An application of autoregressive hidden Markov models for identifying machine operations

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Abstract. Due to increasing energy costs there is a need for accurate management and planning of shop floor machine processes. This would entail identifying the different operation modes of production machines. The goal for industry is to provide energy monitors for all machines in factories. In addition, where they have been deployed, analysis is limited to aggregating data for subsequent processing later. In this paper, an Autoregressive Hidden Markov Model (ARHMM)-based algorithm is introduced, which can determine the operation mode of the machine in real-time and find direct application in intrusive load monitoring cases. Compared with other load monitoring techniques, such as transient analysis, no prior knowledge of the system to be monitored is required.

Keywords. Autoregressive, Hidden Markov Model (HMM), Manufacturing Processes, Intrusive Load Monitoring (ILM)

1. Introduction

In recent years, energy management has become a challenging task for both industrial and domestic users, due to the increased number and complexity of appliances and machines. The European Union has set targets for improving energy efficiency by at least 20% before 2020 [1]. The ability to monitor characteristics such as the operational, peak and idle energy consumptions, the duration of the working cycle and influences of process errors (e.g. worn tooling) in energy signatures will facilitate the scheduling of operations in more efficient ways and result in savings on electricity costs for companies and home users alike.

Research has been published in the area of load monitoring for domestic user appliances [2][3][4], but the industrial domain has received less attention. This is mainly due to easier access and collection of data from home appliances compared with industrial equipment. In domestic environments, the research community has focused on Non-Intrusive Load Monitoring (NILM). The goal is to utilise only one single energy meter for the whole installation instead of one for each appliance or socket, which results in substantial cost-savings for the end-user and adds to the ease of

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installation [5]. However, load appliance disaggregation from a single source of data is complex, especially as the number of appliances rises [6]; as is the detection of devices with rapidly changing or a large numbers of states [3].

These disadvantages make NILM unsuitable for wider adoption in the industrial domain. In addition, although industry is starting to deploy energy meters for machinery, the systems are not "smart" enough, in that their sole capability is to collect data and transmit it to a database. The intention of the work outlined in this paper is to add intelligence to these embedded energy monitors. In this paper, an Autoregressive Hidden Markov Model (ARHMM)-based algorithm is proposed that is able to detect the different process states of a production machine. Further, the ARHMM solution is compared with a standard Hidden Markov Model (HMM) algorithm implementation to demonstrate the improvement in accuracy and reduction in the time of training.

The aim is to develop a Manually Setup Intrusive Load Monitoring (MS-ILM) system, in which the training of the models will be based on data acquired in-situ, instead of being trained remotely prior to deployment [5].

2. Related Work

Techniques to determine signatures within data streams have been developed, such as transient and harmonic analysis [7][8] that can be used in both cases of either NILM or ILM. Processing the transients' profile is not trivial and requires significant computational resources, as high-frequency sampling in the order of kHz is a prerequisite [9]. Harmonic analysis is complex, as it requires kHz sampling rates too and the measured content of the harmonics is often limited by the noisy industrial environment or the quality of the local grid resulting in inconsistent results [10].

A comprehensive review of widely used techniques for intrusive load monitoring, such as Support Vector Machines (SVM) [4], K-Nearest Neighbours (KNNs) [11] and Dynamic Time Warping (DTW) [12] is reported in [5]. The accuracy of the reported results ranges from about 75% up to 99.9% in many cases, depending on factors such as the complexity of the datasets and the training duration. As [13] reports, state-based modelling algorithms, such as Markov methods [2] and Gaussian Mixture Models (GMM) provide great opportunities, due to the possible interpretation of the power signal as a finite number of interconnected states. When machine learning algorithms are used, the sampling frequency can be much lower compared with transient or harmonic-based methods, even as low as 10^{-1} Hz [14].

3. Autoregressive Hidden Markov Model

Hidden Markov models (HMMs) are statistical models which represent a doubly stochastic process [15]. A HMM consists of an underlying unobservable process modelled with a Markov chain (MC) that cannot be directly measured (hidden process) and an observable process which is affected by the underlying one. The model comprises a set of states $\{x_i\}_1^n$ and a set of observation symbols $\{y_l\}_1^m$, along with a group of probability distributions that determine the behaviour. The distributions include the transition probabilities $p(x^t|x^{t-1}, x^{t-2} \dots x^0)$, which are the probabilities of moving from a state x^{t-1} to a state x^t, the emission probabilities $p(y^t|x^t)$, which are

the probabilities of emitting the symbol y^t while being in the state x^t and the initial probability $p(x^0)$ that is the probability of being in the state x^0 at the beginning of a sequence.

Standard time-homogeneous, first order, discrete HMMs have several limitations that affect their performance to classify power signals [16]. Firstly, the power signal needs to be quantized in discrete intervals. The number of intervals and their size tend to be difficult to determine automatically and can have a large impact on the overall performance of the algorithm. As a result, several algorithms have been proposed which use continuous output observation models such as Gaussian, Gaussian mixture and exponential. A continuous output HMM does not need to have its output discretised, however this comes at the cost of increasing the number of parameters that need to be inferred. In addition, all these models suffer from limited dynamic expressiveness due to their finite number of states. Each hidden state is associated with a static distribution of the output and therefore all the dynamic information is encoded in the underlying Markov chain. This means that even for very simple signals, a large number of states is needed.

Autoregressive Hidden Markov Models (ARHMMs) are an extension of the standard discrete HMMs that have been developed with the goal of solving their major issues. They have been applied in speech recognition and synthesis [17], as well as biomedical signal analysis (ECG, EEG) [18][19]. The observation model of an ARHMM consists of a linear combination of previous outputs affected by an additive Gaussian noise, called multivariate linear autoregressive models (mAR). These have been extensively used in many fields such as control theory [20], signal processing and stock market forecasting [21] and they have the following mathematical expression:

$$y^t = \sum_{k=1}^{p} \phi_k y^{t-k} + \varphi + w, \qquad w \sim \mathcal{N}(0; \Sigma)$$

where the coefficients of the linear combination (ϕ_k, φ), the covariance matrix of the Gaussian noise (Σ) and the order of the mAR (p) form the parameters of the observation model θ_l^Y. Unlike univariate autoregressive models, the coefficients (ϕ_k) are represented by square matrices of the same dimension as that of the model output space (d) and the noise term follows a multivariate normal distribution.
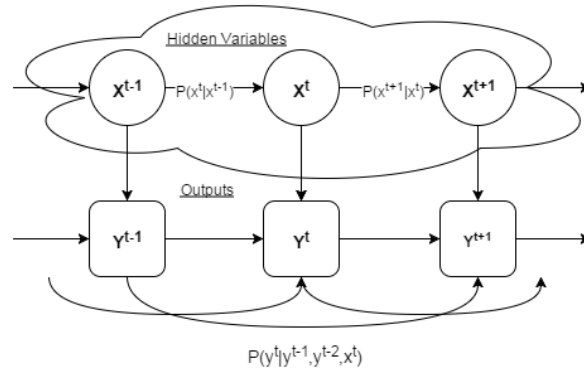

Figure 1. Autoregressive Hidden Markov Model (ARHMM) variable dependencies

In ARHMMs, the Markov independence condition is relaxed because each output y^t not only depends on the current state x^t, but also on the previous outputs $y^{t-1}, y^{t-2} \dots y^{t-p}$ (Figure 1). As a result, this characteristic adds dynamic expressiveness to the observation model, which solves the main problem of static distribution observation models and allows for a representation of more complex signals with a lower number of states.

4. Design of Experiments

A series of experiments was carried out to evaluate the algorithm's performance, using real power consumption data from two different sources. As a first source, a laboratory machine was used to generate the sample data by cycling through 3 different states for 30 minutes. This machine was a VICO Laser manufactured by Hacker Automation GmbH. The second set of datasets originated from an operational industrial machining centre used for the manufacture of automotive engine components and consisted of three different datasets. Two of these included four different machine states, while the third one included only two (one of them always being the idle state). Again, the length of the datasets equalled 30 minutes of sampling. The sample rate for all the test cases was 1Hz.

The sampled signals were divided into two parts; the first part (40% of the total length) was used for training the model, whereas the rest was used as the validation set. Once the model was trained, it was used to determine the decoded state sequence estimation, by relying on the validation set's observations. The testing procedure followed was the same for both the HMM and the ARHMM algorithms.

Lastly, two performance indicators were defined in order to compare the ARHMM and the HMM algorithms:
- Total accuracy, representing the one-to-one state matching percentage, i.e. the percentage of the sample signal where the decoded states exactly match the real states.
- Idle-running accuracy, representing the percentage of the samples where the algorithm managed to classify accurately whether each sample belongs to the idle state or not.

5. Results

The experimentally derived results are summarised in Figure 2. On the left-hand side, the average accuracies for all the cases are presented, whereas on the right bar-chart there is an overview of the results for each separate dataset.

The ARHMM algorithm was able to perform (on average) slightly better (92.2% idle-running accuracy) than the standard HMM (89.3% idle-running accuracy) for the purpose of detecting only the idle state. However, in the case of distinguishing each individual process among the complete dataset, a notably better total accuracy was observed when using the ARHMM (i.e. 89.7% against 75.1% of the HMM). In addition, it is worth noting that the ARHMM needed considerably less training time to achieve the same accuracy as the HMM, resulting in an average training duration of 27 sec, whereas HMM needed almost double that time (average of 52 sec).
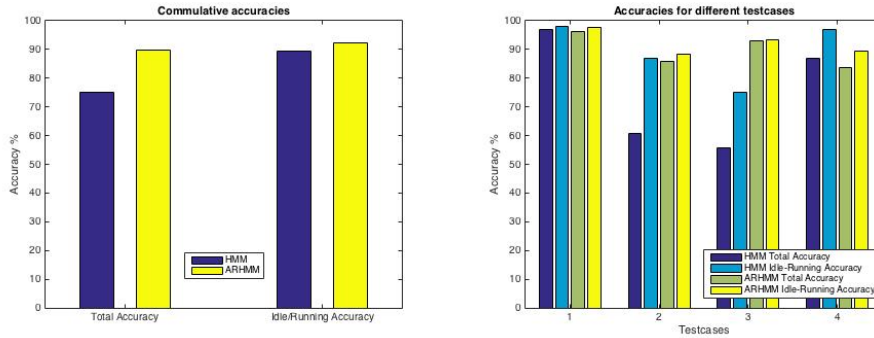
Figure 2. Cumulative & Test-case accuracies

6. Conclusion and Future Work

In this paper, an ILM algorithm application has been proposed for detecting the different processes and states of a shop floor machine. While similar techniques based on HMM already exist, the research outlined in this paper has shown that by regarding the power signature as an autoregressive model the accuracy of the estimated state sequence can be improved.

Future work will include investigating short-time Viterbi decoding [22], with the aim of executing the decoding algorithm on the energy monitor device in real-time. Hidden semi-Markov processes is also another way of modelling the energy signatures, as the relation of the emission probabilities to the duration of each state can further improve the accuracy [23].

Contribution of Work

D. Pantazis developed and provided the methodology for analysing the sample data using the HMM algorithm. A. Ayastuy Rodriguez developed and provided the methodology for analysing the sample data using the ARHMM algorithm. D. Pantazis validated and compared the results using the real power data.

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