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Lab-on-Spoon – a 3-D integrated hand-held multi-sensor system for low-cost food quality, safety, and processing monitoring in assisted-living systems

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Abstract. Distributed integrated sensory systems enjoy increasing impact leveraged by the surging advance of sensor, communication, and integration technology in, e.g., the Internet of Things, cyber-physical systems, Industry 4.0, and ambient intelligence/assisted-living applications. Smart kitchens and "white goods" in general have become an active field of R&D. The goal of our research is to provide assistance for unskilled or challenged consumers by efficient sensory feedback or context on ingredient quality and cooking step results, which explicitly includes decay and contamination detection. As one front end of such a culinary-assistance system, an integrated, multi-sensor, low-cost, autonomous, smart spoon device, denoted as Lab-on-Spoon (LoS), has been conceived. The first realized instance presented here features temperature, color, and impedance spectroscopy sensing in a 3-D-printed spoon package. Acquired LoS data are subject to sensor fusion and decision making on the host system. LoS was successfully applied to liquid ingredient recognition and quality assessment, including contamination detection, in several applications, e.g., for glycerol detection in wine. In future work, improvement to sensors, electronics, and algorithms will be pursued to achieve an even more robust, dependable and self-sufficient LoS system.

1 Introduction

The joint surging advance of sensors, communication, and integration technology allows the realization of more versatile and pervasive systems in nearly all domains of industry and daily life. Established and emerging application domains are, e.g., measurement, instrumentation, and automation, Industry 4.0, the Internet of Things, cyber-physical systems, and ambient intelligence/assisted living. Smart environments, in particular, in homes are a prominent example, where deeply embedded intelligent sensory systems add significant functionality unobtrusively merged into everyday life structures and devices. Miniaturization of such autonomous, potentially wireless, sensory systems for distributed measuring and observation can be found from sensate floors, over leading edge integrated data loggers to lifestyle and sportive gadgets, such as smart watches (Edwards, 2013) or activity trackers (Meyer and Boll, 2014).

Further intriguing research work is done in the field of lab-on-chip devices; see, e.g., Xu and Chakrabarty (2009), Spiller et al. (2006), Yang and Bashir (2008), and Bajwa et al. (2013). Zhao and Chakrabarty (2010) cover a wide field from medical to food applications. Point-of-care diagnostics are one thrilling field of lab-on-chip application systems. Advanced microelectromechanical systems (MEMS) and packaging technology are employed for potentially disposable system solutions with a high level of sophistication and potential price tags. Though this class of systems has numerous features in common with the Lab-on-Spoon (LoS) research presented in this paper, and has inspired the naming of the project, subtle differences, e.g., in cost, embodiment, reuse, mobility issues, autonomous system implementation, and system level integration can be identified. In perspective, a convergence of lab-on-chip technology and the Internet of Things, cyber-physical production systems, and Industry 4.0 application fields, e.g., for in-line and portable measurement, can be expected. The information obtained by such sensory systems can serve to achieve improved or novel assistance functionality in various domains of daily life, e.g., in the domain of nutrition, to assist the user in estimating achieved calorie burning in sports (Meyer and Boll, 2014) and the calorie contents of food, or even in providing better performance to unskilled users or supporting impaired persons in restoring lost sensing capability. In the kitchen environment, numerous product and research activities can be found to improve device performance or to achieve assistance system functionality. Relevant commercial and research work has been summarized, e.g., in König (2008), indicating the potential of sensing and sensory context to achieve a new class of assistance system for this domain, denoted as culinary-assistance systems (König, 2008). A second, related field of application, or better, concern, has emerged in the last years. Sources of unintentional or intentional contamination of soil and sea, e.g., by radiation, chemical, or biological pollution, have increased substantially and, correspondingly, contaminated food can enter the food chain from various sources and reach the consumer unnoticed. For instance, the omnipresent problem of product fraud or falsification, e.g., for frying oil (Qian and Xiaofang, 2014), has also become more noticeable in semi-processed and processed food supplies. The increasing need for food quality and safety monitoring adds further momentum to the outlined research to provide such support at a feasible cost in the consumer's home.

This challenge, in addition to the work presented here, triggered activities on assistive technologies in food safety and food analysis. One example is the portable Bio-Scout of SARAD GmbH (Streil, 2012), designed to discover radiation in food. Quite recently, e.g., the Vessyl (Vessyl, 2014), a metal cup claiming to be able to identify cup contents and give a reckoning of the calories, and the Thai e-tongue (Fuller, 2014), as a particular representative of the research on artificial degustation systems or e-tongues, reviewed in Tahara and Toko (2013), conceived to measure and assure the quality and authenticity of original Thai food, have emerged.

In our research, we aspire to contribute to advanced living-assistance systems for smart homes and, in particular, kitchen environments (see Fig. 1), that receive information from new smart autonomous devices, which are inspired by the technologies summarized above and embodied as common items of daily life, e.g., bowls, cups, forks, or spoons. The focus is on sensing principles and packaging technology that allow the achievement of low-cost, low-power, high-volume, multi-sensory integrated intelligent sensory systems and devices for both cooking assistance and food safety.

To achieve this goal, pioneering work by MIT Media Lab on smart or intelligent spoons by Selker (2013) is picked up and extended to wireless communication, advanced packaging, and low-cost multi-sensor capability, in particular impedance spectroscopy, which is a method of increasing impact and applicability, e.g., in Macdonald (1992), Spiller et al. (2006), and Yang and Bashir (2008). However, in the majority of applications, powerful but expensive and bulky desktop equipment, e.g., an HP4195A network analyzer with an impedance measurement extension, Agilent 4294, LCZ meter model 4277A, or Xiton Hydra 4200, etc., are used. Applications are in the field of bio-impedance spectroscopy (Spiller et al., 2006) and electrochemical-impedance spectroscopy (Yang and Bashir, 2008), and medical tasks like skin cancer or wound healing monitoring (Schröter et al., 2013) or fish, liver, or meat freshness determination (Guermazi and Kanoun, 2013), tea quality (Xi-Ai et al., 2011) or general food monitoring in the food industry (Ghosh and Jayas, 2009), as well as water monitoring and detergent concentration determination (Gruden et al., 2013) in, e.g., dishwashers. The size of common instrumentation equipment hampers the system realization beyond discrete proof-of-principle prototypes. This has motivated various dedicated embedded designs based on off-the-shelf components and PCB integration. However, the existing commercial solutions, such as the AD5933 chip, cover only a small part of the interesting impedance, frequency range, and measurement quality for the different application domains, which stimulates ongoing dedicated chip design activities.

Figure 1. Gesture-controlled interactive cookbook for LoS sensor context acquisition before or after recipe food processing steps.

In this work, the concept and the first prototype of our Lab-on-Spoon will be presented. Section 2 will describe the concept and architecture of LoS, Sect. 3 will give details of the first LoS prototype, and Sect. 4 will describe selected applications and conducted experiments, including applied computational intelligence methods and tools. Concluding, the motivation for a custom CMOS chip and a reconfigurable, potentially MEMS-switch-based LoS will be discussed, and a preview of ongoing activities for an improved LoS version will be given.

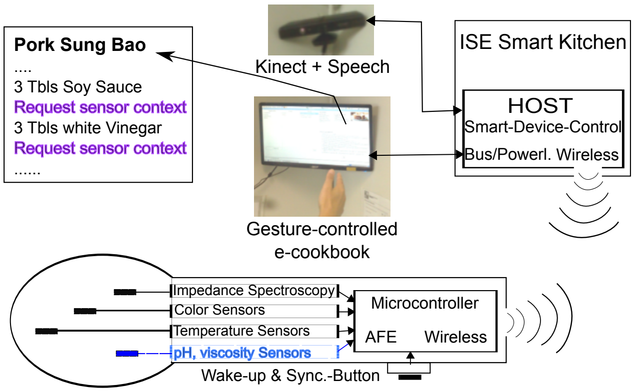

Figure 2. Block diagram of the aspired-to LoS system cooperation with the smart kitchen host for sensor context acquisition.

2 LoS concept and living-assistance system architecture

Figure 2 illustrates by a block diagram the concept of the proposed living-assistance system, and, in particular, the LoS as one possible autonomous sensory front end to it. The institute of integrated sensor systems (ISE) central smart kitchen host is designed to communicate with various smart devices for activity recognition and sensor context acquisition by wire, e.g., standard bus or power-line communication, or standard wireless communication, such as XBee. For instance, Sensitec current sensors are applied for activity recognition and loading assessment of electrical appliances, and the popular MS-Kinect sensor is applied for gesture control together with an emerging electronic or interactive cookbook (see Fig. 1), which is inspired by professional tools like ChefTec (see König, 2008). As exemplified in Fig. 2 for a few extracted recipe lines from a simple Chinese dish, for each step of ingredient inclusion and preparation, the e-cookbook is conceived to call on the sensory context, which will be provided here by the LoS, and by further resources emerging in our current research and development. In this step, ingredients can be checked by LoS for agreement with the current preparatory step, freshness, fraud, or contamination. The LoS is equipped with a microcontroller that runs the measurement control, the sensor readings, and the communication software to collaborate and exchange data with the smart kitchen host indicated in Fig. 2. Power awareness of the autonomous measurement system equipped with a rechargeable accumulator is achieved, e.g, by employing power-saving devices and sleep modes, etc. Conceptually, sensors for integrated temperature, color, infrared, impedance, pH, viscosity, weight, as well as radiation measurement, are aspired to.

Wireless communication with the smart kitchen host is realized by an RF module, e.g., by the XBee standard. The sensory context for each step in the recipe can be acquired and processed by computational intelligence methods on the host for food assessment. Thus, wrong or inadequate or even dangerous ingredients potentially can be detected, indicated to the user, and excluded from further processing. In addition to ingredient monitoring, quantity determination for dosing, and the assessment of intermediate cooking step results are aspired to as part of the concept.

LoS data have to be processed by suitable means to allow the assessment according to common fuzzy textual statements in recipes on color, consistency, crispiness, etc., of the meal components. In addition to standard textual recipe information, LoS sensory contexts from successful (expert) meal preparations could be stored for each step to provide an even better basis for assessment of the current user activities.

It is anticipated that the spoon will be in sleep mode and get woken up by either a button press or, alternatively, a wake-up by radio from the host. The button is allocated in the spoon handle and serves also to synchronize the taking of the measurement. The system can visually, possibly complemented by standard speech output, prompt the user to enter the required ingredient into the spoon and confirm this by pressing the same button. That procedure helps to avoid the spurious analysis of LoS contents, e.g., of an empty spoon, of a spoon filled with residuals of prior activity, or of a spoon in cleaning. Measurement data will be acquired, sensory context data will be communicated to the host, and the LoS will go back to sleep again.

The potentially wide ranges of measurement quantities for different ingredient categories as well as tolerance and calibration issues require the on-the-fly reconfiguration capability for LoS. Some reconfiguration and self-x features are already included; more are under consideration for the implementation of the next LoS version. This will be discussed in more detail in Sect. 4.3.

The physical realization of the concept will exploit contemporary techniques of 3-D printing and the corresponding 3-D integration or packaging of sensors and electronics. 3-D printing allows the easy, low-cost, and rapid realization of arbitrary prototype shapes, including even sintered metals in the spectrum of materials. Suitable spoon shapes can be created in which sensors and electronics could be snapped into place. More advanced system-in-package approaches and technologies, e.g., the molded interconnect device or the active multi-layer technology (Hofmann GmbH, 2013), merge electronics and package design, and also seem very promising for LoS embodiment.

3 First multi-sensor LoS prototype

A subset of the outlined multi-sensor LoS concept and architecture outlined in the previous Sect. 2 has been realized in a hand-held, multi-sensor, and autonomous system implementation and embodied in spoon shape for the first time.

In Fig. 3, the block diagram of the LoS prototype, including three different sensors, is given. Their geometrical alignment in the spoon cavity is outlined in Fig. 4 accord-

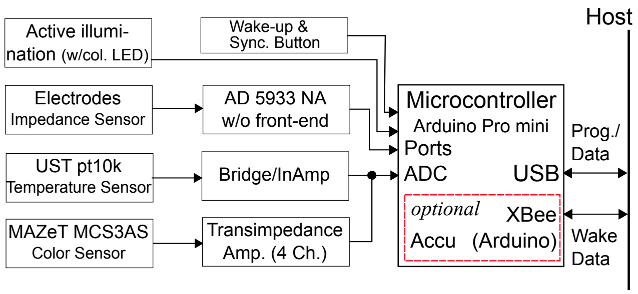

Figure 3. Block diagram of the current multi-sensor LoS prototype.

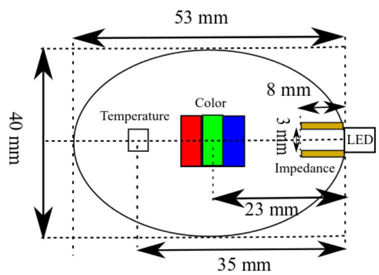

Figure 4. Sketch of the LoS cavity with geometrical information of cavity sizing and sensor placement.

ing to the LoS picture given in Fig. 5. The spoon cavity has a maximum depth of 7 mm. A ceramic substrate pt10k temperature sensor of UST GmbH, which comes with a custom calibrated PCB along with a corresponding third-order calibration polynomial, is placed in the center front of the cavity. The MCS3AS true color sensor with its corresponding MTI04QS transimpedance four-channel amplifier chip from MAZeT GmbH is placed in the center of the cavity with the objective to be always completely submerged in the liquid to be analyzed. The impedance spectroscopy measurement unit consists of the AD5933 (Analog Devices, 2011) network analyzer chip and gold-plated electrodes, which are placed at the center back of the cavity, just below the active illumination LED. By this placement, they will be completely immersed even for a low degree of spoon cavity filling. The placement of the sensors is mainly subject to the constraint to avoid variations in measurement due to uncertainty in filling level. For the impedance spectroscopy, the basic two-wire measurement approach is applied together with an optional simple analog front end for materials of very low impedance, e.g., ingredients of high salinity.

This complementing standard circuit reduces the output voltage and prevents the AD5933 from overloading by excessive output current in low-impedance measurements below the 1 kΩ range. For substances of higher impedance, e.g., oils, the AD5933 will be just used straight, bypassing the front end. Of course, the amplification of the AD5933 input stage has to be reconfigured too with regard to the aspired-to impedance measuring range and the use or bypass of the front end. These setting requirements and calibration issues give rise to the reconfiguration concepts discussed in Sect. 4. Additional reconfiguration requirements come with the color sensor. Depending on the illumination intensity, the transimpedance of the sensor electronics can be digitally adapted or programmed in three stages in the MAZeT MTI04QS chip.

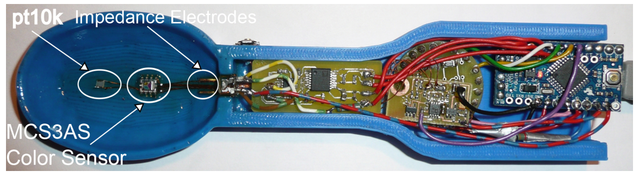

Figure 5. Multi-sensor electronics with USB interface for programming and host communication in a 3-D printed spoon of a LoS prototype before finalization and encapsulation.

However, to provide reduced vulnerability to environmental illumination variations, LoS has been equipped with an active illumination of the spoon content by a white-light LED, which is activated during color measurement. Temperature and color values will be converted to digital by the 10 bit ADC of the microcontroller, while impedance values will be converted by the internal 12 bit AD5933 ADC.

In this context, a further feature for user interaction has been added, which gives a haptic feedback on the spoon contents' temperature. Inspired by previous activities of, e.g., MIT's smart sink (Selker, 2013), where tap water was illuminated by a color coding the temperature, from cold (blue) to very hot (red), to warn the user and avoid injury due to scalding, the LoS was extended. In wake-up state, without host request on data, the spoon in this mode continuously measures the temperature of the spoon contents and illuminates the spoon contents in a corresponding color by a full color LED. This is illustrated in Fig. 6. In addition to that warning function, thresholds and color assignments can be reconfigured by the host, e.g., in tasks where a liquid has to be in an arbitrary interval or even meet an exact value. The water temperature for yeast bacteria cultivation in bread making is one example, which should best be about 30 °C.

The microcontroller and system of choice for LoS, after considering and testing alternatives, in particular the low-power EnergyMicro Cortex M3 EFM32G890 F128 microcontroller, was the Arduino system family, due to the well-known properties of flexibility, easy and rapid prototyping, and a large portfolio of modules and accessories. The Arduino system family with wireless extensions has evolved to be very popular for Internet of Things realizations. For reasons of constrained space, the Arduino Pro Mini board, 5V supply version, equipped with the ATmega 328 microcontroller had been chosen, which provides time-multiplexed ADC inputs for temperature and color sensor reading, I2C bus support for the AD5933 communication, and general purpose digital I/O, including a PWM option for button reading, as well as white light and color LED control.

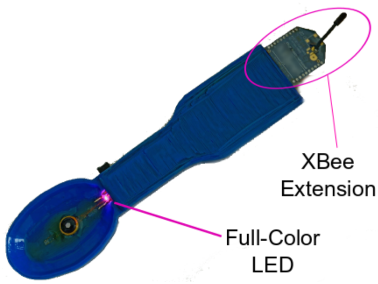

Figure 6. Autonomous LoS prototype with XBee extension board and haptic color feedback on spoon content temperature.

A USB module has been included in the system design for (re)programming of the microcontroller, as well as wired supply, host communication and data transfer for basic LoS operation in the development phase. Figure 5 shows an early prototype of our LoS system without accumulator/XBee extension and before finalization and package sealing. For autonomous operation, the system is completed by a lithium polymer accumulator and a standard XBee communication module. This option is pointed out in Fig. 3 by the only dashed box, labeled Accu/XBee(Arduino), and the corresponding physical realization is illustrated in the top right corner of Fig. 6 as an plug-on board extension to the spoon handle. The spoon package itself has been shaped in a first-cut design employing the Blender software and the Makerbot Replicator I 3-D printer. The currently employed thermoplastic spoon package serves only for the first step of evolution and has to be replaced by a material more robust to the full range of common cooking temperatures and food safety regulations.

The LoS embedded system software is developed in C in the standard Arduino development environment 1.5.6. On the host side, a Python-based interface communicates with the LoS via the serial interface and reads the data in for the application software. Depending on the connection, directly by USB during development or by wireless in the actual application, a second Arduino/XBee module is required as a gateway on the host side.

4 Experiments and results

In the following, front-to-back application of the LoS from sensory registration to data analysis and recognition system design and employment will be investigated for selected liquid food samples. The proprietary ISE QuickCog tool (König, 2008; König et al., 1999) offers the required facilities to analyze, fuse, and recognize the acquired multi-sensor data, but the integration of LoS spoon control and a data acquisition interface seemed to be more promising on a multi-platform flexible and open system, which is provided by the Python-based Orange system (Demšar et al., 2013). So, in this work, Orange was extended on both the Windows and Linux platforms by the LoS interface and a QuickCog interface to immediately exploit features and efficient methods from the field of computational intelligence still unavailable in Orange. Moving these features and methods to Orange and public availability is one of our research goals in the context of LoS research.

Plots for interactive data visualization and analysis can be generated by, e.g., the choice of two particularly relevant variables from the measurement, or by dimensionality reducing mapping techniques, e.g., by Sammon's nonlinear mapping and related fast techniques (König, 2001; König et al., 1999). The first option is very transparent and the axes of such a scatterplot have a clear physical notion. However, in particular, in multi-sensory systems, the required salient information rarely is provided by only two or three measurement inputs or variables. The latter option can deal with measurement data of arbitrary dimensionality and reduces the data dimensionality to a 2- or 3-D plot under the constraint of, e.g., preserving the distances of the data points as undistorted as possible. These distances represent the similarities of data points and their underlying physical measurement data. In such a plot, commonly denoted as a feature map or a feature space projection, the plot axes have no assignment to a particular physical notion.

In gas sensing, commonly linear discriminant analysis is also employed for the same visualization purpose. As this is a supervised method, which includes the labeling or class affiliation of the measurement in the dimensionality reducing mapping, we prefer the unsupervised Sammon nonlinear mapping and employ it for LoS data presentation and assessment in the following.

The maps thus generated can help in understanding and optimizing both data acquisition and processing for ingredient recognition/identification or grading in new applications (see Figs. 10–16). The feature map or feature space projection can be complemented by labeling the data points with class information as well as temperature context information, which could stem from the pt10k sensor in the spoon volume or the AD5933 or other chips' internal temperature sensors. Furthermore, QuickCog provides a set of automated feature selection (AFS) options, which assist in efficient feature-level fusion from the different sensor channels to obtain well-discriminating but lean intelligent systems. For the generation of the following feature maps and the final results table, the q_{oi} overlap measure with k neighbor parameter $k=5$ and the simple sequential-forward selection (SFS) scheme (König et al., 1999) has been employed. AFS leads to more lean, in some cases better performing decision systems, but the particular advantage in impedance spectroscopy is that only a few case-specific spectral components have to be measured, and the measurement time can be reduced significantly. The full sweep will only be needed in the analysis of new tasks and related measurement data.

In the following, two different kinds of experiments were conducted. In the first group, the discrimination capability

```
#Lab-on-Spoon waiting for Button press
#Number of data lines: 516
#Number of measurements: 30
#Temperature:22.70
#Color-B: 1.6396
#Color-G: 1.7476
#Color-R: 1.7932
#Data:
Time,  Mag,   Phas,   Freq
3.205,  37.33,  181.18, 10.000
3.267,  36.47,  176.09, 10.176
3.330,  36.49,  179.43, 10.352
3.391,  37.44,  180.45, 10.528
.
.
.
34.494,56.76,187.05, 99.936
#End of Measurement Cycle: 1
```

Figure 7. LoS output of temperature, color, and 4 of 512 lines of raw uncalibrated impedance data sent to the host for further processing.

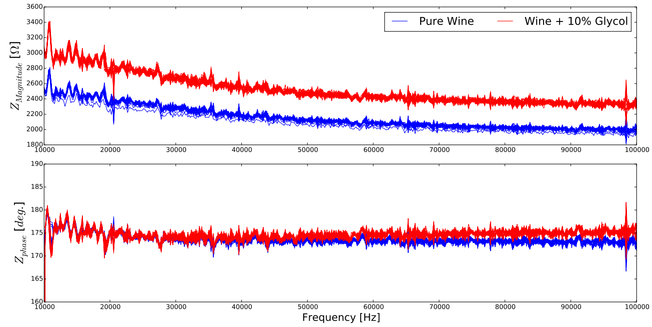

Figure 8. Plot of impedance magnitude and phase spectra for the ingredient data given in Fig. 16. The ordinate values of the magnitude plot have been computed by multiplying the raw data from Fig. 7 by the calibration factor 54.89 of the employed LoS prototype.

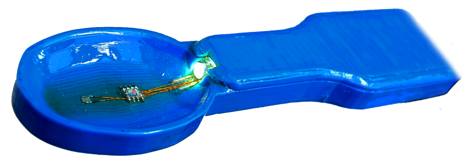

Figure 9. Completed LoS prototype with active white LED illumination for the color measurement phase.

of the LoS for various common cooking ingredients will be investigated and demonstrated.

In the second group of experiments, the LoS grading capability with regard to loss of freshness or the presence of contamination will be tentatively investigated and demonstrated.

For all experiments, the following settings for sensor signal conditioning have been applied. The transimpedance setting of the LoS color sensor is set to 500 k. The frequency sweep range of the AD5933 chip is 10–100 kHz, with a frequency increment of about 175 Hz. The temperature sensor module is calibrated, has no setting options, and returns a temperature value in degrees Celsius. LoS gives, for each measurement, 1 temperature value, 3 values of RGB channels for color registration, and 512 complex impedance values, given as 1024 magnitude and phase values. This amounts to the data vector of 1028 entries exemplified in Fig. 7.

In addition, Fig. 8 illustrates the plot of the impedance magnitude and phase spectra from LoS measurement data for several examples of the contamination recognition and data given in the following Fig. 16. Each point in Fig. 16 corresponds to one measurement, i.e., one of the spectra given in Fig. 8.

For the measurement of substances with a low impedance or high impedance range, two different LoS prototypes with an employed or bypassed analog front end, as indicated in Fig. 3, were employed in the work described in the following.

In the following, 30 measurement repetitions have been adopted as the standard for each substance or ingredient.

The measurement currently proceeds in three phases measuring the temperature first, followed by accumulative color registration of 50 samples of each RGB channel with active white-LED illumination switched on (see Fig. 9), and concluding with the impedance spectroscopy measurement in the given frequency sweep range. After the scheduled number of measurements, which were triggered by the push button and/or by wireless, the LoS goes back to sleep.

4.1 Ingredients recognition

In the first experiment, the discrimination of basic liquid cooking ingredients has been examined, e.g., by filling or immersing the spoon in plain tap water, salted water, soy sauce, or white wine vinegar.

Figure 10 shows the resulting feature map with an AFS result of four features, i.e, three color values and and feature 2 from impedance magnitude, which groups the four ingredients clearly with regard to their basic conductivity.

The next application tried to distinguish four brands of beer. The result along with the brand names is given in Fig. 11. Color was not as helpful as in previous cases, as two of the Pils-type beers nearly feature the same color. The list of the 118 features selected from impedance magnitude data can be found in Appendix A1.

Though the basic discrimination is possible by LoS, the margins between the classes with regard to intra-class scatter are not as favorable as in the previous case. This demands the improvements in the electronics as outlined in the discussion in Sect. 4.3.

The LoS tasting ability has been further challenged by the task to distinguish up to seven kinds of wine. The result along with the wine kind names and origin is given in Fig. 12. The

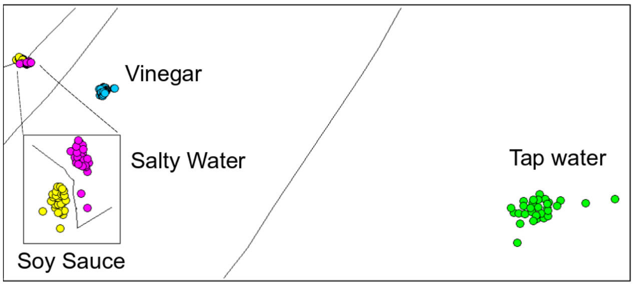

Figure 10. LoS measurement results for the recognition of plain tap water, salted water, soy sauce, and white wine vinegar.

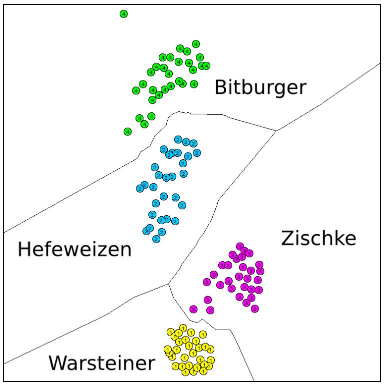

Figure 11. LoS measurement results for the recognition of four kinds of beers.

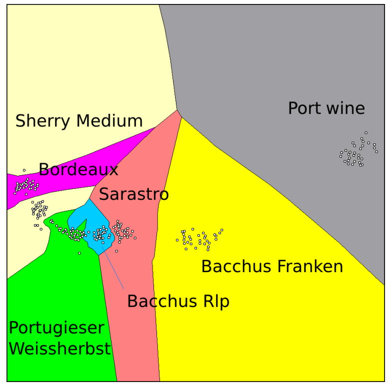

Figure 12. LoS measurement results for the discrimination of seven kinds of wine.

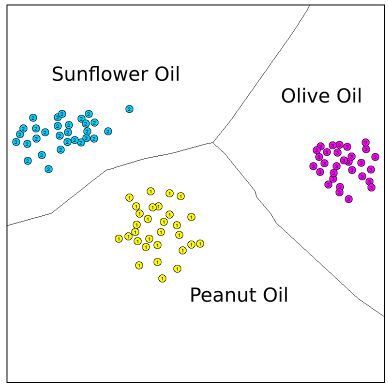

Figure 13. LoS measurement results for the recognition of three plant oils.

list of the 33 features selected from impedance magnitude data can be found in Appendix A2.

This example shows the basic distinguishing capability of the current LoS prototype, but also the need for improvement for more comprehensive and robust operation.

In contrast to the first experiments with ingredients of rather low impedance, oils feature high to very high impedance values. The last experiment of the first group shows the high-impedance LoS capability to distinguish three different kinds of common cooking oils, i.e., sunflower, peanut, and olive oil.

Figure 13 shows the resulting feature map based on six features, i.e., the three color values and the impedance magnitude values 385, 387, and 437, with clear discrimination capability.

4.2 Ingredient grading

In addition to the correctness or appropriateness of the ingredient with regard to the current preparation step, the state or the quality of the ingredient needs assessment. This could be accomplished with the goals of determining the freshness or potential rottenness of the food or the presence of contaminations in the otherwise fine ingredient.

The degradation of oil is a common issue, which will be regarded first in the following. The plant oil of a home frying machine, e.g., for french fries preparation, was investigated with regard to wear-out and the need for oil exchange. Fresh oil was compared to used oil, which according to human impressions of look, smell, and cycles of use, was due for exchange. Data were acquired as in the experiments before and grading pursued in a crisp form, distinguishing just fresh and worn-out oil.

Figure 14 shows the corresponding feature map with two distinct, well-separated clusters for fresh (left) and heavily used (right) frying oil. Here, the color information with the three color values as features itself is already very meaningful. The impedance magnitude delivers similar information with the selections 370, 443, 445, and 491 as features. In the following classification, feature-level fusion of these groups will be applied. It is acknowledged that infrared spectroscopy is a common and successful method for oil and lubricant quality sensors, but in the food domain, a low-cost solution would be welcome.

Also, the spoon embodiment is not required for the frying machine or related machinery. The frying oil classification or grading opens the door to a separate application system, i.e., a stationary oil sensor for indication of wear-out determined

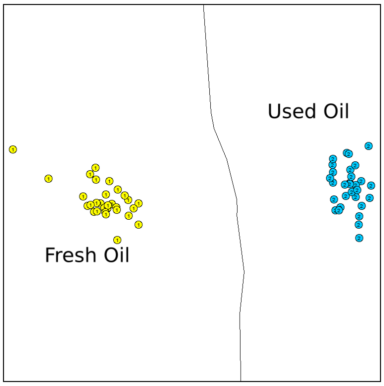

Figure 14. Feature space projection of the frying oil data set.

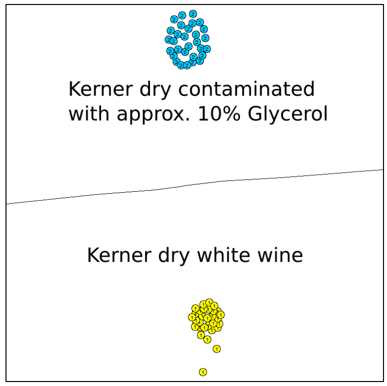

Figure 16. Feature space projection of pure and contaminated white wine.

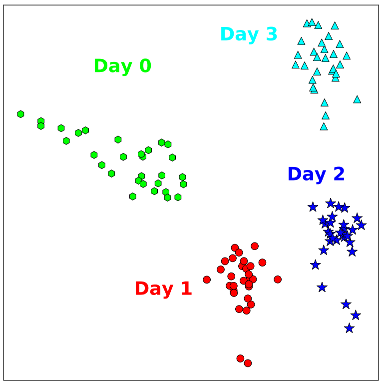

Figure 15. Feature space projection of the milk decay data set.

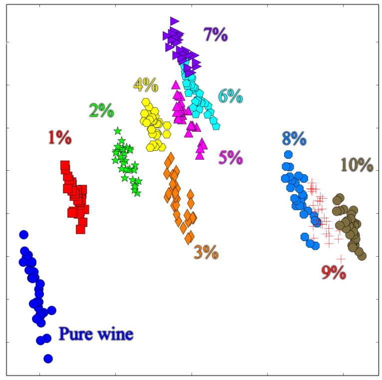

Figure 17. Feature space projection of pure and ten different glycerol concentrations from 1 to 10 % of contaminated white wine.

oil exchange. In the next example, the detection of decay or rotting in milk by LoS, as a common food of daily use, is investigated tentatively. The first sample is taken of fresh milk with 3.5 % fat content. A quantity of about 150 mL of the same milk is left outside the refrigerator and uncovered in a glass and over a period of 4 days; 1 time a day, LoS is filled with about 10 mL taken from the glass and 30 samples of the spoon contents are measured.

Figure 15 shows the feature space projection obtained from 4×30 samples. AFS chose the red color value and the values 4, 18, and 337 from the impedance magnitude as features.

After the fourth day, the milk started to be clearly degraded from visual and olfactory appearance. Due to the variety of milk, involved bacteria, and other potential influences on the rotting process, this experiment is clearly indicated as tentative, but it nevertheless shows the LoS basic ability to give a warning about potential degradation of the ingredient milk and to help the assistance system to dissuade the user from further use.

The last example deals with the issue of detecting food contamination. As an example, we were inspired by a real occurrence about two decades ago, where wine was sweetened by the addition of about 5 % of a chemical substance (diethylen glycol) usually serving as an anti-freezing agent. Here, we use the less poisonous chemical glycerol and add it in a ratio of about 10 % to the dry Kerner white wine in a first experiment, which has been the basis for numerous LoS life demonstrations. Figure 16 shows the result from one of the conducted measurements for selected features 465 and 497 of the impedance spectroscopy magnitude. The obtained data were employed to train and validate an SVM classifier (Muller et al., 2001) as given in Fig. 18. This example was successfully used for life classification in LoS demonstrations, as intended in the actual practical use of the spoon.

In addition to this demonstration, a more detailed investigation of LoS sensitivity has been carried out by acquiring a new data set, measuring pure wine and ten contaminated samples with an increase in glycerol concentration of 1 % from 1 to 10 %. In Fig. 17, the result of this measurement series with 11×30 samples is shown. Clearly, all glycerol concentrations can be well separated from the pure wine data. This has been confirmed by the ensuing classification experiments given in Table 1, both for the full feature set and the AFS reduced set with the impedance magnitude features 1, 3, and 4. In addition to the standard experiments summarized

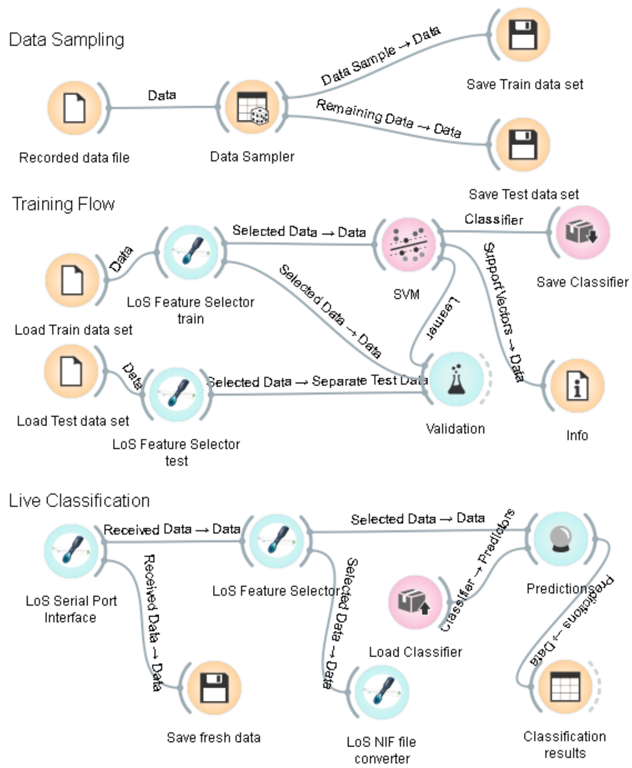

Figure 18. SVM-based classification system for wine contamination detection in Orange running on the smart kitchen server as a subroutine of the e-cookbook.

below, for the complete feature set, data have been sampled with only 20 % training and 80 % testing data. Even then, the same results as in Table 1, i.e., 100 % classification accuracy, have been obtained for all classes, which means perfect generalization. This result implies that LoS could also be employed to predict the concentration, at least in steps of 1 %.

The extension of LoS from the presented multi-class recognition to continuous grading of food properties by function approximation, e.g., RBF networks (Haykin, 1994) and/or support-vector regression (SVR), for oil, milk, wine, and related liquid ingredient assessment, is currently in progress, with promising perspectives.

It is assumed that for each task in ingredient or processing result inspection, trained decision making units are archived and are modularly available in the e-cookbook along with the recipes.

All the described experiments have been subject to classification investigations to also numerically assess LoS discrimination abilities. Table 1 shows the results of a hold-out approach with random data splitting in 50 % training and 50 % testing employing an SVM RBF-kernel classifier. Complete and selected data have been used, based on the detailed feature selection lists given in the text above or in Appendices A1 and A2 for each example. The generalization capability, but for two data sets, was perfect.

Table 1. LoS results for ingredient recognition and grading.

Experiment	Sel. features (col.; mag.)	SVM par. C	SVM par. γ	No. of SV	CA (%)
Soy	All	2	0.03125	31	100
	(3; 1)	512	0.03125	15	100
Beer	All	128	0.125	60	98.33
	(0; 118)	512	0	36	98.33
Wine	All	32	0.125	94	99.05
	(0; 33)	512	0.03125	15	98.10
Oil	All	512	0.125	45	100
	(3; 3)	8	0	17	100
Used oil	All	512	0.5	41	100
	(3; 4)	128	2	7	100
Milk decay	All	128	0	43	100
	(1; 3)	2	0.5	14	100
Glycol in wine	All	512	2	20	100
	(0; 2)	512	0.5	2	100
1–10 % glycol in wine	All	512	0	164	100
	(0; 3)	512	8	165	100

4.3 Discussion

The analysis of the current LoS implementation showed useful sensitivity (see Table 1) and the basic capability to fulfill the raised goals, but also several needs for improvements to sensory data quality and the potential for a significant performance increase. The measurements above show that the intra-class scatter is quite high and, in some cases, approaches the inter-class distances. This can be reduced to about 50 % by the use of an external precision clock, a higher-quality 3V supply, and a front end without DC excitation voltage output as in our related DeCaDrive project (Li et al., 2013) for the AD5933. The DC voltage output degrades the measurement in general, e.g., due to polarization effects. Color measurement currently is impaired by the limited ADC on the microcontroller; i.e., RGB values are sequentially obtained and at mediocre bit resolution. Therefore, the three-channel RGB color sensor will be replaced by the multi-spectral MAZeT MMCS6CS color sensor and related improved signal conditioning and MCDC04 conversion chips with synchronous high resolving measurement of all channels. These changes will significantly improve LoS selectivity and stability. Furthermore, additional digital reconfiguration and self-x features (see, e.g., Johar et al., 2011), based on suitable MOS- or MEMS-switching resources, are considered (Johar and König, 2013). This is required for, e.g., switching from high to low impedance ranges, changing the feedback resistor in the I/O amplifier, and alternating between calibration elements and actual measurement impedance, e.g., immersed electrodes.

The extension of LoS implementation with integrated pH-value and viscosity sensing, the improvement in the 3-D spoon shape and electronics packaging, e.g., with 3-D printing technologies with higher resolution, higher temperature tolerance, and food safety regulation compliance, as well as the advance of related sensor fusion and intelligent system design techniques, are the next steps on the agenda.

A key issue remains employing the range-limited AD5933 chip for impedance spectroscopy realization. Employing an Agilent network analyzer for the same and related tasks showed that, even for a sweep range of up to 2–4 MHz, previously regarded tasks could be solved with higher accuracy, and a wider scope of applications and substances can be distinguished. Thus, the design of a more able dedicated CMOS chip for impedance spectroscopy, which employs differential current stimulation and the four-wire measurement approach, and which is conceived to be applicable for the needs of a wider range of integrated/embedded impedance spectroscopy applications (König, 2008; Li et al., 2013; Guermazi and Kanoun, 2013; Gruden et al., 2013; Schröter et al., 2013), is currently being pursued at ISE.

5 Conclusions

This paper presented the concept and the first embodiment of the Lab-on-Spoon autonomous, hand-held, multi-sensory system as a low-cost front end of an intelligent assisted-living system with a distributed sensor network for home-based smart kitchen applications (König, 2008). The LoS is designed to provide sensory context to the ingredient and preparatory step results monitoring of recipes in an interactive cookbook and, thus, support both unskilled or challenged persons by improving or partially restoring perceptive and assessment ability. Furthermore, LoS is conceived to detect decay and/or contamination in food, which might be imperceptible to humans. With regard to the severe and increasing pollution of soil and water worldwide, contaminations could reach the consumer undetected, and strongly advocate the creation of capable, yet affordable, local sensing capability at the consumer's end of the food chain.

The first LoS prototype was implemented in our work on the favorable Arduino platform with temperature, color and impedance sensing, and integrated into the Orange system for capable multi-sensor signal processing and recognition and life or online classification, e.g., on CeBIT 2014 (König, 2014). With regard to our goals, it showed encouraging capabilities and sensitivity for a challenging application spectrum from food classification to grading. Improvements in electronics, packaging, sensor palettes, and algorithms, as outlined in the discussion above, are on the way. Self-x features for dependable and self-sufficient operation, as needed for related cyber-physical systems, the Internet of Things, or Industry 4.0 domains, are under investigation for LoS. Further inspirations are expected from the thriving lab-on-chip research field.

In addition to advancement of the scientific LoS development and improvement, including the abstraction to alternative devices, e.g., a lab-on-fork, lab-in-bowl, etc., to probe non-liquid food and materials, such as meat or cheese, etc., commercialization with industrial partners is aspired to, with a potential mass market in mind. Recent competitive approaches underpin this view, e.g., Vessyl (2014) and Fuller (2014). From the results on frying oil, and preliminary experiments on combustion engine oil, an extension of the project to simple and low-cost motor and gear oil sensors seems to be promising and straightforward.

Appendix A: Details on feature selection

In the following, the larger selection lists of Sect. 4 will be given. These lists, though extensive, are relevant for the potential data analysis, repetition of experiment, and possible reduction of measurement time in future applications.

A1 Selection list for Beer experiment

The selected 118 magnitude features are 8, 9, 23, 43, 48, 52, 62, 65, 74, 77, 84, 86, 87, 89, 94, 96, 103, 105, 107, 116, 124, 126, 134, 141, 144, 148, 149, 152, 155, 157, 161, 181, 191, 196, 198, 203, 205, 206, 208, 210, 224, 226, 228, 234, 242, 250, 261, 263, 265, 269, 270, 272, 277, 282, 286, 296, 298, 303, 307, 309, 310, 314, 318, 322, 325, 330, 332, 333, 338, 342, 348, 350, 352, 361, 366, 370, 372, 378, 380, 382, 383, 384, 385, 387, 391, 395, 397, 398, 401, 407, 411, 412, 421, 427, 428, 429, 430, 431, 434, 436, 441, 442, 444, 449, 450, 453, 454, 457, 461, 462, 466, 472, 484, 491, 494, 495, 496, and 501.

A2 Selection list for wine experiment

The following 33 magnitude features have been selected: 1, 35, 46, 71, 99, 111, 142, 148, 152, 161, 229, 265, 270, 275, 280, 286, 294, 335, 352, 370, 372, 373, 382, 385, 398, 403, 435, 438, 444, 462, 484, 490, and 494.

Author contributions. Andreas König conceived the Lab-on-Spoon idea, initiated, and guides the research project as principal investigator. He designed and assembled the Arduino-based LoS prototypes shown in this paper, including the embedded software, designed the experiments, did most of the described measurements described in Sect. 4, and evaluated the data and developed recognition systems based on QuickCog. He wrote the majority of this paper. Kittikhun Thongpull developed the interface for LoS communication and data acquisition based on Python and Orange and an interface to QuickCog, did the milk decay and 1–10 % glycol-in-wine contamination experiments, developed and applied a complete trainable SVM-based recognition system, added life LoS data acquisition capability for demonstration purposes to Orange, and conceived a robustly working life demo for contamination detection in wine.

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