On the Applicability of Correlation Filters for Appliance Detection in Smart Meter Readings

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***Abstract*---Communication systems utilise correlation filters to detect waveforms. In a broader sense, these filters examine the amount of resemblance between a template pattern and the input pattern. In the domain of smart grids, many applications require the detection of active electrical appliances, their condition as well as their current state of operation. Furthermore, the identification of power eaters, the recognition of ageing effects, and the forecast of required maintenance represent important challenges in (home) energy management systems.**

In this paper, we examine the applicability of correlation filters as a possible solution to meet such challenges. First, we introduce the concept of predictability to power consumption patterns of electrical appliances. Second, we present our concept and the implementation of correlation filters for this kind of application. The correlation filters utilise a particular consumption pattern of an electrical appliance to detect the respective appliance in energy readings from smart meters and smart plugs. Lastly, we assess the performance of the correlation filters on the real-world energy consumption dataset GREEND, which provides readings from smart meter data as well as appliance-level measurement equipment. As the results approve, the correlation filters show a good performance for appliances with predictable consumption patterns such as refrigerators, dishwashers, or washing machines. Thus, we propose that future work should evaluate the applicability of correlation filters in appliance diagnosis systems.

***Index Terms*---Pattern Recognition, Smart Metering, Correlation Filter, Smart Meter, Appliance Diagnosis**

I. Introduction

Smart meters and smart plugs provide information about the energy consumption of electrical appliances. In general, these energy readings serve to determine the overall consumption of the residents and in a further step also to bill the customer for the consumed amount of energy. By the application of data analysis techniques, it is also possible to utilise these readings to identify active appliances, determine their condition, perform load disaggregation, or to extract behavioural patterns of residents. The shape of the power consumption over time is referred to as power consumption pattern. These patterns provide appliance-specific information, which could be utilised to identify abnormal behaviour of appliances. Such abnormal behaviour could be the consequence of ageing effects or the need for maintenance. In order to save costs for measurement equipment and to detect such abnormal behaviour as fast as possible, it would be desirable to apply a simple and effective detection technique, which is applicable by low-performance measurement equipment such as smart plugs or sensor nodes.

In communication systems, correlation filters (matched filters) are utilised to detect input waveforms and to distinguish between them. Such filters are equipped with a template pattern, which they aim to identify in an input stream of data. In particular, their detection mechanism bases on the correlation method, which can also be applied by low-performance measurement instruments. We propose to utilise correlation filters to detect appliance consumption patterns in smart plug and smart meter readings. Each correlation filter serves to detect a certain electrical appliance by means of a power consumption pattern, which characterises the consumption behaviour of the respective appliance over time. This behaviour can be categorised in predictable behaviour and non-predictable behaviour. As the evaluation will show, the type of behaviour influences the detection performance of a correlation filter.

The focus of this paper lies on the conception, implementation and evaluation of correlation filters for the application as appliance detectors in energy monitoring systems and is organised as follows: Section II presents related work. Section III reviews the Pearson product-moment correlation. Section IV introduces the concept of predictability to consumption patterns of electrical appliances. Section V presents our concept and the implementation of the correlation filter. Section VI assesses the performance of correlation filters through application on an energy consumption dataset. Section VII concludes the paper and provides an outlook to future work.

II. Related Work

Event detection approaches in load disaggregation algorithms utilise either expert heuristics, probabilistic models, or matched filters [1]. Up to present, several detection techniques based on matched filtering have been proposed. Such a filter correlates an unknown input pattern with a known template pattern. The substantive considerations of a transient event detector for the application in load disaggregation were discussed in [2]. The presented detector applies a preprocessor on the aggregate power signal and performs appliance detection on the disaggregated signals. A wide variety of related work evaluated possible applications for matched filters in the context of appliance detection. The authors of [3] suggest to detect and distinguish between appliances by means of their turn-on transient patterns. A related idea is presented in [4], in which the authors suggest to detect appliances by matching subpatterns of power signals such as the transients of rising or falling consumption. The classification system in [5] applies Fast Fourier Transform (FFT) on transient current signals by further analysis of the resulting spectrum in order to detect appliances. The presented detector in [6] employs load transient shapes of current signals. The presented work reveals possible strategies and mechanisms to apply correlation filters (i.e., matched filters) as appliance detectors in measurement systems. A system, which performs load identification, was presented in [7] as well as [8]. This system applies genetic programming as well as a neural network to detect appliances based on their turn-on transients. Contrary to related implementations we propose to use full shapes instead of turn-on transients. A full shape (i.e., pattern) describes the behaviour of a certain appliance as well as the physical task that the appliance performs more precisely. In order to detect appliances on the basis of their power consumption over time we propose a system, which comprises a set of correlation filters (i.e., matched filters) to perform appliance detection, a finite set of template patterns to describe the power consumption behaviour of the appliances over time. The correlation filters in our system apply template patterns that describe one entire workflow, the power consumption over time, for a specific programme of the respective appliance e.g. a certain washing programme of a domestic washer. Due to this, the derived template patterns represent unique shapes with characteristic transients. We hypothesise that such kind of templates are well-suited to detect and distinguish between appliances by applying a correlation filter.

III. Pearson correlation coefficient

The Pearson product-moment correlation provides information about the strength of association between two variables [9]. In particular, to test two variables for linear associations the Pearson correlation coefficient is of interest. This coefficient is a measure of the strength of the linear relationship between two variables x and y. The Pearson correlation transforms the two variables into standard scores, which makes it possible to test distinct physical quantities for correlation. The coefficient is defined for a population as well as for a sample. For a given population the Pearson correlation is denoted by r and is defined as the ratio between covariance and the product of the standard deviations of the respective variables.

$$r = r_{x,y} = \frac{cov(x,y)}{\sigma_x \sigma_y} = \frac{E[(x-\mu_x)\cdot(y-\mu_y)]}{\sigma_x \sigma_y} \qquad (1)$$

The Pearson correlation coefficient r is a real number and takes values in [-1,1]. For $r > 0$ the coefficient indicates a positive association, from which follows that an increasing variable x results in an increasing variable y. On the other hand, the Pearson coefficient indicates a negative association for $r < 0$, which describes that the variable y decreases for an increasing variable x. If and only if the coefficient is equal to zero, then there is no linear association between the two variables x and y. The stronger the association between the variables is, the closer to 1 will be r. In many applications a decision is made on basis of the correlation‘s strength. The authors of [10] propose a categorisation for the strength of the Pearson correlation: For $|r| = 1$, we declare the correlation *perfect*, for $0.8 \leq |r| < 1$, we declare the correlation *high*, for $0.6 \leq |r| < 0.8$, we declare the correlation *medium*, and for $|r| < 0.6$, we declare the correlation *low*. This categorisation of the strength of correlation will be applied throughout the paper.

IV. Predictabiliy of Consumption Patterns

Appliances can be categorised in single-state, multi-state, and infinite-state appliances [11]. These categories describe the power consumption behaviour of a certain appliance for a single operation. The shape of the power consumption over time for a single operation is referred to as the power consumption pattern. Figure 1(a) shows such a consumption pattern. Therefore, the power consumption pattern states the amount of consumed energy as well as the duration of the operation. Furthermore, a power consumption pattern models the behaviour of the respective appliance for a specific programme over time.

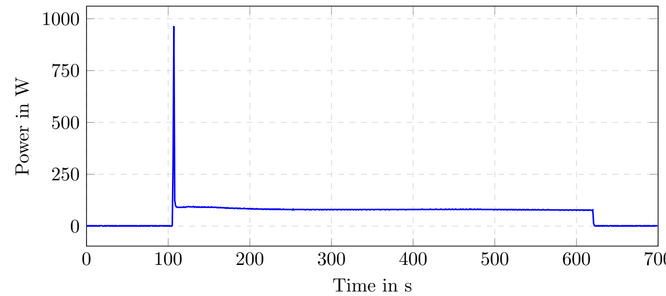
The group of *predictable appliances* represents a specific category of electrical appliances, since the power consumption pattern for every possible programme can be predicted. This means that every predictable appliance comprises a set of programmes, which it is able to execute. This set consists of a finite number of power consumption patterns. Each pattern describes an unique power consumption behaviour i.e. programme of the respective appliance. From this follows that the behaviour of the respective appliance can be described entirely. Furthermore, every possible power consumption pattern can be predicted. Examples for such appliances are washing machines, dishwashers, tumblers, refrigerators, freezers, coffee brewers.

A vast number of appliances does not define a fixed operation duration. This means that neither the energy consumption nor the shape of the power consumption pattern can be predicted. The length of *non-predictable* power consumption patterns highly varies between two operations. For this reason, the behaviour of such an appliance can't be described by a finite set of power consumption patterns since every operation of the respective appliance results in a novel pattern. A high number of household appliances is controlled by the inhabitant. For instance the filling level of a water kettle depends on the amount of water that the inhabitant fills into the kettle. The filling level will influence the amount of energy, which the water kettle requires to bring the water to boil. For this reason, the power consumption pattern of each heating process will highly vary from the previous ones. Examples for such appliances are microwave ovens, water kettles, hair dryers, TVs, or lighting.

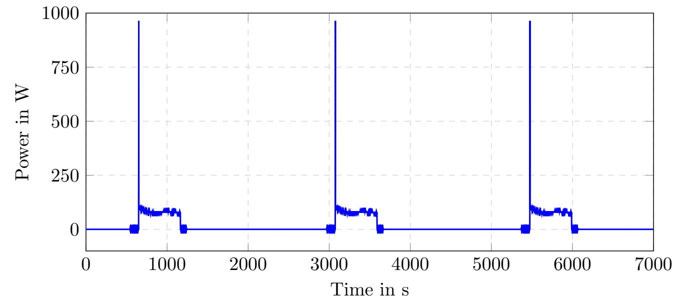
V. Correlation filter

A correlation filter (matched filter) is a signal processing element, in which the input signal is examined for association to a known pattern, the template. This test for association can be implemented by convolution with the conjugated time-reversed template or by correlation of the input pattern with the template. By means of our application we define a correlation filter as a software tool, which examines two input variables for a linear association by means of the Pearson correlation. The correlation filter contains two registers: The *template register* and the *measurement register*. Both registers are of equal length. The former contains the template pattern, which we seek to detect in the content of the latter register, the measurement register. Figure 1(a) shows such a template pattern. The data in this register is updated after every measurement and the organisation follows the first in first out (FIFO) method. As input pattern we define the content of the measurement register, which is updated every time a new power measurement sample is available. Figure 1(b) shows a possible input pattern, which is shifted into the correlation filter. A threshold value, the correlation threshold denoted by γ, serves as basis of decision-making for every correlation filter. As we will see in subsequent examinations, this threshold is an influential parameter for appliance detection. As already mentioned, the correlation filter applies the Pearson product-moment correlation, introduced in Section III, to examine the linear association between the input pattern and the template pattern. To compute the Pearson product-moment correlation, the correlation filter applies the *corrcoef* function, a function embedded in the NumPy package[1]. Depending, if the computed Pearson coefficient exceeds the correlation threshold γ, the return value of the function *correlate* equals zero or the computed Pearson coefficient. The values of the Pearson coefficient lie in the interval [0,1], where a coefficient of 0 indicates no correlation and 1 full correlation between the two input variables. The distance of the Pearson correlation to full correlation $1 - |r|$ will depend on how precisely the template pattern describes the power consumption over time for a given electrical appliance's workflow. If and only if these two patterns are identical, then the result of the Pearson correlation, the Pearson correlation coefficient r, equals 1. Any deviation between the two input patterns will result in a correlation coefficient smaller than 1. This deviation may be the consequence of disturbances, measurement uncertainties, or noise. The significant parameter to decide if the linear relationship is high enough to classify the pattern as detected is the correlation threshold γ. The magnitude of r can be interpreted as an estimation about how well the two patterns resemble each other. To decide if a pattern was detected, we test if r is equal or greater than the certain correlation threshold γ. If r exceeds or equals the threshold, then the correlation filter starts to track the progress of the correlation coefficient over time i.e., the filter computes the correlation coefficients for the next M incoming samples immediately and stores them in a tracking window, where M represents the length of the tracking window. At the moment where this tracking window contains M elements, the filter selects the biggest element since it represents the perfect match of the template pattern in the input stream, as Figure 1(c) indicates. By means of this mechanism the perfect fit of the input and the template pattern can be examined.

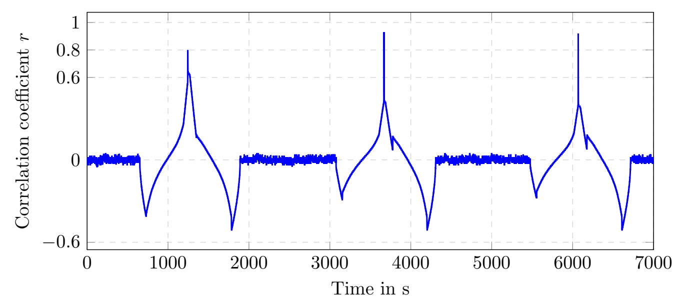
[1]http://numpy.org



(a) Consumption pattern of a refrigerator



(b) Input signal at the correlation filter



(c) Correlation coefficient r over time

Fig. 1: Example detections of a refrigerator

VI. Evaluation

For the purpose of the assessment of energy management algorithms i.e. load disaggregation solutions, several energy consumption data sets were recorded. Widely applied data sets in the domain of smart homes are REDD [12], ECO [13], AMPds[14], and GREEND [15]. The performance of the correlation filter is assessed on the the real-world energy consumption dataset GREEND. The ground-truth data covers one entire year of energy consumption data and integrates a refrigerator (Whirlpool ARG 737), a dishwasher (Whirlpool ADG 555 IX), a microwave oven (Whirlpool AMW 494/IX), a water kettle (Philips HD 4619), a washing machine (Zanussi F1215), and a hair dryer (Braun 3522). For the predictable as well as the non-predictable appliances, one power consumption pattern per appliance was manually extracted from appliance-level power measurements. The reference pattern was selected as the one with the median level of energy consumption out of a set of five arbitrarily selected patterns. This pattern comprises the power consumption of the respective appliance over time for a specific programme. Therefore, the pattern integrates several characteristic events such as turn-on, transients between operational modes, and turn-off.

In this assessment, the *detection rate* serves as measure of performance. This rate is defined as the ratio between the number of detected patterns in the input data and the number of patterns integrated in the ground-truth data. The correlation threshold γ describes the minimum correlation, which has to be exceeded in order for the correlation filter to detect the template pattern in the input data. The performance of the correlation filter is assessed for thresholds in the interval $[0.5, 0.95]$. On the basis of the number of detected patterns, the respective detection rate is computed for γ in the set $[0.5, 0.95]$ with a step size of 0.01. In this way the performance is evaluated for low, medium, as well as high correlation on the data record.

A. Detection on Appliance Level

Data acquired on appliance-level exclusively contains information about the energy consumption of one particular appliance. Devices such as smart plugs are attached to a certain appliance to exclusively monitor its energy consumption. The recorded energy consumption is expressed as a time series of power consumption measurements. A (moving) time window of this time series represents the input pattern (measured pattern) of the correlation filter. The strength of the correlation gives information about the deviation between these two patterns throughout the input data. On the one hand, this deviation influences the number of detected appliances and consequently the detection rate. On the other hand, the correlation filter integrates a parameter, which can be adjusted in order to influence the detection rate, the correlation threshold γ. The purpose of this parameter is to serve as threshold in order to decide if the computed correlation coefficient r is high enough to declare a detection. From another perspective, the correlation threshold defines a minimum amount of resemblance that the correlation has to indicate in order to declare a detection. For this reason, the impact of the correlation threshold on the detection rate has to be determined.

If the threshold γ is defined in the range of high correlation e.g. $\gamma = 0.8$, then this will result in a lower detection rate than for γ in the range of medium correlation e.g. $\gamma = 0.6$. In order to prove this hypothesis, the correlation filter is applied to appliance-level data for a set of correlation thresholds. The utilised appliance-level data covers one year of energy consumption data. Figure 2(a) shows the detection rates over a set of correlation thresholds γ for the selected household appliances. Equal to Section III, we distinguish between low, medium, and high correlation in the case of the correlation threshold γ. As the trajectories show, the detection rates decrease significantly for an increasing correlation threshold.

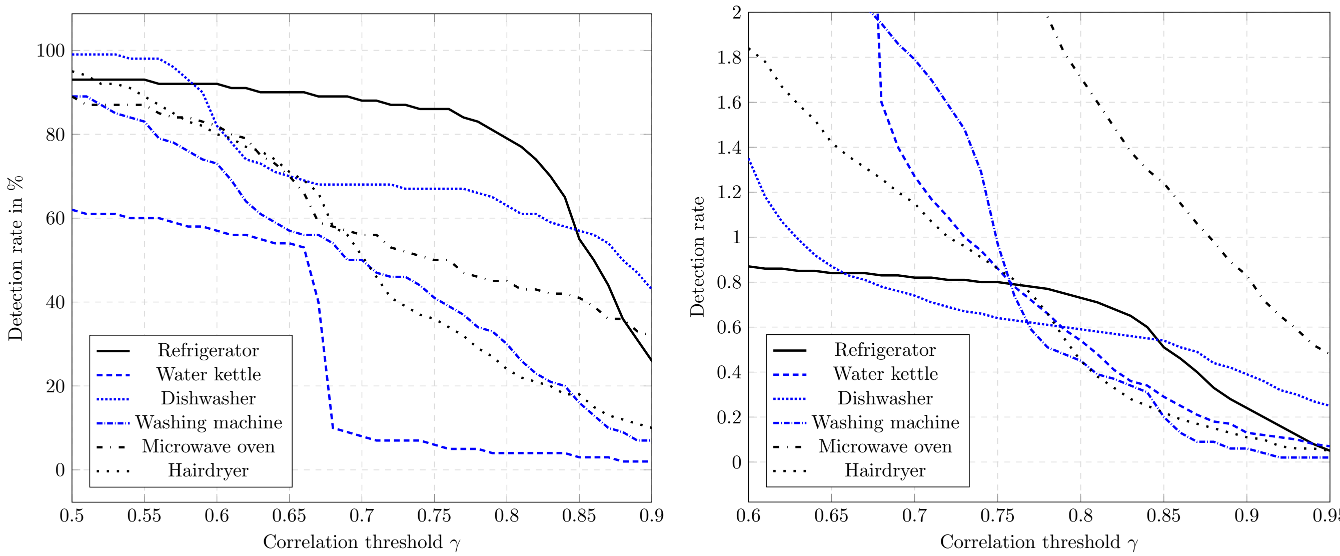
The correlation filter provides the best performance for an appliance with a predictable power consumption pattern, the refrigerator. The refrigerator achieves the highest detection rate for medium as well as high correlation, as Figure 2(a) shows. For a correlation threshold γ in the range of low and medium correlation, the correlation filter is able to detect more than 80% of the patterns in the input data. The reason for this comparably high detection rate is the optimal selection of the template pattern. The utilised template pattern describes a specific physical task that the refrigerator periodically performs. This task is to cool the content of the refrigerator. Due to the repetition of this physical task, the deviation between the template pattern and the measured power consumption is small enough to detect most of the patterns.

The dishwasher as well as the washing machine likewise belong to the category of appliances with predictable power consumption pattern. In contrast to the refrigerator, the detection rate for medium and high correlation is substantially lower than for the refrigerator. For a correlation threshold γ of 0.8, the correlation filter detects 62% of the patterns of the dishwasher and 30% of the patterns in the case of the washing machine. This performance gap is a result of the detection approach. The more distinct programmes an electrical appliance comprises, the lower the detection rate for the correlation filter detector will be.

In contrast to predictable patterns, the duration as well as the energy consumption of non-predictable patterns can't be predicted. Appliances, which produce non-predictable consumption patterns, don't have programmes with a fixed duration. For this reason the shape of the power consumption pattern is not predictable. Examples for appliances with non-predictable consumption patterns are water kettles, microwave ovens, and hairdryers. Figure 2(a) shows the detection rate of the correlation filter over the correlation threshold γ. For a correlation threshold of $\gamma = 0.6$, which corresponds to the range of medium correlation, 80% of the patterns for the hairdryer and the microwave oven were detected, whereas less than 60% of the patterns for the water kettle. In the case of a correlation threshold in the range of high correlation e.g. $\gamma = 0.8$, the detection rate declines under 50% for all appliances with non-predictable power consumption pattern in this evaluation. With a rising correlation threshold, the minimum amount of resemblance decreases. This minimum amount of resemblance is defined by the ratio of the template pattern and the measured pattern, SNR_{min}. In the case of the non-predictable appliances in this evaluation, the ratio between template and measured pattern is below the demanded threshold for more than every second measured pattern. This is a consequence of the strongly varying shape of the power consumption pattern.

B. Detection on Aggregate Level

Instruments such as smart meters measure the aggregate power consumption. Consequently, this aggregate power consumption represents the superposition of multiple power consumption patterns. As Figure 2(b) confirms, decrease the detection rates for the six household appliances for an increasing correlation threshold. In contrast to the evaluation on appliance-level, in this evaluation the detection rates exceed the 1 mark. A detection rate greater than 1 states that more patterns were detected than the ground-truth data contains in fact. This is a consequence of incorrect detections performed



(a) Detection rate over correlation threshold γ for appliance-level data

(b) Detection rate over correlation threshold γ for aggregate-level data

Fig. 2: Detection Rate of the Correlation Filter

by the correlation filter, as a result of false alarms. The lower the correlation threshold γ is set, the higher the number of false alarms and therefore, the higher the detection rate. The correlation threshold defines a minimal amount of resemblance expressed as correlation between the stored template pattern and the measured pattern. If this threshold is defined in the range of high correlation e.g. $\gamma = 0.8$, then on the one hand the detection rate will be lower than for medium correlation, but on the other hand likewise the number of false alarms will be significantly lower. For this reason a trade-off between number of false alarms and the detection rate exists.

Figure 2(b) shows the detection rates for six household appliances over the correlation threshold γ. These detection rates were obtained by application of the correlation filter to the aggregated energy consumption data over the period of one year. For correlation thresholds in the range of medium correlation $0.6 \leq \gamma < 0.8$, the detection rates show a high amount of false alarms. One exception represents the detection rate of the refrigerator, which remains under the 1 mark for all applied correlation thresholds. The highly incorrect detection rates of the other appliances in the range of medium correlation are a consequence of false alarm detections. Such detections are declared by the correlation filter, when the correlation threshold γ is exceeded by the correlation between input pattern and template pattern.

In the context of aggregate-level measurement data, the input pattern is a superposition of several power consumption patterns. If the template patterns of two appliances closely resemble each other, then the correlation filter will very likely perform a false alarm detection. This false alarm detection represents an incorrect detection. In order to minimise the number of false alarm detections for a certain appliance, the correlation threshold γ has to be defined in the range of high correlation i.e. $\gamma \geq 0.8$. As the results of the evaluation in Figure 2(b) confirm, the detection rates decrease under the 1 mark for all electrical appliances with predictable power consumption. In this evaluation, such appliances are the refrigerator, the dishwasher, and the washing machine. In particular, the detection rate of the refrigerator shows a conformable trend to the evaluation on appliance level, which is displayed in Figure 2(a). As the Figure confirms, a clear gap in performance between the refrigerator's pattern and the remaining patterns exists. This gap originates from several characteristics of the refrigerator.

First, the refrigerator periodically performs an identical operation. For this reason the stored template pattern and the (predictable) input pattern resemble each other closely. On account of this close resemblance, the deviations between the template pattern and the measured patterns are small enough to demand a high correlation threshold. Such a high correlation threshold e.g. $\gamma \geq 0.8$ decreases the chance of performing a false detection.

Second, the pattern of the refrigerator contains a characteristic turn-on transient, as Figure 1(a) shows. In particular, the overshoot during the transient phase shapes the power consumption in a specific manner. Such characteristics make template patterns unique and well-distinguishable from other patterns.

In summary, the application of the correlation filter on aggregate-level data faces a trade-off between number of false alarms and detection rate. To minimise the number of false alarms we propose the application of a correlation threshold in the region of high correlation i.e. $\gamma \geq 0.8$. In general, a high correlation threshold decreases the number of false alarms and consequently also the detection rate. On the contrary, we aim to maximise the detection rate in order to provide an optimal performance of the correlation filter. The performance of the correlation filter inherently depends on the applied template patterns, which are correlated with the measured patterns. As demonstrated in Figure 2(b), the filter provides the best performance for appliances with predictable power consumption patterns. Peculiarly, predictable patterns with characteristic transients represent optimal template patterns such as the template pattern of a refrigerator.

VII. Conclusion

In this paper we introduced the concept of predictability to power consumption patterns and presented how correlation filters can be utilised to detect electrical appliances by means of their consumption patterns. The presented correlation filters can be applied by conventional computer systems as well as by embedded computer systems since they demand low hardware requirements. The deployment of a such correlation filters would allow the detection of abnormal appliance behaviour. Due to ageing, some electrical appliances consume more energy than a new appliance of the same kind. Such phenomenons were reported in [16], where a common household device consumed due to ageing effects three times more energy than at the time of purchase. A diagnosis system, which utilises appliance detectors such as the presented correlation filters, would possibly be able to detect ageing effects and would suggest the user to replace the respective device. By means of suggestions like this, such a system assists the owner in saving costs and in detecting power eaters. Furthermore, the system would be able to detect the point in time, where an appliance will require maintenance. Therefore, the presented correlation filters represent a simple and effective tool for a wide variety of applications in smart metering.

The performance of the correlation filters was assessed on the energy consumption data set GREEND. The assessment was performed on consumption data of single appliances and on aggregate consumption data such as readings provided by smart meters. For appliances with predictable features, the results approved a high performance for consumption data from single appliances as well as aggregate consumption data. In contrast to that, the performance of the correlation filters is significantly worse, which indicates that this kind of filters is not an appropriate detector for appliances with non-predictable consumption patterns.

Contemporary research contributions reveal the potentials of sophisticated machine learning techniques in embedded systems. In particular, deep neural networks could represent an alternative to correlation filters for the application as appliance detectors in low-cost metering infrastructure. A feasible approach would involve to run the neural networks on measurement equipment such as smart meters or smart plugs after being trained on high-performance computing infrastructure. Future work will compare the performance of such deep neural networks and the implemented correlation filters.

Future work will also focus how a diagnosis system could be implemented by the combination of correlation filters and artificial intelligence (AI). In particular, the correlation filters represent simple tools that serve to detect specific behavioural patterns. This detection can either be used to identify an appliance or to indicate abnormal behaviour. By means of machine learning an AI is possibly able to precisely study the present appliances in the household as well as their characteristics. Moreover, an AI may serve as cognitive unit that recognises specific events in the household such as the arrival of a resident or certain habits. The application of such a cognitive unit may allow to achieve significant energy savings by the identification of power eaters, the recognition of ageing effects of electrical appliances and the need for maintenance.

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