0.57	0.85	0.67	**0.74**
Mixture of Gaussians [27]	0.44	0.42	0.48	0.36	0.54	0.66	**0.49**

Table 1. Quantitative evaluation and comparison to different methods. The video sequences are Meeting Room, Lobby, Campus, Side Walk, Water Surface and Fountain.

on randomly selected samples from different video sequences, taken from [28]. The metric used is the *similarity measure* between two regions *A* and *B*, defined as $S=[A\cap B]/[A\cup B]$, where region *A* corresponds to the detected foreground, while region *B* corresponds to the true foreground. This measure is monotonically increasing with the similarity of the two foreground masks, with values between 0 and 1.

Table 1 shows the similarity measure for several video sequences where ground truth was available, as analyzed by our method, the mixture of Gaussians described in [27], and the statistical modeling proposed in [28]. It can be seen that the proposed approach clearly outperforms the others, while also producing more consistent results over a wide range of environments. We also emphasize that in the proposed method the thresholds are estimated automatically (and independently at each pixel), and there is no prior assumption needed on the background model.

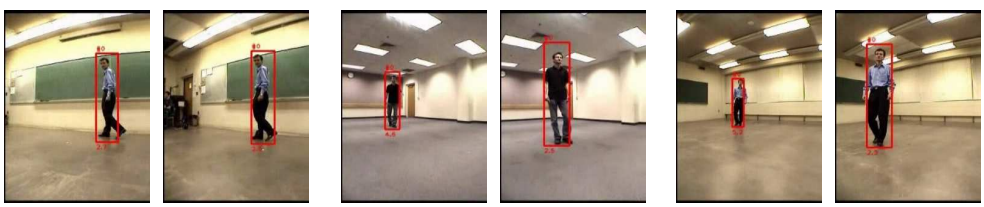
The proposed approach for background-foreground segmentation has the following benefits:

- The recursive formulation allows reliable convergence to the actual background model, without the need to specify a temporal sliding window, while being suitable for slow changes because of its low (and constant) memory and processing time requirements.
- The scheduled learning scheme achieves a high convergence speed, and a fast recovery from expired models, allowing for successful modeling even for non-empty backgrounds (when there are moving objects in every frame); its adaptive localized classification leads to automatic training for different scene types and for different locations within the same scene.

4.2 Estimation of 3D Positions and orientation

We employ the robot-mounted laser rangefinder for estimating the 3D positions of detected agents with respect to the observing robot. For each such agent, its position is obtained by examining the distance profile from the rangefinder in the direction where the foreground object has been detected by the camera. It is assumed that agents face toward the direction of travel. This allows orientation to be estimated using observed changes in position. If the agent maintains a static position, the last known orientation will be preserved until motion resumes.

For the intent recognition stage, once the 3D position and orientation of each agent is known with respect to the camera, a simple change of coordinates allows the observing robot to take the perspective of any participating agent, in order to map its current observations to those acquired during the action learning stage.



(a) Follow (b) Meet (c) Pass

Figure 8. Activity modeling stage.

5 Experimental Results

To validate our approach we performed experiments with a Pioneer 2DX mobile robot, with an onboard computer, a laser rangefinder and a PTZ Sony camera. While we experimented with a mobile robot and not a humanoid, our approach is independent on the platform as it provides cognitive capabilities that are necessary for and that translate directly to a humanoid robot. The experiments consisted of two stages: the activity modeling phase and the intent recognition phase. The frame rate of the system in both activity modeling and intent recognition phases is about 15 frames per second.

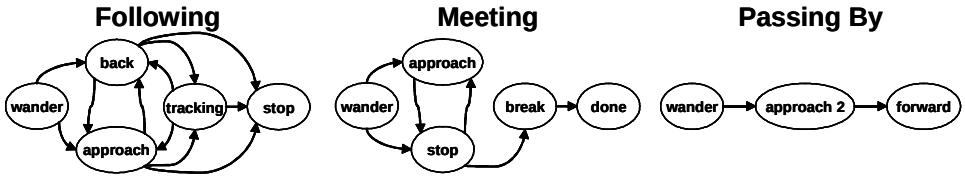
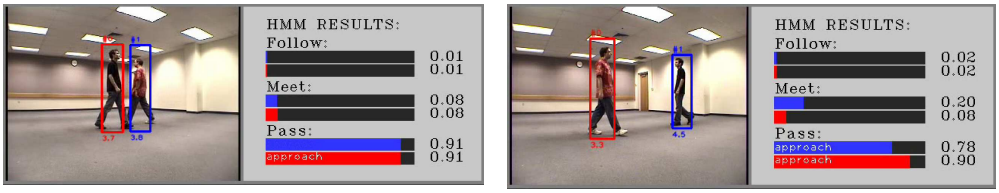


Figure 9. HMM structure for the three activities.

(a) Follow

(b) Meet



(c) Pass

Figure 10. Intent recognition for different activities.

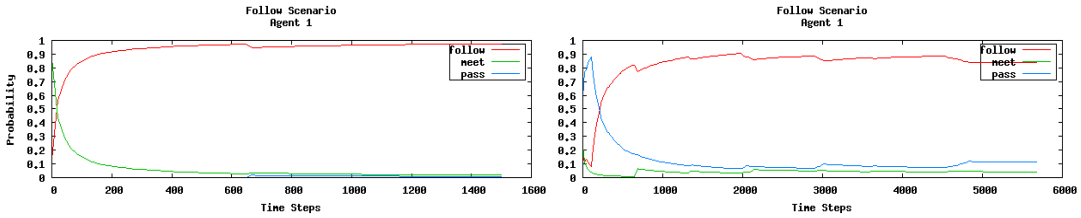
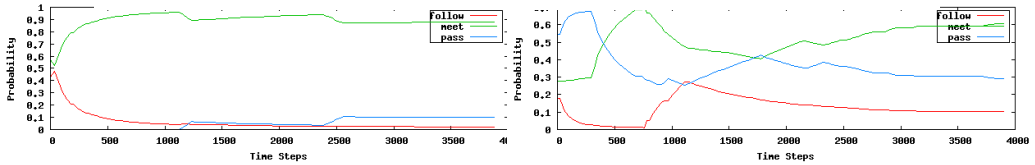
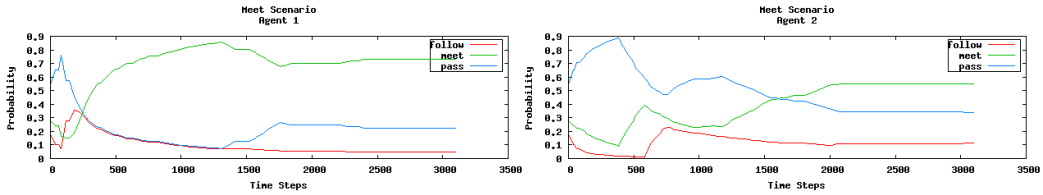


Figure 11. Model probabilities during the two *following* scenarios.

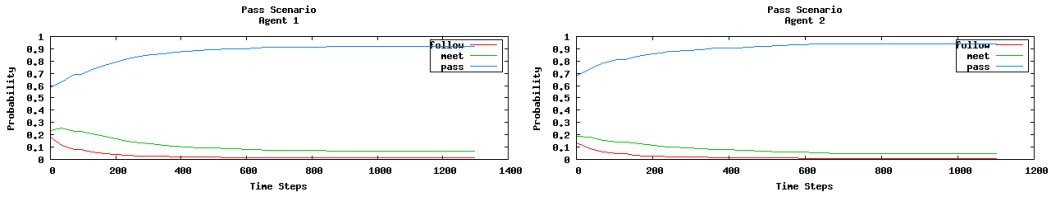


(a) Viewpoint 1

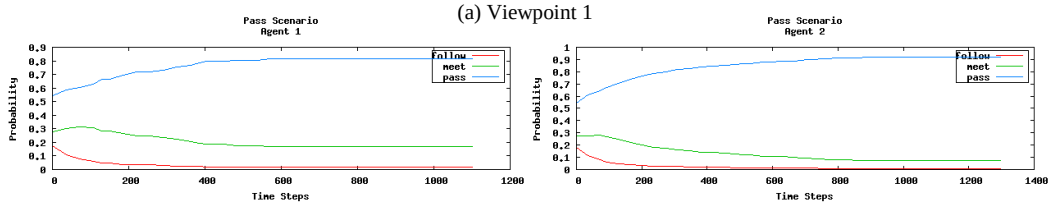


(b) Viewpoint 2

Figure 12. Model probabilities for the two people during the two *meeting* scenarios.



(a) Viewpoint 1



(b) Viewpoint 2

Figure 13. Model probabilities for the two people during the two *passing by* scenarios.

During activity modeling, the robot equipped with controllers for *following*, *meeting* and *passing by* a person performed several runs of each of the three activities. Figure 8 shows sample frames from the robot's perspective during this stage together with the tracking results. The observations gathered from these trials were used to train the HMMs represented in Figure 9, as explained in Section 3.1.1. The goal parameters

monitored in order to compute the observable symbols are the distance and angle to the human, from the robot's perspective.

During intent recognition, the robot acted as an observer of activities performed by two people in five different scenarios, which included *following, meeting, passing by,* and two additional scenarios in which the users switched repeatedly between these three activities. We performed each of the first three scenarios twice, to expose the robot to different viewpoints of the activities and thus to show the robustness of the intent recognition mechanism with varying environmental conditions. The goal of the two complex scenarios is to demonstrate the ability of the system to infer a change in intent as soon as the agents switch from one activity to another.

During each scenario, we recorded the probability that the models produced the observations, for each of the three HMMs. Figure 10 shows snapshots of the detection and intent recognition for the two runs of each scenario from different viewpoints. Under each detection box we show the computed distance from the robot. The blue and red bars correspond to the blue and respectively red-tracked agent. The length of the red and blue bars represents the cumulative likelihood of the models up to that point in time, and the text inside the bars indicates the intentional hidden state of the highest likelihood model.

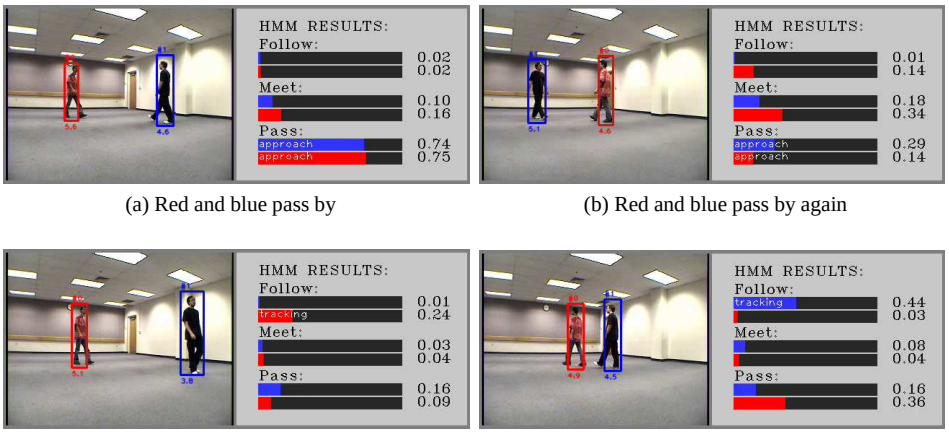
Figure 11 through Figure 13 show the likelihoods of each model at each time step over the course of one video sequence. One time step corresponds to one frame of the sequence. The figures show that the robot is able to infer the correct activity and intent for the *following*, *meeting*, and *passing by* scenarios: the probability for the correct model rapidly exceeds the other models, which have very low likelihoods. Videos available on-line also show the detected hidden states of the most probable model.

For the *following* scenarios (Figure 11), we only present the intent of the person who is performing the following. For the other scenarios (Figure 12 and Figure 13), we show the intent of both people involved in the activities: the robot is able to detect that both have similar intentions, either related to *meeting* or *passing by*.

In the complex scenarios, the two subjects performed the following sequence of activities (agent 0 is tracked in red, agent 1 is tracked in blue):

- Scenario 1: pass by, meet, red follows blue, blue follows red
- Scenario 2: pass by, pass by, blue follows red, red follows blue

During these runs, the system was capable to quickly adapt to changes in people's activities and detect the correct intentional state of the agents, as shown in Figure 14. Although the activities follow each other continuously, the system does not require an explicit indication of when these start or end. The model with the highest current probability is that for which the graph bars has a label indicating the hidden state (such as tracking or approach).



(a) Red and blue pass by

(b) Red and blue pass by again

(c) Red follows blue

(d) Blue follows red

Figure 14. Results from complex scenario 2.

To provide a quantitative evaluation of our method we analyze the following three measures, typically used in evaluating HMMs: *accuracy rate*, *early detection* and *correct duration* [32]:

- *Accuracy rate* = the ratio of the number of observation sequences, of which the winning intentional state or activity matches the ground truth, to the total number of test sequences
- *Early detection* = t^*/T, where T is the length of the observation sequence and $t^* = min\{t|\ \Pr(winning\ intentional\ activity)$ is highest from time t to $T\}$
- *Correct duration* = C/T, where C is the total time during which the intentional state or activity with the highest probability matches the ground truth.

For a reliable recognition, the system should have high *accuracy rate*, small value for *early detection* and high *correct duration*. The accuracy rate of our system is 100%: all 10 intent recognition scenarios – 2 for following, 4 for meeting (for both agents) and 4 for passing by (for both agents) – have been correctly identified. Table 2 shows the values for early detection and correct duration for these experiments. For all except two cases, the robot inferred the correct intent of actions before less than 10% of the activity had been executed, and in five of the cases the correct intent was detected right from the start (*early detection* = 0). As expected, the *correct duration* for these cases had very high values, with the majority over 90%. The only two cases that produced worse results occurred when inferring the intent of

Scenario	Early detection [%]	Correct duration [%]
Follow 1	1.23	98.771
Follow 2	3.70	96.30
Meeting 1 – agent 1	0	100
Meeting 1 – agent 2	47.25	86.09
Meeting 2 – agent 1	8.24	91.76
Meeting 2 – agent 2	52.45	47.55
Passing by 1 – agent 1	0	100
Passing by 1 – agent 2	0	100
Passing by 2 – agent 1	0	100
Passing by 2 – agent 2	0	100

Table 2. Quantitative evaluation of results.

agent 2, during the two meeting scenarios. In the first case (Figure 12(a)), the robot had inferred the correct intent very early on, but had a brief moment when *pass by* seemed more likely at some point during the middle of the run. For most of the scenario, however, the robot correctly inferred that the agent's intent is for meeting (correct duration = 86.09%). In the second case (Figure 12(b)), the robot had mistaken the meeting activity with a pass by, but only from the perspective of the second agent. Toward the end, however, the robot detects the correct intent as *meet* becomes the model with the highest likelihood. From our analysis of the data we observed that this result is due to small variations in computing the observable symbols from agent 2's perspective and due to the high similarity between meeting and passing by.

6 Discussion

The above experiments demonstrate that the robot is able to reliably detect the correct intentional meanings of people's actions from a very early stage. By modeling the interaction of an agent (human or robot) with the environment while performing an activity, we are able to distinguish between intentions that are otherwise hard to disambiguate, such as the goal of meeting somebody or simply passing them by. The differences in activities are modeled by changes in goal parameters, such as the angle and distance to the other person. If the goal is to meet somebody, the distance to that person reduces, just as the angle at which that person is in the field of view (since meeting implies facing the other person directly). However, if the goal is simply to pass by somebody, while the distance might be decreasing, the angle at which that person is in the field of view is mostly increasing. These observations are modeled as the observable symbols for our HMMs, thus encoding how the perceptual information about the world changes while performing an action.

The models above are not necessarily a complete representation of a *meeting*, *following* or *passing by* situation: additional intentional states and modalities of change for the observable states could be added for a more refined and accurate representation. For example, we could add hidden states that encode a *slowing-down* of the two agents before meeting and we could also consider varying rates of change for distance, angle and speed (e.g., fast increase, slow decrease, etc.). Additionally, we are also looking into ways for our system to automatically detect and use features that are appropriate for a given intent recognition task.

Once an intentional state has been detected, the robot can use information specific to the task to respond to that information (e.g. provide help, turn around, etc.). It is outside the scope of this paper to address this problem, which in most cases would be task specific. In our future work, we will design collaborative scenarios that take advantage of the capabilities provided by our approach.

We are currently performing experiments that involve object manipulation activities, to detect the intent of *offering* or *being offered* an object, as well as the intent of *abandoning* or *stealing* an object (such as a bag) from someone. We are also working on expanding the repertoire of activities for the robot to more complex navigation scenarios involving *hiding* or *interception.*

7 Conclusion

In this paper, we proposed an approach for detecting intent with application to the robotic domain. So far, this problem has not been sufficiently addressed, although the ability to infer others' intentions is essential for effective communication and

collaboration, and should be a key component of a robot's cognitive system. The method we proposed is based on experience acquired through the robot's own sensory-motor capabilities, then using this experience while taking the perspective of other agents. We proposed a novel formulation of Hidden Markov Models (HMMs) to encode a robot's experience and interaction with the world when performing various actions. These models are used through perspective taking to infer the intent of other agents and can perform this inference well before the agents' actions are finalized. This is in contrast with the wide spectrum of activity recognition approaches, which only detect an activity after most of its stages were done. To allow the robot to observe and analyze its environment, we developed a vision-based technique for target detection and tracking, that uses a non-parametric recursive modeling approach. We validated this architecture with a physically embedded robot, detecting the intent of several people performing multiple activities.

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