Appliance State Estimation based on Particle Filtering

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Abstract — *Non-Intrusive Load Monitoring is a single-point metering approach to identify and to monitor household appliances according their appliance power characteristics. In this paper, we propose an unsupervised classification approach for appliance state estimation of on/off-appliances modeled by a Hidden Markov Model (HMM). To estimate the states of appliances, we use the sequential Monte Carlo or particle filtering (PF) method. The proposed algorithm is tested with MATLAB simulations and is evaluated according to correctly or incorrectly detected on/off events.*

1 Introduction

To create a more efficient, reliable and sustainable power grid, the future smart grid requires new information and telecommunication technologies. One key factor determining the success of the smart grid will be the introduction of smart metering. Modern metering methods will provide fine-grained consumption information, making it possible for consumers to access information about when energy was consumed and the cost of that energy. With fine-grained consumption information, it is possible to show the consumers not only when and what quantity of energy is consumed, it is also possible to provide information about which appliance is consuming which amount of energy at which time. One possible technique for compute energy information on appliance level was introduced by Hart [4] and is named Non-Intrusive Load Monitoring (NILM). In contrast to for example an optimization approach [2],we propose in this paper an unsupervised classification approach which is based on particle filtering, which applicable for nonlinear and non-Gaussian disturbed problems. We show that PF can be used for estimating the inference of a Fractional Hidden Markov model FHMM, where the aggregated household profile is modeled by a Hidden Markov Model HMM.

2 Household and Appliance model

The load of a household is characterized by the power profiles of each appliance in a household. Thus, the total power load is the aggregated sum of power profiles, where each appliance is modeled by a HMM and the total power consumption by a FHMM. An HMM is a Markov model, in which the states are not directly observable. The state of the HMM are hidden and are characterized by a probability distribution function. Although states can not be directly observed, states can be estimated from the available measurements. An HMM is defined by its transitions matrix A providing the transition from one to the next state, the emission matrix B, which represents a symbol in an actual state and the initial probability π. A vector $z = \{z_1, z_2 \dots z_t\}$ is the result of the hidden states $x = \{x_1, x_2, \dots x_t\}$, where the next state of the HMM is dependent on the HMM's current state and is independent of past states. This property is the well-known Markov property $P(x_{t+1} \mid x_t, x_{t-1} \dots x_1) = P(x_{t+1} \mid x_t)$. The on/off appliance model is defined by the states *on* and *off*, the probabilities $prob_{on}$ and $prob_{off}$ and the power demand, which can be observed in each appliance state. The household power profile can be observed by the aggregate power profile of N different appliances such as $Y = \{y_1, y_2, \dots y_t\}$ and is generated by the state sequence of $x = \{x^{(1)}, x^{(2)}, \dots x^N\}$, which is the superimposition of the appliance states at each time slice $x^{(n)} = \{x_1^{(n)}, x_2^{(n)} \dots x_t^{(n)}\}$. The household model is based on FHMM. An FHMM is commonly used to model multiple independent hidden states and to decrease the number of parameters in contrast to using a simple HMM with a large set of operational states to model this type of problem.

3 State Estimation of Appliances

The power consumption of a household is modelled by an FHMM, where each HMM is independent from each other and represents an appliance used in the home. In the case of an FHMM, the Viterbi algorithm,a well-known technique for computing the inference of an HMM is not longer usable for computing the exact inference, thus, methods such as Gibbs sampling [3] and inference approximations [5] are used to estimate the states of a FHMM. In this paper, we propose a method for computing the inference of an FHMM by particle filtering. Particle filters are suitable for non-linear problems and non-Gaussian noise, which is in generally the case for aggregated appliances. To solve the problem of appliance state estimation of on aggregated power data, we estimate the aggregated household power profile and measured data y_t and the current appliance hidden state x_t^n. Accordingly, one estimated particle filter state x_t is a combination of n hidden appliance states[1]

[1] $n \in \{1 \dots N\}$. We assume that the number of appliances N is known

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$x = \{x_t^1, x_t^2 \dots x_t^N\}$. To be able to estimate the hidden states, the particle filter has the information about the used appliance models defined by the HMM and the total household power consumption defined by the FHMM.

4 Experiments

Our experiments are executed by simulations in MATLAB. For this, we defined our on/off appliance model by an HMM model. This appliance HMM model is defined by the following three parameters $\{\pi, A, B\}$. The initial state π is set to zero for our evaluations. The transition matrix A represents the transition probabilities between the on and the off state by the probabilities $prob_{on}$ and $prob_{off}$ for each appliance $n \in \{1 \dots N\}$. In our experiments, we choose the parameters $prob_{on}$ and $prob_{off}$ by an uniformly distributed variable θ in the range of $\theta \in [1, 10]$, where θ is additionally divided by the time observation window T in seconds resolution. The Emission Matrix B is characterized by an uniformly distributed variable in the range $B_{on} \in [100, 3000]$ for the on state and $B_{off} = 0$ for the off state. We computed 100 simulation runs and calculated the mean value for the mentioned metrics in Section 4.1. The observation window was $T = 86400$.

4.1 Evaluation Metric

To evaluate the performance and the precision of the particle filter based appliance state estimation, we used the classical classification terms such as *true-positive* (TP), *false-positive* (FP), *false-negative* (FN), *true-negative* (TN),*true-positive rate* (TPR), and *false-positive rate* (FPR) [1]. The metric TPR is formulated by $TPR = \frac{TP}{TP+FN} \in [0, 1]$ and FPR by $FPR = \frac{FP}{FP+TN} \in [0, 1]$.

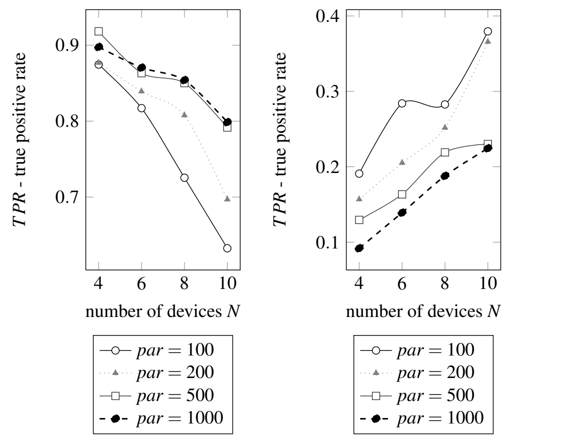
4.2 Influence on the Particle Number

The efficiency of the particle filter is directly proportional to the number of particles, thus, we evaluate the state estimation behavior of the algorithm under the influence of varying numbers of particles $par \in \{100, 200, 500, 1000\}$. The noise value σ for the aggregated power consumption is $\sigma = 1$. In Figure 1, the TPR and the FPR are presented for a varying number of particles par and appliance number N. The number of appliances was $N \in \{4, 6, 8, 10\}$.

For TPR and FPR it can be seen that the quality of the state estimation behavior is proportional to the number of particles and in contrast decreases if the number of appliances increases.

5 Conclusion

In this paper, we presented a new appliance state estimation approach based on particle filtering, applicable to non-linear problems with non-Gaussian noise. We used the knowledge of the appliance model (HMM) and aggregated household power consumption (FHMM) to estimate the operating states (on or off) for each desired device. We performed Matlab simulations and showed that the particle filtering based appliance state estimation



(a) True Positive Rate (b) False Positive Rate

Figure 1. Influence of the particle number *par* on TPR and FPR with a varying number of appliances *N*

approach is visible to be used as an Non-Intrusive Load Monitoring technique. Our simulations showed that the algorithm can be improved by increasing the number of particles, how the method is dependent on the number of appliances that need detecting and how noise is influencing the estimation result.

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