Liu JJ, Nie L. A functional sensing model and a case study in household electricity usage sensing. JOURNAL OF COMPUTER SCIENCE AND TECHNOLOGY 29(2): 182–193 Mar. 2014. DOI 10.1007/s11390-014-1421-1

A Functional Sensing Model and a Case Study in Household Electricity Usage Sensing

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Received December 25, 2013; revised January 28, 2014.

Abstract Sensing is a fundamental process to acquire information in the physical world for computation. Existing models treat a sensing process as an indivisible whole, such that sampling and reconstructing of signals are designed to be highly associated with each other in a unified procedure. These strongly coupled sensing systems are efficient, but usually lack reusability and upgradeability. We propose a functional sensing model called SDR (Sampling-Design-Reconstruction) to decouple a sensing process into two modules: sampling protocol and reconstruction algorithm. The core of this decoupling is a design space, which is a common data structure constructed using functions of the sensing target as prior knowledge, to seamlessly bridge the sampling protocol and reconstruction algorithm together. We demonstrate that existing types of household electricity usage sensing systems can be successfully decoupled by introducing corresponding design spaces.

Keywords sensing model, household electricity usage, design space, sampling protocol, reconstruction algorithm

1 Introduction

With the development of computing technology, the significant evolution of computing technologies explores more uncharted possibilities to enlarge its scopes. Physical systems should be efficiently managed with new computing approaches[1-2]. In these applications, the sensing process plays a key role to monitor physical objects and obtain the needed information. Embedded microprocessors and wireless communication links bring sensing techniques into a smart era[3]. The research on sensing processes is an interdisciplinary field, which merges physics, electronics engineering, computer science, and mathematics. For diverse applications, a common question is how to design a sensing process to meet the needs of applications. To simplify the design process, a lot of work is established in different disciplines[3-9].

The most classic type of sensing is to directly measure some specific signals of a sensing target. This method is a procedure of signal processing, which is limited by the Nyquist-Shannon sampling theorem[4]. According to this theorem, designers only need to focus on the bandwidth of the signal. A signal processing technique named compressive sensing[6] was presented in the last decade. It can dramatically reduce the amount of sampled data, if the signal of a sensing target is sparse in a representation domain[7]. To reconstruct the signal, there are some requirements[8] of sampling domain and representation domain.

According to these methodologies, designers need to know the details of sampling and reconstructing, which are the two modules of sensing process. The two modules belong to different disciplines, so the lack of background knowledge places the first barrier. Moreover, these designing methodologies provide a strongly coupled perspective to consider the relationship of sampling and reconstructing of signals. In many sensing systems and techniques, such as single-pixel camera[10], measurement design for fMRI[11] and ViridiScope[12], the sampling method and reconstruction algorithm are highly associated with each other in a unified procedure. This situation weakens the reusability and upgradeability of these sensing systems.

Attempting to decouple cost-efficient sensing processes, we provide a functional sensing model, called SDR (Sampling-Design-Reconstruction) model, to define a sensing process as three components. The most important component is the design space. It decouples the sensing process into the rest two components: samp-

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Supported by the Strategic Priority Program of the Chinese Academy of Sciences under Grant No. XDA06010401, the National Basic Research 973 Program of China under Grant Nos. 2011CB302800, 2011CB302502, and the Guangdong Talents Program of China under Grant No. 201001D0104726115.

ling protocol and reconstruction algorithm. To justify the universality of our model, we utilize this model to various sensing systems for household electricity usage. Although these systems are originally designed following traditional methodologies, they can be successfully decoupled by introducing corresponding design spaces according to our SDR model.

The rest of this paper is organized as follows. Section 2 presents our functional sensing model and two methodologies to build sensing systems following our model. Section 3 gives the analysis and comparison of four typical systems in the scenario of household electricity usage sensing based on the SDR model. The last section concludes this paper.

2 Proposed Functional Sensing Model

2.1 Motivation

Sensing is an input method of computer systems, which maps the physical information into cyberspace. There are two kinds of inherent objects related to a sensing process: targets and results, which can be view as the input and output of the process respectively. A sensing target is a predetermined set of objects in the physical world. Sensing is to measure specific properties of these physical objects. Usually, we do not care about all details of these properties. Our interest is to find out comprehensible properties or behaviors of the sensing target for users. For example, electric current curves of a washing machine are meaningless to ordinary users. They may be interested in whether this washing machine is rinsing or spinning.

We call the properties that users concern as the functions of the sensing target. A sensing process is a functional sensing process, while the sensing result is a record of the functions of the sensing target. Functions provide the prior knowledge about how to sample and reconstruct them. Taking household electricity usage sensing for example, a typical function is the electricity consumption of an appliance. This function can be reconstructed with the current and voltage information sampled from the appliance. How to define functions of a sensing target is a domain specific task, which will not be discussed in this paper. We focus on building a functional sensing model to decouple a sensing process, if functions of sensing targets are given as prior knowledge.

2.2 Definitions

A sensing process consists of two executive components: sampling protocol and reconstruction algorithm. Firstly, acquire the behavior of the target by a sampling protocol, and then reconstruct the functions of the target from sampled data using a reconstruction algorithm. Naturally, there should be a data space that connects the two steps together. This space determines the output of the sampling protocol and the input of the reconstruction algorithm. It means that this space highly impacts the design and implement of the whole sensing model. We notice that this space is constrained by the functions of a sensing target. We call this data space as design space which plays a central role in a sensing model. Moreover, the design space is directly affected by the requirements of sensing results and the constraints of feasible recourses. In this paper, we conjecture that how to get a design space is a central problem in functional sensing. We formally define design space, sampling protocol, reconstruction algorithm and our functional sensing model as follows:

Definition 1. *A design space is a data structure to store and organize the sampled data. It defines the type and relationship of the sampled data, and also provides some operations that may be performed on it. The sampling protocol and reconstruction algorithm can access the elements through these operations.*

A design space defines the details of sampled data. The most important thing is that the relationships among data points are constrained by the design space. These constraints are designed according to the prior knowledge about the functions of sensing targets. With a design space, the sensing process can be divided into two loosely-coupled parts. Taking the ICT electricity sensing system[15] as an example, its design space is a pair of vectors. The data in one vector is the instantaneous value of total current. The other is the instantaneous value of voltage. Both of these values are sampled at 12 800 Hz. The operations in this design space are Add and Read. Add is an operation to insert voltage and current data into the vector simultaneously. Read is to access the data in the vectors.

Definition 2. *A sampling protocol is an implementable procedural method to acquire sufficient information and to project data into the design space with given operations.*

The most fundamental requirement of a sampling protocol is implementable. If required signals cannot be measured by available types of sensors, these signals should be transformed by physical processes or devices into measureable signals. For example, the DMD in the single-pixel camera encodes the image with random basis[10], and current signals can be converted to measurable magnetic signals according to the Ampere's law[12]. We regard the sampling protocol as a complex of cyber-physical-social components based on the theory of ternary computing[13-14]. It can not only utilize physical sensors, but also take advantage of computing power and intelligence of humans. After the sufficient data is acquired, the protocol performs a given operation on the design space to add a new record.

Definition 3. *A reconstruction algorithm is a calculation procedure to obtain the function of a sensing target based on the information from the design space.*

A reconstruction algorithm is executed in cyberspace. Its input is achieved through the operation of the design space, and the output is the executed functions of the sensing target. For example, the reconstruction algorithm of the ICT electricity sensing system is based on regression[15]. This algorithm reads the total current and voltage from the design space, and converts their frequency domain with fast Fourier transform (FFT). Using the frequency information, a group of linear formulas are built. The result is calculated from a regression analysis on these formulas.

Based on the sampling protocol, design space and reconstruction algorithm, we define our functional sensing model, called SDR model, as follows:

Definition 4. *The SDR model is a functional sensing model which consists of three components: a sampling protocol, a design space and a reconstruction algorithm. According to the given operations in the definition of design space, the protocol and algorithm interact with the design space respectively.*

Fig.1 shows the structure of the SDR model. The sampling protocol and reconstruction algorithm are executable components, which are carried out using ternary resources and computational resources respectively. The design space is a logic component to connect the sampling protocol and the reconstruction algorithm together as a unified whole. According to the sampling protocol, physical information is transformed into a measureable form and acquired by proper sensors. The sampling protocol also needs to preprocess the sampled data to satisfy the requirement of the operations of the design space. Then, the data is imported into the design space. Lastly, the reconstruction algorithm infers the functions of the target using the data, which is similar to a classic machine learning procedure.

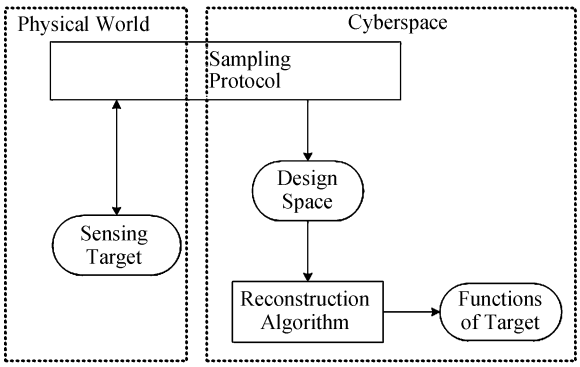

Fig.1. Structure of the SDR model.

The design space is an agreement between the sampling protocol and the reconstruction algorithm. Determining the design space is a critical task, because it decouples other two components in this functional sensing model. This loose coupling ensures the independence between the sampling protocol and the reconstruction algorithm. The construction of the design space is guided by the prior knowledge about the function.

To further describe the difference between the SDR model and traditional sensing models, we take the ICT electricity sensing system[15] as an example. Fig.2(a) shows the execution logic of this system. The analog front end composed of integrated circuits is deployed at the electric utility entrance to get the analog signals of total current and voltage. The data acquisition card converts the analog signals into digital forms. All the calculation is implemented on the MATLAB platform. In their design process, the sampling process and reconstruction process are tightly coupled with each other. Once the sensor configuration is changed, the whole program should be rewritten to match modified data. With our SDR model, the introduction of design space suggests novel execution logic of sensing process as Fig.2(b). The analysis program should be divided into two modules: preprocess program and reconstruction algorithm. The former one is part of the sampling protocol. These two modules are connected with the design space.

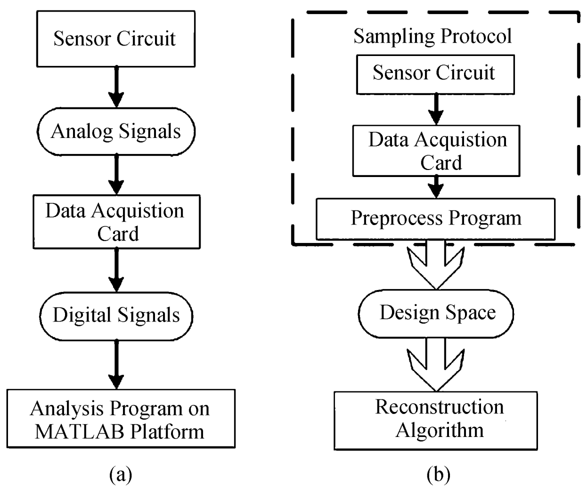

Fig.2. Differences between traditional sensing model (a) and the SDR model (b).

2.3 Design Methodologies

The ultimate goal of our model is to provide a theoretical prototype for designing a cost-efficient sensing system. The most important difference between the SDR model and traditional sensing models is that design spaces are at a central position in the SDR model. The design space connects the other two components of the model by simultaneously constraining both the output of the sampling protocol and the input of the reconstruction algorithm. Based on this observation, we propose two types of methodologies for designing an instance of the SDR model: sampling-prior design and reconstruction-prior design.

The sampling-prior design is to construct a design space mainly based on the constraints of the sampling protocol. These are various types of constraints. The number of sensors is limited due to the budget of the system. The complexity of system implementation requires only a few types of devices are used. Some biases and noises cannot be eliminated because of physical deficiencies. In this methodology, the design space and sampling protocol are firstly designed at the same time, because they are deeply impacted by each other. After that, the reconstruction algorithm is primarily based on the properties of the design space. Fig.3 depicts the process of this design.

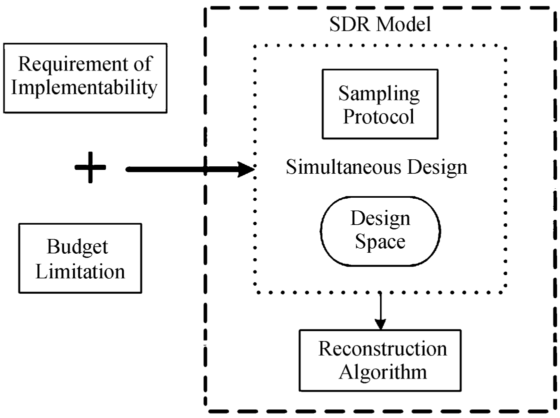

Fig.3. Process of the sampling-prior design.

The methodology of sampling-prior design starts from the constraints of sampling in the physical world. There are two main advantages of this methodology. Firstly, implementability, which is the most fundamental requirement of a sampling protocol, can be met explicitly. Following this methodology, the cost of the sensing system is within the budget. Other physical limitations are systematically considered. Secondly, the input, the output and corresponding requirements of the reconstruction algorithm are clearly determined. This will improve the efficiency of designing an algorithm. Thus, sampling-prior design is a good choice if the budgets and physical limitations are strict.

The design of NIALMS[16] is typically sampling-prior. The functions in NIALMS are the usages of electric appliances in a house, including on-off states and energy consumptions. There are intrinsic demands of NIALMS. One is that the household electric circuits cannot be modified. The other is that there is only one sensor measuring current and voltage. According to its sampling protocol, this sensor is placed at the electric service entrance and records the total current and voltage. The design space in this case is a pair of vectors to store the values of total current and voltage respectively. The real power and reactive power can be calculated using those values. The reconstruction algorithm is edge detection based on clustering.

The reconstruction-prior design is to construct a design space mainly based on the requirements of the reconstruction algorithm. These requirements can be divided into two categories. One is the quality of input data, including accuracy, quantity, density, etc. The other one is the relationships of data points. For example, some algorithms require two successive data points are adjacent in the time or space domain[16]; while others require all data points are sampled randomly according to a specific distribution[10]. In this methodology, the reconstruction algorithm is firstly determined. Following that is the design space. The last problem is how to design an implementable sampling protocol to acquire data for the design space. Fig.4 shows the process of this design.

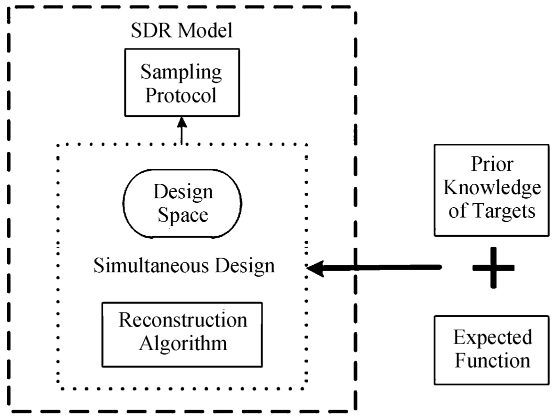

Fig.4. Process of the reconstruction-prior design.

The methodology of reconstruction-prior design starts from the requirements of the reconstruction algorithms in cyberspace. Following this methodology, reconstruction algorithms can adequately utilize functions of sensing targets as prior knowledge, because the design space is forced to hold the valuable prior knowledge. The merits are obvious. For example, the algorithm is able to deeply explore the sampled data. Thus, the number of required data will be dramatically reduced. However, the implementability of sampling protocol becomes a difficult problem. Although some properties of a design space are feasible in theory, they cannot be preserved in reality.

ViridiScope[12] follows the reconstruction-prior design. The functions in the ViridiScope system are the power consumptions of each electric appliance in a house. Their key observation is that the power information is not only encoded into electric signals (e.g., current and voltage), but also other physical signals (e.g., sound, light, and magnetism). The performance of the reconstruction algorithm is significantly improved by exploring these non-electric signals. Thus, the design space is designed to maintain the non-electric information. The remaining problem of ViridiScope now is to choose or develop suitable sensors to measure these signals.

3 Case Study in Household Electricity Usage Sensing

3.1 Scenario

The total electric power consumption is increasing. The consumption of USA in 2011 is 13 times higher than that in 1950, and the consumption of household electricity accounts for 37% of the total consumption①. Electricity providers need to record the usage of every user. This information is not only used for energy bills, but also for optimizing strategies of power supply. With the increasing types of electric appliances, the electricity usage becomes more complex. The efficiency of electric usage varies greatly for different users. The electricity usage can help users improve their electric efficiency if the details of usage is accessible[17-18].

Fig.5 shows the scenario of household electricity usage sensing. Household electric power systems can be simplified as a single-phase electric power system. There are two electric wires: hot wire and neutral wire. All electric appliances are connected in parallel between the two wires. The voltages for all appliances are approximately equal. The total current over the hot wire is the sum of all currents of appliances. Thus, the total power is the sum of the power of all appliances.

There are two types of targets in a house. One is the entirety of all appliances in a house. The other is every appliance in a house. The main surveyed systems in this paper focus on the second type. The functions in these systems are the electricity usage for each individual appliance. The information of each appliance is distributed over a house, which increases the difficulty of sensing.

Four types of sensing systems in this scenario will be surveyed in this section, whose relevant literatures are listed in Table 1. At the end of this section, we will analyze these systems with our SDR model and give a brief comparison.

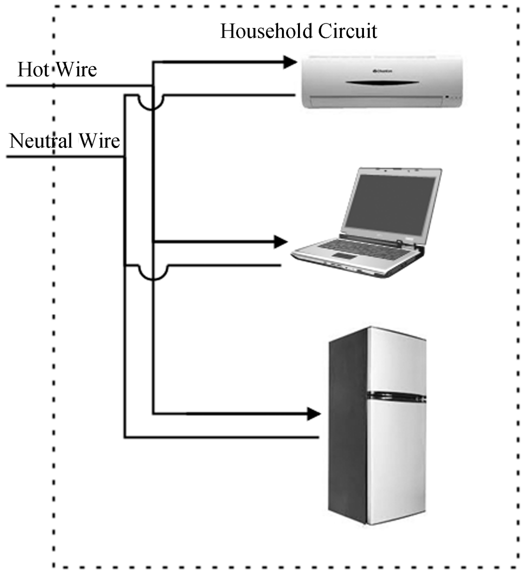

Fig.5. Typical scenario of household electricity usage sensing.

Table 1. Four Types of Household Electricity Usage Sensing Systems

Type	Reference
Smart outlet system	[19-23]
Indirect sensing system	[12, 24-26]
Non-intrusive load monitoring system (NILM system)	[15-16, 27-33]
Noise-based system	[34-36]

3.2 Smart Outlet System

The number of user-connected electric appliances, which are connected to the power grid by outlets, is increasing. Commonly, only lighting facilities and a part of Heating, Ventilation and Air Conditioning system (HVAC) are hard-wired to the main power lines. If the sensing target is a set of user-connected appliances, a direct method is to sense the usage by the corresponding outlets. There are several commercially available products aiming at monitoring the consumption on device level, like Kill a Watt②, Current Cost IAM③, WeMo Insight Switch④. Using wireless network technology, the outlets can be linked together as a unified whole. The combination of sensors at outlets, a wireless network, and the background server is called a smart outlet system[19-23].

①http://www.eia.gov/energyexplained/index.cfm?page=electricity_use, December 2013.

②http://www.p3international.com/, Dec. 2013.

③http://www.currentcost.com/product-iams.html, Dec. 2013.

④http://www.belkin.com/us/p/P-F7C029/, Dec. 2013.

The sensing target of a smart outlet system is a set of appliances connected to the outlets. The only assumption is that all these appliances are working independent. There are no further assumptions about the usage of an appliance. Thus, all the electricity consumption behaviors of each sensing target should be monitored simultaneously. The data is sampled using several homogeneous sensors and transmitted to the central unit through the wireless network. It is essentially a direct application of wireless sensor network[19]. The architecture of smart outlet systems is shown in Fig.6.

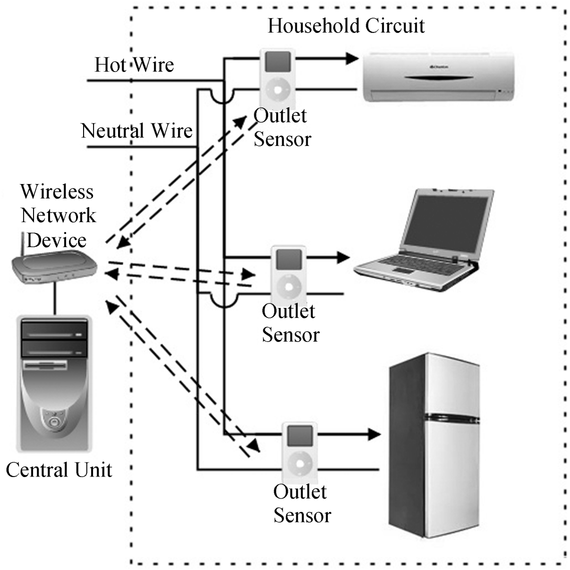

Fig.6. Architecture of smart outlet systems.

Usually, there are several outlet sensors in a house, which sense current and voltage signals of the electric appliances independently. All information is gathered up to a central unit by a wireless network. The sensors can be dynamically deployed. When the requirement of application changes, a user can add or delete sensors during the sensing procedure. The modified sensor needs to be registered on the central unit.

From the perspective of our SDR model, the design methodology of smart outlet systems is reconstruction-prior. The function to be sensed is the real-time power consumption of the appliances plugged into specific outlets. The reconstruction algorithm is directly using the definition of electric power. The power for each appliance is calculated by its current and voltage. To decouple the sensing process, we can define a design space consisting of several homogeneous substructures. Each of these substructures is a pair of vectors to store the current and voltage of an individual appliance. Because each substructure corresponds to an identified appliance and the appliances are distributed in a house, a smart outlet system must be composed of multiple homogeneous outlet sensors. Those sensors obtain sufficient information to meet the need of each substructure. The wireless network gathers all the substructures to form an entire design space.

A smart outlet system is a scalable real-time sensing system, which benefits from its briefness. Every appliance is monitored by an individual outlet sensor. To handle a growing amount of appliances, users can simply add new sensors into this system. A smart outlet system does not need to perform complicated calculation on the sampled data. The sensing result will reflect promptly the actual situation in the physical world.

The deficiency in a smart outlet system is hard to control the cost spent on the sensors. Every sensor needs some common components to restore and transmit data. The cost of adding a sensor is not negligible. To reduce the cost spent on sensors, sharing hardware is a common strategy in smart outlet systems. In WPCOM[20], one microprocessor is used to receive and process the data monitored from six sockets. It means that six sensors share one suit of storage and communication devices.

3.3 Indirect Sensing System

Using direct electricity sensors to monitor every appliance suffers from two main drawbacks. The first is the fact that too many electricity sensors leads to high hardware cost. The other drawback is that direct electricity sensors are inconvenient to monitor the appliances directly connected to the main power line. A sensing system with true ubiquity should satisfy following three features[12]: 1) All the appliances in the house should be monitored by this system. 2) The system should be able to report the power consumption for every individual appliance. 3) The system should be installable by an untrained end-user. To simultaneously satisfy these criteria, indirect sensing systems were proposed to obtain real-time power estimation for each appliance by extensively leveraging ubiquitous sensors[12,24-25]. These sensors are not aimed at electricity information, but the indirect context information, like magnetic field, sound, vibration, temperature, and light.

The sensing target of an indirect sensing system is the set of all the appliances in a house. The most important observation is that every appliance emits measurable signals when it consumes energy. The data sampled indirectly is sufficient to estimate the power consumption of an appliance. Different analysis rules are defined for the appliance monitored by distinct sensors. For example, in ViridiScope[12], four functions are used to map the measured signals to the power consumption. Then a numerical optimization problem to calibrate the parameters is built by these functions. The architecture of an indirect sensing system is shown in Fig.7.

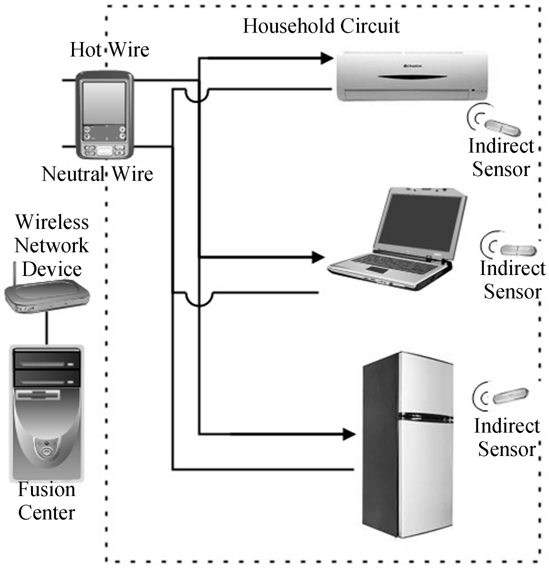

Fig.7. Architecture of indirect sensing systems.

In indirect sensing systems, there are two types of sensors. The first type is deployed near the appliances to sample the physical signals (e.g., light, acoustic). The second type is a single sensor to monitor the main power line. The global power consumption is necessary to analyze the electricity usage for every appliance. Both the two types of sensors contain a wireless communication module to connect to the fusion center, which completes this calculating process. In ViridiScope[12], every appliance needs one or two sensors. Users need to manually deploy proper sensors near every appliance. For example, the refrigerator has two main components: a light and a compressor. A combination of a light sensor and an acoustic or vibration sensor can effectively detect all operation states of this refrigerator. In TinyEARS[25-26], a sensor node is used to monitor the sound in one room.

Taking the ViridiScope system for example, the reconstruction algorithm is using explicit calibration functions defined for each type of physical signals. The following function is built from Maxwell's Equation for magnetic signal[12]:

$$p_i(t) = \alpha_i s_i(t) + \beta_i.$$

Here, $p_i(t)$ is the power consumption of the i-th appliance at time t. $s_i(t)$ is the magnetic signal sampled near the power cord at time t. α_i and β_i are the non-calibrated parameters, which are influenced by the installation of the sensor. These parameters can be calculated automatically with a numerical optimization problem. This numerical optimization problem is to minimize the difference between the total power sampled from main power line and the sum of estimated power for each appliance, as[12]:

$$\min \left\| y_0(t) - \sum_{i=1}^{N} p_i(t) \right\|,$$

where

$$p_i(t) = \begin{cases} a_i s_i(t) + \beta_i, & \text{for magnetometers,} \\ \sum_{j=1}^{K_i} P_{i,j} s_{i,j}(t), & \text{for light/acoustic sensors,} \\ P_i s_i(t), & \text{if unistrumented,} \\ \tilde{p}_i(t), & \text{for direct meter input.} \end{cases}$$

Here, $y_0(t)$ is the total power, $p_i(t)$ is the estimated power for the i-th appliance. For the appliances monitored by different sensors, their explicit calibration functions have their own forms[12]. Since $\| \bullet \|$ is an arbitrary norm, this optimization problem can be solved in known polynomial time. In this algorithm, $y_0(t)$ and $s_i(t)$ for each appliance is necessary.

As we mentioned earlier, the designing process of ViridiScope is reconstruction-prior. The design space in a ViridiScope system is limited by the reconstruction algorithm. It includes multiple heterogeneous substructures to store the total electricity information and the physical signals for individual appliance. The substructure for total electricity information is similar to the substructures used in smart outlet systems. According to the types of sensors, the rest substructures are classified into three groups to store different signals. For example, the acoustic signals will be treated as Boolean variables in the reconstruction algorithm. Thus, the corresponding substructures store the Boolean values of the acoustic signals. How to get these Boolean values is determined by the sampling protocol.

There are three advantages of indirect sensing systems: low-cost, easy installation, automatic calibration. In indirect sensing systems, the appliances are monitored by an indirect sensor, which is much cheaper than the magnetic sensor. This also means that there is no need to modify power lines or power cords. An end-user can simply operate the sensors in this system. Once a new sensor is added into this system, the parameters used in the corresponding functions can be calibrated automatically.

3.4 Non-Intrusive Load Monitoring System

Non-intrusive load monitoring (NILM) systems are a large sort of sensing systems in the scenario of household electricity usage sensing. Some researchers[27-28,30] claimed that a load monitoring systems should minimize its effect on the household circuit. They constrained that the systems could not change the original circuit and could only connect to the circuit at a single point[28]. By analyzing sampled data, the system provides the usage state of individual appliances, their electricity consumption, and other relevant information.

The architecture of a typical NILM system is shown in Fig.8. Considering the need to calculate the electricity consumption, the aggregated current information is necessary to be sampled. The single sensor is suggested to be deployed at the electric utility entrance. The sampled data are the current and voltage waveforms of the total load and other derivation properties (e.g., real power, reactive power). According to the operation mode of an appliance, there are three types[28]: on-off, finite state machine, and continuously variable. From the analysis method, the research on NILM systems can be divided into two types: operation state analysis[16,27-32] and waveform analysis[15,33]. The former one is appropriate for the appliances belonging to on-off mode and finite state machine mode. The latter one is appropriate for continuously variable loads.

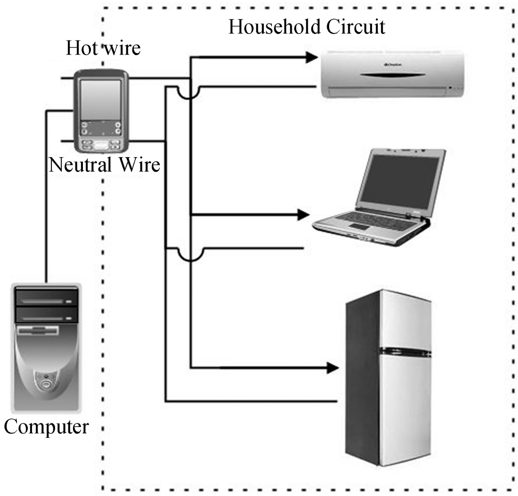

Fig.8. Architecture of a typical NILM system.

Operation state analysis is a type of NILM systems, in which the total electricity usage is used to calculate the operation states of appliances. It is widely accepted that the operation processes of one appliance mainly comprise steady states and transient events[28]. The transient events last only a short time. Every identified steady state has a fixed reference power. To estimate the power consumption of one appliance, the information of steady states is sufficient.

There are two categories of signatures used to recognize the change of operation states for individual appliances: steady-state signatures[16,27-29] and transient signatures[30-32]. A steady-state signature reflects the difference between steady operation states. Such difference is defined by the change on some steady-state properties (e.g., real and reactive power[16], normalized power[28], harmonic currents[29]) of appliances. A transient signature is the behavior of an appliance during the transient events. The behavior can be described by a subsequence of dynamic properties (e.g., spectral envelopes[31] corresponding to specific harmonic[30]).

Any changes on the operation states will be detected by NILM systems. Then NILM systems will track the operation states of all appliances in the house. The total power consumption will be decomposed according to the operation states of all appliances.

The waveform analysis is a type of NILM systems, in which the total electricity usage is used to trace the real-time load waveforms of appliances. There are some continuously variable loads (e.g., variable speed drives[33], computers[15]), which are changing their loads continually without distinct transient events.

For these loads, several models have been developed to track and disaggregate the power consumption. Two waveform models have been built to accurately predict the power consumption[33]. One is based on the prior knowledge of variable speed drives (VSD). In this model, the internal circuit in VSD is analyzed to obtain an equation for estimating the fundamental harmonic current from higher harmonic currents. The other model is based on analyzing the structural features of current waveform. In this model, five distinct waveform features are translated into linear constraints. A Fourier matrix equation is established from these constraints. This equation is reduced to a functional relationship between the fundamental harmonic and other selected harmonics. In another paper[15], a linear manifold is used to approximate the variable space of the current waveform for one appliance. This manifold can be generated by principal component analysis on the training data. A regression is used to disaggregate the total current with these manifolds.

With these waveform models, the NILM systems can track the power consumptions caused by continuously variable loads. These consumptions can be eliminated from the total power. The rest can be analyzed by operation state analysis.

In both of the two types of NILM systems, reconstruction algorithms need the training dataset to get parameters in their model. Usually, the process to get this dataset is called training procedure. It is an intrusive process, and needs the participation of users. A user needs to operate a specific appliance and input information following the instruction from the system.

From the perspective of our SDR model, the designing processes of NILM systems are sampling-prior. The function to be sensed is the usages of electric appliances in a house. Due to the constraint of non-intrusive, different NILM systems have similar sampling protocols. In all NILM systems, total current and voltage are sampled from the electric utility entrance. The values stored in the design space are predetermined by the constraint of the sampling protocol. Every design space comprises two vectors to store the current value and voltage value respectively. Different reconstruction algorithms give different constraints on the design space. Taking NIALMS[16] as an example, the sampled data is used to calculate the power consumption, which does not need a high sampling rate. However, in the ICT electricity sensing system[15], higher harmonics are used in the model. They need a sampling rate twice the frequency of a harmonic signal. After the design spaces have been fixed, the construction algorithms can be designed independently from the sampling protocols.

NILM systems are static-deployed and low-cost. For each system, there is one sensor connected into electric circuits. NILM systems obtain the detailed information of individual appliance using only the data sampled by this sensor. Once the sole sensor is deployed at the electric utility entrance, its position does not change after the starting of sampling. Eventually the uninstall process of an NILM system is simply completed by removing the sole sensor.

The deficiencies of NILM systems are the uncertain accuracy and excessive training. The accuracy of an NILM system is influenced by the type of appliances. The accuracy becomes poor obviously[32] while several air conditioners are operating simultaneously. Excessive training requires users to spend a lot of time before the system starts to work. Every appliance needs to be learnt when it is appended in the house.

3.5 Noise-Based Sensing System

Noise-based sensing systems are a sort of infrastructure-mediated sensing systems[34-36], in which the electric noise transmitted through the infrastructure (i.e., power lines) is used as the signatures caused by individual appliances. These systems are based on such an observation that every power consuming behavior is accompanied by its own noise. If the noises on the power line are identified, the behaviors of appliances can be recognized by a suitable machine learning algorithm. Most of noises caused by appliances are distributed on the voltage signal. It means that those noises can be measured by a single voltage sensor deployed at arbitrary outlet in the house. From the duration of noises, electric noises can be divided into two classes[34]: transient noise and continuous noise. Transient noises last for a short time, generally tens of nanoseconds to a few milliseconds. They are generated while a transient event occurs. Continuous noises can be observed while the specific appliance is working.

Noise-based sensing systems based on the transient noises try to identify transient events of electrical loads[34-35]. Events such as turning on/off a particular appliance will make a transient noise onto the power line. These systems use support vector machine (SVM) to recognize the events from their noises[34]. In a more recent work[36], ElectriSense system aims at the electromagnetic interference (EMI) generated by switch mode power supplies (SMPS). SMPS is a novel power supply technique used in most modern appliances (e.g., fluorescent lights, laptop computers, and the charger for digital devices). The oscillators in SMPS create the EMI continuously. EMI signals can be seen as a kind of continuous noises. It provides rich information about the operation states of the appliances with SMPS. ElectriSense system analyzes the EMI signals to identify the working appliances and their states.

The architecture of a noise-based sensing system is shown in Fig.9. The power line interface is plugged into an arbitrary outlet in the home. The tasks of power line interface include isolation from the power grid and the filtering process. To avoid the interference from the AC power signal, the noise signal should be filtered before sampling. A high-pass filter is necessary to filter out the signal around the power line frequency, which is too strong and useless in the subsequent calculation.

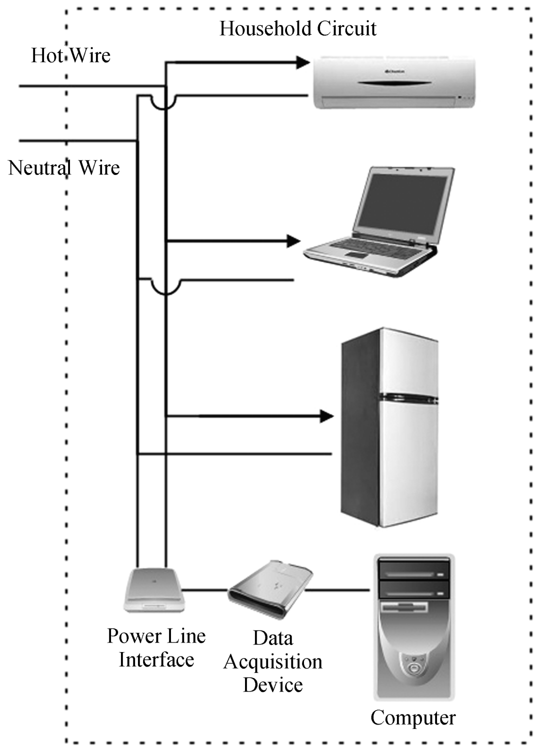

Fig.9. Architecture of noise-based sensing systems.

A data acquisition device samples the filtered signal at a high sample rate (e.g., 1 MHz[36], 100 MHz[34]). The sampled data will be sent to a computer on which the analysis program is running. The program analyzes the input data to get the information of every appliance (e.g., the operation states[36], the transient event[34-35]).

From the perspective of our SDR model, the designing processes of noise-based sensing systems are sampling-prior. The function to be sensed is the operation states of electric appliances in a house. The output of the sampling protocol is predetermined to be the electric noise. The design space is a vector to store these electric noises, which are the filtered voltage values sampled with a high sample rate. The reconstruction algorithm is focused on the classification of transient noises to identify the changes of operation state[34-35]. SVM is selected to be the core algorithm. In ElectriSense system[36], the reconstruction algorithm is focused on the appearing and vanishing of continuous noises. An event detection algorithm tracks the change of total noises. After the detection of an event, the difference vector will be processed by a feature extraction algorithm to identify the change of operation state.

There are three advantages of noise-based sensing systems: single point, easy installation, and position sensitive. The sensor used in this system is only a voltage sensor. The cost on hardware is a constant. Since the sensor can be deployed at arbitrary outlet, the installation is simply plugging the modified plug into an outlet. An interesting observation is mentioned as[36]: an appliance in different locations will generate different noises. This difference can be used to differentiate between the same devices located at different positions.

One deficiency of noise-based sensing systems is the lack of the ability to obtain the information about energy consumption. These systems only use a voltage sensor to sample the noise signal. This is not sufficient to calculate the power consumption. Only the information of operation states is not enough to fully satisfy the requirement in the scenario of household electricity usage sensing.

3.6 Analysis and Comparison

Table 2 shows the details of the four typical systems on their functions, design methodologies, sampling protocols, design spaces, reconstruction algorithms, and three performance features.

In smart outlet systems and noise-based sensing systems, the sensing target only covers a part of appliances in the house. The smart outlet systems cannot monitor the appliances directly connected to the main power line. The noise-based sensing systems are unable to deal

Table 2. Comparison of the Four Typical Systems for Household Electricity Usage Sensing

Features	Smart Outlet System	Indirect Sensing System	NILM System	Noise-Based Sensing System
Sensing target	Appliances plugged in the smart outlets	All the appliances in the home	All the appliances in the home	Appliances making particular noise
Function	Operation state & power consumption	Operation state & power consumption	Operation state & power consumption	Operation state
Design methodology	Reconstruction-prior (require data source)	Reconstruction-prior (require data relation)	Sampling-prior (limit sensor number)	Sampling-prior (limit sensor type)
Sensor number	N	$N+1$	1	1
Type of sensor	Homogeneous	Heterogeneous	Single sensor	Single sensor
Sensor placement	Every used outlet	Electric entrance & every appliance	Electric entrance	Arbitrary outlet
User participation	Sensor installation	Sensor installation	Sensor installation & training	Sensor installation & training
Structure of sampling space	N sub-structures	$N+1$ sub-structures	One uniform structure	One uniform structure
Physical quantities in sampling space	Current & voltage	Current, voltage, sound, light, magnetic	Current & voltage	Voltage
Core algorithm in reconstruction	Direct calculate	Regression	Clustering, genetic algorithm, PCA & regression	SVM, KNN
Scalability	High	Medium	Low	Unknown
Latency	Low	Low	High	High
Cost on hardware	High	Medium	Low	Low

Note: the total number of appliances is N.

with the appliances which are operating with no noise or few noises. Limited by the sampling protocol, functions defined in noise-based sensing systems are only the operation states of a sensing target.

Smart outlet systems and indirect sensing systems use multiple sensors in their sampling protocol. The former installs homogeneous sensors to monitor all the appliances. The latter uses heterogeneous sensors to sample different physical quantities from different appliances while monitoring the main power line. To store the sampled data from those sensors, their design spaces are composed by multiple substructures. NILM systems and noise-based sensing systems use single sensor. In the first kind of systems, the only sensor is placed at the electric entrance. In the second kind of systems, the sensor is plugging into arbitrary outlet. Thus, the design space is a uniform structure. In these two kinds of systems, users should not only deploy the sensors, but also take part in the training procedure.

Most of NILM systems and noise-based sensing systems need a training procedure to extract the signatures of each appliance. Even the extraction of the signatures is completely unsupervised learning methods[16]. They still need the users to match the signature to its actual meaning.

At last, we give three performance features to evaluate different sensing processes. In the household, the number of appliances is dynamically varying. The scalability of a system in this scenario is the maximum number of appliances which can be handled by this system. In smart outlet systems and indirect sensing systems, the number of sensors can increase as the number of appliances increases. The sensors in the former kind of systems can work independently. These systems have high scalabilities. In the latter kind of systems, the increasing of sensors leads to the increase of the number of regression parameters, which reduces the accuracy of the result. Thus, the scalability of indirect sensing systems is medium. In NILM systems, their accuracies are obviously decreasing if the appliance number is increasing[32]. Thus, the scalabilities of the NILM systems are limited by their accuracies. Their scalabilities are low. In the noise-based sensing systems, the issue of scalability was not discussed[34,36]. We have not found experimental data about the scalability of noise-based sensing systems. Intuitively, we consider these systems are similar to NILM systems. Their scalabilities should be limited by their accuracies.

The latency in this scenario is the difference between the operation state changed and the output changed. Smart outlet systems and indirect sensing systems do not need to perform complicated calculation to get the change of operation state. They can obtain the results with a low latency. In NILM systems and noise-based sensing systems, the operation state for each appliance is determined by a complicated computational process. These systems output the results with a high latency.

The cost on hardware also is an essential criterion to evaluate the sensing system. In smart outlet systems and indirect sensing systems, multiple sensors are required. In the former case, each of these sensors can sample the current and voltage signal simultaneously. In the latter case, every sensor only monitors one physical quantity. And the sensors are much cheaper than those in smart outlet systems. In NILM systems and noise-based sensing systems, only one sensor is needed. The sensor network is not necessary to be deployed. The cost is much lower than the previous two classes.

4 Conclusions

Decoupling, which aims at dividing a whole system into several modules and reducing the dependence among these modules, is a class of fundamental tasks in the field of computer science. Several bridging models and techniques, such as the von Neumann model, IP address and APP store, were proposed to undertake decoupling tasks in cyberspace. This paper addressed the problem of how to efficiently decouple a sensing process. Different from previous tasks, a sensing process is not only executed in computers, but also affected by physical objects and even humans. The key observation is that the functions of a sensing target, which are predefined by the user of the sensing system, are essential prior knowledge to connect the physical world and cyberspace. We defined a new concept, design space, to formalize this prior knowledge. In our functional sensing model, a design space divides a sensing process into a sampling protocol and a reconstruction algorithm. To the best of our knowledge, our functional sensing model is the first attempt to decouple a sensing process using prior knowledge given by users. To demonstrate the feasibility of our model, we analyzed 21 household electricity usage sensing systems. Although these systems were originally designed following traditional methodologies, they can be successfully decoupled by introducing corresponding design spaces.

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