Detection of Behavioral Data Based on Recordings from Energy Usage Sensor

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Aim and Novelty

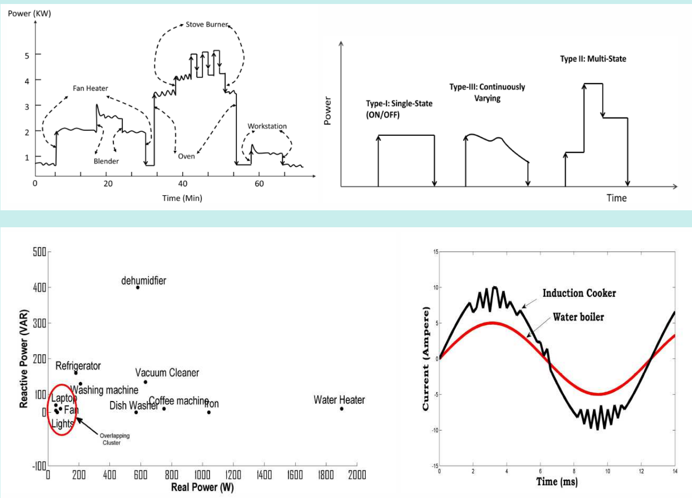
Monitoring of human behavior in the natural living habitat requires a hidden yet accurate measurement. Several previous attempts showed, that this can be achieved by recording and analysing interactions of the supervised human with sensorized equipment of his or her household.

We propose an **imperceptible single-sensor measurement**, already applied for energy usage profiling, to detect the usage of electrically powered domestic appliances and deduct important facts about the operator's functional health.

The sensor is maintenance-free, mains-powered and WiFi-enabled.

What are (Smart) Energy Usage Sensors ?

[1]



Learning Device Load Signatures

Before application the sensor has to fill the device database covering all appliances possibly used in the household. A supervised learning session is performed in which each device is manually turned on and off unless correctly recognized.

For behavior tracking purposes we used only operator-dependent, immobile devices. This category includes devices directly operated by the human, which allow to determine their usage and operator's position; example of such appliances is an electric mixer.

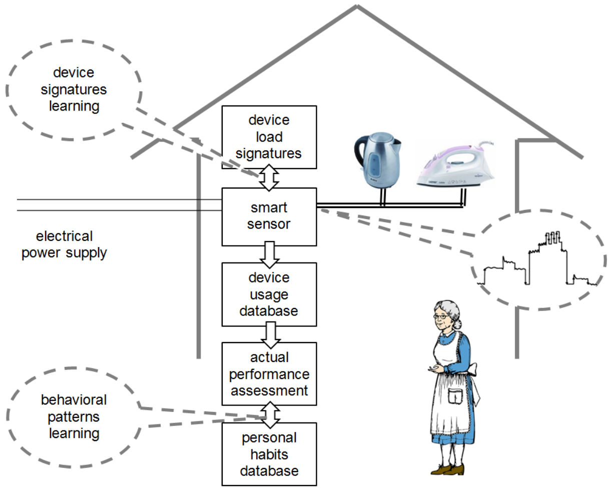
We used only original off-the-shelf household products without any modification.

Learning behavioral patterns

With completed learning of device load signatures, the system has to fill behavioral database of the inhabitant in order to detect any irregular events. To this point the records were analysed and examples of safe behavior were extracted to the database.
All inhabitual behavior was reported and analysed during subsequent learning session.

The apartment topology was also considered at this stage in order to assess the inhabitant's mobility.

Human Surveillance with Energy Usage Sensor



Results

Device recognition accuracy

device name	recognition accuracy %
hair dryer	96.3
iron	98.5
electric kettle	99.1
microwave	97.2
toaster	95.4
coffee maker	96.7
oven	98.9
electric mixer	97.0
average	97.4

Device usage frequency ([%]) and average duration ([s])

device name	morning activity (MA)	evening activity (EA)	housekeeping action (HA)
hair dryer	15/180	25/240	10/240
iron	10/300	70/2700	20/600
electric kettle	100/100	30/100	100/180
microwave	20/120	0/n.a.	35/600
toaster	50/300	0/n.a.	30/400
coffee maker	75/180	15/180	30/180
oven	0/n.a.	15/3600	70/1800
electric mixer	10/120	20/600	20/600

Results of irregular behavior detection and operator's mobility

volunteer and scenario identifier	changing of events duration [%]	changing the events sequence order [%]	average bathroom to kitchen transfer time [s]
Vol1.MA	93.3	96.7	5.5
Vol1.EA	89.7	92.1	5.2
Vol1.HA	81.4	67.4	6.1
Vol2.MA	96.4	98.1	6.1
Vol2.EA	94.3	96.0	5.8
Vol2.HA	88.2	84.4	6.8
Vol3.MA	91.1	94.3	5.4
Vol3.EA	89.7	92.1	5.2
Vol3.HA	77.2	57.4	5.6

Discussion

Particular domestic devices are reliably identified by the sensor. Usage data may also be interesting to build a personalized profile of energy consumption, device usage and thus individual habits of each inhabitant. Erroneous operation of devices may also be detected based on comparison of actual and habitual usage profiles.

[1] Zoha, A., Gluhak, A., Imran, M.A., Rajasegarar, S.: Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey, Sensors, **12**(12), pp. 16838-16866 (2012) doi:10.3390/s121216838