Context-Aware Kitchen Utilities

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ABSTRACT
We report on approaches for context-awareness in a kitchen environment. Two devices, an augmented cutting board and a sensor-enriched knife, enable the environment to determine the type of food handled during the preparation of meals.

INTRODUCTION
Context is the information which surrounds and gives meaning to an object or an action. Many times a sensor in the environment provides only a small window of information related to the activity taking place, but it is valuable in the form of context. In order to correctly detect the activities that occur in a kitchen scenario, where the need for unobtrusiveness limits the choice of available sensors, the clues obtained from the context become very important. One example in that scenario is detecting that people are preparing a meal by noticing when they cut the ingredients.

We present two devices that are currently used in nearly every kitchen: a cutting board and a knife (see Fig. 1). Both have been augmented with sensing capabilities to gather information. After processing the raw sensor data, the activities of the person in the kitchen can be inferred to form the context details. From this, the intentions of the person can be estimated. For example, knowing that a meal is being prepared, a system controlling a smart kitchen can provide assistance by giving advice regarding the recipe.

Augmenting objects with sensing capabilities without modifying their original appearance and handling is challenging, but it is the only way to gather natural usage data from participants in a non-laboratory environment.

RELATED WORK
Activities like cooking and eating have recently been investigated to exploit the possibilities of supporting humans through context information during their every-day actions like cooking and eating.

Mankoff et al. did research on shopping lists with the intention of increasing nutritional awareness [4] by suggesting healthier alternatives for nutrition.

The intelligent spoon [2] is an everyday object used during the preparation of meals. This project showa how this information can be used to improve cooking skills by giving hints, e.g. about missing salt.

Chang et al. [3] show how awareness regarding the amount and type of consumed food can be supportive during a diet.

Amft et al. [1] analyze the sound of chewing with microphones in the ear (measuring bone sounds) to give supportive feedback during a diet.

SYSTEM DESCRIPTION
The ingredients for meals have to be washed (e.g. lettuce), peeled (e.g. kohlrabi and potatoes) and cut into pieces (e.g. leek) before they can be cooked and seasoned. We present two devices for unobtrusively acquiring in-place sensor data in real kitchen scenarios.

We explicitly opted for augmenting the environment and not the user to keep the system as natural and unimposing as possible and to allow us to capture real-world data in a natural, integrated way. The system should not require complicated devices to allow other researchers to use this approach themselves.

Cutting Board
Much of the meal preparation is done on a cutting board as it protects the kitchen workspace from damage and it can be cleaned easily. Meat, fruits and vegetables usually have to be chopped or cut before they are used for cooking. Since almost all ingredients will be handled on a cutting board, augmenting this place seems promising.

We equipped a standard wooden cutting board with four load cells and a sensitive acceleration sensor. Each load cell can carry up to 5 kg, resulting in a maximum load in the middle of the cutting board of 20 kg. This is adequate even for the heaviest ingredients like big pieces of meat.

The weight perceived by the cutting board gives only minimal information regarding the type of food being handled. More meaningful data is acquired through the acceleration sensor which detects small movements while cutting the ingredients, even with regular knifes. The change of the load distribution on the load cells also gives useful information. It is possible to detect the type of food being handled on the cutting board using this data.

Microphones and Cameras
For labeling and annotating the captured data, we placed two microphones close to the cutting board. Additionally,

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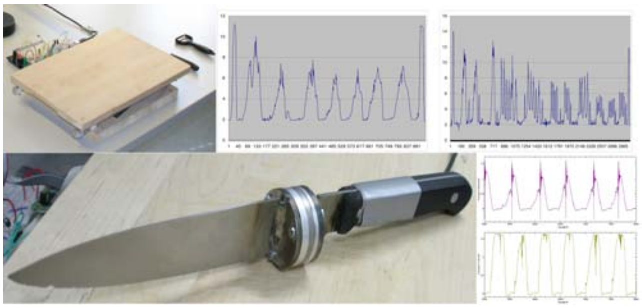

Figure 1. The cutting board is placed on four load cells. Data from cutting a carrot (left) and a kohlrabi is shown (right). The overall sum of the load cells is very different.
A six axes force/torque transducer, model SI-40-2 from ATI Industrial Automation, has been soldered between blade and handle. The sensor can measure torques up to 2 N-m and forces up to 120N; both are adequate values for normal tasks in the kitchen. The data is recorded using a National Instruments PCI-6221-37 data acquisition card which supports sampling rates up to 250 kHz. Cutting a banana (top) is different from cutting a carrot (bottom)

two cameras capture images. Object recognition works very well using computer vision in a controlled environment, or within certain limited conditions. This is e.g. the case for automated license plate recognition. We therefore believe that by applying techniques from computer vision to the limited scenario of a cutting board, it is feasible to recognize the objects placed on the board before the cutting starts. The boundaries of interest are defined by the rectangular area of the cutting board. By building models of the objects and using characteristic properties, like color or size it is possible to distinguish between different types of ingredients. We do not focus on the analysis of the video data for context acquisition and just use it for annotation.
Some ingredients have to be peeled before they are handled. This is normally done using a small peeler, but not on top of the cutting board. Therefore, this cannot be detected with the proposed sensors. We believe that by analyzing the sound of the peeling and the cutting, we could provide additional features for classification.

Knife
As a Chef's knife is very versatile and the most used knife in the kitchen, we decided to equip it with a force/torque transducer. To maintain the comfortable grip of the knife, the sensor was placed on the heel of the blade, very close to the handle. After testing, we confirmed that the addition of the sensor does not affect the normal use of the knife.
The system records the information from the force/torque transducer 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.
The classification would benefit from the additional information from the other axes and from a faster sampling rate, but those values were chosen in order to evaluate the feasibility of an inexpensive commercial implementation, which would only be 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 micro-controller with an integrated analog to digital converter. Modern low-cost micro-controllers are appropriate for the task.
Fig. 1 (bottom, right) 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, and we can expect an automated classificator to perform well if provided with an appropriate set of features. The same applies for the other ingredients tested.
When the knife cuts through any material, the produced forces have a certain signature that enables our classification system to distinguish between them. To successfully train an automated classifier for the different types of materials, it is necessary to obtain labeled samples of data, process them to isolate each cutting episode (one cut from the knife), and obtain a group of features that describe the episode richly enough. So far we have done experiments cutting apples, carrots, bananas, leek, kohlrabi, and bell peppers.

CONCLUSIONS AND FUTURE WORK
Why would a user want to have an intelligent cutting board or a sensor knife? Technology usually makes its way to the end-user for different reasons: it saves time and thus money, or it adds new comfort.
The cutting board can also serve as a kitchen scale, and gives additional information like recognizing the type of food processed and giving tips and hints on cooking and preparing the meals.
The augmented knife can offer additional advantages, like analysis of cutting habits and cutting technique, which would be interesting to hobby chefs. Both devices, when trained to detect the most common ingredients, can be used to build a detailed history of the prepared meals. In this paper we described in detail the technical platform for two context-aware kitchen tools. We provided reasoning for the chosen tools and for the location and types of the sensors. We argued that unobtrusive integration is crucial for the data acquisition of natural usage.
Our experiments show that the cutting of several fruits and vegetables produced very different signal patterns on each of the sensors available: cutting board, knife and microphone. We are confident that this will allow us to recognize the objects being cut.

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