A Knife and a Cutting Board as Implicit User Interface - Towards Context-Aware Kitchen Utilities

ABSTRACT

In this paper, we report on approaches for detecting context in a kitchen environment. The sensors used are unobtrusively integrated and do not disturb the task.

We describe in detail the technology for the tools we built and place our work in context.

1. INTRODUCTION

In everyday life we interact with a multitude of objects, tools, and devices which are optimized to support us in a particular activity. Up to now they are typically passive and we do not regard them as user interfaces. With sensor technology however it becomes possible to record the way they are used. Analysing these measurements can reveal information about usage and handling.

The key principle for implicit and embedded user interfaces is that the way users perceive and operate a tool is not altered. In our work we transformed a kitchen knife and a cutting board into such implicit user interfaces. The goal was to acquire information without changing the way they are used.

Our focus on the kitchen was twofold. Firstly the kitchen offers an interesting environment that is rich on special purpose tools that are commonly known and understood. Secondly many applications, such as integrated dietary monitoring, could be of benefit to a large set of people. The knife and cutting board were chosen to illustrate the potential of this approach, however our initial experience shows that is can be generalised to a multitude of domains.

With the knife and the cutting board we provide means to identify:

- What food was prepared?
- In what quantities was the food prepared?

This information is useful in different scenarios and we show that this can be automatically detected without a user's need for inputting it into a system.

2. RELATED WORK

We want to place our work in context regarding the time line of events in the presented context. Before meals can be prepared, a certain dish has to be chosen and a shopping list has to be written. The ingredients must be bought and brought home. The food has to be prepared now, which is the point we specifically look at. After cooking it, it will be consumed.

Taylor et al. investigated the use of fridge magnets [6] and identified planning of activities (e.g. shopping) as key issues supported by this surface.

Mankoff researches on shopping lists for rising nutritional awareness [4].

The intelligent spoon [2] is an example for the augmentation of everyday objects for sensing in a natural context. Though the look and feel (weight and size) have been changed and thus we feel that this hinders real world data acquisition.

After meals have been cooked, they are consumed. Chang et al. [3] show how healthier eating and awareness regarding the amount and type of food consumed during dinner can be supported.

Amft et al. [1] analyze the sound of chewing with bone sound microphones in the ear and thus determine the type of food eaten. Thereby they can give the user supportive feedback on his diet.

We enable context-awareness and recognition in the course of preparing food for cooking. To our knowledge, this has so far not been researched on.

3. SENSOR - ENHANCED CUTTING BOARD

Cutting or chopping protect the work space from damage and also facilitate the cleaning of the work area. Much of the meal preparation is done on a cutting board. Meat, fruit and vegetables usually have to be chopped or cut before they are used for cooking. Therefore augmenting the place where the process naturally takes place seems promising.

Figure 1: Cutting Board on load cells.

We augmented a cutting board with four load cells and a sensitive acceleration sensor. The setup is depicted in Fig. 1. The load cells suspend the cutting board in the edges as the outmost place of the cutting board maximising the area where interaction can be tracked. The load cells each can carry weight up to 5 kg, resulting in a maximum weight in the middle of the cutting board of 20 kg. The selected load cells offer enough range for typically kitchen activity and still provide a high resolution (see Fig. 2).

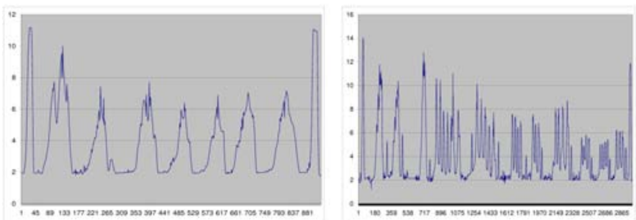

Figure 2: Load cell data. Cutting an apple in 8 parts (left). Data from chopping up a kohlrabi (right). Both data is framed by start/stop markers caused by pressing on the board before and after the cutting.

The board can measure the overall weight, the position of the weight on the board, as well as changes in these forces. The overall weight is useful to detect absolute quantities of things on the board where as the changes in load distribution and the changes in overall load provide a good indication of interaction with the board, and in particular cutting food.

To capture additional horizontal forces in the course of cutting through a piece of food, an acceleration sensor (ADXL203) is mounted in the centre underneath the board. This sensor can senses even very small forward-backward and right-left accelerations from the cutting process. The overall mechanical setup and data acquisition is similar to the system described in [5]. All load cells and the accelerometers provide analog outputs which are measured by a microcontroller and transmitted to a PC.

4. SENSOR-ENHANCED KNIFE

Knifes are another ubiquitous tool for cooking and eating. In our prototype we equip a Chef's knife with a force/torque transducer. Such knifes are very versatile and commonly used in the kitchen. Having a large knife made it easier for a first prototype to included the sensors, however the general approach is applicable to smaller knifes, too.

Figure 3: Sensor-enhanced knife

To maintain the comfortable grip of the knife, the sensor was placed between the blade and the handle. To create the prototype the knife was cut apart at the end of the handle and the sensor was welded between both parts, see Fig. 3. During our tests, we could confirm that the addition of the sensor doesn't affect the normal use of the knife.

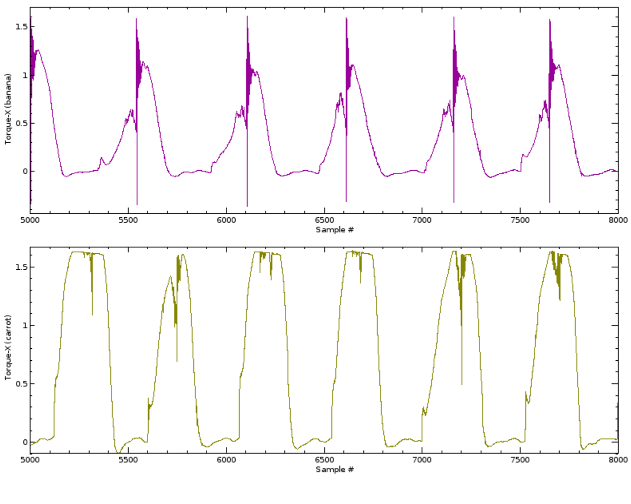

Figure 4: Knife sensor data. Data plot of carrot (upper graph) and a banana (lower graph).

The sensor is attached to a analog digital converter that records the information from the force torque/sensor at a rate up to 40kHz, the maximum recommended by the sensor's manufacturer. Six measurements are available: force on three axes, and torque on three axes. After a preliminary comparison, the torque around the X axis (perpendicular to the side of the blade) was selected as input for the classification system. A low sampling rate of 1kHz was also chosen.

A commercial implementation of this knife is possible if the component costs are kept low. The necessary data can be obtained by using an inexpensive strain gage mounted on the blade at assembly, and a microcontroller with an integrated analog to digital converter.

Fig. 4 shows a small sub-set of data from the knife's force/torque transducer during cutting of carrots and bananas. The difference in both curves is easily noticeable. In our experiments we could confirm that an automated classifier can perform this separation as well.

When the knife cuts through any material, the forces produced have a certain signature that enables our classification system to distinguish between them. Sometimes the differences are very visible as seen on Fig. 4, and other times they are more subtle. Currently we are optimizing the classification of different vegetables based on sample data collected. As a testing example, we have run experiments cutting apples, carrots, bananas, leek, kohlrabi, and bell peppers. If prior information is available, e.g. a shopping receipt as suggest in [4] the classification task becomes easier.

5. DISCUSSION AND CONCLUSION

With a sensor enhanced cutting board and a sensor enhanced knife we showed that it is feasible to include sensors unobtrusively into everyday objects to collect meaningful information. Based on the data we can find out what the user was cutting and how much of it. Such context information, acquired by implicit interaction without additional burden to the user, can help to monitor food preparation.

We are, from investigating the initial results, confident to be able to distinguish a great variety of food by analysing the data from the cutting board and the knife.

6. REFERENCES

[1] O. Amft, M. Stäger, P. Lukowicz, and G. Tröster. Analysis of chewing sounds for dietary monitoring. In M. Beigl, S. Intille, and J. Rekimoto, editors, *UbiComp 2005: Proceedings of the 7th International Conference on Ubiquitous Computing*, pages 56–72. Springer: Lecture Notes in Computer Science, Sept. 2005.

[2] C. Cheng and L. Bonanni. Intelligent Spoon, MIT Media Lab, Counter Intelligence Group, 2006.

[3] K. hao Chang, S. yen Liu, H.-H. Chu, J. Hsu, C. Chen, T. yun Lin, C. yu Chen, and P. Huang. The diet-aware dining table: Observing dietary behaviors over a tabletop surface. In K. P. Fishkin, B. Schiele, P. Nixon, and A. J. Quigley, editors, *Pervasive Computing, 4th International Conference, PERVASIVE 2006*, volume 3968 of *Lecture Notes in Computer Science*, pages 366–382. Springer, May 2006.

[4] J. Mankoff, G. Hsieh, H. C. Hung, S. Lee, and E. Nitao. Using low-cost sensing to support nutritional awareness. In *UbiComp '02: Proceedings of the 4th international conference on Ubiquitous Computing*, pages 371–376, London, UK, 2002. Springer-Verlag.

[5] A. Schmidt, M. Strohbach, K. van Laerhoven, A. Friday, and H.-W. Gellersen. Context acquisition based on load sensing. In *UbiComp '02: Proceedings of the 4th international conference on Ubiquitous Computing*, pages 333–350, London, UK, 2002. Springer-Verlag.

[6] A. S. Taylor, R. Eardley, S. Hodges, A. Sellen, K. R. Wood, and L. Swan. Augmenting refrigerator magnets: why less is sometimes more. fourth nordic conference on human-computer interaction, nordichi '06, oslo, norway. 2006.