Intelligent Signal Processing for the Use in Device Identification Using Smart Sockets

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Abstract. In an era, that has seen an increase in smart socket adoption in homes, greater sensor data acquisition and data analytics within the Internet of things (IoT) platforms; new developments in hardware design and converging sensor data with big data introduces new research opportunities in the energy sector. Smart meters currently provide an overall energy usage for a household, by introducing socket level identification of electrical devices an itemised bill or detailed breakdown for device type or category can be achieved. Voltage and current waveforms extracted from sensors within a smart socket is processed using signal processing techniques for the use of pattern recognition. Experimental results for single device identification show that a low equal error rate can be achieved, therefore, increasing the likelihood of a successful device recognition.

Keywords: Smart socket · Signal processing · Pattern recognition · Smart meters · Energy monitoring

1 Introduction

The United Kingdom government has committed to the roll out of 53 million gas and electricity meters to all homes and small businesses by the end of year 2020 [1]. The new smart meters aim to provide a better management for energy use as they can inform the user on how much energy they have been using in near real time via a display in the house linked wirelessly, commonly by 802.11 (Wi-Fi) or 802.15.4 (ZigBee) to the smart meter. With the introduction of device energy monitoring a breakdown can be made of what a typical smart meter provides which is just an overall house usage, this breakdown could be in the form of categories such as lighting, heating, always on devices etc. or a further breakdown of individual appliances such as kettle, toaster or washing machine.

The Smart Systems Research Team at the University of Hertfordshire have developed a smart socket that will be used as the primary testing platform for device identification. Similarly, other smart sockets available on the market provide the ability to remotely control the on/off status of each socket however, with the addition of sensors to monitor the energy that is being drawn by a device. Data can be sent via a wireless transmission to the cloud where algorithms are conducted to provide results of a most likely device match. Obtaining a current waveform allows the system to identify and differentiate between known devices as oppose to the new generation of smart meters, which are only capable of reading overall energy utilised. This research

E.T. Lau et al. (Eds.): SmartGIFT 2017, LNICST 203, pp. 81–86, 2017.
DOI: 10.1007/978-3-319-61813-5_8

presents the ability for the identification of electrical devices and appliances wired to a traditional UK mains socket. Using a socket as an instrument to monitor, control and measure energy utilisation as a simple means to integrate more sophisticated and smarter devices around a smart home or building [2].

There are key benefits that can help this research contribute to smarter buildings and the future of energy management.

Control and convenience: Having a smart outlet will allow remote control either by individuals or by a local or remote control strategy, for example demand-side management. If the concept of device identification is introduced it could grant a level of security to what can be plugged in to the outlet or control the load as part of an energy saving policy. This could be particularly beneficial to institutions such as hospitals, government buildings or public places by refusing an outlet to supply electricity to either unauthorised or power hungry devices.

Maintenance and business continuity: Digital data is a big part of information gathering and exchange for the majority of businesses and is essential to operations and business continuity. The potential exists for the smart outlet socket to be part of an innovative system that would monitor a device's electrical signature therefore determining its health status; pre-empting a product failure [3].

Electricity monitoring: Finally, a potential significant benefit would be the categorisation of electrical usage by device type. This could offer the energy provider or consumer full disclosure by itemising and categorising electricity consumption by time of day, device, consumption, priority etc. [4].

This paper presents the findings of using a signal processing technique with current waveforms, from varying electrical devices. Section 2 describes the experimental setup as well as the gathering of current waveform data, feature extraction process and the comparison of devices. Section 3 highlights the results of experiments conducted in Sect. 2. Section 4 concludes the results and summarises this paper.

2 Experimental Setup

2.1 Data Acquisition

The smart socket with integrated energy monitoring was utilised to conduct the identification of devices at socket level connected to a single outlet. The internal hardware is capable of measuring voltage waveforms and current measurements from an individual outlet.

Voltage is measured using a fully-differential isolation amplifier to safely insulate high side live electrical connections from the low side logic controllers. A voltage divider circuit is used to step down from 240 VAC to a manageable 3 VAC.

Current measurements were attained using Hall Effect linear based current sensors (Allegro MicroSystems, Inc., Worcester, MA, USA, model ACS758) wired in series between the live electrical feed and socket outlet.

Voltage and current measurements were sampled using a 16-bit analogue-to-digital converter (ADC) (Maxim Integrated, San Jose, CA, USA, model MAX1300) at a sampling rate of 26ksps. Data collected was streamed in near real-time to a microcontroller connected via a personal computer that extracted the measurements and processed the data before being uploaded to a cloud platform that performed a pattern recognition algorithm.

2.2 Device Recognition

For the purpose of this experiment, four common household electrical devices (Table 1) were selected to ascertain different loads. Each device was connected individually to a single outlet ensuring a dedicated and clean signal, which was free from noise induced by other devices. All devices were powered 'on' to their respective operating states. To digitise an analogue signal by using an ADC, a devices waveform is continuously sampled at intervals to capture discrete points along a time domain in order to accurately reconstruct the original sampled signal. By sampling at an insufficient rate, there may not be enough samples to capture the changes in frequency or amplitude; thereby causing a problem where information is getting missed which may

Table 1. Electrical devices used in experiment for training and device identification.

Device	Device type	Figure
1	Desk fan	Fig. 1(a)
2	Incandescent lamp	Fig. 1(b)
3	Personal desktop computer	Fig. 1(c)
4	LCD TV	Fig. 1(d)

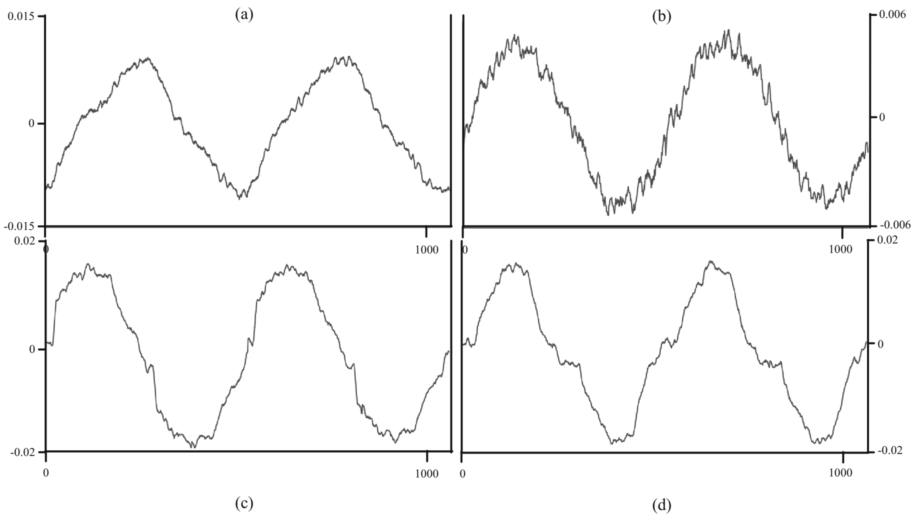

Fig. 1. Current waveforms of tested electrical devices sampled over 40 ms: (a) Desk fan, (b) Incandescent lamp, (c) Personal desktop computer, and (d) LCD TV. X-axis units - # of samples, Y-axis units - mV

also lead to the wrong signal being perceived entirely, this is known as Aliasing [5]. Alternatively, the greater the sampling rate the more accurate the wave reconstruction will be which will result in a higher identification rate amongst known devices.

2.3 Feature Extraction

Measurements were taken simultaneously from all sensors (i.e. one voltage and two current) to maintain that all samples are in sync with one another, thereby accurately detecting if devices connected to the smart socket outlets were resistive, inductive or capacitive loads. Resistive loads are recognised where the voltage and current are in phase; on the contrary, inductive and capacitive loads occur when the voltage and current are out of phase. Inductive loads affect the phase by delaying the current to the device and the opposite happens to the capacitive loads.

Extracted measurements consist of 40 ms analysis windows (European voltage frequency is 50 Hz $\times$ 2 cycles), for all sensors and discards data before and after to capture a single waveform. The real power values are also computed from current and voltage measurements using the trimmed analysis windows.

Signal processing techniques were applied to the device waveforms which produced training data that was uploaded to a database. A further experiment was conducted to attain the most suitable parameters by varying the number of coefficients, windowing methods, and percentage of window overlap. A total of 52,800 training data were stored for each device.

2.4 Pattern Classification

Pattern classification is performed by a cloud server after receiving the data from the real-time feature extraction process. This data is compared against trained data stored in the database as a series of clusters. In order for a match to be found, this comparison is calculated using Euclidean distance, the process measures the distance of the resultant features derived by the signal processing technique to provide a distance or error rate closest to a known pattern. A second stage verification is performed on a successful match to determine if the deviation of features are within a known device.

3 Results

The results shown in Figs. 2 and 3 illustrate the normal and cumulative distribution scores for trained devices within the database to determine an acceptable Equal Error Rate (EER) used for an identification threshold. By using the normal distribution scores to establish a successful match vs. an incorrect match, a False Rejection Rate (FRR) and False Acceptance Rate (FAR) plotted onto a cumulative distribution graph can be used to compute an EER where the points of FRR and FAR intersect. In the case of an ‘incandescent lamp’, the identification algorithm is able to differentiate between a known and an imposter device.

Furthermore, these results illustrate each device grouped by its category type to an individual curve, the curves are plotted against a measure of Euclidean distance

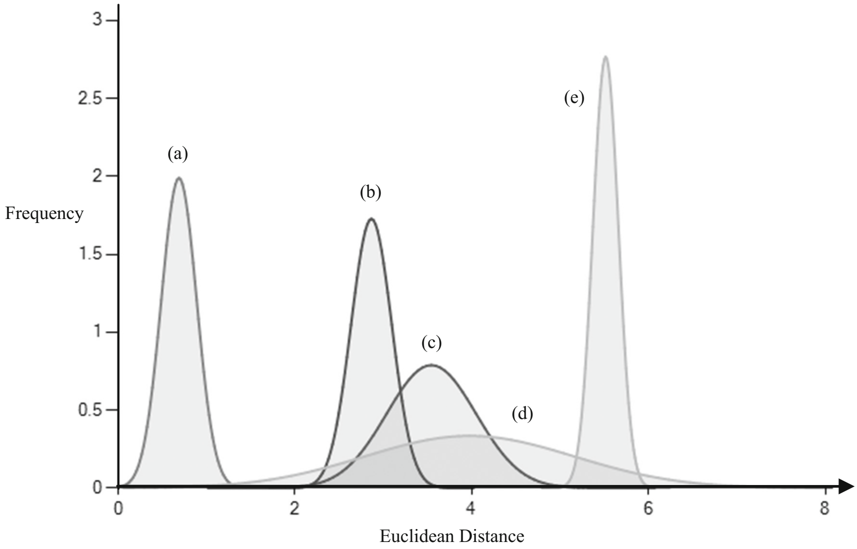

Fig. 2. Normal distribution curves of trained devices compared against an incandescent lamp: (a) Incandescent lamp, (b) LCD TV, (c) Personal desktop computer, (d) All devices, and (e) Desk fan.

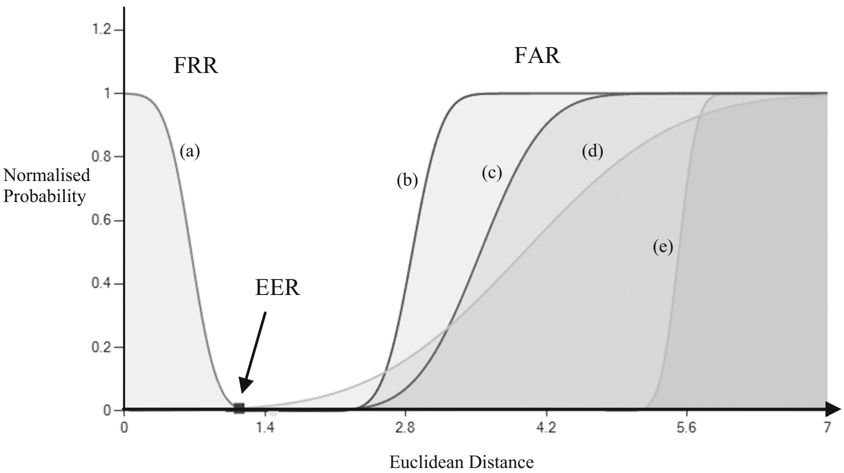

Fig. 3. Cumulative distribution curve of trained devices compared against an incandescent lamp; results show FRR, FAR and EER. (a) Incandescent lamp, (b) LCD TV, (c) Personal desktop computer, (d) All devices, and (e) Desk fan.

returned by the identification algorithm. A distance closest to zero indicates a high probability of a known device, vice versa for devices that are unknown or not identified as the primary device will return a result which is greater than a known device. In the instance of this experiment, Fig. 2 device (a) has been identified as the known device between a distance range of 0 to 1; incorrect Fig. 2 devices (b), (c), (d) and (e) have returned distance results greater than 2. As Fig. 2 device (a) is the sole device category closest to zero with all other categories not intersecting this curve a positive match is made. This is shown by the separation in distance between FRR and FAR in Fig. 3, additionally the EER is close to zero indicating a low threshold where only the known device will be accepted. If a two or more device category curves were to intersect one another, the EER would be used as a threshold value therefore decreasing the FAR.

4 Conclusion

The experiment into using signal-processing techniques to identify a single device plugged into a smart socket has been demonstrated successfully, this is shown by the low EER in Fig. 3.

Future work will concentrate on the secondary experiment into establishing which set of parameters used by signal processing techniques to extract current waveforms provide optimal features and results. Further training data will be attained by the introduction of new devices to expand the overall system recognition rate and fine-tune the EER.

The present results look very encouraging when identifying single devices, however, it becomes challenging when multiple devices are plugged into a single outlet (via an extension cord) as a new current waveform would be created with combined features which the system would not be able to identify. Furthermore, as new devices are added, the probability of new combined waveforms trained to the system would exponentially increase therefore making it increasing difficult to handle multiple devices at this time.

Acknowledgments. The authors would like to acknowledge the funding provide by Building Research Establishment (BRE) and the Smart Systems Research Team based at the University of Hertfordshire.

References

1. Ofgem, Transition to smart meters (2016). https://www.ofgem.gov.uk/gas/retail-market/metering/transition-smart-meters. Accessed 16 April 2016
2. Asare-Bediako, B., Ribeiro, P.F., Kling, W.L.: Integrated energy optimization with smart home energy management systems. In: 2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Eur.), pp. 1–8 (2012)
3. Yaqub, R., Hamid, B., Ul Asar, A.: Appliance performance monitoring and warranty alert system. In: ICOSST 2013 - 2013 International Conference on Open Source Systems Technologies Process, pp. 13–17 (2013)
4. Zhou, L., Xu, F.Y., Ma, Y.N.: Impact of smart metering on energy efficiency. In: 2010 International Conference on Machine Learning and Cybernetics, ICMLC 2010, vol. 6, pp. 3213–3218 (2010)
5. Marks, R.J.: Introduction to Shannon Sampling and Interpolation Theory. Springer, New York (1991)