Grounding of Robots Behaviors

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Abstract

This paper addresses the problem of learning robot behaviors in real environments. Robot behaviors have not only to be grounded in the physical world but also in the human space where they are suppose to take place. The paper briefly presents a learning model relying on *teaching by demonstrations*, enabling the user to transmit its intentions during real experiments. Important properties are outlined and the *probabilistic learning process* is described. Finally, we indicate how grounded behavior could be interfaced to a symbolic level.

Introduction

It has been shown in numerous works that behavior paradigm is a good way to specify the actions of robots in real environments. Once clearly identified and named, behaviors can be incorporated into complex action/selection schemes and can be referred to, symbolically, by deliberative processes at upper levels. Thus behaviors provide a nice human designer/robot interface. However behaviors are still difficult to model and formulate in the real world. In realistic applications, robots behaviors have to be adapted to the Physical space and the Human space. In the *Physical Space* behaviors have to deal with sensors incertitude and imprecision, incompleteness of real world models and actions too peculiar to be easily defined and specified. In the *Human Space* they have to be adapted to our intentions and requirement , our habits, the way we organize our environment (signs, stairways...) and the importance we give to various contexts.

Behaviors have to be grounded either in Physical and Human space, and explicit programming of behaviors or optimization processes (genetic algorithms, reinforcement learning..) cannot alone provide a satisfying adaptation to those both spaces. Teaching behaviors by showing them to the robots permits to face this problem. By showing them directly (ie: using a remote control device) robots behaviors are anchored from the beginning in the only space that matters, the space of the final user's intentions in its real physical environment.The learning process can take benefit of real experiences containing pertinent associations of perception and action.

Teaching by Showing

The works related to this view are Programming by Demonstration (Cypher 93), Imitative Learning (Demiris and Hayes 96) or Supervised learning methods such as in the ALVINN system (Pomerlau 93).

Figure 1: Three examples which may be used to shape the behavior "Exit by the door".

We propose a model for behavior learning by demonstration - more details can be found in (Hugues and Drogoul 2001). The approach do insists on the following points:

- *Shaping a behavior with a few examples:* The user must be able to incrementally shape the behavior by showing a few examples. To show a behavior such as "Exit by the door" in figure 1 we would like to demonstrate it by showing only a few significative *facets* of the behavior.
- *Finding a Perceptual Support for the behavior* A behavior needs a support in the perceptual field, some features to rely on for choosing the right actions. The features to be detect cannot be modeled a priori, they must be inferred from the demonstrations. In a way inspired by Gibson's Theory of affordances (Gibson 86), the environment is viewed as directly providing a support for possible behaviors. This leads us to learn actions by relating them to the elements of the perceptual field at the lowest level.
- *Context of the behavior :* The behavior has to be independent of irrelevant features of the contexts of realization and it also must be triggered only in valid contexts. The identification of contexts has to be associated tightly to a behavior description.

Behavior Synthesis

A synthetic behavior is represented by a large *population of elementary cells.* Each cell observes, along each examples, a particular point in the perceptual field and records statistically the value of the effectors. Cells are activated by detection of specific properties (visual properties mainly) of the perceptual field such as color, density, gradient of small pixel regions. A cell records the arithmetic mean of the robot's effectors taken over its periods of activations, the importance of a particular cell depends on the number of its activations. During the reproduction of the behavior, the current values of the effectors are obtained by the ponderated combination of active cells.

The synthetic behavior also contains a context description formed by several histograms recording distribution of perceptual properties (again color, density etc ...) over all the examples.The behavior synthesis is divided into four main steps: (1) individual synthesis of each example by a population of cells and context structure. (2) Fusion of separate synthetic behaviors in a unique population. (3) Real-Time use of the cells structure. (4) Eventually, on line correction by the tutor.

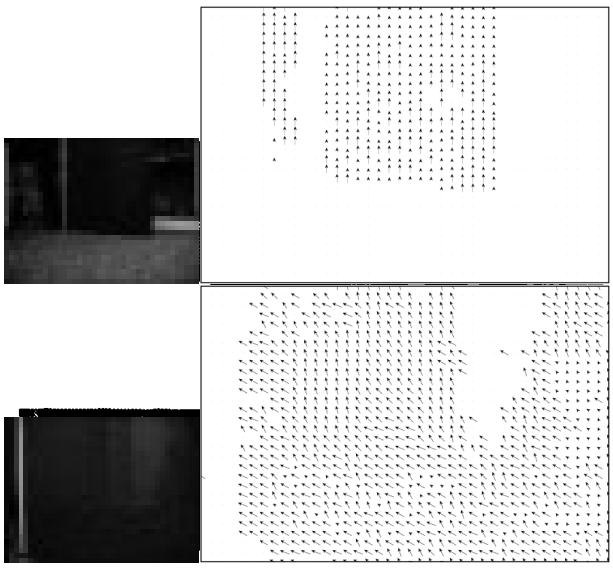

Figure 2: Collective reaction of the cells in two different situation of "Exit by the door" behavior. (Top) Far form the door the cells propose to go forward - (Bottom) near the door a lot of cells tells to turn left.

Step 1 : Examples Capture Each example is shown using a joystick, the robot vision and movements are recorded. Cells are activated by video frames of the example. The mean of the effectors values is stored in each cell for periods of activation of the cell. A *Context Histogram* is deduced from perceptual properties observed along the example. *Step 2 : Fusing examples* The final behavior is obtained by fusing separate cells population coming from several examples into a unique cell population . Context histograms are merged by multiplication and important features are highlighted.

Step 3 : Real-time use At replay time, the behavior can be activated if the context histogram matches current video images. Robot is controlled in real time by deducing effectors values from those stored in active cells (using a majority principle). The set of cells reacts like a population with dominant opinion (possible opinion are the possible values for the effectors). Video images have only to overlap partially the recorded data so as to produce correct control values.

Step 4 : On line correction The final behavior can be corrected on line by the tutor. The tutor corrects the robots movements by using the joystick in contrary motion. Active cells are corrected proportionally to their importance.

Behavior interface with symbolic level

Modules operating at symbolic level (action/selection mainly) can interface with a grounded behavior by referring to its logical definition (what it is supposed to do in logical/symbolic terms) and its associated *context stimuli.* The user can re-shape the behavior real definition independently of the symbolic modules. The value of the stimuli corresponds to the quality of matching of context histogram and is used to trigger the behavior. The model thus provides support for programming at the high level and grounding in real data at the behavior level.

Conclusion

This model is implemented on pioneer 2DX robots equipped with color camera. In a preliminary phase we have obtained promising results for simple behaviors such as object approach and door exit. Despite its simplicity the population of cells encodes a large number of situations and is robust to noise. Few examples (< 10) are needed to synthesize this kind of behaviors. We are currently extending the work in three directions : Validation of context detection, validation over more complex behaviors,(integrating time and perceptual aliasing). integrating behaviors into an action/selection scheme.

References

L. Hugues and A. Drogoul (2001) Robot Behavior Learning by Vision-Based Demonstrations, 4th European workshop on advanced mobile robots (EUROBOT 01).

A.Cypher, (1993) Watch what I do, programming by demonstration. MIT Press. Cambridge MA.

J.Demiris and G.M. Hayes (1996) Imitative Learning Mechanisms in Robots and Humans. In Proc. of 5th Europena Workshop on Learning Robot, V Klingspor (ed.).

J.J. Gibson (1986) The Ecological Approach to Visual Perception,LEA Publishers, London.

D.A Pomerlau, (1993) Knowledge-based training of artificial neural networks for autonomous robot driving. In J.Connell and S. Mahadevan (Eds.) Robot Learning (pp. 19-43)