Teaching Robot Companions: The Role of Scaffolding and Event Structuring

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For robots to be more capable interaction partners they will necessarily need to adapt to the needs and requirements of their human companions. One way that the human could aid this adaptation may be by teaching the robot new ways of doing things by physically demonstrating different behaviours and tasks such that the robot learns new skills by imitating the learnt behaviours in appropriate contexts. In human-human teaching the concept of scaffolding describes the process whereby the teacher guides the pupil to new competence levels by exploiting and extending existing competencies. In addition the idea of event structuring can be used to describe how the teacher highlights important moments in the overall interaction episode. Scaffolding and event structuring robot skills in this way may be an attractive route in achieving robot adaptation, however there are many ways in which a particular behaviour might be scaffolded or structured and the interaction process itself may have an effect on the robot’s resulting performance. Our overall research goal is to understand how to design an appropriate human-robot interaction scenario where the robot will be able to intervene and elicit knowledge from the human teacher in order to better understand the taught behaviour. In this article we examine some of these issues in two exploratory human-robot teaching scenarios. The first considers task structuring from the robot’s viewpoint by varying the way in which a robot is taught. The experimental results illustrate that the way in which teaching is carried out, and primarily how the teaching steps are decomposed, has a critical effect on the efficiency of human teaching and the effectiveness of robot learning. The second experiment studies the problem from the human viewpoint in an attempt to study the human teacher’s spontaneous levels of event segmentation when analysing their own demonstrations of a routine home task to a robot. The results suggest the existence of some individual differences regarding the level of granularity spontaneously considered for the task segmentation and for those moments in the interaction which are viewed as most important.

Keywords: robot teaching, robot learning, human-robot interaction, robot task segmentation, robot event structuring, robot task scaffolding

1. Introduction

We can imagine that one day robots may truly become helpers, caregivers and even companions (Cogniron 2004) to people. To do this a robot will need to provide utility over and above that of a simple machine by employing some form of social learning whereby, through interaction with humans, it is able to dynamically modify its behaviour (for a review of socially interactive robots see (Fong et al. 2003)). Moreover it will be essential that non-expert humans are able to exploit this adaptation mechanism to mould robot behaviours to their needs. In this article we study the interaction between humans and robots specifically in robot social learning situations which focus on humans teaching robots. We do this in order to understand how to design appropriate scenarios where the robot will be

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able to intervene and elicit knowledge from the human teacher in order to better understand the taught behaviour. We start this study by first considering ideas and concepts from human-human teaching which might indicate appropriate research directions for a human-robot teaching mechanism. The concepts of scaffolding and event structuring are central to this work and these are now described in more detail.

The idea of scaffolding when used in the context of human teaching and learning comes from developmental studies in children and specifically from the Belarusian psychologist Lev Semenovich Vygotsky and the concept of the “zone of proximal development” (ZPD) in his theory of the child in society (Vygotsky 1978, 1986, Wertsch 1985). Vygotsky emphasised the idea that teaching and social interaction allow higher competence levels to be achieved through staged learning and building upon existing skills. ZPD is the gap between two competence levels. The first competence level is called the ‘actual’ development level and is the stage that a child can reach without the help of a teacher. The second is the ‘potential’ development level. This is the level that a child can attain given help and guidance of a teacher. Guiding the pupil though the zone of proximal development is called ‘scaffolding’. Vygostsky’s view emphasised the need for a more experienced teacher and the ability of the teacher to mould the child’s behaviour in order to discover and exploit new opportunities.

In previous work (Saunders et al. 2007a) this idea of scaffolding has been implemented and validated in a computational robot teaching architecture, implemented and tested on physical robots, that allows non-experts to teach a robot new skills and competencies in an open-ended way. This is achieved by firstly allowing the human trainer to create sets of robot competencies via a process of putting-through. Putting through is where the trainer physically moves the robot in a given and sometimes modified environmental state in order to allow the robot to exploit affordances via its physical effectivities (Zukow-Goldring and Arbib 2007). The robot learns new competencies based on its own grounded sensorimotor experiences, this learning ability being complimentary to both Vygotsky’s and Piaget’s (Piaget 1945/1962) view that a learner’s own activity is at the centre of the learning process. Secondly, in order to construct more complex behaviours based on previously taught components the trainer can exploit these previously taught components as available competencies. Thus further rounds of teaching guide the robot learner through each developmental zone1.

During this scaffolding process the focus is on the (human) teacher in that the teacher must be aware of the existing set of robot skills, must conceive how these skills can be exploited to create more complex behaviours and must be aware of where new skills are required and where existing skills must be extended. There is also the associated issue of how the physical environment perceived by the robot during the teaching process can be modified by the teacher in order to allow the robot to focus its attention on relevant attributes of the task. In a human-human teaching scenario this is analogous to creating purpose built teaching environments where extraneous distractions are minimised e.g. a lecture theatre or classroom. However the teacher also faces the issue of how to structure the teaching task so as to exploit the possibilities or limitations inherent in the robot’s perception and learning systems. We consider this issue as one of event structuring.

Clearly there will be many ways in which the scaffolding and event structuring of behaviours can be approached and some ways may be ‘better’ than others. In

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1 Full details of the robot control system, comparisons with other methodologies, pseudo-code etc. are available from (Saunders 2006).
examining this issue the perspective of both the robot and the human need to be considered. From the robot’s viewpoint execution efficiency of the learnt task may be important, thus a ‘better’ taught behaviour might be one which reduces processing and computation time whilst still retaining its effectiveness. In contrast, from the human teacher’s point of view the ease of teaching the robot by teaching a behaviour in only very few teaching episodes or teaching steps may be considered to be the ‘better’ approach. Although both approaches may be complimentary the interaction between the human and robot will be of prime importance. For instance, how could the robot inform the human of its existing competencies and how can it signal that more information is required? From the human viewpoint, when and where should key points in the demonstrated task be emphasised and how can the human cater for the limitations inherent within the robot’s sensory or cognitive systems?

Thomaz and Breazeal (2008) present five experiments that elucidate important points regarding how lay people would like to teach machines in explicit human teaching machines scenarios. Their work highlights how a Reinforcement Learning perspective can be informed by studies focusing on the investigation of interactions between people and machines in teaching/learning situations. The results from the first experiment show that:

- people want to be able to direct the agent’s attention towards what they regard as relevant issues during the teaching;
- people’s rewarding behaviour might serve different purposes, suggesting both instrumental and motivational issues;
- people do make the effort to acknowledge the agent’s learning needs by adapting to its learning capabilities.

These results led to the design a set of four experiments to evaluate possible enhancements to the learning/teaching procedure. Their results strongly suggest that allowing people to direct the agent’s attention when teaching, making the agent publicise its internal state, and differentiated strategies to deal with the meaning of distinct feedback from the human teacher, all have an impact on the agent’s learning efficiency and teacher’s teaching efficiency. Thomaz and Breazeal stress the need to consider a systemic perspective of the human teacher and the learning agent. Understanding the interactions and underlying meaning between the partners is crucial, particularly with non-expert users, and highlights the social nature of learning.

In this paper we explore similar issues by describing two experiments designed to explore how different event structuring and scaffolding approaches have different effects. The first experiment considers teaching a robot a task where the teacher must train the robot to visually track an (already) known object. In this experiment the effectiveness of robot learning and the ease of human teaching when following different teaching strategies is studied and the results indicate that dramatic learning and teaching efficiencies can be gained by following an alternate teaching and event structuring approach. Clearly a task can be decomposed in many ways which may lead to improved machine learning efficiencies (for an overview see for example (Mitchell 1997)). Here we are attempting to highlight how such efficiencies can be realised by both the robot in improved performance and the human in reduced teaching effort. In the second experiment we focus on the human side of the teaching process in a user study which considers in detail how humans structure teaching events by asking them to segment their own demonstrations of the teaching process. This is achieved by allowing participants to review their own robot teaching episodes and then allowing them to manually segment areas where key
explanatory points exist. The overall goal of the user study being an attempt to ascertain from the human teachers where key scaffolding and structuring points exist, this information allowing us to derive the nature and timing of the robots interventions (or feedback) in order to elicit knowledge from the teacher to enhance its understanding of the on-going teaching task.

This article proceeds in section 2 in examining in more detail background issues from human-human teaching in order to gain insights and contrast approaches here with those being carried out in human-robot teaching. We then describe in section 3 the experiments and the experimental results from the robot’s perspective. This first teaching experiment uses the robot teaching/learning system described in (Saunders et al. 2007a) and this system will be briefly described in section 3.2. The second experiment described in section 4 takes the form of a user study where participants attempt to teach a robot a common household task. In this study the robot responses are controlled by a human operator. Finally in sections 5 and 6 we draw appropriate conclusions for future human-robot teaching approaches.

2. Background

Research on human learning and building supportive computational artifacts has a long tradition in many disciplines. Although our present focus, humans teaching robots, might somehow seem to be a distinct problem space we would argue that it maintains the general research challenges. For example, duBoulay (2000) reviewing the progress of artificial intelligence in education points out challenges facing the teacher and identifies difficulties in understanding the level of consonance between the teacher’s and learner’s goals. In terms of human and robot teaching these could be construed as follows:

- how easily can the teacher clearly formulate his goals and requirements to the learner?
- how can the teacher give a good demonstration (including stating the goals and requirements explicitly and in line with the learners’ abilities)?
- how can the teacher know when to re-state a demonstration?
- when can the teacher provoke a response in order to assess the state of the learner?

In the above bullet points we stress the importance of being able to communicate efficiently the goals and requirements of the task and the need to couch the explanation to the learner. The way people perceive the unfolding of events of the teaching activity has an impact on the whole process of teaching and learning, considering the dialogical nature of the interaction cycles between teacher and learner. Furthermore, the activity of teaching also appears to involve, at least initially, some degree of planning. It seems reasonable to assume that people’s segmentation of demonstrated events can be a general indicator of:

(a) their understanding of what are the different steps of the demonstration, including goals, sub-goals and the level of detail that underlies the demonstration step, and/or
(b) what are considered to be the important moments of the overall interaction episode (for example, acknowledgement of understanding or misunderstanding from the learning partner).
Researchers investigating how people structure events consider that “Event perception can be regarded as the temporally extended analog of object perception” (Zacks and Tversky 2001, p. 5). People recognise events based on the unfolding of temporal structure, the features of objects and objects’ configurations present at a particular time-window (or time scale) within a particular space (Zacks and Tversky 2001). Similarly to objects, events can be viewed as hierarchical ensembles of parts and sub-parts that reflect the relationships between them (Zacks and Tversky 2001, Zacks et al. 2001). Furthermore, Zacks and Tversky (2001) state that people are able to use distinct time scales when considering event structure (and consequent characterisation). However, the range of the time scales is not unlimited and the saliency of the features of the event vary according to the time scale considered: “In general, it seems that as the time scale increases, events become less physically characterised and more defined by the goals, plans, intentions, and traits of their participants” (Zacks and Tversky 2001, p. 7).

Zacks et al. (2001) specifically investigated how people perceive routine events and argue that the results obtained from their experiments of event segmentation indicate that people regard events as goal-directed partonomic hierarchies (meaning that events can be decomposed into part and sub-parts and are hierarchically structured). The authors above also discovered that asking people to describe the events facilitates this hierarchical organisation and that familiarity with the event also strengthens this effect, although to a much lesser extent. Furthermore, where participants were asked to segment the events into coarse or fine detail units and then describe these units it was found that the description of coarse units defined objects more precisely than the description of fine units, but the description of fine units specified actions better.

Hard et al. (2006) investigated to what extent hierarchical encoding of events affects observational learning. Participants were asked to segment at a coarse or fine detail level a film showing an object assembly task and afterwards to assemble the objects themselves. Hard et al. (2006) found that increased hierarchical encoding led to better learning. Moreover, they also found that hierarchical encoding increased when participants started the segmentation tasks with the coarse level (taking into consideration the within-subject design of the study), paid attention to the underlying hierarchical structure and described actions while segmenting.

In considering the above issues we first demonstrate the importance of appropriate segmentation from the robot’s viewpoint. In this study the human teacher has the choice of a number of teaching strategies and we show how a parsimonious approach may provide a more optimum result for both robot and human. Taking a more human centered perspective, in the second study people were asked to segment their own demonstrations of tasks being taught to a robot. The aim of the data analysis in this study was to investigate people’s spontaneous levels of event segmentation regarding their own demonstrations of routine home tasks to a robot. Considering the exploratory nature of this study we chose to formulate the following research questions instead of fully fledged hypotheses:

(1) Can restructuring a taught task to a robot improve the robots learning effectiveness and reduce the human’s teaching effort?
(2) What are the key moments that the participants consider to be dividing points of their own demonstrations?
(3) Does the feedback from the robot stating its misunderstanding at specific points of the demonstration alter the level of detail of the segmentation and corresponding demonstration effort?
(4) Do participants report difficulties regarding specific events on their demonstrations?
(5) Do participants consider to have been influenced by the robot’s feedback?

3. The Robot Perspective - Experiments and Results

The concepts of ‘scaffolding’ and ‘putting through’ can play an important part in animal learning (Saunders et al. 2006). They support a form of ‘self-imitation’ that may be the natural precursor to more complex forms of imitative learning. Putting through describes the actions of the trainer in physically manipulating the body of the learner and self-imitation describes how the learner repeats and generalises that training in new situations. In our framework we use the idea of putting through directly. The human teacher has the ability to control the robot by remotely moving it through actions derived from a set of pre-defined basic primitives or more complex and subsequently taught competencies. A conceptually equivalent mechanism to remote control is to move the robot’s actuators by hand. This relies on the robot having appropriate proprioceptive feedback. The robot described below does not have such feedback and therefore a remote controlled tele-operation approach is taken (see (Calinon et al. 2006) for an example of a robot whose limbs are physically moved by hand). By manipulating the robot in this manner two difficult problems are avoided, firstly the observation by the robot of the human actions and secondly, the ‘correspondence problem’ (Nehaniv and Dautenhahn 2002) where the human and robot may not necessary share the same morphology and may not be able to exploit the same affordances (other approaches to the correspondence problem can be found in Alissandrakis et al. (2002), Johnson and Demiris (2004), Nehaniv (2003)).

In this experiment the overall event structuring and scaffolding choices are compared in order to assess which would benefit both the trainer and the robot. The benefit to the trainer lies in having to carry out less training and the benefit to the robot is in reduced processing. To explore this idea a set of possible training strategies are explored and analysed in an object visual tracking task where the main sensory feedback to the robot is provided by its pan/tilt unit and the vision system. We use this visual tracking task in order to provide a means whereby alternative training strategies can be explored and to emphasise how task structuring and scaffolding can play a major role in increasing the efficiency of the training regime. For this experiment, the robot is trained to visually track a coloured object by orienting its camera. The teacher trains the robot to move its camera so that from the teacher’s viewpoint, the camera is always directed at the object. The teacher does this by organising the robot’s learning experience (using the idea of putting through) by remotely teleoperating the robot pan/tilt unit. There are a number of different strategies that the teacher can employ to do this and these are considered in section 3.3 below.

3.1. Experimental Framework

The trainer teaches behaviours to a Pioneer P3-DX robot (ActivMedia Robotics). The Pioneer robot has 16 sonars, 10 bump sensors, a Canon VCC4 Video camera with a pan/tilt unit and a 5-DOF arm (see figure 1). The robot perceived state has 41 separate elements (shown in table 1) and a set of basic actions (shown in table 2). However the learning system (briefly described in section 3.2 below) is able to automatically weight attributes relevant to the trained task. The key sensory attributes in the visual tracking study are the centre point and area of a chosen object together with the current state of the pan/tilt unit. Note that all sensory
state attributes continue to be recorded. The robot, by then analysing the information gain realised when classifying the sensory state against the actions carried out, can automatically ignore sensory attributes such as sonar, bump sensors and arm proprioceptive angles. The robot is initially pre-trained to detect coloured objects before applying the learning framework. The object is detected in the camera frame using the CAMSHIFT algorithm (Bradski 1998), part of the Intel OpenCV image processing library (OpenCV 2006) (see figure 2). The algorithm returns the object XY location as a pixel coordinate pair in a 480x768 pixel image.

During the training process the robot monitors its full state vector and this full vector is paired with the teacher directed primitive actions (or higher level previously taught competencies) to form entries in each of the ‘memory models’ (see 3.2 below) that the teacher invokes. Thus each entry in a memory model represents a trainer directed action at a given robot perceived state with the memory model itself being the set of such actions representing the particular competence that the trainer wishes to teach to the robot.
Table 1. State Vector for the Pioneer Robot.

<table>
<thead>
<tr>
<th>State Component</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pan</td>
<td>Current Pan Setting</td>
</tr>
<tr>
<td>Tilt</td>
<td>Current Tilt Setting</td>
</tr>
<tr>
<td>X-value</td>
<td>Location of object in camera X-direction</td>
</tr>
<tr>
<td>Y-value</td>
<td>Location of object in camera Y-direction</td>
</tr>
<tr>
<td>Distance</td>
<td>Distance of object from camera</td>
</tr>
<tr>
<td>Size</td>
<td>Size of object tracking area</td>
</tr>
<tr>
<td>Sonar</td>
<td>Values of the 8 front and 8 rear sonars</td>
</tr>
<tr>
<td>ObjectAngle</td>
<td>Angle in degrees to nearest object</td>
</tr>
<tr>
<td>Bumpers</td>
<td>Values of the 10 bump sensors</td>
</tr>
<tr>
<td>BumpFront</td>
<td>Set if any of the front bumpers have fired</td>
</tr>
<tr>
<td>BumpRear</td>
<td>Set if any of the rear bumpers have fired</td>
</tr>
<tr>
<td>Arms</td>
<td>Angles of 6 arm joints</td>
</tr>
</tbody>
</table>

Table 2. Pre-defined Primitives for the Pioneer Robot.

<table>
<thead>
<tr>
<th>Primitive</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pan Left</td>
<td>Pan Left 5° or continuously</td>
</tr>
<tr>
<td>Pan Right</td>
<td>Pan Right 5° or continuously</td>
</tr>
<tr>
<td>Tilt Up</td>
<td>Tilt Up 5° or continuously</td>
</tr>
<tr>
<td>Tilt Down</td>
<td>Tilt Down 5° or continuously</td>
</tr>
<tr>
<td>Move Forwards</td>
<td>Move forwards 10cm or continuously</td>
</tr>
<tr>
<td>Move Backwards</td>
<td>Move Backwards 10cm or continuously</td>
</tr>
<tr>
<td>Turn Right</td>
<td>Rotate Right 5° or continuously</td>
</tr>
<tr>
<td>Turn Left</td>
<td>Rotate Left 5° or continuously</td>
</tr>
<tr>
<td>Increase Joint Angle(n)</td>
<td>Increase one of the six joint angle by 5°</td>
</tr>
<tr>
<td>Decrease Joint Angle(n)</td>
<td>Decrease one of the six joint angle by 5°</td>
</tr>
<tr>
<td>Move Arm (angle vector)</td>
<td>Move the arm to a given position using the six angles (angle vector)</td>
</tr>
<tr>
<td>Goal</td>
<td>Instruct the robot that a goal state has been achieved</td>
</tr>
</tbody>
</table>

3.2. The Learning System

The main features of the robot learning system are briefly described here, however for a complete description of this system we refer the reader to Saunders et al. (2007a).

The robot can be operated in two ‘modes’. The first is ‘execution’ mode, which is its normal mode of operation and where its current behaviour is executed. Alternatively the robot can be in ‘learning’ mode where the human trainer can ‘put through’, ‘scaffold’ and create new activities for the robot to eventually use in execution mode. The Learning mode allows the human trainer to create hierarchies of ‘memory models’. These models contain a set of environmental states paired against trainer directed actions (thus each row in the model would contain a concatenation of sensory state and the action that the human chose in that state). Thus in order to create a memory model the trainer will move or ‘put through’ the robot by signalling it to carry out an action. These actions are then paired with extero- and proprioceptive state of the robot at that time and added as an individual entry in the memory model. Each memory model will therefore contain many entries which refer to the training operations of the trainer. These memory models are labelled at creation time by the trainer via a keyboard. Once labelled the models can be used as actions in other models and thus the trainer can build increasingly complex sets of models, each model recursively executing models lower in the hierarchy. Three types of memory model can be taught and subsequently extended (or entirely removed) by the trainer, we call these ‘sequences’, ‘goal-directed tasks’ or ‘behaviours’ (figure 3 shows an example of a trained hierarchy).

The sequence type is where the robot can be directed through a given sequence
of ‘primitives’ (defined as operations which are indivisible from the viewpoint of the trainer - e.g. ‘lower gripper’, ‘turn right 5 degrees’ etc.) which it records without reference to its state i.e. sequences are entirely independent of the internal or external environment. This is similar to the ethological idea of Fixed Action Patterns where, once triggered, animals display certain sequences of movements which are independent of environmental stimuli (Tinbergen 1951). An example of a sequence might be to move the arm to a particular position. This could, for example, be labelled as the ‘readyArm’ sequence. The readyArm sequence would then become part of the available set of competencies available for the trainer to use. These new sequences could then be used in combination with other primitives and other sequences to create further sequences. Note that when requested to perform a sequence the robot will simply execute the recorded list of competencies taught by the trainer sequentially. It will make no reference to the environmental state.

The goal-directed task type differs from a sequence in that during training the actions taken by the robot will depend on the robot’s internal and external state at that time. The trainer now has the opportunity to select not only basic primitives, but sequences and other goal-directed tasks. The tasks are goal-directed because the trainer is able to inform the robot when the task has been completed with the resulting state being recorded as a target to achieve. This ‘goal’ condition is paired with the robot’s state and becomes a further training record in the memory model for that particular task. In execution mode the task is iterated until the environmental state is close to a goal state and the task will then terminate. Note that the signalling of a goal-state by the trainer to the robot does not automatically imply that teaching has stopped, it simply signals that this state is a goal-state. The trainer could continue training the robot by placing it in situations that are not goal-states. Learning only terminates once the trainer is happy with the training regime.

The behaviour type allows the trainer to construct the complete behaviour for the robot from the component set of tasks, sequences and primitives. The construction of a behaviour is the same as for a task except that no goal state is required. The behaviour will run continually in execution mode and base its decision of what task, sub-task, sequence or primitive to use on the current environmental state. A behaviour can also be used by another behaviour, task or sequence as required, the only constraint being that the hierarchy must have a behaviour as its topmost node. A key difference between a behaviour and a task is that a task will only yield control to a parent node once its goal state is reached, a behaviour will yield immediately. With careful training the trainer can now build a hierarchy of tasks, sequences and primitives as required (see figure 3).

We use a memory based “lazy” learning method (Mitchell 1997) to allow the robot to execute what it has learned. This is a k-nearest neighbour (kNN) approach where the value of each feature in the robot’s sensorimotor state vector (captured at each training action) is regarded as a point in n-dimensional space, where n is the number of features in the state vector. When the task is executed the robot continually computes its current state vector. It then computes the distance (in this case a 1-norm or Manhattan distance) from the current state to each of the training examples held in the memory model. In computing this distance we weight particular state attributes according to how well a given attribute separates the set of recorded state vectors according to the target primitive or recursive action. This weighting is calculated using ‘information gain’ (also equivalent to ‘mutual information’). Further explanations of information gain can be found in (Mitchell 1997, Quinlan 1993). The information gain measurement allows particular attributes in the state vector to have greater relevance by using it to weight the appropriate
dimensional axes in the \( k \)NN algorithm. This has the effect of either lengthening or shortening the axes in Euclidean space thus reducing the impact of irrelevant state attributes. For example during tracking of an object using the robot’s pan/tilt camera the values of the object tracking values (held as Cartesian coordinates in the state vector) may be of more relevance than the values of the sonar sensors or arm angles and thus would be more highly weighted.

This form of state attribute selection can also be enhanced by the human trainer. It is assumed that the trainer already understands the task that the robot should perform from an external viewpoint and therefore is able to construct the training environment appropriately so as to ensure that irrelevant features are removed. The modification of the environment allows the technical selection of relevant state features to be enhanced as the other features will now tend to have constant values and therefore a low information gain. This process of creating favourable conditions for learning would seem a quite natural phenomenon in social animals and is of course fundamental to all forms of human teaching. From a robotics viewpoint this could mean simple actions such as placing the robot (in this case a mobile robot) away from obstructions when teaching a visual task (and thus the sonar/obstacle detection sensor readings would be minimised). Similarly if we were teaching a robot via an audio channel (with for example spoken instructions) it would be beneficial to reduce the amount of visual activity (by keeping the head stationary on a humanoid robot for example).

### 3.3. Training Procedures

For this experiment, the robot is trained to visually track a coloured object by means of the human orienting its camera. The teacher trains the robot to move its pan/tilt unit so that from the teacher’s viewpoint, the robot’s camera is always directed at the object. The teacher is attempting to teach the robot to keep the object in view, thus as the object moves to the edge of the camera frame the teacher should instruct the robot to carry out actions which serve to bring the object back to the centre of the image. There are a number of ways in which the teacher can achieve this:
• Carry out a continuous training regime covering as many possibilities as possible. This is achieved by placing the tracked object in many parts of the camera frame and invoking the appropriate pan/tilt primitive action to centre the object in the frame. The trainer chooses to represent this teaching activity in two memory models, a behaviour and a goal-directed task. The behaviour is used to invoke the goal-directed task (in essence continually calling it). The goal-directed task contains all of the training steps directed by the human to the robot (see diagram 1 in figure 7).

• Train for the X and Y directions together in the camera frame. This can be carried out by giving many training examples in either the horizontal or vertical directions. The trainer again chooses two memory models (see diagram 2 in figure 7).

• Train for the X and Y directions separately. In this example three memory models are created. The behavioural component being used here to provide a scaffold which by providing a simple X/Y training session giving only extreme examples in each direction invokes either of the separate training regimes shown as goal-directed tasks (see diagram 3 in figure 7).

As described above three training strategies were taught to the robot. Additionally one extra strategy was also used. This latter strategy was a ‘control’ strategy which was pre-generated by a specifically written computer program. The control strategy ensured that the training memory model that was created provided exact training examples in all parts of the camera frame (see the right graph of figure 4). The strategy serves to provide a ‘best possible’ outcome for the task and as such can be used as a benchmark to compare the other strategies against. Given that the robot is making discrete moves in a given direction via the pan/tilt camera (either up/down/left or right) the ‘control’ strategy grid reflects the minimum number of elementary moves needed to move the camera to the centre of the image. Other strategies (such as going down a number of units and then left a number of units) may result in an equivalent number of elementary moves but would not result in a more efficient route to the centre. Each of these strategies is shown pictorially in figures 4, 5 and 6.

The robot is trained to move the camera to a point at the centre of the camera frame. This is achieved by initially placing the object away from the centre and then training the robot to move the camera so that it is facing the object (using only the panLeft, panRight, tiltUp and tiltDown primitives). When at the centre of the frame the teacher signals that a goal condition has been reached (using the goal primitive). The three training strategies are as follows:

(1) The robot is trained to track the object in all parts of the camera frame (the allPts-user strategy, see diagram 1 of figure 7 and the left graph of figure 4).

(2) The robot is trained to track in the X and Y planes together (the udlr-user strategy, see diagram 2 of figure 7 and figure 6).

(3) The robot is trained to track in the X plane only (the lr-user strategy) and the Y plane only (the ud-user strategy). These are then combined in a hierarchical scaffold (see diagram 3 of figure 7 and both graphs in figure 5).

All of the memory models produced were subject to attribute weighting using the Information Gain criteria (see section 3.2 above). As all of the state attributes are numeric these were first discretised using the methods proposed by Fayyad and Irani (1992). Each of the memory models were then analysed for classification performance based on stratified 10-fold cross-validation (this is where part the training set is divided randomly into 10 parts, each part repeatedly used to test the classification performance of the remaining set and the 10 error rates averaged (for
Figure 4. Training Strategies for the Visual Tracking Task. The graphs show the training points used in the tracking study. The graph on the left is labelled allPts-user and shows the teacher attempting to provide tracking primitives for the coloured object in all segments of the camera frame. The graph on the right shows a pre-programmed computer generated training session labelled control. Here all parts of the frame are covered with the correct training primitive. This strategy serves as a control against which the other training strategies can be compared.

Figure 5. Training Strategies for the Visual Tracking Task. The graphs show training using the Y or X tracking directions only. In the graph on the left the teacher trains using the tiltUp and tiltDown primitives. This is labelled ud-user. The graph on the right shows the teacher using the panLeft and PanRight primitives. This is labelled lr-user.

detailed discussion on 10-fold cross validation see (Witten and Frank 2005, p.50)). The classification method gives a numerical indication of how well each training method performs by estimating how well the recorded state vector (trained by the teacher) performs in choosing the appropriate primitive.

3.4. Results

Table 3 shows the results from the analysis. The control sample (control), as expected, gave the best estimated performance. However to achieve this level of per-
Figure 6. Training Strategies for the Visual Tracking Task. The X and Y plane training are combined into one training session labelled \textit{udlr-user}.

Figure 7. Behaviours, tasks and primitives for the Visual Tracking Task. Diagram 1 shows the \textit{allPts-user} strategy. The bulk of the training occurs in the \textit{allPts-user} task which invokes each of the primitives given the current robot state. This hierarchy is similar to that of the \textit{udlr-user} behaviour shown in diagram 2. The hierarchy for the separated X and Y plane training is shown in diagram 3. Here the same behaviour is used to invoke the tasks, however the training is further segmented into the x (or left-right) plane and the Y (up-down) plane.

Performance, a high number of very accurate training examples would be necessary and the accuracy required would be beyond the limits of human teaching. A more typical training session is shown in the \textit{allPts-user} strategy where no attempt is made to segment the task, the user takes a 'one shot' approach to training the robot. Performance drops considerably due to noise resulting from inaccuracy in
training and the number of training examples also remains relatively high. In the second strategy (udlr-user) only the X-Y plane directions are taught although these are again taught in one training session. Using only the X and Y planes relies on the generalisation mechanism underlying the classification process to operate (thus points near the diagonal planes would invoke the action represented by the training point closest to it). Fewer training examples are needed and performance improves over the allpts-user strategy as noise is reduced.

Further segmentation into separate X and Y plane teaching strategies (ud-user and lr-user) which are then scaffolded into the overall behaviour further improves performance to very near the control strategy level of control (although the overall number of training episodes remains the same as that in udlr-user). This improvement comes about because environmental scaffolding via the information gain criteria can now weight the appropriate state attributes more effectively. For the ud-user training additional weight would be given to the Y-value component in the state vector but not the X-value, similarly for the lr-user training the X-value component will be amplified rather than the Y-value. However, for the less efficient combined udlr-user strategy both have to be weighted. This degrades performance, firstly because one will inevitably receive a higher weighting than the other due to the inherent inaccuracy of the teacher, and secondly the Y weighting will adversely affect classifications made from sensor feedback in the X direction and similarly the X weighting will adversely affect those made in the Y direction.

Table 3. Predicted Classification Performance of Differing Training Strategies. The table shows the five memory models used for the visual tracking task. The first is a pre-generated control model using all of the camera segments. The second is the same strategy except as trained by a human. The third model shows training where only vertical and horizontal training is used. The fourth and fifth models break down the third model into its component horizontal and vertical directions. The '% accuracy' column shows predicted classification accuracy based on 10-fold cross-validation. The number of training steps is equivalent to the number of entries in each memory model. The k value shown is that which produced the optimal performance and was obtained through cross-validation.

<table>
<thead>
<tr>
<th>Memory Model</th>
<th>% Accuracy</th>
<th>No. Training Steps</th>
<th>k Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>control</td>
<td>98</td>
<td>975</td>
<td>7</td>
</tr>
<tr>
<td>allPts-user</td>
<td>68</td>
<td>223</td>
<td>14</td>
</tr>
<tr>
<td>udlr-user</td>
<td>86</td>
<td>123</td>
<td>2</td>
</tr>
<tr>
<td>ud-user</td>
<td>94</td>
<td>58</td>
<td>2</td>
</tr>
<tr>
<td>lr-user</td>
<td>95</td>
<td>65</td>
<td>4</td>
</tr>
</tbody>
</table>

3.5. Summary

The results presented above serve to emphasise the need for appropriate behavioural decomposition and scaffolding when training. Our original research question was:

- Can restructuring a taught task to a robot improve the robots learning effectiveness and reduce the human’s teaching effort?

From our results it would appear that appropriately segmenting the behaviour not only allows task re-use and less training time but can also serve to enhance the algorithmic effect in the environmental scaffolding process (in this case information gain). Thus the robot benefits with better performance, both on the task taught and from reduced computation via smaller memory models. The human teacher also benefits as the number of training steps is significantly reduced as compared to a direct (i.e. teach everything at once) approach. There is however the issue of how the robot can assess whether it has been taught efficiently and elicit ‘correct’
training examples. One possible direction in resolving this issue may be for the robot to compare its set of existing taught experiences against the experience it is currently being taught. This mechanism is discussed and implemented in Saunders et al. (2007a) to allow the robot to recognise novel experiences and signal the human that it already has task knowledge. An extension of this idea might be for the robot to compare the number of teaching steps or episodes between similar tasks and signal to the human that, given its past experience, the current teaching regime may be inefficient.

4. The Human Perspective - Experiments and Results

The experiment above demonstrated how effective task segmentation and scaffolding could benefit both teacher and robot. In the following experiment we take a different perspective in studying how a human could effectively structure the teaching effort. A user study was conducted with a participant sample consisting of 5 female and 6 male participants, recruited in our university through advertisement in the university’s general computer network. For this exploratory study the number of participants was considered suitable in order to provide input for future studies involving larger numbers of subjects. None of the participants were familiar with our general research aims or specifics of the present study.

The study took place at the University of Hertfordshire ‘Robot House’ (see section 4.2 below) and a ActivMedia PeopleBot robot (ActivMedia Robotics) was used as the interaction partner. The feedback from the robot was controlled by a human wizard (see Dahlback et al. (1993) for more details about the Wizard-of-Oz methodology). The wizard tried to follow the rule of providing feedback whenever an object was placed on the table. The participants were asked to set a table by bringing objects from the kitchen. In order to simulate laying a table for one person the following objects were used: one cup, one plate, a fork and a knife. Taking into consideration that there were four objects to be placed on the table, the robot gave positive acknowledgement of the participants’ actions when the first, third and fourth objects were placed in their final location on the table. For example, the participant moves the fork next to the plate and the robot says “I understand” or “I am following” or “OK”. However, for the second object the robot would declare a misunderstanding twice in a row. For example, when the person places the glass on the table the robot would say “Sorry, I don’t understand what you are doing” or “Sorry, it is not clear to me”. At the third attempt of the placement of the second object, the robot would state its understanding and it was expected that the participants would move on to the third object. A video-recording camera was used to capture the participants’ demonstrations and interaction with the robot.

4.1. The questionnaire

A post-session questionnaire was used to cater for issues concerning possible difficulties with the overall segmentation task, moments that the participants felt particularly challenging when segmenting their demonstrations and to collect their opinion about the role that the robot’s feedback had on the way they chose to segment the task. Finally, at the end of the questionnaire the participants had to rate, in a five point Likert type scale, the degree of importance that they thought particular actions had in their segmentation. The actions under scrutiny were: “grasp the object”, “acknowledging the robot”, “indicating location”, “showing the object”, “transporting the object”, “speaking to the robot”, “release the object” and
“indicating the final position of the object”.

4.2. **Physical setting: the Robot House**

The study took place at the University of Hertfordshire ‘Robot House’. The Robot House is an apartment fitted with furniture, common household goods and some data collection facilities like video cameras. This setting was arranged in order to achieve some degree of ecological validity regarding the interaction of people with robots in home scenarios. The Peoplebot robot used here is equipped with a range of sensors and other devices, however for these experiments only the robot’s video camera was used together with some voice synthesis software enabling the robot to respond to the participant. The robot’s responses were controlled by an experimenter sitting on a sofa behind the participant and therefore outside the participant’s view. Figure 9 shows the layout of the experiment. The robot’s video camera was used to record the participant’s actions.

4.3. **Software used for task segmentation**

A specific and easy to use video annotation software tool called Annotate (developed in-house by the Adaptive Systems Research Group of the University of Hertfordshire) was used for the task segmentation. The tool displayed a video file of the participants own demonstration. By clicking on a key on the computer keyboard specific interaction moments were recorded and saved to a text file with the time marker from the video file. At any moment the participants were allowed to go back and correct the segmentation previously marked. The files produced and specifically the moments of the segmentation breakpoints with these files were subsequently analysed by one of the experimenters.

4.4. **Procedure**

At the beginning of the session the experimenters explained to each of the participants the nature of the task, and introduced them to the different objects and the robot. The participants would then proceed with the completion of a demographics questionnaire (not being covered in this present paper). The next step was the demonstration of the task to the robot by the participant. After the
Figure 9. The Internal Layout of the Robot House. This section of the robot house contains a living room and a kitchen. Each participant lays a table and demonstrates the procedure to an ActivMedia Peoplebot robot equipped with a video camera which records the demonstrator’s actions. The participant also moves between the kitchen and the living room. The robot responses are controlled by the experimenter (acting as the ‘wizard’) sitting on a sofa just behind the participant. (PeopleBot picture source: ActivMedia Robotics).

demonstration the participants were asked to complete a second questionnaire regarding their experience with the task (please note the participants’ responses to this questionnaire are not covered in this paper). The study proceeded with the participants’ segmentation of their own demonstration. It involved asking the participants to view their own demonstration (video-recorded) and use a specific software (see 4.3 above) to mark the points that they thought would correspond to relevant events. Finally, the participants were asked to answer a third questionnaire about the segmentation (also see figure 10). Two sets of instructions were given

Figure 10. Experimental steps for the Human Perspective experiment.

regarding the demonstration and segmentation tasks. The following instructions were given regarding some suggestions on how the demonstration should unfold
(these instructions were informed by our Cogniron partners (at the University of Karlsruhe, Germany) responsible for the development of a software system for the recognition and classification of gestures, see (Otero et al. 2006a)):

The task that you will demonstrate is: how to set a table for one person. So you will need to move the plates and cutlery from the cupboard to the table and lay the table. However there are a few constraints on how the task can be completed:

- only one object at a time can be manipulated
- the objects must be manipulated with one hand only
- you should try to follow two stages:
  1. show the object and
  2. demonstrate where to put it, and try to find words that define clearly these two stages and define the positions of the objects with clear indications (for example, pointing)
- bear in mind that your demonstrations should be in the robot’s field of view
- try to carry out slow movements

For the segmentation task we adapted the instructions used by Hard et al. (2006). The instructions were:

“Human experience is very complex. As we go about our day-to-day lives, we encounter a lot of information that we need to make sense of. One way that we do this is to break down our experiences into events. For example, when you think about your day, you think about it in terms of the events that happened, such as eating lunch or going to class. These are examples of events that you were directly involved in. You can think about all of these events on a variety of scales. For example, you can think about the day in terms of very small events, like reaching for the alarm clock, picking up a box of cereal, or dropping your keys on the floor. You can also think of the day in terms of larger events, such as eating lunch, riding to class, or attending a party. Thus, we can think about events as being as big or as small as we want. In this experimental task we are interested in the way you divide explanations. Basically, we will give you two videos for you to divide: your own explanation and another person’s explanation. How to do it? You will watch the videos of the explanation and, using the software provided, tap the key whenever one unit starts or ends NOT in the middle.”

4.5. Results

The results are presented taking into consideration the research questions formulated in section 2 above.

- What are the key moments that the participants consider to be dividing points of their own demonstrations?

Table 4 shows some variation regarding the number of events people reported when asked to segment their own demonstrations. In order to highlight these differences the participants were grouped into three groups based on the number of segmentation events reported. Furthermore, we also analysed the specific moments chosen for the segmentation by the participants and classified these based on the actions being displayed at that moment. Based on these reported moments the following categories were considered:
(1) Signalling the beginning of the overall demonstration.
(2) Signalling the end of the overall demonstration.
(3) Signalling the beginning of a demonstration step.
(4) Signalling the end of a demonstration step.
(5) Robot’s feedback (positive and negative).
(6) Participant’s transition from one place to another in the physical setting (from the kitchen to the living room).
(7) Participant showing an object.
(8) Participant picking an object.
(9) Participant further explains the step.
(10) Interactional episodes.

It seems reasonable to consider that the level of detail/ granularity is different for some of the categories referred to above. Categories (1) and (2) are of a higher level, while categories (6), (7), (8) and (9) are of a lower level. Categories (3), (4) and (5) can be considered of an intermediate level. The difference in

Table 4. Number of events recorded by participants and grouping based on the corresponding ranking. For the computation of the ranking the ties concerning the number of events reported was solved by applying the average of the ranks involved.

<table>
<thead>
<tr>
<th>Group</th>
<th>Participant Number</th>
<th>Rank based on Number of Events Reported</th>
<th>Number of Events Reported</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>3</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>Medium</td>
<td>5</td>
<td>4</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>5</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>6.5</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>11</td>
<td>6.5</td>
<td>11</td>
</tr>
<tr>
<td>High</td>
<td>9</td>
<td>8.5</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>8.5</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>10</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>11</td>
<td>17</td>
</tr>
<tr>
<td>Total</td>
<td>11</td>
<td>11</td>
<td>11</td>
</tr>
</tbody>
</table>

Table 5. Participants rating of importance for the segmentation of different actions considered relevant for the demonstrated task (1 - not important; 5 - very important)

<table>
<thead>
<tr>
<th>Group</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3</td>
<td>4</td>
<td>6</td>
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<tr>
<td></td>
<td>1</td>
<td>4</td>
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<td>4</td>
<td>5</td>
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<td></td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

the number of reported events between the ‘Low’ group and the ‘High’ group is quite substantial (see Table 4). This difference reflects a choice of the categories deemed important (as one would expect from the difference itself). Participants in the Low group chose to report only moments when the robot was giving feedback. This seems to indicate that for them the robot’s feedback was particularly
salient, probably signalling the possibility of progressing to the next step. However, they did not mark the moment when the beginning of the demonstration step started. For the participants in the High group, the range of categories considered is much wider, in fact, covering all the categories proposed above (although not all the categories can be used for the moments chosen by each participant). In relation to the Medium group, participants 1, 2 and 5 marked moments corresponding to the beginning of the demonstration steps and the robot’s positive feedback (and not when the robot states its misunderstanding - negative feedback). This seems to support the interpretation made regarding the function of positive feedback (signal the possibility to progress to the next step). This indicates that positive and negative feedback may mark different levels of event segmentation - positive feedback might be considered at a higher level than negative feedback. Participant 11, also from the Medium group, considered both positive and negative feedback from the robot. It is also interesting to point out that although the number of events reported by participants 2 and 11 are the same, participant 2 reported two events of higher level category which signalled the overall beginning and end of the demonstration. If these two events were not reported then the number of events would be similar to participants 1 and 5. In other words, participant’s 2 pattern of event reporting seems more similar to participant 1 and 5 than 11.

As stated in sub-section 4.1 the post-trial questionnaire asked the participants to rate from 1 (not important) to 5 (very important) different actions that we deemed relevant for the segmentation of the demonstrations. One point should be made beforehand, we do acknowledge that some of the categories presented to the participants are different from the ones that seem to have been spontaneously considered. Nevertheless it seems reasonable to assume that such a rating still gives us some indication of people’s thinking regarding the segmentation task they performed. Table 5 shows the participants rating.

For the participants in the Low group show object and final location of object were the actions considered more relevant. The participants opinions about the remaining categories seem rather scattered.

For the Medium group, speak to robot was the action that received higher marks while transport object received the lower marks. It seems also worth noting that the action indicate location seemed to polarise opinions: two participants rated it 2 while the other two rated it 4.

For the High group, indicate location, show object and final position of object were the actions more highly rated.

- Does the feedback from the robot stating its misunderstanding at specific points of the demonstration alter the level of detail of the segmentation?

The analysis of the demonstration’s segmentation strongly suggests that the majority of the participants did not change the level of detail of the segmentation following the robot’s negative feedback. The number of segments following the robot’s feedback does not change except for participant 7 who clearly marks the change by considering the separation between showing the object and the remaining demonstration of the step.

- Do participants report difficulties in regard to segmenting their demonstrations?
Five participants reported affirmatively. One considered a specific technical detail regarding the setting. Two of them (participants number 2 and 3) considered that the instance when the robot gave negative feedback posed problems. Curiously, one of the two participants referring to the robot’s negative feedback instance explicitly stated that when doing the segmentation he thought of breaking it down into a finer detail segmentation but ended up choosing to stay with the overall strategy. One participant mentioned the overlay of conversation, meaning, particular instances when robot and human would talk at the same time.

- Do participants consider themselves to have been influenced on their segmentation task by the robot’s feedback?

Ten of the eleven participants claimed to be influenced by the robot’s feedback when segmenting the task. Three mentioned the robot’s feedback in a general sense but three clearly stated the negative feedback instances. However, two of these three, participants 2 and 5, did not mark the moments when the robot’s negative feedback was given in their segmentation. Such inconsistency might come from the nature of the question itself which might have made people re-think the role of the robot’s feedback when answering the questionnaire. Quite interestingly, participant 7 explicitly mentions its changing of level of detail.

4.6. **Summary**

The results suggest that people might differ regarding the level of detail they spontaneously consider when asked to segment routine home tasks. However, it is worth noting that all the participants considered breakpoints corresponding to the end of an demonstration step (marked by the positive feedback from the robot). This suggests that these breakpoints mark the higher level of detail that the participants spontaneously considered (the exception is participant 2 who also marked the overall beginning and end of the demonstration). In addition the results indicate that participants did not segment the task differently when analysing the moment when the robot gave negative feedback, although in the post-session questionnaire the feedback was considered important for the segmentation.

5. **Synthesis and Discussion**

In the first social learning experiment we considered the importance of task decomposition and scaffolding in terms of robot learning and processing efficiency together with human comfort in terms of a reduced teaching burden. What was clear from this study was that the hierarchical breakdown of a task is beneficial to both parties. In that study however there was no mechanism that the robot itself could use to recognise where a breakdown might be beneficial and thus no help could be given to the teacher in the signalling of such events.

In relation to the second study, the main aim was to start investigating how people segment demonstrations of routine home tasks. We believe that studying how people spontaneously segment their own demonstrations might: (a) give us some understanding concerning which moments people regard as closure acts for the different teaching events; (b) highlight what people regard as the more salient
moments on their demonstrations and learning episode. In turn, this information will serve to guide research concerning the timing and nature of the robot’s feedback regarding the people’s demonstrations. It seems clear that the relevance of this work is in the design of robotic systems, such as those described in the first study, which are able to learn in human social contexts.

More specifically, in previous work we have already shown that people’s common demonstrations of these type of tasks are far from explicit (Saunders et al. 2007b). By asking people where event breakpoints lie we can start grasping when the robot’s feedback can be better introduced, what actions are involved near the breakpoints and between breakpoints. In other words, we think that user studies that give information about how people spontaneously see their demonstrations in conjunction with information regarding what is actually said and done (see for example, Otero et al. (2006b), Saunders et al. (2007b)) is crucial to the better design of a robot’s interactional capabilities and may enable it to learn in a way that was comfortable to humans, and especially so in natural and realistic human social scenarios. Our considerations concerning the timing and nature of the robot’s feedback have some parallel to the issues raised by Thomaz and Breazeal (2008) concerning how people manage the relationship between the meaning of a certain reward and the timing of that reward as well as their comment concerning the benefits of communication of the agent’s internal state. It seems that more research is needed to pinpoint the particulars of this on-going dialogue so that both partners are able to benefit: the communication will need to be more explicit about the function of the partner’s feedback, both agent/robot and human teacher.

Our present results suggest the existence of individual differences regarding the way people choose to segment routine home tasks: not only in the number of breakpoints but also in the nature of the moments chosen and relative importance given to the different moments. Nevertheless, all the participants marked the moment when the robot gave positive feedback - thus, to some extent, we can say that these were the most common higher level breakpoints in our study (however, we appreciate that the robot’s feedback was triggered by the experimenter, based on the rule that the feedback would be provided after each object was placed on the table).

How can we exploit the implications of our initial findings concerning the nature of the higher level breakpoints? One possible line of research could try to clearly identify actions in the setting that can help the robot to pick cues that signal possible event breakpoints. This follows the approach of Barker and Wright (1954) who identified six characteristics of basic event segmentation boundaries, e.g. the ‘displacement of objects as distinctive moments’ (i.e. a change in the behaviour setting). However, on their own these may not be enough.

More research is also needed to investigate if interactional moments can be fostered and enhance the on-going iterative process of demonstration refinement. For example, when the teacher explicitly indicates that he is awaiting some kind of response from the robot or that the actions being taken are still not finished. It seems plausible to envision a system that is able to recognise interactional moments and track possible actions in such a setting. Satisfying both conditions, recognition of actions in the setting and relevant interactional moments, would prompt the robot to indicate its current state regarding the apprehension of the information being conveyed. We believe that the robot’s feedback concerning its state should be as complete as possible (in line with Thomaz and Breazeal (2008) finding regarding the value of making explicit the agent’s internal state and its value to people’s re-evaluation of the agent’s model). For example, in our present teaching scenario, if the positioning of the object was apprehended but the particular object being
displayed was not, then the robot should say so. The next step, though, considering the findings from the first study regarding the benefits of task decomposition and efficient scaffolding, is to find out how the robot can trigger the human teacher to move down the hierarchical structure of the demonstration.

The research by Tversky et al. (see for example Zacks and Tversky (2001), Zacks et al. (2001)) strongly suggests that people encode information regarding events in a hierarchical fashion. Our assumption was that people’s demonstrations to the robot could also reflect some hierarchical structure. In our study, quite surprisingly, the majority of the participants did not alter their segmentation strategy and level of detail of the breakpoints following the robot’s statement of misunderstanding of the demonstration step.

We were expecting that participants would have identified “moving down” within the hierarchy when segmenting their explanation (i.e. breaking down the misunderstood step into smaller parts). However, the results hint that even if there were refinements on the demonstration they may not be considered in a distinctive way. We are not claiming that the demonstrations might have a distinct structure but that in order for the refinement to be considered (or happen) the robot’s feedback needs to be more informative (both in its content and timing): a statement of misunderstanding needs to be produced at a moment in time that facilitates the precise identification of the problem.

The results of this study also suggest that positive and negative feedback from the robot concerning the demonstration step played distinct roles in the segmentation for different people. For the Low group, the feedback, both positive and negative, served as breakpoints. For the Medium group, the negative feedback is not regarded so it seems reasonable to assume that positive feedback took the role of “end of demonstration step”. For the High group positive feedback still maintained its role as a signal for the end of the demonstration step, but negative feedback was also addressed. Thomaz and Breazeal (2007, 2008) have investigated the communicative role of people’s positive and negative feedback in Human-Robot teaching tasks. They argue that people’s positive and negative feedback have distinct communicative roles. These findings once again reinforce the point that more research is needed to investigate the possible relationships between positive and negative feedback given by both interaction partners and the implications for the design of algorithms.

6. Future research

Given the state of the art of conversational and object/motion recognition systems, these results seem to strengthen our belief that the success of the robot’s interventions requesting further enhancements to the demonstration given is dependent on a complex interaction of the following factors:

- The robot’s successful publicising of its basic abilities (including sensory and object/motion recognition constraints).
- Fine tuning of the timing of the robot’s interventions with the nature of its basic abilities so the human can better screen where an demonstration is not being efficient.
- Finding sets of basic actions relevant for the context of use being envisioned that the robot can display as building blocks of further learning/teaching activities.
- Implementation of a mechanism able to keep an interaction history of the learning/teaching so that the human partners can relate to the teaching/learning
relationship, sense progress and experience positive and rewarding moments.

One way in which a robot learning system can aid in publicising its current learnt abilities is by recognising similarities between what is being taught and what it already knows. In fact the system described in the first experiment exploits the notion of competencies stored as memory models by continually polling all of its models on each taught step looking for such similarities. When a similarity threshold is reached the robot is then able to aid the teacher by reporting that it may already have part of all of this competence already available.

Such reference to existing learned competencies could also aid in the second item above. One could envisage for example the robot using its existing models in a predictive way (effectively as ‘forward models’ - see for example (Johnson and Demiris 2005)) whereby the robot recognises what actions might occur and the timing of such actions. When such actions or timings do not occur in the same way as that predicted the robot could ask for further explanations.

Of course the hierachical nature of the teaching scenarios presented here lend themselves to task re-use of the kind envisioned in the third item above. The architecture described in the first study considers all elements of the hierarchy relevant for re-use and these are available for use by the teacher. However, recognition by the robot of when to offer these blocks to the teacher is not available and would clearly be helpful.

In regard to the final item above, some early research on interaction histories is showing positive results in both the ability to exploit such histories and the fact that they can be grounded directly in the robot’s sensorimotor space (see for example Mirza et al. (2007)).

Following the findings concerning robots’ feedback, one possible theme for future controlled experimental investigations is the manipulation of the robot’s intervention timing. For example, can the exact same utterance produced by the robot stating its misunderstanding at distinct points of the demonstration elicit responses from its teacher with distinct levels of detail?

In the relatively young research domain of human-robot teaching, many important issues remain to be studied in future work. However, we hope that the work presented in this paper is a step towards the development of future generations of ‘human-aware’ robots that are able to learn from people in a manner that is not only efficient and useful, but also acceptable and comfortable to its users.

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