A New Modular Strategy for Action Sequence Automation using Neural Networks and Hidden Markov Models

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ABSTRACT

In this paper, the authors propose a new hybrid strategy (using artificial neural networks and hidden Markov models) for skill automation. The strategy is based on the concept of using an “adaptive desired” that is introduced in the paper. The authors explain how using an adaptive desired can help a system for which an explicit model is not available or is difficult to obtain to smartly cope with environmental disturbances without requiring explicit rules specification (as with fuzzy systems). At the same time, unlike the currently available hidden Markov-based systems, the system does not merely replay a memorized skill. Instead, it takes into account the current system state as reported by sensors. The authors approach can be considered a bridge between the spirit of conventional automatic control theory and fuzzy/hidden Markov-based thinking. To demonstrate the different aspects of the proposed strategy, the authors discuss its application to underwater welding automation.

Keywords: Artificial Neural Networks (ANNs), Hidden Markov Models (HMMs), Normalized Gaussian Modified Lagrange Neural Network (NGML), Sequence Automation, Underwater Welding

INTRODUCTION

With conventional automatic control problems, there exists a sequence of system desired (reference) outputs. Some control law is used to determine the necessary sequence of system inputs that forces the system to track the desired sequence of reference outputs as a function of the error between the system desired output and its actual output. There is a large bulk of literature regarding the details of designing such control laws depending on the system model whether it is linear or non-linear. However, for many important tasks and skills there exists no explicit model relating the control system inputs and outputs. For such systems, a sequence of
reference outputs does not exist. Instead, we have a desired performance available. For example, consider a wheeled-robot path tracking task. The system inputs are the robot actuators (motors moving the wheels) inputs (voltages) and its outputs are the actuators outputs (wheel speeds). However, what is available is not the desired actuator outputs instead we have a series of desired robot positions. That is to say, what is available in many tasks is not the desired value for the output that is under our direct control (motors outputs in our example). Instead, what is available is a desired value for some quantity (robot position in our example) that is implicitly related to the output under our direct control. For most cases, the relation between the system inputs and the indirect outputs (robot positions in the example) is complex, especially that environmental disturbances and noise are taken into account to be able to guide the system (robot in our example) to perform its task successfully in real-life environments. In such cases, where no comprehensive explicit model exist, conventional control methods are usually replaced by fuzzy control, artificial neural networks (ANNs), hidden Markov models (HMMs). The parameters of these systems can be initialized based on available knowledge and designers’ experience and can be fine-tuned using available training data (whether online or offline). Such systems usually take as input the sensory inputs reflecting the current system state (which implicitly contains information regarding the error between the system desired and actual output) and give as outputs the desired inputs to the system to be controlled.

However, in this paper, we adopt a new approach to such control problems that we believe to be more appropriate than both the conventional and the current approaches that use ANN/fuzzy/HMM approaches. Instead of totally abandoning the conventional automatic control paradigm and adopting the current practice of fuzzy control, artificial neural networks (ANNs) and hidden Markov models (HMMs), we develop a new strategy that uses ANNs and HMMs as tools within the conventional automatic control thinking paradigm. Our approach, like with the conventional automatic control thinking, determines the system inputs based on the error between its overall indirect output (which is not under our direct control) and its desired value but it does so indirectly as we will explain later. However, our point of view is that for such systems to be able to cope with environmental disturbances and noise, this desired value should not be fixed (pre-determined). Instead, it should be computed adaptively based on knowledge of the system current state and its goal state. To our knowledge, this point of view (using adaptive desired to compute the control error and necessary control inputs based on it) is not currently available in literature and thus, we consider it one of the contributions of this paper.

Our strategy trains an ANN to take as input sensory inputs reflecting the current system state and gives as output a prediction of the expected future sensory inputs if the task is being progressing correctly. Throughout the paper, we will call the ANN trained to perform this function “the target generation module”. An HMM inverts these desired expected future sensory inputs into the corresponding system inputs necessary (the inputs if applied to the system will lead the system state to change such that the sensory inputs that will be recorded actually will be the same as those predicted). Let us contemplate a little on how this strategy is to be considered a merge between conventional control thinking paradigm and the ANN/fuzzy/HMM paradigms. In conventional automatic control the system inputs are computed as a function of the desired and actual system states. Similarly, in our approach the system inputs are computed by the HMM as a function of the adaptive desired which is function of the current actual system state.

In what follows, we give two examples to illustrate the importance of using an adaptive desired.

The first example is actually a “toy example”. However, it clearly illustrates why intelligent adaptive feedback is important and how the automated system performance without it can be unacceptable. The example is shown in Figures 1 and 2. Assume the robot arm task to write the digit 8. The red path is then the