Recognizing the Use-Mode of Kitchen Appliances from Their Current Consumption

Gerald Bauer, Karl Stockinger, and Paul Lukowicz

Embedded Systems Lab, University of Passau
Innstr. 43, 94032 Passau, Germany
www.wearable-computing.org

Abstract. This paper builds on previous work by different authors on monitoring the use of household devices through analysis of the power line current. Whereas previous work dealt with detecting **which** device is being used, we go a step further and analyze **how** the device is being used. We focus on a kitchen scenario where many different devices are relevant to activity recognition. The paper describes a smart, easy to install sensor that we have built to do the measurements and the algorithms which can for example determine the consistency of the substance in the mixer, how many eggs are being boiled (and if they are soft or hard), what size of coffee has been prepared or whether a cutting machine was used to cut bread or salami. A set of multi user experiments has been performed to validate the algorithms.

1 Introduction

Human activity recognition is a key element of many pervasive computing applications [10]. The work described in this paper is part of a large European Union funded project (MonAMI[1]) aimed at the specific application domain of ambient assisted living. As a consequence, our activity recognition research is directed at the monitoring of activities of daily life in the home. An important aspect of the project is large scale deployment in real life environments (planned for hundreds of existing homes). This means that the sensing infrastructure must be cheap, easy to deploy, and simple to maintain. In previous work we have investigated camera based location systems [1] and microphones attached to the plumbing systems [2] as initial components of such a system.

This paper focuses on another component: the analysis of electrical power consumption of different household appliances. To this end we have implemented a simple measuring device (iSensor) which can be inserted between the plug of an appliance and the socket. Multiple devices can be connected to the sensor using a standard multi-plug adapter. It requires no power supply (it is powered from the mains) and no cabled connection (uses a ZigBee transmitter for connection with a gateway). Thus it fulfills the requirement of easy installation and maintenance. At the same time previous work (e.g. by [4] and [3]) has shown that this type

[1] www.monami.info

P. Barnaghi et al. (Eds.): EuroSSC 2009, LNCS 5741, pp. 163–176, 2009.

of sensor can detect which device is used when, which in turn is a valuable clue to the recognition of more complex activities. We build on this work to detect **not just which** device is being used, but also **how** it is used. We focus on a kitchen scenario and demonstrate how it is possible to for example determine the consistency of the substance in the mixer, how many eggs are being boiled, what size of coffee has been prepared or whether a cutting machine was used to cut bread or salami.

Related Work. So called infrastructure mediated sensing [9] has recently generated considerable interest as unobtrusive, easy to install and maintain method for activity recognition. Published functionality includes motion tracking through pressure changes in the HVAC system [9], the analysis of water flow in the plumbing [2], [5] and various electric current sensing systems. The latter include different power measuring adapters for the sockets similar to our iSensor device [7,8], the analysis of transient noise to identify different devices [3] and general current consumption based activity recognition [4].

An alternative approach for recognizing interactions with home appliances has been sound analysis (e.g. [6],[11]), and a huge body of research on using different sorts of other body mounted sensors (in particular accelerometers) which will not be listed here, since our work is directed at non body worn approaches. This is because, in our case, the requirements analysis within the MonAMI project has revealed such approaches to be preferred by the users (which is not meant to imply that body worn system are in general less desirable than infrastructures solutions).

Paper Contributions and Organization. The main contribution that this paper makes beyond state of the art described above is to show that power measurements are not only able to determine *what* device is being used, but can also provide relevant information about *how* this device is being used.

The paper starts with an overview of our approach including the description of the iSensor, the scenarios and the principle of our recognition method. We then discuss in detail how the recognition rules are derived from the device signal characteristics. Finally we present an empirical evaluation that includes several devices connected to the same iSensor running simultaneously.

2 Approach Overview

2.1 The iSensor

We have designed and implemented smart wireless sensors, called iSensors, which can be connected to any power socket in a home environment. One or even several different devices can be connected directly or using a multi-contact plug to an iSensor. By analyzing the current consumption the iSensor is able to recognize pre-defined devices when they are in use and also what they are used for. Once a device event (like "toaster on", "bread toasted (brown)") is recognized it is sent via ZigBee to a central home monitoring unit (see figure 1).

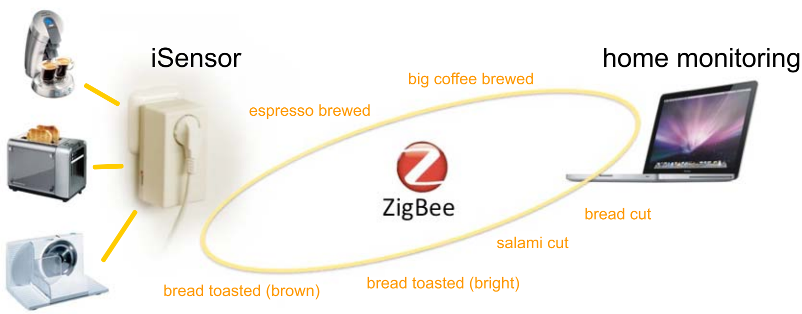


Fig. 1. iSensors send detailed information about activities of several connected devices to a home monitoring unit via ZigBee

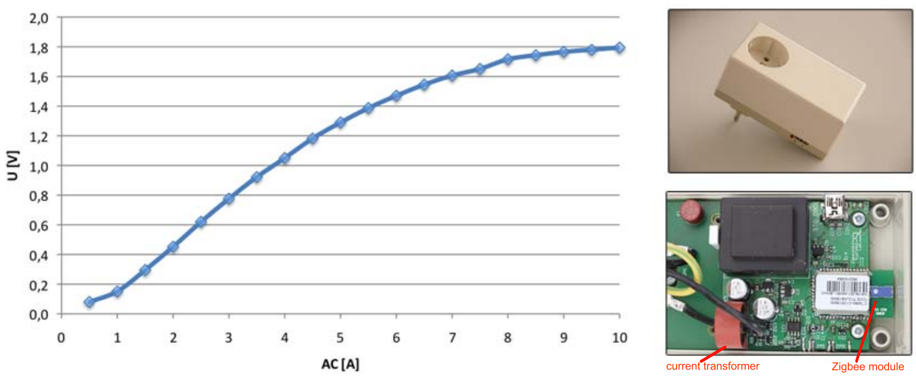


Fig. 2. Left: used ampere value and belonging inductive voltage. Right: iSensor out- and inside.

The current consumption is measured using electromagnetic induction. When devices connected to the iSensor are powered on, the induced voltage is digitalized using an AD converter (ADC)[2]. We used a current transformer which is able to handle devices which need between 0A and 10A. Figure 2 shows the dependency between a device's ampere request and the inductive voltage. As can be seen the resolution is quite good between 1.0A and 7.0A. Unfortunately the used current transformer shows saturation behavior when reaching values higher then 7.0A. Hence when using more devices at the same time a current transformer which provides both higher range and better resolution is needed. To avoid wired connections we used a Jennic ZigBee microcontroller (see http://www.jennic.com/) to send data via ZigBee to a processing unit. The Jennic microcontroller is also powerful enough to do some easy processing tasks. Hence our objective was to implement the later described algorithms using this

[2] ADC conversion time: 36μs; feasible voltage range: 0.04V to 2.4V.

microcontroller and to avoid ADC value streaming. Figure 2 shows some pictures of the described iSensor. The iSensor can be integrated in any existing home environment without effort - the sensor is just connected to an existing power socket. The iSensor provides the same interface to other devices as a common power socket. This means that every device can be connected in the same way as without using the iSensor - especially for elderly people this is a quite important fact. There is also no need to care about the power supply of the iSensor - the sensor itself is supplied by the connected power socket.

2.2 Scenarios

Household devices can be assigned to application areas regarding their use. For example there are electric devices for home entertainment (e.g. TV, sound systems, DVD and Blue-ray player or beamer), for kitchen applications (e.g. toaster, coffee machine and egg boiler) or personal hygiene (e.g. electric teeth brusher, fan or electric shaver). In the following we will restrict our experiments to devices which are used for kitchen applications. We found these devices the most interesting ones because they provide lots of functionalities as different operating modes (e.g. coffee machine: espresso or normal coffee).

In this paper we analyze in detail the following devices which can be found in most households: water boiler, egg boiler, mixer, bread cutter, toaster, juicer, coffee machine and fridge (see figure 3). To simulate a realistic kitchen scenario we use a single iSensor for the fridge and connect all other devices to another iSensor using a multi-contact plug. We envision such information to be useful among others for the monitoring of dietary habits and general assessment of stability of daily routines which are both important for ambient assisted living applications.

2.3 Recognition Idea

The general idea is to use ADC peak values (calculated using the last 600 ADC values) as representatives for the current power consumption. After that the last

Fig. 3. Left: Devices that can be found in many common kitchen households. Right: iSensor with several simultaneously connected devices using a multi-plug.

21 representative values are collected and used to calculate the following features: sum, maximum, minimum, average and variance. The resulting feature vector of size five is used to distinguish between different devices and their operating modes. In this way the iSensor provides two feature vectors per second.

The next sections show that we use only simple classification rules based on thresholds which depend on both feature values and the time duration of a specific operation. Such rules can be efficiently implemented in real time on even the simplest microcontrollers as demonstrated by our system.

3 Signal Analysis and Recognition Methods

This chapter discusses the signals measured from different devices when using them in specific operating modes. For each device and each operating mode rules are defined that capture the current consumption characteristics. Impulses which appear when switching on a device are used to distinguish between different device types following a similar method as described in [3]. The description in the rest of the paper will focus on the detection of specific modes of operation assuming that the device has already been identified. All in all we analyzed more then 3600 measurement points for each device. Note: In the following all time axes are in ADC cycles.

Water Boiler. The voltage of the used water boiler ranges from 220V to 240V and its rated power is between 1850W and 2200W. As figure 4 shows the water boiler delivers a constant ADC value of about 2330 when turned on. It can also be seen that the ADC values are independent from the amount of boiled water - only the duration is quite different. The duration feature values are about 469 (1.0l) and 663 (1.5l). As a result we assume that in average 0.002195 liters of water are boiled per calculated feature value. All in all we found thresholds as described in table 1 suitable for recognizing a water boiler device and calculating the about amount of boiled water.

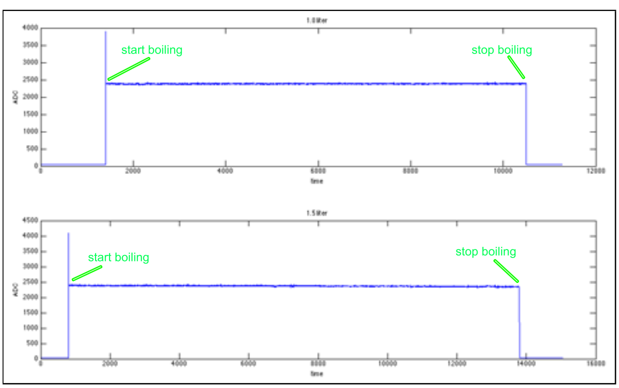


Fig. 4. ADC peak values when boiling 1.0l and 1.5l water

Table 1. Rules: Water boiler

Device:	$if \quad ((0 =< variance <= 650) \quad and \quad (2300 =< average <= 2450))$ $then \quad device = waterBoiler$
Boiled water:	$duration * 0.002195l = boiledWater$

Table 2. Rules: Fridge

Activities:	$if \quad ((sum > 842) \wedge (duration == 1)) \quad then \quad doorActivity$
	$if \quad ((sum > 842) \quad \wedge \quad (duration > 1)) \quad then \quad fridgeCooling$
	$if \quad (fridgeCooling \quad \wedge \quad ((thr_{powerCooling} - sum) < -70))$ $then \quad doorOpen \quad else \quad doorClosed$

Fridge. When analyzing ADC values generated by a fridge we can detect door opening actions as well as cooling actions. When opening the fridge door, a small light will be turned on, which results in a clearly visible change of ADC value. Unfortunately the fridge light consumes only relatively little power (about 10W, 240V) which is below the minimum power value that can be measured by our ADC (see chapter 2.1). Thus, the current version of our device can detect left open doors only when the fridge is cooling (then the power consumption is above the threshold of our ADC). When analyzing data we found out that the power consumption during a cooling process is mostly constant but varies between different cooling periods. Hence we use the first twenty seconds of a cooling period to calculate the current average power consumption ($thr_{powerCooling}$)[3] before we can look for door opening events. The rules, described in table 2, have been derived to detect cooling periods, door opening events and - during cooling periods - door closing events. A visualization of measured ADC values can be found in figure 5.

Bread Cutter. When analyzing the power consumption of a bread cutter it can be seen that resulting ADC values are quite constant and characteristic when the device is powered on and nothing is cut. During cut events the device needs more power and hence ADC values raises a lot while something is cut. As can be seen in figure 6 it is possible to distinguish between bread and salami cuts when analyzing both the maximum adc value and the duration of a cut process. The operating voltage of the used bread cutter is 220V and its rated power 100W. Table 3 shows extracted classification rules.

Juicer. Figure 6 shows ADC values of a common juicer device when extracting juice twice from a half piece of orange. As can be seen ADC values are around 90 when extracting juice. The juicer we used has a voltage of 230V and a rated power of 30W. When analyzing in detail feature vectors of a juicer we found rules as shown in table 4 for detecting juicer activity.

[3] Note: During this time door activities cannot be recognized.

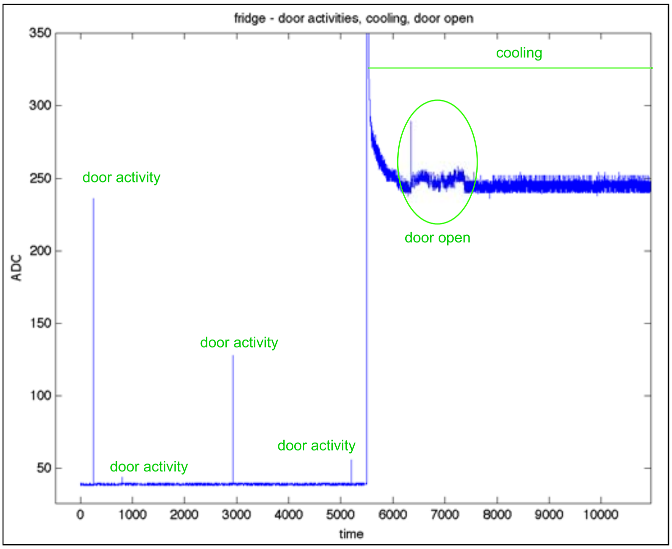


Fig. 5. ADC values indicating fridge events

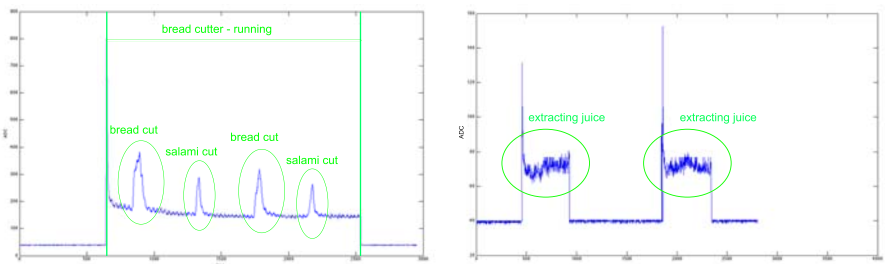


Fig. 6. Left: ADC values when cutting bread and salami. Right: ADC values when extracting juice.

Toaster, Egg Boiler and Coffee Machine. Toaster, egg boiler and coffee machine behave much like the water boiler when turned on. Thus ADC values (current drawn) are used to identify the device and the duration of an operation is used to distinguish between different device actions. In case of a toaster device we are able to differentiate between three toasting levels - bright, brown and dark toast. For egg boiler devices it is possible to recognize if three or five eggs were boiled and if the eggs are soft, medium or hard boiled. In case of a coffee machine we distinguish between a normal size coffee and a big one. Table 5 shows extracted classification rules. Note: The toaster/egg boiler/coffee machine voltage is 230V/220-240V/220-230V and their rated power is 800W/350W/1450W.

Table 3. Rules: bread cutter

Device:	$if \quad ((0 =< variance < 4000) \quad \wedge \quad (700 < max < 900))$ $then \quad device = breadCutter$
Activities:	$if \quad ((variance < 60) \quad \wedge \quad (100 < average <= 250)) \quad then \quad running$
	$if \quad ((32 < variance < 7000) \wedge (130 < average < 600)) \quad then \quad cutting$
	$if \quad ((cuttingDuration < 4) \wedge (maximum < 300)) \quad then \quad salamiCut$
	$if \quad ((cuttingDuration >= 4) \wedge (maximum >= 300)) \quad then \quad breadCut$

Table 4. Rules: Juicer

Device:	$if \quad ((0 =< variance <= 16) \quad \wedge \quad (50 =< average <= 90))$ $then \quad device = juicer$

Table 5. Rules: toaster, egg boiler and coffee machine

Rule toaster:	$if \quad ((0 =< variance <= 600) \wedge (1100 =< average <= 1250))$ $then \quad device = toaster$
Activities:	$if \quad ((110 < duration <= 194) \quad then \quad bright \quad toast$
	$if \quad ((194 < duration < 271) \quad then \quad brown \quad toast$
	$if \quad ((271 <= duration <= 342) \quad then \quad dark \quad toast$
Rule egg boiler:	$if \quad ((0 =< variance < 15) \wedge (600 < average < 700))$ $then \quad device = eggBoiler$
Activities:	$if \quad ((450 < duration < 650) \quad then \quad 3eggs \quad soft$
	$if \quad ((750 < duration < 850) \quad then \quad 3eggs \quad medium$
	$if \quad ((2000 <= duration <= 2200) \quad then \quad 3eggs \quad hard$
	$if \quad ((250 < duration < 450) \quad then \quad 5eggs \quad soft$
	$if \quad ((650 < duration < 750) \quad then \quad 5eggs \quad medium$
	$if \quad ((1300 <= duration <= 1600) \quad then \quad 5eggs \quad hard$
Rule coffee machine:	$if \quad ((0 =< variance < 1000) \wedge (1700 =< average <= 1890))$ $then \quad device = coffeeMachine$
Activities:	$if \quad ((25 < duration <= 58) \quad then \quad small \quad coffee$
	$if \quad ((58 < duration < 200) \quad then \quad big \quad coffee$

Mixer. As can be seen in figure 7 the current drawn by the mixer device depends on the level to which it is set and on the consistency (fluid, medium,creamy) of the substance in the mixer. To recognize mixer devices and to distinguish between different mixing levels and liquids we use thresholds which are shown in table 6. Note: The used mixer has a voltage of 220V to 240V and a rated power of 100W.

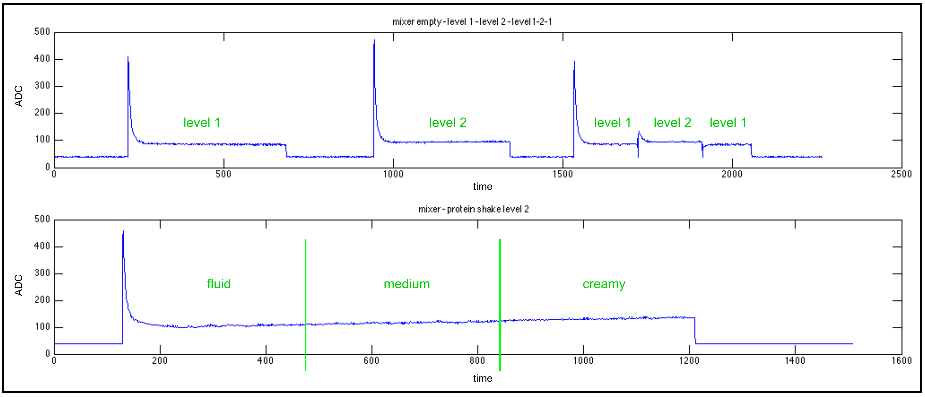


Fig. 7. ADC values of a mixer device: Upper image: Mixer off and on (empty tank - operating level 1, level2, level1-2-1), Lower image: Mixer on (level2) when mixing a protein shake (consistency from fluid to creamy)

Table 6. Rules: mixer

Device:	*if* $((0 =< variance <= 30) \wedge (78 =< average <= 150))$	
	then $device = mixer$	
Activities:	*if* $(78 =< average <= 88)$	*then* $mixer$ $level1$
	if $(89 =< average <= 110)$	*then* $mixer$ $level2 - fluid$
	if $(110 < average <= 125)$	*then* $mixer$ $level2 - medium$
	if $(125 < average <= 150)$	*then* $mixer$ $level2 - creamy$

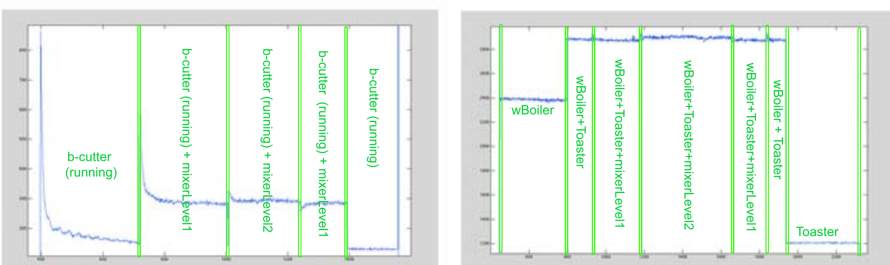


Fig. 8. Simultaneous device usage - Left: bread cutter and mixer; Right: water boiler, toaster and mixer. For each figure the vertical axes specify ADC values and the horizontal ones the time.

3.1 Simultaneous Device Usage

Above we have demonstrated that each of the devices has a characteristic current signature for each of the investigated operating modes. However, so far, we have looked at each device in isolation. In real kitchen environments on the other hand, more then one device is used at the same time. In many cases such devices may all be connected to the same multi-plug connector which is plugged into one iSensor. Hence we also analyzed if it is still possible to recognize devices and operations when using more then one device at the same time. As figure 8 shows thresholds for device combinations can also be found.

4 System Evaluation

During the following evaluation process we connect all devices to one iSensor using a multi-plug (only the fridge was connected to a single one). In most of the cases (about 90%) we can recognize a turned on device using a similar approach as described in [3]. The following sections show how accurate we can distinguish between different device actions when a device was recognized correctly[4].

Evaluation: Mixer. When evaluating a mixer device we tried to distinguish between mixing something fluid and creamy. Hence we asked seven users to prepare both a chocolate milk (250ml milk and two spoons of chocolate powder) and a quark-yoghurt dish (250g quark and 1 yoghurt) using mixing level two. As result 100% of chocolate milks were recognized as fluid and 100% of quark-yoghurt dishes were recognized as creamy. In about 57% of quark-yoghurt dishes we could also see a change from medium consistency to a creamy one.

Evaluation: Juicer. We asked six people to extract juice from two half pieces of orange. Hence twelve juice extractions were performed. As result our system was able to detect 91.66% of performed juice extractions (see table 7).

Table 7. Evaluation: Juicer

performed juice extractions	recognized juice extractions	classification rate
12	11	91.66 %

Evaluation: Egg boiler. Six people were asked to prepare three soft boiled eggs and after that five soft boiled eggs. As can be seen from table 5 this is the combination of usage modes that have the most similar threshold values (=the most difficult recognition task). Still, our system was able to distinguish between the mentioned two types of egg boiling with an accuracy of about 83.33%. As table 8 shows two times three soft boiled eggs were recognized as five soft boiled eggs. This is because some users were not very accurate when filling the required water amount. For other combinations of modes the recognition tends to be better, however, because of the excessive number of eggs needed for the test we did not do a systematic evaluation.

[4] For all performed evaluations we stream raw peak ADC values to a processing unit and apply the introduced rules there.

Table 8. Evaluation: Egg boiler

real / recognized	5 eggs soft boiled	3 eggs soft boiled	classification rate
5 eggs soft boiled	6	0	100.00 %
3 eggs soft boiled	2	4	66.66 %
			88.33 %

Evaluation: Toaster. Again we asked six people to evaluate a toaster device. Every person was asked to prepare a bright and a brown toast. Hence users had to choose the time for toasting to get the desired result. As result our system recognized 83.33% of the prepared toasts. As table 9 shows one bright toast was confused with a brown one. In fact there is no clear definition when a toast should be called bright or brown - therefore for some users a light brown toast was still a bright one and the other way round.

Table 9. Evaluation: Toaster

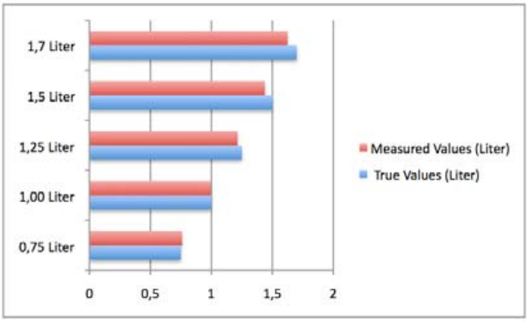
real / recognized	bright toast	brown toast	classification rate
bright toast	5	1	83.33 %
brown toast	1	5	83.33 %
			88.33 %

Evaluation: Coffee Machine. We asked six persons to prepare a double-sized coffee (big) as well as a normal one. As table 10 shows our system could distinguish between big and small coffee brews with an accuracy of about 91.66%. After each brew event the coffee machine is heating its water tank and therefore it consumes the same amount of power as for brewing coffee - but the variance is much higher. Hence we can filter out such water heating events. But every time when the coffee machine is turned on for the first time - which means that both water and heating rods are cold - also the variance of a water heating event is the same as when brewing coffee. Hence our system can't filter out such heating events and a big coffee brew event is wrongly recognized.

Table 10. Evaluation: Coffee Machine

real / recognized	big coffee	small coffee	classification rate
big coffee	6	0	100.00 %
small coffee	1	5	83.33 %
			91.66 %

Evaluation: Water Boiler. As described in section 3 multiplying the time duration which is needed for boiling water with 0.002195 is a good approximation of the amount of water that was boiled. As figure 9 shows this simple formula approximates the real amount of boiled water quite well for the whole water boiler's



Calculation results for 1.3l

water used	water calculated
1.3l	1.26871l
	1.25554l
	1.25334l
	1.26871l
	1.26432l
Average:	1.262l
Variance:	0.0000532

Fig. 9. Left: This chart visualizes the difference between the calculated (measured values) and the real (true values) amount of boiled water for 0.75, 1.0, 1.25, 1.5 and 1.7 liter. Right: calculated amount of water for 1.3liter.

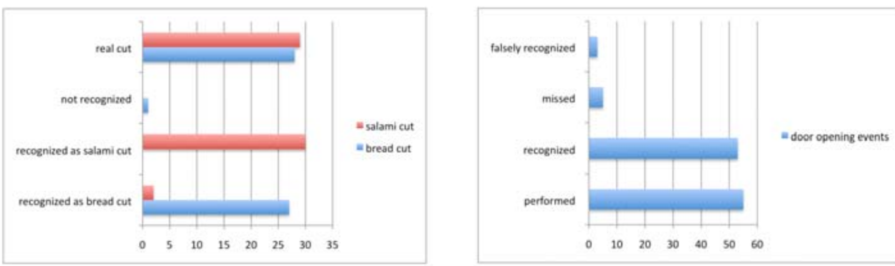


Fig. 10. Left: Evaluation results when cutting bread and salami. One bread cut was not recognized, two salami cuts were recognized as bread cuts and all in all three salami cuts more were recognized as performed. Right: Evaluation results when monitoring a fridge for about 35 hours.

capacity range (0.75 - 1.70 liters). Testing five different water levels (0.75l, 1.0l, 1.25l, 1.5l and 1.70l) the deviation was between 0.006 and 0.076 (average 0.038 liters). In order to see how strong the results vary between different calculation steps, 1.30 liters of water were boiled five times. As figure 9 shows the estimated amount of boiled water is nearly constant and accurate.

Evaluation: Bread Cutter. Figure 10 shows classification results when evaluating a bread cutter device. There six people were asked to cut all in all 28 slices of bread and 29 slices of salami. As can be seen the number of bread and salami cuts is recognized quite well with an accuracy of 96.42% for bread cuts and 93.10% for salami cuts. However there are 10% insertions for salami and 7% confusions between salami and bread. This is because some users had problems when cutting salami/bread and pieces of salami/bread for example clamped between the blades.

Evaluation: Fridge. We monitored a fridge in our lab kitchen for about 35 hours. Our objective was to detect when the fridge door was opened and also to count door opening events. Hence all persons had to note down when and how many times they have opened the fridge door. Figure 10 shows that our system is able to detect nearly 91% of door opening events. As it is mentioned in chapter 3 our system is not able to detect door opening events during the initialization time of a cooling process. Hence we missed 9% of door opening events. Also three door events were recognized two times.

5 Discussion and Future Work

An obvious lesson from the work presented in this paper is that current measurements from household appliances contain more information then just a binary on/off signal. In some cases (e.g. the water boiler) this was to be expected, in others (the consistency of the substance in the mixer or the bread cutter) we found it a bit surprising.

The accuracy of the recognition depends on three things. The biggest factor are variations in how the user operates a device, even when using it in the same mode. This includes the amount of water filled into the egg boiler, or the bread cutter usage. Another source of errors are ambiguities in the definition of the classes (e.g. what is a light and what is a brown toast) In some cases (e.g. like the coffee machine) there are also variations in the way the device works.

Overall the accuracies were in the range of 80% to 90%. Clearly, for applications that require exact counting of individual actions this would not be enough. However, for monitoring trends (e.g. long term nutrition trends or just the stability of a persons routine) or as features in a more complex, multi-modal recognition system it is a reasonable performance.

We have shown that this information can be extracted with an easy to install and maintain sensor and very simple algorithms. In terms of wide scale deployment the biggest problem is the fact that the thresholds have to be tuned to each specific device. A possible way around this problem is to use unsupervised learning techniques during an initial phase of the deployment. In particular in applications where we look for routines or use the information as features for more complex recognition tasks this might be a good solution. In such cases we do not need to know what a certain usage mode corresponds to in real life. It is sufficient to identify that there are different usage modes and be able to spot them.

As next steps we intend to deploy our devices for longer periods of time in real environments (together with our camera based indoor location system [1]) and attempt to recognize the cooking of different meals. This will show how useful the information about the use mode of kitchen appliances really is.

References

1. Bauer, G., Lukowicz, P.: Developing a Sub Room Level Indoor Location System for Wide Scale Deployment in Assisted Living Systems. In: Miesenberger, K., Klaus, J., Zagler, W.L., Karshmer, A.I. (eds.) ICCHP 2008. LNCS, vol. 5105, pp. 1057–1064. Springer, Heidelberg (2008)

2. Ibarz, A., Bauer, G., Casas, R., Marco, A., Lukowicz, P.: Design and Evaluation of a Sound Based Water Flow Measurement System. In: Roggen, D., Lombriser, C., Tröster, G., Kortuem, G., Havinga, P. (eds.) EuroSSC 2008. LNCS, vol. 5279, pp. 41–54. Springer, Heidelberg (2008)
3. Patel, S.N., Robertson, T., Kientz, A.J., Reynolds, M.S., Abowd, G.D.: At the Flick of a Switch: Detecting and Classifying Unique Electrical Events on the Residential Power Line. In: Krumm, J., Abowd, G.D., Seneviratne, A., Strang, T. (eds.) UbiComp 2007. LNCS, vol. 4717, pp. 271–288. Springer, Heidelberg (2007)
4. Berenguer, M., Giordani, M., Giraud-By, F., Noury, N.: Automatic detection of Activities of Daily Living from Detecting and Classifying Electrical Events on the Residential Power Line. In: Proc. 10th IEEE Intl. Conference on e-Health Networking, Applications and Service, HEALTHCOM 2008 (2008)
5. Fogarty, J., Au, C., Hudson, S.E.: Sensing from the basement: a feasibility study of unobtrusive and low-cost home activity recognition. In: Proceedings of the 19th Annual ACM Symposium on User Interface Software and Technology, Montreux, Switzerland (October 15-18, 2006)
6. Chen, J., Harvey Kam, A., Zhang, J., Liu, N., Shue, L.: Bathroom Activity Monitoring Based on Sound. In: Gellersen, H.-W., Want, R., Schmidt, A. (eds.) PERVASIVE 2005. LNCS, vol. 3468, pp. 47–61. Springer, Heidelberg (2005)
7. Logan, B., Healey, J., Philipose, M., Tapia, E.M., Intille, S.: A long-term evaluation of sensing modalities for activity recognition. In: Krumm, J., Abowd, G.D., Seneviratne, A., Strang, T. (eds.) UbiComp 2007. LNCS, vol. 4717, pp. 483–500. Springer, Heidelberg (2007)
8. Lifton, J., Feldmeier, M., Ono, Y., Lewis, C., Paradiso, J.A.: A platform for ubiquitous sensor deployment in occupational and domestic environments. In: Proceedings of the 6th international conference on Information processing in sensor networks, pp. 119–127 (2007)
9. Patel, S.N., Reynolds, M.S., Abowd, G.D.: Detecting human movement by differential air pressure sensing in HVAC system ductwork: An exploration in infrastructure mediated sensing. In: Indulska, J., Patterson, D.J., Rodden, T., Ott, M. (eds.) PERVASIVE 2008. LNCS, vol. 5013, pp. 1–18. Springer, Heidelberg (2008)
10. Schmidt, A., Beigl, M., Gellersen, H.W.: There is more to context than location. Computers & Graphics 23(6), 893–901 (1999)
11. Stäger, M., Lukowicz, P., Tröster, G.: Power and accuracy trade-offs in sound-based context recognition systems. Pervasive and Mobile Computing 3(3), 300–327 (2007)