國 立 台 灣 大 學　碩士學位論文
資訊工程學研究所
指導教授：朱浩華 博士

飲食感測餐桌 –
感測飲食行爲之智慧平面

Diet-Aware Dining Table –
A Smart Surface to Observe Tabletop Dietary Behaviors

研究生：張耿豪 撰
學　號：R93922018

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To my parents

Acknowledgments

This research started in April 2005 and is a joint work among several students and faculty members.

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Abstract

We are what we eat. Our everyday food choices affect our long-term and short-term health. In the traditional health care, professionals assess and weigh each individual's dietary intake using intensive labor at high cost. In this paper, we design and implement a diet-aware dining table that can track what and how much we eat. To enable automated food tracking, the dining table is augmented with two layers of weighing and RFID sensor surfaces. We devise a weight-RFID matching algorithm to detect and distinguish how people eat. To validate our diet-aware dining table, we have performed experiments, including live dining scenarios (afternoon tea and Chinese-style dinner), multiple dining participants, and concurrent activities chosen randomly. Our experimental results have shown encouraging recognition accuracy, around 80We believe monitoring the dietary behaviors of individuals potentially contribute to diet-aware healthcare.

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Chapter 1

Introduction

1.1 Motivation

Our dietary habits affect our health in many ways. Research [30] has confirmed that dietary habits are important factors for healthy living and have profound impacts on many chronic illnesses. The vast majority of the population has chronic illnesses [11] such as heart disease, diabetes, hypertension, dyslipidemia, and obesity. A recent Surgeon General Report indicated that approximately 300,000 U.S. deaths are associated with obesity and overweight each year. The total cost attributed to overweight and obesity amounts to 117 billion in 2000. Proper dietary intake and related interventions are effective in ameliorating symptoms and improving health. [16][30][37]

Nutritious dietary is one of the most accessible means for people to prevent illness and to promote well-being [16]. Unlike traditional healthcare in which professionals assess and weigh one's dietary intake and then develop a plan for behavioral changes, ubiquitous healthcare technologies provide an opportunity for individuals effortlessly to quantify and acknowledge their dietary intake [16][13]. For example, at home patients face the cumbersome need to record everything they eat, a task which can take a minimum of 15-20 minutes per day [7]. Ubiquitous computing technologies provide a means for individuals to proactively monitor their intake and act upon it, leading to better food selection and more sensible eating.

1.2 Problem and Solution

This thesis proposes a diet-aware dining table that *automatically tracks what and how much each individual eats* over the course of a meal. We have augmented a dining table with two layers of *sensor surfaces* underneath - the *RFID (Radio Frequency Identification) surface* and the *weighing surface*. By combining the RFID and weighing surfaces, our system can trace the complete *food movement path* from its tabletop container source to other containers, and eventually to the individual. To validate our diet-aware dining table, we have performed experiments, including live dining scenarios (afternoon tea and Chinese-style dinner), multiple dining participants, and concurrent activities chosen randomly. Our experimental results have shown encouraging recognition accuracy around 80%, which is as good as the 80% accuracy of the traditional dietary assessment methods. [1]

1.3 Challenge and Contribution

Diet-aware dining table in accord with the *vision of disappearing computers* [21], where computing hardware (HW) & software (SW) are hidden into everyday object (i.e., dining table) and remain *invisible* to human users. There are no digital access devices (such as cell phones, PDAs, or PCs) needed in order for human users to interact with this digital dietary service. In comparison, traditional dietary tracking software requires human users to recall the amount of food consumed, and then manually enter the data. This is less precise due to mistakes in visual measurement and imperfect memory. More importantly, the traditional method requires explicit human effort to operate digital devices.

Our diet-aware dining table *supports multiple people sharing a meal on the same dining table*. Fig. 1.1 shows a typical meal setting for a Chinese family - the family members sit around a circular table with the main dishes placed in the center. Individual rice bowls and plates are arranged on the table periphery. Participants first use shared utensils to transfer food servings from the main dishes to their personal plates or rice bowls, and then eat from there. In this dining scenario, multiple table participants are *continuously* and *concurrently* engaging in food transferring and eating motions. This creates *multiple, concurrent person-object interactions* (objects are tabletop objects such as plates, bowls, etc.) from which a single table surface needs to observe, track, and then infer high level interaction semantics. This is the *main technical challenge* addressed in this paper - how to design a sensor-embedded tabletop surface to track food consumption from each of many table participants.

Figure 1.1: Typical Chinese dining table setting.

1.4 Generalization into a Smart Surface

Furthermore, the design of diet-aware dining table is able to be further generalized as a *smart surface* in which two more applications in the area of healthcare are investigated and reported in this thesis. The first application is *Persuasive Game* which demonstrates the possibility of building just-in-time persuasive feedbacks to encourage better healthy dining behaviors , since this table can track tabletop person-food interactions in real time. In the *Persuasive Game application*, we have explored the design of an interactive, persuasive game to assist adult parents to improve dietary behavior of their young children. The second application is *Smart Kitchen* which shows the possibility to record food content while cooking and further to promote healthy cooking.

1.5 Thesis Organization

The remainder of this thesis is organized as follows. Section 2 describes the related work. Section 3 states the design choices, assumptions, and limitations. Section 4 presents our design and implementation. Section 5 describes the experimental set-up and results. Section 6 and 7 introduces the two applications generalized from our diet-aware dining table. Finally, Section 8 draws our conclusion and future work.

Chapter 2

Related Work

The related work is organized into the following six categories: traditional dietary assessment methods, ubiquitous dietary tracking systems, intelligent (tabletop) surfaces and behavior recognition, including related work of two generalizing applications: persuasive technologies and smart kitchen.

2.1 Traditional Dietary Assessment Methods

The traditional dietary assessment methods consist of keeping food records, using twenty-four-hour recall, and filling food frequencies questionnaires [34]. In the food record method, food quantities can be either accurately weighed or estimated by household measures before a meal. The twenty-four-hour recall method asks a user to recall the amount of food intakes within the past 24 hours. Food Frequencies Questionnaires (FFQ) list popular food items and ask a user how often and how much these food items are consumed within a defined period, e.g., a week or a month. All traditional assessment methods fail to capture actual energy intakes precisely [1]. Most methods underreport actual energy intake by at least 20 percent. Some of the errors are inevitable because human beings tend to misreport their food intakes. In other words, underreporting errors can be higher (30 percent or more) for certain groups of users. In comparison, our method can achieve 80% plus accuracy, which is as good as the accuracy from these traditional assessment methods.

In addition, MyFoodPhone [3] is a market product build on camera phone, which can reduce human efforts on dietary diary keeping. Users take pictures of what they eat. Then, the nutritional advisors analyze pictures manually, and give personal video feedbacks to make change of users' eating habits. However, this system still require users' manual effort. In the following we describe ubiquitous dietary tracking systems, which target to eliminate human efforts.

2.2 Ubiquitous Dietary Tracking Systems

For the dietary-tracking systems, Mankoff et al. [20] has designed a low-cost tracking system based on scanning shopping receipts to estimate what food items people buy and consume. By analyzing the nutritional values of the purchased food items, their system detects missing nutrients and recommends healthier food items to achieve a better nutritional balance. However, their system does not perform individual dietary tracking. The purchased food items in a family setting may be consumed by different household members in different quantities. The household purchased food items can be considered healthy, but the dietary consumption of individual household member can be nutritionally unbalanced due to personal dietary preferences and habits.

Dietary tracking at the individual level has been proposed by Amft et al. [5]. Their approach is to place a microphone around a person's inner ear to detect chewing sound from the mouth. Since different types of foods (e.g., potato chips, apples, pasta, etc.) can give different chewing sound, their system can infer what a person is currently eating in hisher mouth. However, different food sources that vary in nutritional contents give out similar chewing sound, e.g., similar sound from drinking water vs. beer. Rather than tracking food intake from chewing sound, this work takes a different approach. It creates a smart dining table, enabling the table to track food transfers among containers and into the individuals' mouths.

2.3 Intelligent (Tabletop) Surfaces

The 3rd category of related work is about intelligent surfaces that can infer tabletop human-surface interactions. The closest system to our work is the load sensing table [31] from Lancaster University. They utilized four weighing cells installed at four corners of a rectangular table to acquire the positional information of tabletop objects, and infer interaction events such as adding, removing an object from the surface, or knocking an object over. They demonstrated success with these interaction events. However, their main limitation is recognizing complex, concurrent interactions involving multiple objects. For example, their positioning algorithm fails if two or more objects are moved concurrently on the tabletop surface. In comparison, this paper expects such complex, concurrent interactions to be relatively common in family dining scenario; therefore, they are the paper's target.

Other related but less relevant works apply load sensing to derive context information. Smart floor [27] demonstrated that by applying pressure sensors underneath the floors, it is possible to identity users and to track their locations. The posture chair by Selena [23] deployed two matrices of pressure sensors (called pressure cells) in a chair to recognize the posture of children, and then infer their affective interest level. To our knowledge, no work that attempts to address complex, concurrent person-object interactions from a load sensing surface. This paper is believed to be the first to augment the load sensing surface with a RFID surface to enable tracking of multiple, concurrent person-object interactions over a tabletop surface.

2.4 Behavior Recognition

Recognizing dietary behaviors is categorized in inferencing ADLs *(activities of daily living)*. Most of the researches perform high-level inferencing from low-level sensor data reporting. Projects in this approach are more application-oriented, and have their own idiosyncratic sensors and algorithms on those sensors. The diet-aware dining table belongs to this category. Other projects in this category are described below. Mihailidis et al. [22] used cameras and a bracelet to infer hand washing. Wan [36] used RFID tags functionally as contact switches to infer medication taking. In addition, Tran [35] leveraged computer vision to recognize meal preparation, but Barger et al. [12] used rule-based approach to combine contact switches, temperature switches, and pressure sensors to infer. Moreover, Glascock [14] combined motion and contact sensors into a custom-built medication pad, to get rough inference on meal preparation, toileting, taking medication, and up-and-around transference. There are also other related projects [18] [24] [9] [15]using different sensors to infer behaviors and activity level.

Furthermore, there are some other researches focus on an object-based approach. Based on the sequence of objects people use, Philipose et al. [28] use RFID technology, data mining, and a probabilistic inference engine to recognize ADLs. The shortcoming for this system is that it requires users to wear a RFID-installed glove. Nonetheless, its probabilistic inferencing method is flexible to general activities. This approach shows fine-grained measurement of object use is a good indicator of activity. MIT's House_n project [19] also uses the object-based approach.

2.5 Persuasive Technologies

For the persuasive technologies, Fogg [4] listed basic principles for designing persuasive technology. These principles are adapted in our design. In addition, we emphasize on the fun aspect of the persuasion, as a means to attract the attention of young children and keep them engaged during the persuasion process. Out [29] designed a high-tech doll that looks like a human baby to simulate how hard it is to care for a baby. The doll contains an embedded computer that triggers a crying sound at random intervals. To stop the crying, the caregiver must pay immediate attention to the doll. The caregiver must insert a key into the back of the baby and hold it in place to stop the crying. Rather than persuading people by using negative reinforcement, our work provides a positive reinforcement as encouragement for young children.

2.6 Smart Kitchen

CounterActive [17] is an interactive kitchen counter that teaches people how to cook by projecting multimedia recipes onto a touchpanel-like kitchen counter. Experiments show users benefit from this interactive recipe. However, this system cannot be aware of a user's cooking situation and further provide just-in-time feedback to result in better cooking(e.g., please add more carrots into the big bowl.) Cook's Collage [35] aims to aid a cook in remembering specific past actions. By playing a sequence of action snapshots, Cook's Collage provide a visual summary of recent cooking activity along a kitchen countertop. Though this system provides cues for user to review actions, it still lacks adaptive, active advices to teach cooking. In addition, Siio [33] concentrates on automating the creation of web-ready recipes. When a user operates one of the foot-switches, images of the cooking workplace are captured with voice memos into a multimedia recipe. However, without automatically tracking the amount of food ingredients, images and voice memos may not be sufficient enough to create a complete recipe (e.g., adding 500 grams of carrots).

Counter Intelligence [8] takes different approach to design kitchen of the future. They augment kitchen with ambient interfaces to improve the usability of a physical environment. For example, augmented reality kitchen assists users in determining temperatures, finding things, following recipes and timing various steps of preparing a meal.

Chapter 3

Design Choices, Assumptions, and Limitations

Although the ultimate design objective is to create a *restriction-free*, automated dietary-tracking system that can achieve both *high accuracy* and *precision*, this is a grand challenge requiring extensive future research efforts [20]. We acknowledge this fact, and consider our dietary-tracking system as an early effort to address this problem. Since our work is not yet a perfect solution, we need to state our assumptions, present our design rational, and discuss our design limitations.

3.1 Why RFID and Weighing Surfaces?

Our diet-aware dining table tracks tabletop interactions such as transferring food among containers and eating food by an individual. To correctly infer individuals' dietary behaviors from their tabletop interactions, our system needs to track how much (weight) and what food items are involved in these interactions. To observe these interactions, a weighing surface and a RFID surface are embedded into an ordinary dining table. Assume that food items are correctly labeled by the RFID tags on food containers, the surface can then be used to identify these RFID-tagged containers. Furthermore, the RFID surface can obtain nutritional information such as calorie count by looking up a food label database indexed by RFID code [26].

This assumption raises a question as to who would perform the work of inputting the food information for the RFID tags into the database. Three possible scenarios apply: (1) prepared foods (e.g., microwave-ready) are purchased from supermarkets are heated and then placed on the dining table with their original containers and packages containing RFID tags. This is applicable to people who subscribe to a weight-loss dietary program; (2) when the food containers (dishes) are first placed on the dining table, the table explicitly asks users for the food contents through a natural, easy-to-input UI, such as speech interface; and (3) when food is prepared in the kitchen, the cooking person can input the food's content as the food is placed in a serving container.

The weighing surface is used to measure (1) the amount of food transferred across different tabletop containers, as servings of food are transferred between different tabletop containers, and (2) the amount of food consumed by an individual, as personal plates lose weight. More details on how the weight measurements are used to detect food transfer and food consumption events are described in Section 3.

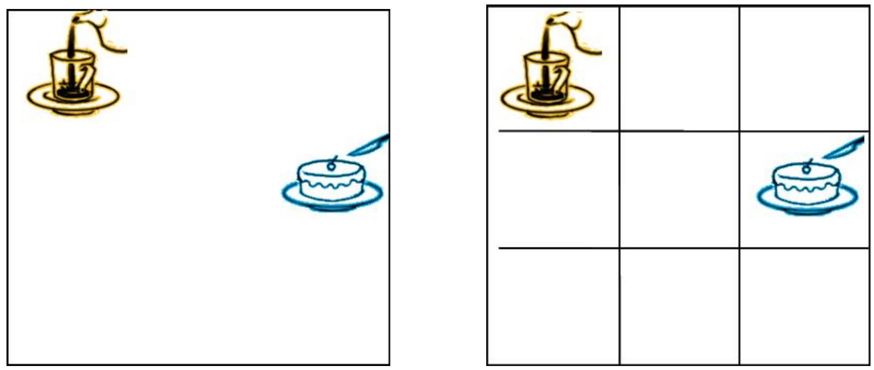
3.2 Complex and Concurrent Interactions Involving Multiple Tabletop Objects

In a typical family meal setting, there are multiple people dining together on a dining table, and table needs to track multiple, concurrent person-object interactions. In an afternoon tea scenario, if one person is pouring tea to a cup while another one is eating cake, it is impossible to use a single weighing surface to distinguish the amount of tea weight transfer to the cup vs. the amount of cake weight lost through a person's consumption. This scenario is shown in Fig. 3.1-(a). This is also called the *single-cell-concurrent-interactions problem* where it is impossible to distinguish multiple, concurrent person-object interactions over a single surface using the weight information from only one sensor[1]. To address this problem, our solution is to divide the tabletop surface into multiple cells, shown in Fig. 3.1-(b). When the size of each cell is small enough, it is likely that each tabletop object occupies a different cell. Therefore, our solution uses multiple weighing sensors at different cells to distinguish the weight-change of the tea cup from the weight-change of the cake plate. This idea is generalized as follows: the larger the size of each weighing cell relative to the average size of objects, the higher the likelihood that multiple, concurrent person-object interactions can occur within the same cell, therefore the higher the probability of single-cell-concurrent interactions. To reduce this probability, we divide the weighing surface into cells of an appropriate size that just fit the average size of tabletop food containers, such as plates, bowls, etc.

Where *single-cell-concurrent-interactions problem* still occurs, we introduce *common sense semantics* to discern the amount of weight-changes in these concurrent interactions. Consider the situation where a cup and a plate are placed at the same cell X at the same time. When a user pours tea from a tea pot to a cup (leading to weight increase at cell X), we can correctly infer the tea is transferred to a cup rather than to a plate by using common sense in normal dining behavior.

Also, relying only on a weighing surface (i.e., without RFID surface) is insufficient to identify tabletop objects. Distinguishing a tabletop object by its weight is difficult, given

[1] In the Lancaster's approach [31], the scale is made up of four weighing sensors at four corners of a table.



(a) **(b)**

Figure 3.1: Surface structure [This illustrates that a multi-cells surface (b) can track multiple person-object interactions whereas a single-cell surface (a) cannot.]

that the weights of food containers change over the course of a meal as people transfer food servings. Therefore, we augment the weighing surface with a passive RFID surface to help identify tabletop objects. Each cell contains a RFID antenna that can read the unique IDs from RFID-tagged objects on that cell.

3.3 Intelligent Surface vs. Intelligent Containers

Early in our design, we faced a fundamental design choice between embedding intelligence into the table or into the food containers. One advantage for choosing the intelligent food containers is that they do not have the *single-cell-concurrent-interactions problem*, because each food container can weight itself and detect its own weight-change events. However, the intelligent containers approach also has many disadvantages. First, it may result in high cost since every food container must have a weight scale and wireless networking module. Second, the smart food containers require battery installments and replacements, whereas the dining table is a piece of stationary furniture that can be plugged into a wall socket. The third disadvantage is that people may buy prepared food

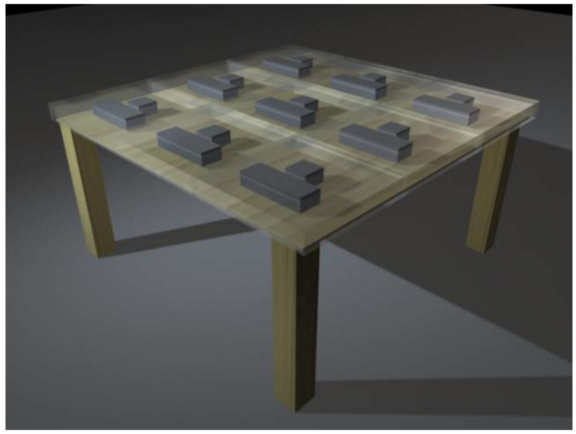


Figure 3.2: Design Picture of Diet-aware Dining Table

items from restaurants that have their own disposable packages and RFID tags. It is inconvenient to have people transfer the food into the intelligent containers every time, in contrast to the convenience of putting tagged packages directly on the intelligent table.

3.4 Assumptions

From the above discussion on design choices, our assumptions for our system in this paper are:

- The dining table, its RFID-tagged tabletop objects (food containers), and table participants form a closed rather an open system. That is, all food transfers can occur only among the tabletop objects and individual mouths. External objects and food sources are not allowed on the table.
- All dining participant have their personal containers (personal plates and cups) that are usually placed in front of their seating. They are used to identify each individual user.
- Food containers must be tagged with RFID tags. We assume that weight, nutrition,

and ingredients of the food, as well, as, the weight and owners of food containers are known a-priori.

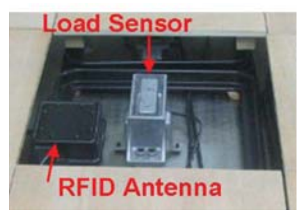
- Tabletop objects are placed within each individual cell. No cross-cell objects are allowed.
- Dining participants avoid leaning their hands and elbows on the table.

Chapter 4

Design and Implementation

Our system is consisted of HW & SW components. The HW component is made up of the RFID and weighing sensors embedded underneath the table surface shown in Fig. 4.1 in page 17. The SW component is made up a rule-based system that aggregates, interprets, and infers tabletop dietary behaviors shown in Fig. 6.3 in page 46. The HW component is described first, followed by the SW component.

(a)



(b)

Figure 4.1: Current version of embedded RFID and weighing table surfaces

(a) **(b)**

Figure 4.2: First version of embedded RFID and weighing table surfaces

4.1 Hardware Design and Implementation

Our current table prototype has a dining surface of 90x90 cm^2, which is about the size of a small dining table. To detect multiple, concurrent person-object interactions on the tabletop surface, the tabletop surface is divided into a matrix of 3x3 cells, each with the size of 30x30 cm^2, about the average size of food containers. Each cell contains a weighing sensor and a passive RFID antenna as shown in Fig. 4.1 in page 17. The RFID reader is the i-scan MR100 made by Feig. The RFID antennas are connected to the RFID reader through a multiplexer. Each RFID antenna is positioned underneath the table surface such that it has an average, effective read rage of 3 *cm* above the table surface. The weighing sensor is attached to a weight indicator with a resolution of 0.5 *gram* which can output weight readings through a serial port at a frequency of 8 samples per second.

In the first version table prototype, each cell contains a load sensor and a passive RFID reader/antenna as shown in Fig. 4.2. The RFID reader is the Skyetek M1 RFID reader with an average read rage of 30 mm.

4.1.1 Stable Weight Detection Algorithm

As users interact with objects (e.g. cups, plates, etc.) over a dining table, interactions such as to place them on surfaces or to remove them from surfaces are of interest to be recognized. As shown in Fig. 4.3 in page 19 [31], weight data changes when an object is placed on the surface at position E1 and E4, an object is knocked over at E2, and the object is removed from the surface at E3. To interpret the weight data into interactions, we disregard how weight changes (jitters) while an interaction happens. Instead, we consider the weight value difference if an interaction happens. For example, after a object is placed on the load surface, weight value increases. And, after the object is removed from the load surface, weight value decreases.

We invent a *Stable Weight Detection Algorithm* which calculates stable weight vaules over time. The values will be reported to be further checked for weight difference, and details will be described in Section 4.2. Using a slide window of 5 weight samples by empirical experiment results, algorithm detects a stable value if all the weight samples in the window are approximately the same.

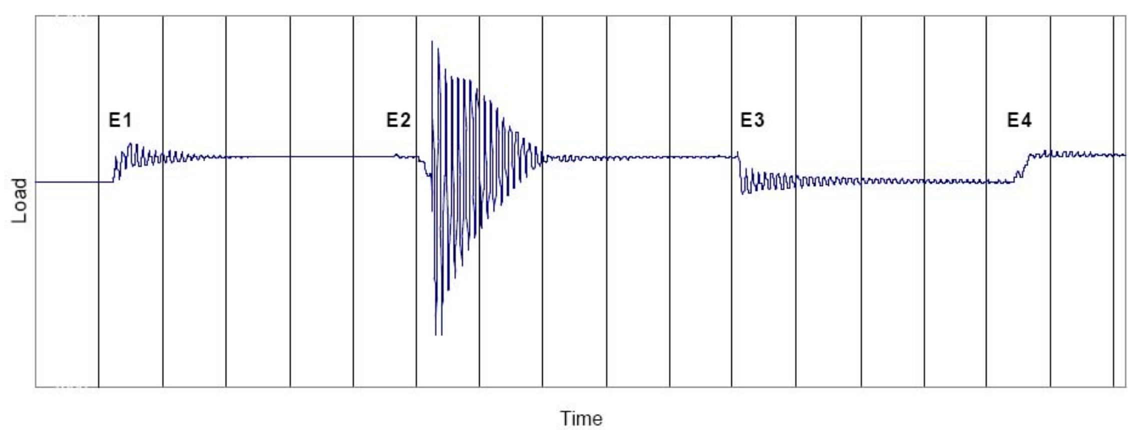


Figure 4.3: The weight data (load) recorded over time. An object is placed on the surface at position E1 and E4. At E2 an object is knocked over and at E3 the object is removed from the surface.

4.2 Software Design and Implementation

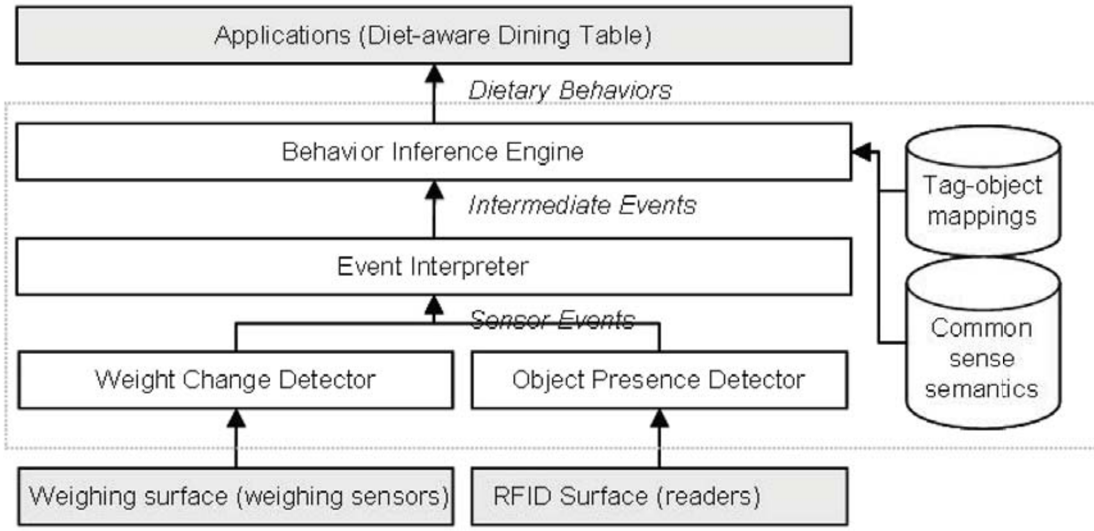


Figure 4.4: System architecture

We have come up with a rule-based approach that applies our multi-cells weighing and RFID surfaces to detect multiple, concurrent person-object interactions. The system and inference rules are implemented in JESS rule engine [2].

The system architecture is based on a bottom-up event-triggered approach shown in Fig. 6.3 in page 46. High level dietary behaviors, such as *pour-tea* and *eat-cake*, can be inferred by interpreting sensor *Cell-Weight* events and *RFID-Presence* events. We describe each software component as follows.

The *weight change detector* performs the following two tasks: (1) it aggregates weight samples collected from each of the 9 weighing sensors; (2) it reports *Cell-Weight* events when the weight has changed by filtering out noises in the stream of weight samples. The *object presence detector* performs similar tasks: (1) it continuously checks for presence and absence of RFID-tagged tabletop objects within each of the 9 RFID reader cells, and

Table 4.1: Intermediate events, sensor events, and internal states

Intermediate Events	**Descriptions**
$\mathit{Weight\text{-}Change}(Object_i, \Delta w)$	$Object_i$'s weight is changed by Δw.
Sensor Events	**Descriptions**
$\mathit{RFID\text{-}Presence}(Object_i, Cell_j)$	$Cell_j$ detects the presence of $Object_i$.
$\mathit{Cell\text{-}Weight}(w, Cell_j)$	$Cell_j$ measures weight w.
Internal State	**Descriptions**
$Location(Object_i, Cell_j)$	$Object_i$ locates on $Cell_j$.
$Weight(Object_i, w)$	$Object_i$ has weight w.

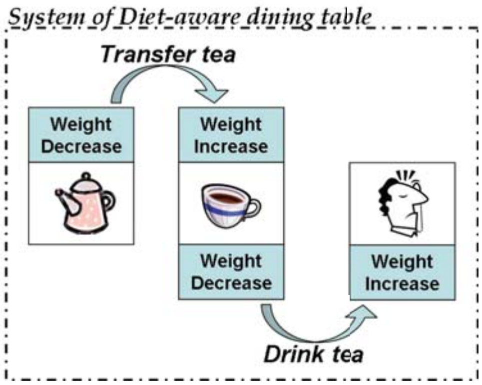
Table 4.2: Rules for recognizing intermediate events

Event Interpretation Rules
$Weight(Object_i, w_1) \cap Weight'(Object_i, w_2) \rightarrow \mathit{Weight\text{-}Change}(Object_i, w_2 - w_1)$
State Update Rules
$\mathit{RFID\text{-}Presence}(Object_{i1}, Cell_j) \rightarrow Location(Object_{i1}, Cell_j)$
$Location(Object_i, Cell_j) \cap \mathit{Cell\text{-}Weight}\ (w, Cell_j) \rightarrow Weight'(Object_i, w)$

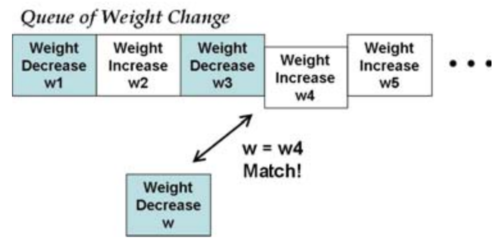
reports *RFID-Presence* events as long as the change happens.

The *event interpreter* interprets *intermediate events* shown in Table 4.1 in page 21. The event interpreter builds internal states using sensor events from the weight change detector and the object presence detector, and then interprets *Weight-Change* events. Table 4.2 in page 21 shows the rules to interpret events. For example, the $\mathit{Weight\text{-}Change}(Object_i, \Delta w)$ event represents that the $Object_i$'s weight is changed by Δw, where $Object_i \in \{\textit{object on the table}\}$ and $Cell_j \in \{Cell_{[1-9]}\}$.

The *behavior inference engine* infers *dietary behaviors* initiated by the user u shown in Table 4.3 in page 24. Behavior inference engine is essentially the core of the system. It infers food transfer and eating behaviors over the table. In the real world scenarios, there are often different food items on the table, meaning that multiple food sources can be



(a)



(b)

Figure 4.5: (a)Illustration of Law of Conservation of Mass. (b)Illustration of Weight Matching Algorithm

transferred to the same personal container. For example, the weight-increase to a cup may be contributed by pouring of coke, juice, or tea from different bottles and pots. Moreover, given that there are multiple food transfer interactions happening concurrently, how does the system identify and differentiate the food being transferred from which food source container to which user's personal container?

4.2.1 Law of Conservation of Mass

The *behavior inference engine* follows an important law in physics, *Law of Conservation of Mass*, to infers dietary behaviors. The Law of Conservation of Mass states that the mass of a system of substances will remain constant, regardless of the processes acting inside the system. Applying this law in our system, it turns out to state that the weight (the amount of food) doesn't disappear. As illustrated in Fig. 4.5-(a), for the *transfer tea* example, if there is a weight decrease of a tea pot on the dining table, there must be a weight increase of a cup. In addition, for the *drink tea* example, if there is a weight decrease of a tea cup, there must be a weight increase of someone sitting around the table.

4.2.2 Weight Matching Algorithm

To track a food movement path from the food's source containers to personal containers, we design a *weight matching algorithm* based on the *Law of Conservation of Mass*. The basic idea is to match a weight-decrease from one container to a complementary weight-increase from another container. This matching process can be thought as *a hop of food transfer* from the source food container in the center of the table, to the personal containers on the table periphery. This weight matching model is realized by maintaining a queue of recent *Weight-Change* events. When a new *Weight-Change* event is detected, our model applies a matching function to find a complementary *Weight-Change* event(s) in the waiting queue. A good match is found when the difference between the weight-decrease and the weight-increase pairs is smaller than a chosen weight *matching threshold value* (ε). This weight matching model is coded as rules in Table 3. For example, $Transfer(u,w,type)$ means that a serving of cake with a weight w has been transferred from the share-plate containing food of $type$ to the user u's personal plate, where $type$ is obtained from RFID mappings. This behavior event can be inferred by first observing a weight decrease Δw_1 (< 0) in the share-plate, followed by a matching weight increase Δw_2 on the user u's $Object_{i2}$. A match is found when $|\Delta w_1 + \Delta w_2| < \varepsilon$. The tag-object mappings provide two relations: $Contains(Object,type)$ shows $Object$ contains food of the $type$, such as cake or tea, and $Owner(Object,u)$ means the owner u of the $Object$. In addition, *Eat* is inferred if there is a weight-decrease in any personal container.

In real world scenarios, there are special, complex interactions that require matching among three or more events. For examples, a person may pour tea from a tea pot to two cups within one continuous motion, or another person may transfer soup from a soup bowl to a personal bowl through multiple scoops. These two examples can be mapped to (1) the amount of one weight decrease matches with the sum of multiple weight increases, or (2) the amount of one weight increase matches with the sum of multiple weight decreases.

Table 4.3: Inference rules for dietary behaviors

Dietary behaviors	Behavior Inference Rules
$Transfer(u,w,type)$	$\textit{Weight-Change}(Object_{i1},\Delta w_1)\cap(\Delta w_1<0)\cap \textit{Weight-Change}(Object_{i2},\Delta_{w2})\cap(\Delta w_2>0)\cap Contains(Object_{i1},type)\cap Owner(Object_{i2},u)\cap(\lvert\Delta w_1+\Delta w_2\rvert<\varepsilon)\rightarrow Transfer(u,\Delta w_2,type)$
$Eat(u,w,type)$	$\textit{Weight-Change}(Object_{i1},\Delta w)\cap(\Delta w<0)\cap Contains(Object_i,type)\cap Owner(Object_i,u)\rightarrow Eat(u,-\Delta w,type)$

To address this issue, the weight matching algorithm is extended to match more than two weight transfer events.

4.2.3 Common Sense Semantics

Although dividing the table into cells can reduce the probability of multiple objects on one cell, the situation mentioned in Section 3.2 may still happen. To address this situation, we *add common sense semantics* to extend the inference routines that can disambiguate the multi-objects on one cell problem. For example, if there are one *cup* and one *plate* on the same cell, and the user pours tea from the *pot* to the *cup*; the *Weight-Change* event of {*cup, plate*} will be reported by the *Event Interpreter*. According to the common sense, tea should be poured into the cup rather than the plate. Therefore, the *behavior inference engine* matches the weight-decrease of the *pot* to weight-increase of {*cup, plate*} and generates *Transfer(pot, cup, w)* behavior.

Chapter 5

Experimental Set-up and Results

5.1 Evaluation metric, dining scenarios, and dining settings

We have conducted several experiments to evaluate the accuracy of our dietary tracking table under different dining scenarios. The evaluation metric, *weight accuracy*, measures how well the system can correctly recognize the amount of weight from different food items consumed by the dining participants. It is determined by how well the system can correctly recognize the high-level dietary behaviors: specifically the food *transfer* event and *eat* event. Therefore, the intermediate evaluation metric, *behavior accuracy*, is listed as well.

$$\text{weight accuracy} = \frac{\Sigma \text{weight of recognize food intake}}{\Sigma \text{weight of actual food intake}}$$

$$\text{behavior accuracy} = \frac{\text{\# of recognized behaviors}}{\text{\# of actual conducted behaviors}}$$

Note that both behaviors are associated with attributes defined in Table 3. The *transfer* event has three attributes (source object, destination object, weight), whereas the *eat* event also has three attributes (user, source object, weight). Correct event recognition is defined as the event's attributes, except the weight attribute, are correctly identified. Since the weight measurements have inherent sensor errors, they are evaluated separately. Specifically, the behavior accuracy is the number of behaviors recognized divided by the number of behaviors conducted by participants. The weight accuracy is the sum of measured weight divided by the sum of actual weight corresponding to dietary behaviors.

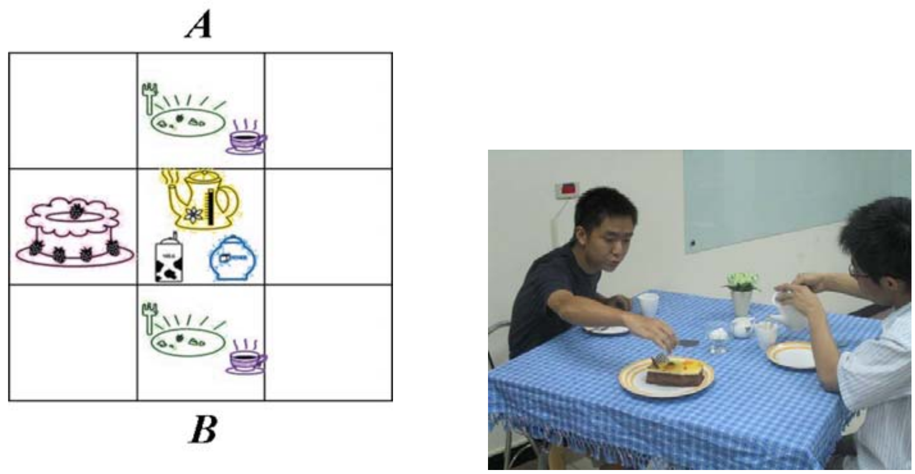
The experiments involve three participants. The first two participants are graduate students from our research team who are familiar with our system. The third participant is a graduate student from our department, who is not familiar with our system.

Dining scenarios (# participants, predefined vs. random activity sequences)

We have designed four different dining scenarios. The varying parameters are (1) *the number of dining participants* and (2) whether dietary behaviors are *predefined* or *random*. As the number of dining participants increases, we expect that they will generate higher number of non-overlapping and concurrent events. Predefined activities mean that the dining participants repeat some pre-arranged sequences of dietary steps which we expect in normal dietary behaviors. The predefined activities may include both sequential and concurrent activities. The exact activity sequences depend on the dining settings described in later subsections. Random activities mean that the dining participants are more or less free to follow their natural eating behaviors within the assumptions of our system defined in Section 3.4.

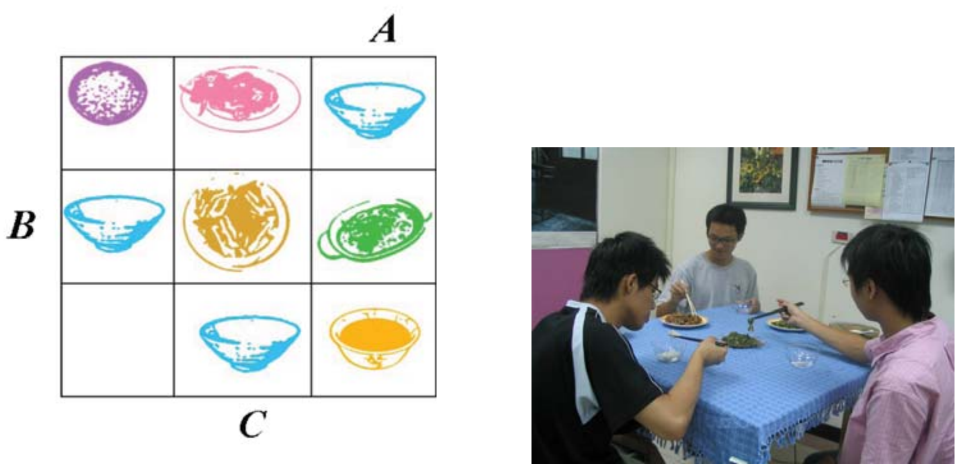
Dining Settings (afternoon tea vs. dinner)

There are two dining settings: an *afternoon tea* setting and a Chinese-style *dinner*



(a) **(b)**

Figure 5.1: Afternoon tea scenario showing the placements of table objects and participants



(a) **(b)**

Figure 5.2: Chinese-style dinner scenario showing the placements of table objects and participants

setting. The dinner setting is more complex than the afternoon tea setting since it involves a larger number of food containers. We describe these two settings in more details as follows. In the afternoon-tea scenario, participant(s) enjoyed an afternoon tea with a cake, a pot of tea, sugar, and milk. The objects (food containers) on the intelligent table are shown in Fig. 5.1-(a) in page 27, including a tea pot, a cake plate, a sugar jar, a milk creamer, personal cake plates, and tea cups. The personal cake plates and tea cups are placed on the cells in front of each participant. The cake plate is placed on one center cell. The tea pot, the sugar jar, and the milk creamer are placed together on another center cell. Possible high-level dietary behaviors are *transferring-cake (to a personal plate), pouring-tea (to a personal cup), eating-cake (from a personal plate), and drinking-tea (from a personal cup)*. In the dinner scenario, three dining participants enjoyed a sumptuous dinner with three shared dishes, one shared soup bowl, and a shared rice bowl. The objects (food containers) on the table are shown in Fig. 5.2-(a) in page 27, including these shared plates & bowls, as well as personal bowls located on cells in front of each of three participants. Possible high-level dietary behaviors are *transferring-food (to a personal bowl) and eating-food (from a personal bowl)*. Note that given the weight and type of the food items consumed, it is relatively straight-forward to compute the calorie count by looking up a nutritional table for these food items.

We describe the result for each of four dining scenarios as follows. A summary of their experiment results are shown in Table 5.1 in page 29.

Table 5.1: Experimental results for 4 dining scenarios & their recognition accuracy.

Scenarios			Event Statistics		Results	
Dining Scenarios	# of users	Activity Sequence	Time Duration (seconds)	# of Dietary Behaviors	Dietary Behavior Recognition Accuracy	Dietary Weight Recognition Accuracy
#1 Afternoon tea	1	Predefined	73	12	100%	-
#2 Afternoon tea	2	Predefined	162	24	100%	-
#3 Afternoon tea	2	Random	913	78	79.49%	-
#4 Chinese style dinner	3	Random	1811	162	83.33%	82.62%

5.2 Dining Scenario #1: Afternoon Tea - Single User - Predefined Activity Sequence

The first dining scenario involves the afternoon tea setting, single user, and predefined activity sequence. The predefined activity sequence is consisted of the following steps: (1) cut a piece of cake and transfer it to the personal plate; (2) pour tea from the tea pot to the personal cup; (3) add milk to the personal cup from the creamer; (4) eat the piece of cake from the personal plate; (5) drink tea from the personal cup; and (6) add sugar to the personal cup from the sugar jar. This 6-steps sequence is repeated twice during the experiment. The results are shown in Table 5.1. Based on our measurements, the dietary behavior's recognition accuracy (i.e., transfer & eat events) is 100%. This result is expected, given that the predefined activity sequence has been anticipated and tested extensively during our prototyping. In addition, this scenario involves only a single user with no concurrent interactions.

5.3 Dining Scenario #2: Afternoon Tea - Two users - Predefined Activity Sequence

The second dining scenario also involves the afternoon tea setting and predefined activity sequence, but with two users performing concurrent activities. The predefined activity sequence is consisted of the following steps: (1) A cuts cake and transfers it to A's personal plate; (2) B pours tea from the tea pot to B's personal cup; (3) A pours tea to A's personal cup while B cuts a piece of cake and transfers it to B's personal plate; (4) A adds sugar from the sugar jar to A's personal cup while B adds milk from the creamer to B's personal up; (5) A eats cake and B drinks tea; (6) B eats cake from B's personal plate while A drinks tea from A's personal cup; and (7) A pours tea from the tea pot to both A's and B's personal cups. This 7-steps predefined activity sequence is repeated twice during the experiment. The results are shown in Table 5.1. Based on our measurements, the dietary behavior recognition accuracy is 100%. This result shows that our table is accurate in recognizing concurrent activities from multiple participants.

5.4 Dining Scenario #3: Afternoon Tea - Two Users - Random Activities

The third dining scenario involves the afternoon tea setting and two users, but with random dietary activities. Random activities mean that the table participants are more or less free to perform any impromptu dietary behaviors for 913 seconds over the table within the bound of our assumptions described in Section 2.4. The results are shown in Table 5.1. Based on our measurements, the recognition accuracy is 79.49%. Table 5.2 in page 31 shows the recognition accuracy for each of the two dietary behaviors. The eat events have better recognition accuracy than the transfer events, because they can be directly deduced by personal container's *Weight-Change* event.

To determine the causes for the misses in activity recognition, we videotaped the afternoon tea scenario. By analyzing the video in combination with the system event logs, we derive four main *leading causes* shown in Table 6. They are described as follows.

Table 5.2: The accuracy of activity recognition under afternoon tea scenario #3

Dietary Behavior	**# of Actual Events**	**Recognition Accuracy**
Transfer event	41	70.73%
Eat event	37	89.19%

Table 5.3: Causes of miss recognition in afternoon tea scenario #3. There are 78 activities analyzed from the video log. The number of misses counts both false positives and false negatives.

Causes of misses	**# of misses of transfer events**	**# of misses of eat events**	**Total**
(c1) Event interference within the weighing cell's weight stabilization time	6	2	8
(c2) Weight matching threshold	2	0	2
(c3) Slow RFID sample rate	3	0	3
(c4) Noise from weighing cell	1	2	3
Total of misses	12	4	16

(c1) *Event interference within the weighing cell's weight stabilization time*: for activities such as putting down an object on the table, it takes about 1.5 seconds for our weighing sensor to output a stable weight value. If two events occur on the same cell and their time interval is less than the weighing cell's stabilization time, our system cannot differentiate these two *Weight-Change* events. Instead, our system will incorrectly recognize them as a single *Weight-Change* event. Consider the case where user A puts down the tea pot at cell X while user B immediately (within 1.5 seconds) grabs a sugar cube from the sugar jar on the same cell X. There are actually two *Weight-Change* events of amount (Δw_1) and of amount ($-\Delta w_2$). However, due to two events interfering with each other within the weight stabilization time, our system can only detect one erroneous *Weight-Change* event of amount $|\Delta w_1 - \Delta w_2|$.

(c2) *Weight matching threshold*: the current threshold value is set to be four grams to filter out noises in the weight readings from weighing cells. However, in some cases, such as transferring one cube of sugar, this threshold value may still be too large. As a result, it may lead to false weight matching involving unrelated weight transfers of similar amounts. Consider the example that user A is removing a cube of sugar from the sugar jar. This results in a *Weight-Change* of approximately four grams in the sugar jar. At the same time, user B is transferring food weighted approximately eight grams. Eight grams is twice as much as four grams, but they are still within the weight matching threshold. Therefore, this leads to false weight matching. To address this issue, we may change the weight matching threshold to be a percentage of transferred weight rather than an absolute value of four grams.

(c3) *Slow RFID sample rate*: we have found cases when a user picks up a cup and quickly puts it down. This interval is less than the amount of time the RFID reader performs one round of reading over nine antennas. Therefore, a *Weight-Change* event is generated without any corresponding RFID-Presence event. This leads to false inference.

(c4) *Noises from weighing cells*: although we ask users not to touch the table, some still do during the experiment out of personal habits. This leads to erroneous generation of *Weight-Change* events.

5.5 Dining Scenario #4: Chinese-style dinner - Three users - Random activities

The fourth dining scenario involves the Chinese-style dinner setting, three users, and random dietary activities for 1811 seconds. Similar to the third scenario, three participants perform impromptu dietary behaviors within the bound of our assumptions described in Section 2.4. The results are shown in Table 4. Based on our measurements, the recognition accuracy is 83.33%. Note that increasing number of table participants only slightly increases the activity rate. The reason is that as the number of table participants increases, out of politeness they try to go the dishes less frequently to avoid in-the-air conflicts over the dishes.

Table 5.4 in page 34 shows the recognition accuracy (for the transfer and eat events) and weight accuracy for each of dietary behaviors. The weight accuracy is computed as the ratio between the measured and the actual weight transferred or consumed during dietary behaviors. Both the recognition and weight accuracy for the food transferring behaviors are between 80 85%, except for dish A, which is fluid-covered food. The reason for lower accuracy on transferring fluid-covered food is that juices from the fluid-covered food can easily drip from the chopsticks during food transfer (from a very lousy chopstick user). The juice dripping leads to erroneous generation of Weight-Change events with both positive and negative values, causing mismatches in the weight matching algorithm. Furthermore, the weight accuracy of transferring dish A is low at 68.42%, because these transfer recognition misses can accumulate to a large weight sum. Similar to the afternoon tea scenario, the eat events have better recognition accuracy because they can be directly deduced from the personal container's Weight-Change event.

To determine the causes for the misses in activity recognition, we videotaped the Chinese-style dinner scenario and analyzed the video in combination with the system

Table 5.4: The accuracy of the Chinese-style dinner scenario #4

Dietary Behavior	# of times	Recognition Accuracy	Weight Accuracy
Transfer dish A events	19	73.68%	68.42%
Transfer dish B events	29	79.31%	78.75%
Transfer dish C events	23	82.61%	79.19%
Transfer rice events	12	83.33%	81.88%
Transfer soup events	19	84.21%	80.16%
Eat events	60	88.33%	91.23%
Overall	162	83.33%	82.62%

event logs. We derive five main leading causes shown in Table 8. They are described as follows.

Table 5.5: Causes of miss recognition in Chinese-style dinner scenario #4. There are 162 activities analyzed from the video log. The number of misses counts both false positives and false negatives.

Causes of misses	# of misses of transfer events	# of misses of eat events	Total
(c1) Segmented weight-change events	5	0	5
(c2) Eating before transferring food on personal containers	5	5	10
(c3) Weight matching ambiguity	7	0	7
(c4) Noises from weighing cells	3	2	5
(c5) Slow RFID sample rate	3	0	3
Total of misses	23	7	30

(c1) *Segmented Weight-Change events*: during a lousy food transfer where a user drops a part of food back into the container or on the table, the weight matching algorithm fails because of the difference between weight change values of the container and the personal plate. In addition, such category also includes a case (which didn't happen in our experiment) that a user holding a personal bowl in the air and scoop soup from a soup bowl to the personal bowl several times. In this case, the weight matching algorithm also fails because it cannot match a weight decrease with a several weight increases.

(c2) *Eating before transferring food on personal containers*: this occurs when a user picks up a serving of food from a shared plate. However, before the user completes the transfer to his/her personal plate, he/she eats a bite of food. This violates one of our assumptions in Section 3.4 that eating must come from food in the personal plates. In this case, weight matching method fails to recognize the food transfer event due to the disappearing weight on the intermediate bite. Although the users are told about this restriction, some of them still do it out of personal habits.

(c3) *Weight matching ambiguity*: weight matching ambiguity occurs when two unrelated Weight-Change events of similar weight values are mismatched by our system. If two people transfer food with approximately the same weight, this introduce weight decrease from two share containers equal to weight increase in two personal containers. The system cannot accurately pair up the source and destination containers in these two concurrent food transfers.

(c4) *Noises from weighing cells*: the same as (c4) in afternoon tea scenario.

(c5) *Slow RFID sample rate*: the same as (c3) in afternoon tea scenario.

5.6 Discussion

Our experimental results have shown reasonable recognition accuracy of around 80%, which is at least as good as the accuracy of the traditional dietary assessment methods.

5.6.1 Methods to Reduce Recognition Misses

Below we proposed some methods to address some of the main causes of inaccuracy from our experimental results, and relax some of the assumptions and restrictions. Note that some of the restrictions can be solved by making simple design changes.

Design (Hardware) Change

In our experiment, users may grab food directly from the shared containers without transferring it to personal containers first ((c2) in Section 5.5). The system therefore cannot tell who has consumed what food. However, this problem can be solved if we tagged personal utensils with RFID tag. If a user picks up food with *RFID-tagged utensils*, the system could identify which user picks up the food and then regard the interaction as *eat* interaction instead of a *transfer* food interaction, if there is no weight match between a source container and a personal container.

There is also *Weight matching ambiguity* ((c3) in Section 5.5) between concurrent transfer interactions. Again, this problem can be solved if we tagged personal utensils with RFID. Our system can use the RFID-tagged utensils as a *complement evidence* to the Weight Matching Algorithm to infer a *transfer* interaction. By sensing a RFID-tagged utensil around when a share container decreases its weight and sensing the utensil around again when a personal container increases weight, a *transfer* interaction can be inferred

Software Change

In addition, *Segmented Weight-Change events* (in (c1) in Seciton 5.5) can be addressed by extending weight matching algorithm with *Bin packing*. Since the current version of Weight Matching Algorithm does only *one-to-one* weight matching, it can not match segmented *Weight-Change* events if there is one weight decrease of a share container and multiple weight increases of other containers. *Bin packing* algorithm can extend weight matching algorithm into *one-to-many* or even *many-to-many* matching.

5.6.2 Removing No Cross-cell Objects Assumption

Here, we proposed a method to remove the no cross-cell objects assumption. Since we divide the table into nine cells, a container may be placed across different cells. Multiple containers' weight change can be identified by the sum of weight change of the cells under them. Sometimes, they may be placed across the same cell. When weight change happens to the cell that has multiple containers crossing on, we can not decide how much weight gain or loss is contributed by which of these containers, because only the amount of total weight changes on the cell is determined.

Weight distribution history belong to one container was updated every determined food transfer event happens. Each time simultaneous food transfer event happen and these two containers cross the same cell, we can take advantage of each container's non-crossed cell and weight distribution history to derive crossed cell's weight distribution. Consider the scenario as shown in Fig. 5.3. Assuming containers A and B across the same cell #5 are put on the cell one by one, we can identify which cells are crossed by each container, obtain the weight distribution of each container on its crossed cells, and then record the information into weight distribution history (Fig. 5.3-(a)(b)). After all containers being placed on the table, suppose weight loss are detected on cell #5 and #2 at the same time, we can look up the weight distribution history and find that cell #5 and #2 are crossed by container A. Then the sum of weight loss on cell #5 and #2 is viewed as the weight loss on container A, and weight distribution history is updated accordingly (Fig. 5.3-(c)). If cell #2, #4, and #5 all detect weight loss at the same time, we can find that container A and B have weight change simultaneously. Then we use weight distribution history and

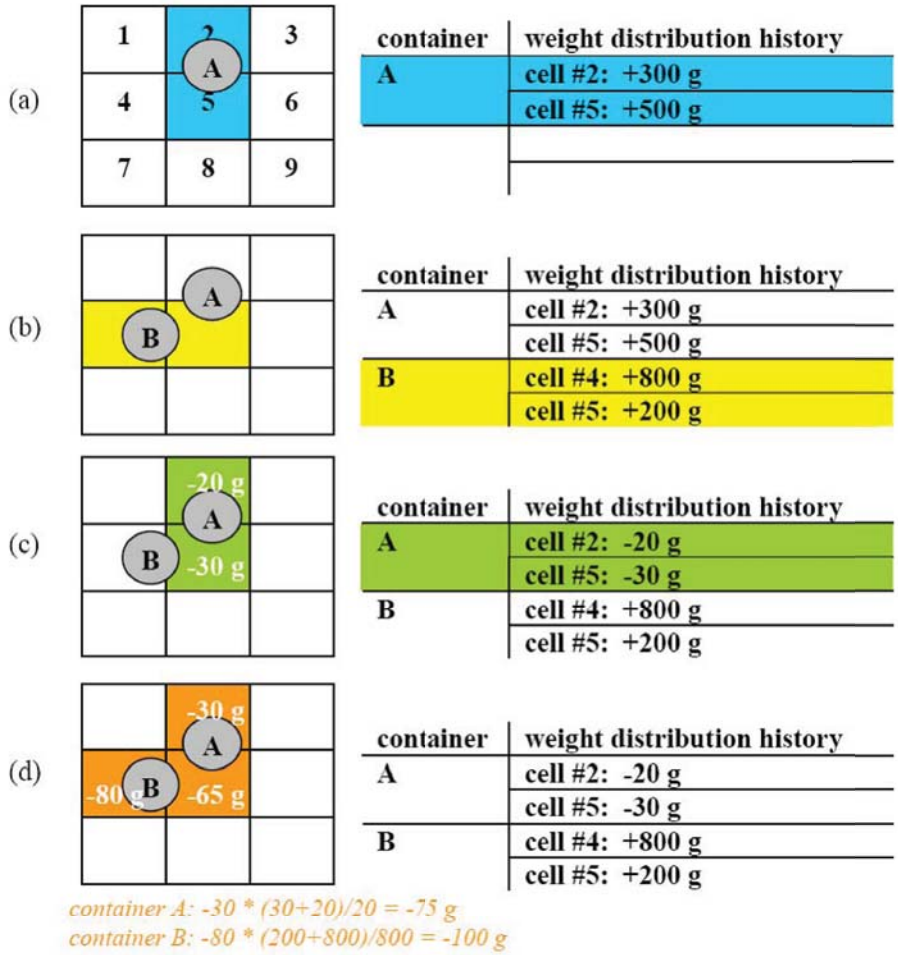


Figure 5.3: Illustration of proposed method to remove no cross-cell objects assumption.

weight loss on cell #2 and #4 as determinative proportional scale to estimate weight loss of container A and B (Fig. 5.3-(d)), while weight distribution history is not updated.

We evaluated how accurate our proposed method could track multiple-objects cross-cell interactions. The setup of this experiment is: two people drink one big bowl of cocktail using cups and eat one cake using plates. The big bowl and cake are placed across the middle cell, as shown in Fig. 5.4. We test 12 runs of cutting cake and scooping cocktail. Some of them are done simultaneously and others are done non-simultaneously.

Figure 5.4: Experiment setup: two users eating a cake and drinking cocktails. Cake and cocktails are placed across cells.

Although the average error in non-simultaneous runs is still 1 g, the average error in simultaneous runs reaches X g with a large variance Y g. The Y variance is primarily due to different position every time one pickups. We tell the weight distribution of the crossed cell by the distribution history of the two dishes last time. If one often pickups food from similar position, the mean error and variance go down to A and B. This experiment shows that weight history help us to derive current weight distribution in an appropriate amount, but where the user pickup is a random distribution. In other words, the user is not necessary to pickup food nearby last time. Probably, in the future we can improve our accuracy by using the latest several weight-distribution-histories, even a distribution, to estimate current weight distribution. However, in the second stage, plates are assumed to contain only cake and cups are assumed to be filled only with coke, which is not feasible in real world settings. In the next design, we try to solve the problems when multiple kinds of food can be hold in plates or cups.

5.6.3 Probabilistic Inference

The inference accuracy strongly depends on selectivity of the match function. If the match function is selective enough, the target can be easily distinguished from other weight change events, else mismatches would happen frequently and lead to poor accuracy. For example, a arbitrate *Weight Matching Threshold* ((c2) in Section 5.4) may lead to false weight matching. To make the match function flexible and selective at the same time, it's possible to use probabilistic inference by the match function we defined below:

$$\text{match probability} = \begin{cases} \frac{1}{|weight_1 - weight_2|}, & \text{if } |timestamp_1 - timestamp_2| < T \\ 0, & \text{otherwise} \end{cases}$$

The idea to use the two parameters are described below:

- *Weight*: Since the weight of food would not vary a lot during transfer, the weight decrease and the weight increase should be almost the same. Consequently, if a weight decrease and a weight increase differ a little i.e. smaller than some threshold value, these two events probably match with each other.
- *Timestamp*: The process of one hop food transfer takes less than T seconds, so a loss event and a gain event can not be a match if the difference between their timestamps is greater than T seconds.

Every time a new event comes, it uses this predefined match function to compute match probabilities with each existing events. Only if the event that has the largest match probability greater than some threshold value can be the target to match with the new event, otherwise the new event remains unmatched and is inserted to the queue to wait for later matching.

Chapter 6

Application I: Persuasive Game

6.1 Abstract

We have explored the design of an interactive, persuasive game to assist adult parents to improve dietary behavior of their young children. The persuasive game is played over a smart lunch tray. The smart lunch tray incorporates both the context-awareness principle in ubiquitous computing and the interactive media technique in persuasive computing, enabling the creation of a smart object that is not only aware of human behavior but can also influence and shape human behavior through their natural interactions with the object.

6.2 Motivation

Studies have shown that our dietary habits are developed during the first few years of our childhood experiences with foods. Our preferences for specific foods come about mainly through the following three factors: *(1)the sensory flavor of the food, (2) the post-*

ingestional effects of the food, and (3) the frequency of the food eaten. Among them, the frequency of the food eaten can be controlled by proper parenting. That is, a child may obtain a dislike of a certain food because he/she has *never tried* to taste the food or tried frequently enough to become accustomed to its taste, shape, color, texture, etc. Over time, this dislike grows into a permanent dietary habit. Proper and smart *parenting* can help to reverse such specific food aversions through appropriate verbal encouragement and disciplines. However, most parental experiences can reflect that verbal persuasion can be ineffective and overly time consuming for many young children. More often than that, verbal communications turn into unpleasant confrontations between inpatient parents and unrelenting young children.

To address this problem, we have designed and implemented an interactive game to assist parents (or educators) in encouraging healthy dietary behavior of their young children (3 5 years old). The interactive game is played over a sensor-augmented lunch tray that can detect a child's dietary behavior. In addition, a ceiling-mounted projector is used to display the state of the interactive game on the lunch tray. Our design combines the context-awareness concept in ubiquitous computing and the interactive media technique in persuasive computing, creating a smart object that is not only aware of human (i.e., the child's) behavior, but can also influence and shape human behavior through their natural interactions with the object. In this chapter, we would like to explore such an interface design providing awareness and persuasiveness.

6.3 Design Considerations

Since our target users are young children, we have identified the following *three design considerations*.

- The first design consideration takes into account that *most young children are not* *capable of operating digital devices.* Therefore, our game design relies on using the child's natural eating actions as inputs to this interactive game. This is in accord with the vision of ubiquitous computing, where computing hardware and software are hidden into familiar, everyday objects.

- The second design consideration is about *minimizing the change on the lunch-ware (objects) accustomed to young children during their normal eating routines*. This is to prevent our installed sensors from adversely affecting the young children's normal eating. To find out the usual lunch-ware used by young children, we have conducted a survey with local day care centers and found that food is usually served in a lunch tray. The lunch tray contains two or more rows of smaller cups serving different food items. Young children can either use forks/spoons, or sometime hands, to transfer already-cut food from cups to their mouth. To mimic their usual lunch-ware, we have prototyped a smart lunch tray. Underneath the smart lunch tray contains an array of weight sensors that can track what and how much food is eaten by a young child from these cups. This smart lunch tray is a scaled down version of our prior work on a diet-aware dining table [10]. A child's natural eating actions can be recognized by the smart lunch tray and used as inputs to the interactive game.
- The third design consideration takes into account the *limited cogitative level of young children.* The design of our interactive game must be simple enough for them to understand and attractive enough to draw and maintain their attention. More importantly, the game must have a persuasive ingredient in encouraging the desirable behavior - eating and finishing all the food items placed on the lunch tray. The game design adapts a common strategy used in behavior modifications - applying a *positive reinforcement* to the desired behavior. The game design is based on a *simple coloring of the young child's favorite cartoon character.* Note that this positive reinforcement has been verified by the young child's parents to be effec-

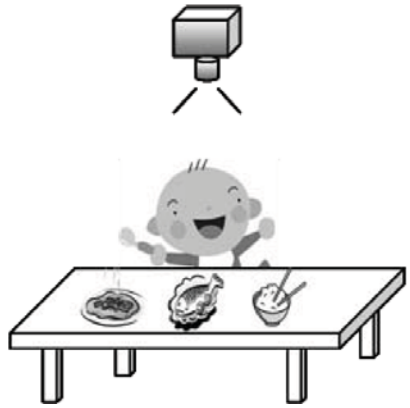


Figure 6.1: A child eats on an awareness-enhanced smart lunch tray with a media-feedback projector above.

tive. The cartoon character is projected on an empty area of the lunch tray through a ceiling-mounted projector. If the young child finishes all the food items, the cartoon characters will be fully colored and look gorgeous. On the other hand, if the young child avoids eating a specific food item, the color corresponding to that food item will be missing and the cartoon character will look incomplete and unattractive.

The remainder of this description is organized as follows. We first present the design and implementation of this persuasive game over the smart lunch tray. Secondly, we describe our preliminary experiment. Finally, we draw conclusion and our future work.

6.4 Design and Implementation

The design of our system is shown in Fig. 6.1. A child eats on an awareness-enhanced smart lunch tray with a media-feedback projector mounted on top of the ceiling. The smart lunch tray is made up of an array of weighing sensors embedded underneath the bottom shown in Fig. 6.2. The smart lunch tray contains software components to recognize tabletop dietary behavior of a child. The recognized behavior are then fed as inputs to the interactive game to provide persuasive feedback. We will describe the smart lunch tray first, followed by eating activity recognition over the smart lunch tray.

6.4.1 Smart Lunch Tray

Our current smart lunch tray prototype has a dining surface of $30x45cm^2$, which is about the size of a small lunch tray for children. The tray is divided into a matrix of 2x3 cells, each with the size of $15x15cm^2$. Each cell contains a weighing sensor, and the weight sensor detects how much weight a child eats from the food container placed on the cell. The weighing sensor is attached to a weight indicator with a resolution of 0.5 gram which can output weight readings through a serial port at a frequency of 8 samples per second. Since this work is focus on the interaction of a persuasive game rather than the dietary behavior recognition in our previous work [10], we have made a simplified prototype without installing a passive RFID antenna underneath each cell. Instead of identifying food content by RFID-tagged containers, we add a restriction that each food container is affixed on one and only one cell. This is done by simply gluing the food container to a corresponding cell. The mapping between the food content and each container is entered manually into our system by the child's parents. We also assume that a child can use a fork/spoon or hands to pick up food from a food container and puts into mouth directly.

A child's eating activity is recognized by the *Weight Change Detector* shown in Fig. 6.3. It performs two tasks: (1) it aggregates weight samples collected from each of the 6 weighing sensors; and (2) it reports *Weight-Change* events of food containers by filtering out noises in the stream of weight samples. These weight change events are interpreted into the amount (weight) of food consumed by a child from these food cups on the tray. These weight change events are then fed as inputs to the *Persuasive Game* component described next.

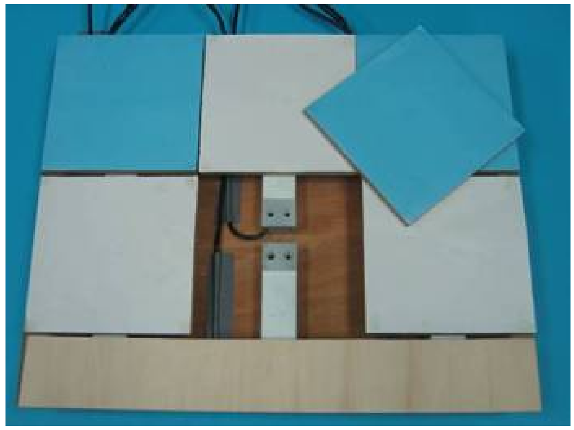


Figure 6.2: The smart lunch tray. The tray is divided into 2x3 cells, and each cell is embedded with a weight sensor. Only one food container can be put on a single cell.

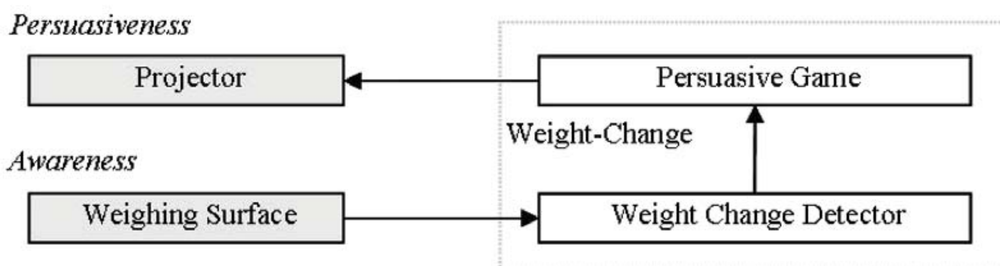


Figure 6.3: System architecture of persuasive game.

6.4.2 Persuasive Game

To persuade children to eat all food items on the lunch tray, we take the strategy of *positive, just-in-time* feedback. The positive feedback isn't just about giving praises, but it also means rewards and incentives. Just as adults are motivated to work, in part, for the paycheck, children need to be motivated toward a reward like a back rub or an extra bedtime story, for trying to eat food items which they dislike. Experts say that the positive feedback is the most powerful tool parents have to improve their children's behavior [32]. By sensing a desirable behavior and then providing just-in-time feedback, a computer system can help a child easily learn the causal relationship between a desirable behavior, e.g. finishing all food items on the lunch tray, and a positive feedback. In addition, as the targets of our work are children, we have added the ingredient of fun in the persuasion, by making it an interactive game.

Based on the idea of positive feedback, we have designed a game to let a child play while they are eating as shown in Fig. 6.4. The game is to color the picture of a child's favorite cartoon character. The positive feedback of our persuasive game is turning their favorite character into a pretty and colorful one. Specifically, each food item corresponds to a particular crayon color, and the color will be drawn on the character when the corresponding food item is eaten. The amount of coloring depends on the amount of weight of the food consumption. For example, if a child only consumes $1/10$ of the apple and apple corresponds to the red crayon shown in Fig. 6.4, he/she will see only $1/10$ of the mouth area being colored on the cartoon character. To make his/her favorite cartoon character colorful, a child is then motivated to eat and finish all food items on the table, including food items that he/she dislikes.

Figure 6.4: The persuasive game: a child can color his/her favorite cartoon character by eating food on the tray.

6.5 Preliminary Experiment

We have tested our prototype implementation on a child (Alicia) who is 3 years and 8 months old. We have placed 5 cups of fruits shown in Fig. 4, containing small bites of apples, bananas, papayas, wax apples (tropical fruit), and dragon fruits (tropical fruit). Alicia's parents have told us that (1) she does not like dragon fruit and banana, (2) she enjoys coloring cartoon character very much, and (3) her favorite cartoon character is a tiger-like character shown in the upper middle block of Fig. 6.4. Our experiment was done in a lab. Given the unfamiliarity of the laboratory setting, Alicia was shy at the beginning and unwilling to grab fruit directly from the table. Instead, Alicia stood beside the table and asking her nanny to transfer fruits of her choices from the table to her small cup held by her hand. Then, she ate from her small cup. The result showed that she comprehended the game and was willing to eat different fruits to color her favorite character.

6.6 Summary

We describes the design and implementation of a persuasive game to encourage healthy dietary behavior of young children. By leveraging the idea of just-in-time, positive reinforcements, we envision children to develop healthy dietary habits while playing the game. In the future, we will perform detailed experiments and evaluations on this game and compare its effectiveness with traditional verbal persuasion. In addition, we would like to address the monitoring and persuasion of other long-term eating habits, such as eating in rush and over-eating.

Chapter 7

Application II: Smart Kitchen

7.1 Abstract

We present a smart kitchen that can promote healthy cooking by raising user's awareness of healthy food ingredients and healthy cooking methods. Our smart kitchen is augmented with sensors to detect activities related to cooking process. Then it provides feedbacks to recommend healthy cooking alternatives.

7.2 Motivation

A kitchen can be viewed as a playground for family members to enjoy the process of preparing lunch and dinner. Most people consider food preparation as a joyful and self-accomplishing process, rather than just a daily routine or hard work. More importantly, they regard food preparation as an act of caring for a whole family. Through cooking healthy food for their beloved family members, they receive self satisfaction in promoting health and reduce risks of chronic diseases in the family. For example, if a family member is diabetic, special cares should be given to prepare meals with lower fat, protein, and sodium [6].

Many research efforts [8] [17] [35] [33] have focused on augmenting kitchens with a variety of digital media to create rich, interactive experiences for users cooking in the kitchen. Some work has focused on providing awareness to support multi-tasking activities in the kitchen. For example, Counter Intelligence project from MIT [8] has augmented a kitchen with ambient interfaces to improve usability of a physical environment. Their augmented reality kitchen can assist users in determining temperatures, finding things, following recipes, and timing intermediate steps during meal preparation. Other work has focused on capturing or using digital interactive recipes that can guide users through a step-by-step cooking process. For example, Siio et al. [33] automates the creation of web-ready multimedia recipes in a kitchen. By operating one of the foot-switches, a user can capture images of the cooking workplace with voice memos and organize into a multimedia recipe. Such digital recipes can provide a more interactive experience than that from reading a paper-based recipe book. The CounterActive project [17] utilizes digital recipe to teach people how to cook by projecting multimedia recipes onto a touch panel-like interactive kitchen counter.

Rather than augmenting kitchens with a variety of digital media to create interactive cooking experiences, our smart kitchen is focused on promoting healthy cooking by raising awareness of healthy food ingredients and healthy cooking methods. Our kitchen is augmented with sensors to detect activities in the cooking process. Then it can infer how well these activities conform to healthy cooking, and provide corresponding feedbacks to raise healthy cooking awareness and recommend healthy cooking alternatives. For example, while a user is making a beef & broccoli stir-fry disk, our kitchen can detect when he/she is adding too much red meat or cooking the broccoli for too long. The kitchen shows the amount of fat from the red meat or the loss of vital vitamins and minerals in the

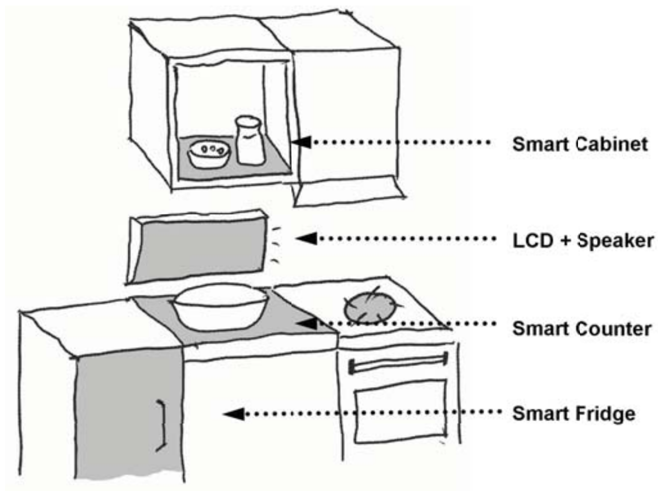


Figure 7.1: Setup of a Smart Kitchen.

broccoli from lengthy cooking time. The kitchen can recommend replacing some meat with vegetables and reducing cooking time on the vegetables.

7.2.1 Healthy Cooking

Nursal et al. [25] and Willet [38] have identified the following key factors in healthy cooking: type and amount of food ingredients and cooking methods. Furthermore, quality of a healthy cooking method depends on several factors, such as cooking temperature, cooking duration, and cooking styles (e.g., fried, boiled, searing, microwaving, etc.).

7.3 Design

To detect food ingredients and cooking methods, we have designed a smart kitchen shown in Fig. 7.1. The smart kitchen consists of a smart counter, a smart cabinet, a smart fridge, and a smart stove. It also contains a LCD display and a speaker system to provide awareness feedbacks to users.

We illustrate the design of our system through a simplified cooking scenario. In general, the first step of meal preparation is to gather food ingredients on a kitchen counter. A user takes out containers holding food ingredients from the fridge and/or the cabinet, and then places them on the kitchen counter. We assume that all food ingredients are stored or packaged in RFID-tagged containers, in which RFID tags include food nutritional labels. In addition, our fridge, cabinet, and counter are augmented with a smart sensor surface consisting of RFID antennas/readers and weight sensors. This sensor surface enables detection and tracking of food ingredients among the kitchen fridge, cabinet, and counter. In addition, our kitchen can recognize the type and amount of food ingredients placed on the kitchen counter.

The second general step involves a user chopping and mixing food ingredient in some containers on the kitchen counter. Given food ingredients on the kitchen counter, our kitchen can raise user's awareness on healthy quality of food ingredients through LCD and the speaker, as well as provide recommendation on the healthy cooking alternatives.

The third step involves cooking mixed ingredients on a stove. The stove contains a variety of sensors to detect cooking temperature, cooking duration, and cooking styles (fried, boiled, etc.). Additional awareness and recommendation about alternative cooking styles can be provided to the user.

7.4 Detecting Context

The surface of each smart counter and smart cabinet is constructed from a weighing sensor and a RFID reader/antenna embedded underneath the surface shown in Fig. 7.2. This surface design is similar to our work in diet-aware dining table. The smart surface is divided into cells, and each cell is installed with a weighing sensor and a RFID sensor to observe food transfer actions. Regarding each smart counter and cabinet as a cell, they

Figure 7.2: The sensors of a smart counter. The counter surface is embedded with a weighing sensor and a RFID reader/antenna.

can collaboratively recognize interaction of transferring food ingredients from the smart cabinet to a food mixer bowl on the smart counter. This can be done by matching the equal amount of the weight decrease of a food container from the smart cabinet and the weight increase of the food mixer bowl on the smart counter.

7.4.1 Benefits for Diet-aware Dining Table

Moreover, it is feasible to *calculate the nutritional value of a meal* by this design. Throughout the entire process of cooking a meal, by recording the three situations which consist of information of the food ingredients, the nutritional value of a meal is obtainable by summing up nutritional values of food ingredients added while cooking. As a result, there is a significant *kitchen automation* benefit: it *strengthens the RFID assumption* made in Section 3.1 that every food container on the diet-aware dining table is tagged with a RFID tag and there is a mapping database between a tag-id and nutritional value. The reason is that if a meal is prepared in the smart kitchen, the mapping database can be automatically build and there is no need for a cooking person to manually input the meal's content as the meal is placed onto the dining table.

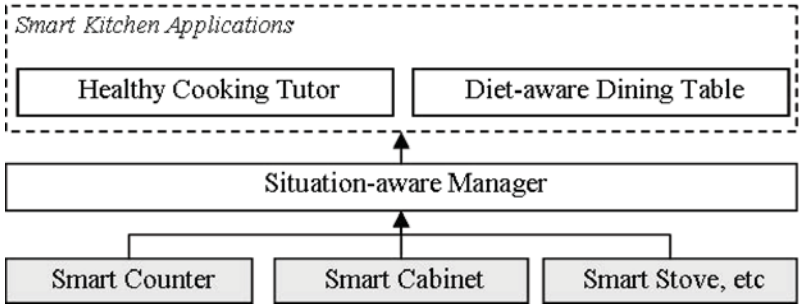


Figure 7.3: System architecture of Smart Kitchen.

7.5 Summary

We describes the design of a smart kitchen to achieve healthy cooking. By generalizing the method used diet-aware dining table, we regard a smart counter and a smart cabinet installed as two cells to collaboratively recognize cooking situations, such as adding food ingredients. A LCD and speaker system then give healthy-cooking advices to a cooking person. We believe those situations being aware of in this system well demonstrates the idea of smart kitchen to promote healthy cooking. Further extension the idea of situation-awareness by adding new situations to be aware could make a kitchen of the future realizable and approachable.

We are planning to prototype the smart kitchen and develop an effective user interface to promote healthy cooking. Since users are typically busy during their cooking process, the design of the interface should be simple and intuitive as not requiring high cognitive load on users. We are interested in exploring what is the appropriate amount of awareness information presented to users, and what are the best times of delivering such information. We will invite experienced household cooks to participate in the design and evaluation of our kitchen environment.

Chapter 8

Conculsion and Future Work

We are what we eat. This paper describes the design and implementation of our diet-aware dining table. We have augmented an ordinary dining table with two layers of sensor surfaces underneath the table - *the RFID surface and the weighing surface*. Given certain assumptions, the diet-aware dining table automatically tracks what and how much each individual eats from the dining table over the course of a meal. We have performed several experiments, including live dining scenarios (afternoon tea and Chinese-style dinner), multiple dining participants, and random concurrent activity sequences. Our experimental results have shown reasonable *recognition accuracy of around 80%*, which is at least as good as the accuracy of the traditional dietary assessment methods.

Our future work will further improve the recognition accuracy, address some of the main causes of inaccuracy from our experimental results, and relax some of the assumptions and restrictions. Note that some of the restrictions can be solved by making simple design changes. For examples, the current prototype does not allow hands or elbows on the table. To relax this restriction, we can add a slightly protruding frame around the edge of table, so that users can rest their elbows on the frame without affecting our system. We also believe in multi-sensor approach. For example, by deploying a video camera above the table, it is possible to observe events that cannot be detected by RFID and weighing surfaces.

Furthermore, the design of diet-aware dining table is able to be further generalized as a *smart surface* that two more applications in the area of healthcare are investigated. Since this table can track tabletop person-food interactions in real time, it's feasible build just-in-time persuasive feedbacks to encourage better healthy dining behaviors. As a result, we have explored the design of an interactive, *persuasive game* to assist adult parents to improve dietary behavior of their young children. The persuasive game is played over a smart lunch tray, extended from our diet-aware dining table. In addition, we have designed a *smart kitchen* which is installed with a smart counter and a smart cabinet, extended from our diet-aware dining table as well, to aware what and how much food a user is cooking. After recognizing cooking behaviors, a LCD display and speaker system will guide the user to healthy cooking. The smart kitchen also calculates the nutritional value of a meal which is build into a RFIDtag-nutrition mapping database for diet-aware dining table. This initiates the *automation from a kitchen to a dining table*.

The smart kitchen application is now in the design phase, and we will start to build it. In addition, for these two applications, further user study is required. Responses from the users could help inventing better interface to persuade healthy dining and cooking behaviors.

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Appendix A

Publication of Keng-hao Chang

Below is a list of publications that I have achieved in the study of master program:

1. Keng-hao Chang, Shih-yen Liu, Hao-hua Chu, Jane Yung-jen Hsu, Cheryl Chen, Tung-yun Lin, Polly Huang, **"Dietary-Aware Dining Table - Observing Dietary Behaviors over Tabletop Surface"**, *in Proceedings of the 4th International Conference on Pervasive Computing (Pervasive 2006)*, Dublin, Ireland, May 7, 2006 pages 366 - 382 (with acceptance rate 13%).

2. Shun-yuan Yeh, Chon-in Wu, Keng-hao Chang, Hao-hua Chu, Jane Yung-jen Hsu, **"The GETA Sandals: A Footprint Location Tracking System"**, to appear in *Springer/ACM Personal and Ubiquitous Computing (ACM PUC*), 2005.

3. Keng-hao Chang, Shih-yen Liu, Jr-ben Tian, Hao-hua Chu, Cheryl Chen, **"Dietary-Aware Dining Table - Tracking What and How Much You Eat"**, in *Proceedings of Workshop on Smart Object Systems*, in conjunction with the Seventh International Conference on Ubiquitous Computing (ACM UbiComp 2005), Tokyo, Japan, September 11, 2005, pages 61-68

4. Kenji Okuda, Shun-yuan Yeh, Chon-in Wu, Keng-hao Chang, Hao-hua Chu, **"The**

GETA Sandals: A Footprint Location Tracking System", *Workshop on Location- and Context-Awareness (LoCa 2005)*, in Cooperation with Pervasive 2005 , (also published as Lecture Notes in Computer Science 3479, Location- and Context-Awareness), Munich, Germany, May 2005, pages 120-131.

5. Shun-yuan Yeh, Keng-hao Chang, Chon-in Wu, Okuda Kenji, Hao-hua Chu, **"GETA Sandals: Knowing Where You Walk To"**, *the demo paper (adjunct proceedings) of the Seventh Interna-tional Conference on Ubiquitous Computing (ACM UbiComp 2005)*, Tokyo, Japan, September 11, 2005.

6. Keng-hao Chang, Tsung-Han Lin, Hao-hua Chu, Polly Huang, **"Modeling and Simulation Com-parison of Two Time Synchronization Protocols"**, submitted to *ACM Transactions on Sensor Networks*