Hidden Markov Models (HMMs) are a probabilistic approach to describe a collection of observed \{O_1, \ldots, O_t\} and their corresponding hidden random variables \{Q_1, \ldots, Q_t\} which, for our purpose are indexed by a discrete time parameter. There are two assumptions: the occurrence of \(Q_t\) depends only on its most immediate predecessor and \(O_t\) depends only on \(Q_t\). Such models have been used for speech recognition and bioinformatics. In this work we explore the potential use of HMMs for process identification and control.

The typical stochastic model form used for process identification and control is a linear system driven by a white noise. However, such a model is limiting in that common plant behavior like intermittent drifts or jumps cannot be modeled effectively. In addition, the statistical patterns of a disturbance may not stay constant with time in practice. In this sense, HMMs can offer a significant generalization of the current model form used for process control.

Various forms of Markovian switching systems, which can be regarded as a special form of HMMs, have been studied in the context of state estimation and the research thus far has predominantly been centered around sub-optimal multiple-model based algorithms \[1, 2, 3, 4\]. To our knowledge, HMMs have not been explored in the context of process identification.

Since changes in operating modes are observed through stochastic noise-corrupted signals, a framework based on HMMs seems intuitive. This work tackles state estimation and system identification by taking advantage of algorithms pertaining to HMM's to track these underlying shifts, manage hypotheses and estimate the state transition probabilities. Several examples will be provided to demonstrate the final closed-loop performance improvement possible through the use of HMMs.


