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# HYBRID TOOLS IN INTELLIGENT ROBOT CONTROL

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ABSTRACT . Machine learning in an uncertain or unknown environment is of vital interest to those working with intelligent systems. The ability to garner new information, process it, and increase the understanding/ capability of the machine is crucial to the performance of autonomous systems. The field of artificial intelligence provides two major approaches to the problem of knowledge engineering - expert systems and neural networks. Harnessing the power of these two techniques in a hybrid, cooperating system holds great promise.

## 1. INTRODUCTIONS

Expert systems and fuzzy expert systems [5] - [7] are strongly tied to knowledge-based techniques for gathering and processing information. Knowledge representation in such systems is most often in the form of rules garnered through consultation with human experts. Coupling the methods of approximate reasoning with knowledge-based techniques yields systems which model human decision-making. There are many examples of rule based systems which function as experts in a given domain, e.g., trouble-shooting for complex mechanical processes, medical diagnosis systems, and financial risk assessment. Expert systems provide a ready mechanism for explanation why certain decisions are made, even when the human expert is unable to articulate the chain of reasoning leading to a decision. This trace of the reasoning process is often crucial to those maintaining the system.

A major disadvantage of knowledge-based systems is their reliance upon consultation with human experts for new information. Furthermore, autonomous learning in an expert system does not usually include the capability to synthesize new knowledge but is limited instead to dependence upon structures the designer builds in to asses the similarity between situations or to generalize upon sets of similar rules.

Neural networks are data-driven systems based on an architecture of many simple processing units which are interconnected. The knowledge of a neural net resides in the connections between these processing units and in the strengths of the connections. Neural networks are especially applicable to problems which involve large numbers of weak constraints. They have been successfully applied to perceptual tasks such as pattern recognition, vision processing, and speech synthesis.

The ability to gracefully handle minor inconsistencies or conflicts in the data is an advantage that neural network systems hold over most expert systems. A robust intelligent system must be able to handle conflicting information from different experts, or some degree of contamination in incoming data, without too much degradation in performance.

There are many scenarios in which both types of reasoning, knowledge-based and data-driven, are appropriate. Harnessing the power of both expert systems and neural networks in a system which allows for imprecise information and/or uncertain environments would yield a system more powerful than either system standing alone [3] - [4].

## 2. HYBRID INTELLIGENT SYSTEMS

Learning is an essential component for any intelligent system. One focus of this proposal is on learning in a hybrid system, especially learning in an autonomous or unsupervised mode. Michalski et al [12] summarize the classic strategies and orientations in machine learning. An autonomous system should be able to learn in an unsupervised situation by experimentation, classification, recognition or similarity, generalizing and applying appropriate previous solutions or hypothesizing new solutions to situations never before encountered by the system.

Learning in a neural network without the benefit of an initial base of knowledge can be very slow to converge. Therefore, the premise in this proposal is that learning can be implemented more efficiently in the neural network when the expert system supplies the metaknowledge to begin the learning process as well as accumulated knowledge in the system.

We are currently evaluating several models for the hybrid system proposed. As a general premise, we believe that the most effective model is one in which the expert system begins with a base of knowledge which is necessarily incomplete, a neural network layer takes the knowledge from the expert system and modifies it through learning, and all information can be passed easily and transparently from one part of the system to another as needed.

Under consideration are several configurations of this basic model which have different uses:

(1) Everything learned in the neural network is passed back to the expert system. In effect, the neural network is training the expert system. In this version, the user of the system is always able to trace the decision-making process via the expert system.

(2) When a problem is presented to the hybrid system, it is partitioned into segments which are evaluated to be appropriate for solution by either the expert system layer or by the neural network layer. The solution to the problem is a hybrid of the segment solutions. In this version, the two layers act as cooperating partners, each doing what it does best, keeping functional overlap to a minimum.

(3) An entire network of smaller systems, expert systems and neural networks, cooperate and communicate to learn in different modes, or in different domains. Each part is designed with a different part of the problem solution process in mind.

The fluid transfer of information from one type of system to the other obviously is crucial to the models proposed. Having thoroughly checked the interface with off-the-shelf packages, we plan to utilize an expert system which may incorporate fuzzy linguistic quantifiers, hedges, and weights, such as FEST [6], or develop other systems as needed.

Another issue of interest is the application of uncertainty management techniques within the hybrid intelligent system to better model the human reasoning process. Most conventional rule-based systems allow the use of certainty factors to represent the fact that a rule does not hold true for all situations satisfying the antecedent conditions. In fuzzy reasoning, we consider the degree to which a rule agrees with our current understanding of reality rather than the probability that it is a true description of that reality.

The sensitivity of learning in the neural network to the use of linguistic variables as weights and linguistic hedges will be investigated. One way to measure this sensitivity is to compare the rate of change in what has been learned against the change in the certainty factors or weights.

The expert system, neural network, and learning algorithm are implemented as separate functional units. The only means of communication between the units is the relevant data structure. The data structure common to the expert system and neural network is the rule base, whereas the data structure common to the neural network and the learning unit is the collection of state arrays.

It should be pointed out that the transfer of knowledge between system components is bidirectional and it is precisely the learning capabilities of neural networks that enable the intelligent system to infer new rules or modify existing rules based on neural network performance. The division of labor, by providing the system with whatever knowledge is available a priori through the expert system and the knowledge-base, and by developing optional learning strategies for the neural network, is precisely the technology that will provide us with fast, autonomous effective learning on top of previously acquired knowledge.

It is the cooperation of an expert system with a given knowledge-base and a neural network with the learning capabilities that enables this technology to execute tasks in an autonomous imprecise and somewhat unpredictable environment.

As was shown before [8], the functional components of the inference engine in the expert system can be mapped to the functional components of a node in the neural network, as shown in the following table:

| Neural Network | Expert System |
|---|---|
| Internal state | Internal |
| Combining function | Internal state |
| Output value | Evidenciary combining function |
| Activation function | Output value |
| | Firing function |

Work by Kuncicky and Kandel [9], which is based on [2], notes graceful degradation and restoration from partial inputs using the fuzzy expected value (FEV) and the weighted fuzzy expected value (WFEV) as combination functions. In a translation model, the choice of a combining rule is dependent upon the combining rule of the particular expert system that is used. This places qualitative limitations on the properties of the network dynamics. Some combining rules, such as max-min composition, do not meet the criterion of threshold sensitivity.

## 3. INTELLIGENT ROBOT CONTROL

Conventional control systems design methodology involves the construction of a mathematical model describing the dynamic system to be controlled and the application of analytical techniques to this model to derive a control law. Robust control design produces a constant gain controller which stabilizes a class of linear systems over a range of system parameters. Adaptive control adjusts the controller characteristics to stabilize a system with unknown parameters. Adaptive control is particularly critical for enhanced functionality and error detection and correction. Error detection and correction are associated with monitoring-execution mechanisms to ensure compliance with the expected task sequence, to measure expected errors, and to correct them dynamically.

Conventional control techniques break down, however, when a representative model is difficult to obtain due to uncertainty, or sheer complexity. Model uncertainty is a serious problem in designing intelligent robot control laws. Often it is impossible to adequately represent system characteristics such as nonlinearity, time delay, saturation, time-varying parameters, and overall complexity. Thus, autonomous intelligent control systems require significantly enhanced capabilities to achieve real-time operational responses when the decision-making process is based on incomplete information, uncertainty, and competing constraints.

Biological systems, on the other hand, handle ill-structured problems with remarkable ease and flexibility. They are quite successful in dealing with uncertainty, complexity, and nonlinearities. They coordinate smoothly many degrees of freedom during the execution of dexterous manipulative tasks within unstructured environments, solve complex planning problems with apparent ease, and are able to adapt their structure and function.

Important features of biological control systems include:

(1) Hierarchical and modular processing architecture.

(2) Distributed computation among the various levels of the hierarchy.

(3) Utilization of tightly integrated, yet distinct, forms of sensorimotor process-ing during the acquisition of motor skills.

It seems therefore desirable to turn to biologically-inspired paradigms in developing efficient processing architectures and learning procedures to improve the performance and adaptability of intelligent control systems. These biological paradigms, namely, artificial neural networks, seem to be potentially useful in treating many problems that cannot be handled by traditional analytical approaches. For example, back-propagation neural networks currently are the most prevalent neural network architectures for control applications because they have the capability to 'learn' system characteristics through nonlinear mappings.

## 4. THE NEURAL NETWORK APPROACH

Current adaptive control techniques reveal fundamental shortcomings in terms of implementing robot control laws. Adaptive control laws, such as Model Reference Adaptive Control, Self Tuning Regulator, and Gain Scheduling [1], [11] are nonlinear control laws which are difficult to derive, their complexity grows geometrically with the number of unknown parameters, they are not robust, they are conditionally stable, and often they are not suitable for real-time applications.

In contrast, control architectures based on neural networks are specifically suitable to implement general purpose trainable adaptive controllers for robotic control. Trainable adaptive controllers are process controllers where much of the design is done online via training rather than programming.

Neural networks are inherently robust and are massively parallel, adaptive, dynamical systems modeled on the general features of biological networks. Due to the availability of advanced VLSI implementation techniques and the demand for massive parallelism to achieve real-time information processing, there has been tremendous interest in the applications of neural networks to achieve human-like performance in the field of robotics.

Neural networks interact with objects of the real world and its statistical characteristics in much the same way living beings do. They consist of densely interconnected processing elements, or neurons. Each neuron is provided with the ability to self-adjust some of the coefficients in its governing differential equations. Thus, the network as a whole becomes a self-adapting dynamic system, capable of learning and self-organizing, and operating in a highly parallel distributed manner, most suitable for high-performance information processing.

Collectively, neurons with simple properties, interacting according to simple rules, can accomplish complex functions such as generalization, error correction, information reconstruction, pattern analysis, and learning. Their paradigmatic strength for potential applications, which require solving intractable computational problems or adaptive modeling, arises from their ability to achieve functional synthesis, and thereby learn topological mappings and abstract spatial, functional, or temporal invariances of these mappings. Thus, relationships among multiple continuous-valued inputs and outputs can be established, based on presentation of various representative examples.

Once the underlying invariances have been learned and encoded in the topology and the interconnections weights, the neural network can generalize to solve arbitrary problem instances. Since the topological mappings for problem-solving are acquired from real-world examples, the functionality of the neural network is not limited by assumptions regarding parametric or environmental uncertainty. Thus, neural networks provide an attractive algorithmic basis for solving fundamental design problems of autonomous intelligent control systems.

In addition to that, neural networks also provide a greater degree of robustness or fault tolerance than the conventional von Neumann sequential machines. Damage to a few neurons or connections does not impair overall performance significantly. Since most neural network models tend to adapt connection weights so as to self-organize internal representations in response to the continuously changing inputs, adaptation also provides a degree of robustness by compensating for minor variabilities in the characteristics of neurons.

## 5. THE HYBRID INTELLIGENT SYSTEM SOLUTION

The hybrid intelligent system carries a step further the approach presented in the previous section. It provides a integrated tool which could form the basis for a potentially fruitful approach to intelligent robot control problems. The expert system provides us with a tool to handle a priori knowledge whereas the neural network offers potentially powerful collective-computation techniques, as well as learning capabilities in an adaptive environment.

We see the use of hybrid intelligent system in robot control as a natural step in the evolution of robot control methodology to meet new challenges. The cooperative structure of the hybrid system, incorporating a priori knowledge, learning capabilities, and massive parallelism, offers solutions to several critical issues that are essential for intelligent solving robot control problems.

Knowledge based systems provide a convenient mechanism for automated complex decision-making with task-specific knowledge being defined explicitly. Neural networks, on the other hand, encode knowledge implicitly, adjusting internal weights so that their input/output relationships remain consistent with observed training data.

Our emphasis is on the mechanism for shifting knowledge and control between the two components of the hybrid system, in order to utilize the strengths of each processing technique. First, the knowledge-based system determines how to accomplish a given control objective using rules and algorithms within the knowledge base. It then teaches the neural network how to accomplish the same task by having the neural network observe and generalize on knowledge-based task execution. As the neural network assumes more control responsibilities, its task execution becomes optimized through reinforcement learning. Based on the performance of the neural network, knowledge is transferred back to the knowledge-based system to infer new rules or modify existing ones if applicable.

One scheme proposed to classify memory and learning distinguishes between declarative and reflexive mechanisms [10]. Motions involving declarative mechanisms are characterized by inference, comparison and evaluation, and provide insight into how something is done and why it is done. Motions involving reflexive mechanisms relate specific responses to specific stimuli, are automatic, and require little or no thought. Tasks initially learned declaratively often become reflexive through repetition. Conversely, when familiar tasks are attempted in novel situations, reflexive knowledge must be converted back into declarative form to become useful. This shifting of task-specific knowledge between declarative and reflexive forms plays a fundamental role in skill acquisition.

In terms of this scheme, the declarative form of processing is implemented in our hybrid intelligent system by knowledge-based expert systems whereas the reflexive form of processing is implemented using neural networks.

In order to be effective in a dynamic and uncertain scenario, an intelligent robust robot control system must be able to automatically acquire necessary information from the environment. The learning capabilities of our proposed system would thus facilitate two main advances for intelligent robot control:

(1) Autonomous knowledge acquisition via learning; and

(2) Continuous system refinement to improve the performance of the identification system.

The integration of the expert system and neural network would minimize the "learning time" through the use of the expert system for a priori knowledge, as well as utilizing the learning capabilities and the parallelism of the neural network. The use of the hybrid system to achieve just these two modifications could serve to significantly advance the present capabilities of robotic control systems. The learning capabilities of the system are one of the main strengths of the hybrid approach. Integrated with expert system technology it could be used as a powerful tool for addressing robotic needs for adaptation to both task and environment changes, selection of optional task features, and incorporating a priori knowledge regarding uncertain environments.

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