

An RFID reader with onboard sensing capability for monitoring fruit quality

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Abstract: We report on the development of an RFID reader with onboard micromachined metal oxide sensors aimed at monitoring climacteric fruit during transport and vending. By operating the sensors under an optimized temperature-modulation mode, we show that the system has good potential for the application envisaged.

Keywords: micromachined metal oxide gas sensors, temperature modulation, calibration models.

SYSTEM ARCHITECTURE

A reader and a flexible tag microlab for monitoring climacteric fruit during transport and vending are under development in the framework of the FP6 Integrated Project "GoodFood". A recently developed prototype of the reader has the following characteristics: Based on TI MSP430 low power microcontroller, ISO15693 RFID communication, Onboard gas sensors: Pt-doped and Au-doped tin oxide (sensors A and B), and Au-doped tungsten oxide (sensor C) [1] + sensor driving hardware, High resolution and accurate data acquisition, I²C/SPI interface, IEEE1451.3 over I²C compliant.

RESULTS

Extensive tests to foresee the performance of the reader with onboard sensing capabilities have been run. Here we report on the study of its performance in the discrimination and quantification of gases relevant to apple quality and safety during storage and transport. Therefore, 165 independent measurements of different concentrations of ethylene, acetaldehyde, ethanol, ammonia and their mixtures were conducted. The sensors had their operating temperature modulated by a signal resulting from the sum of 6 sinusoids. These frequencies were selected by an optimization process that involves using a multi-level pseudo-random maximum-length sequence [2]. This method allows for determining the optimal modulating frequencies to be used in a particular gas analysis application. Full details on this process will be given at the conference.

The response signals of the temperature-modulated micro-sensors in the presence of the different gases studied were obtained and processed as follows. The absolute value of the FFT was computed and the values of the 6 harmonics corresponding to the modulating

frequencies were extracted. These were the 6 features used to build identification and quantification models. Figure 1 shows the FFT spectra of the transient response of a sensor in the presence of acetaldehyde and ethylene.

A fuzzy ARTMAP classifier was built and validated (using the leave-one-out approach) to discriminate among the different species (i.e. 6-category classification). See results in table 1.

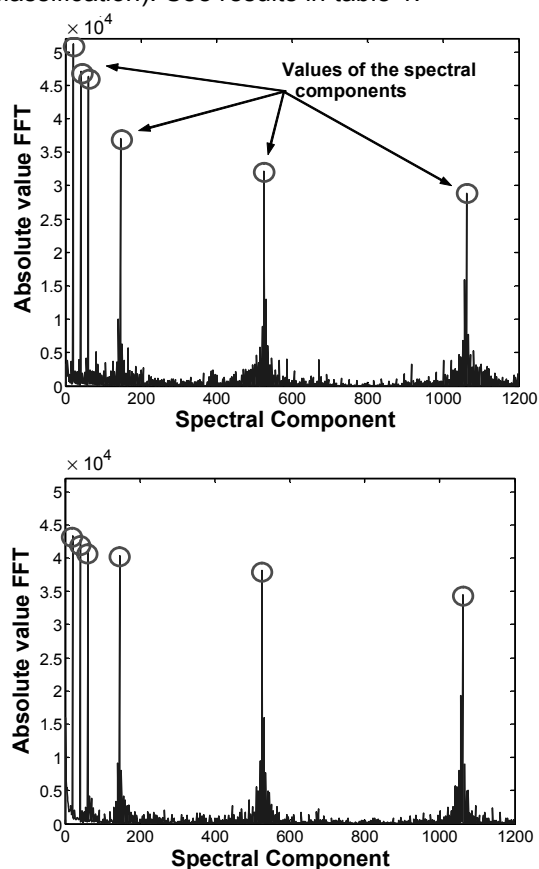


Figure 1. FFT of the transient response of a temperature-modulated WO_3 micro-hotplate sensor in the presence of 50 ppm Acetaldehyde (up); 50 ppm Ethylene (bottom).

Table 1. Success rate in gas identification (%)

Sensor A	Sensor B	Sensor C	All sensors
98.20	97.00	96.36	100

A very high success rate in discrimination is reached, even using a single sensor. When the information from sensors A, B and C was combined gases and gas mixtures could be identified with a 100% success rate. These results prove that the modulating frequencies that are important for discriminating among the gases studied have been correctly identified. In the second step the building of PLS calibration models was envisaged. Specific calibration models for every gas or gas mixture were built and validated. The process used to build and validate the specific PLS calibration models was as follows. The number of latent variables (LV) to be used in each model was determined using the measurements in selection data sets (different from validation ones). Leave-one-out cross-validations were performed with these measurements and the root mean square error of cross validation (RMSECV) versus the number of latent variables was computed. The number of LV selected was the value after the first sharp decrease in RMSECV. Once the number of LV had been determined, PLS models were built (one for each gas or gas mixture) using the measurements in the selection data sets. These calibration models were validated using the measurements that had been left out, i.e. those that belonged to the validation data sets. Table 2 summarizes the validation results for the different PLS models built.

The gas identification and quantification problem was re-considered using the steady-state sensor response, which is the traditional way to operate gas sensors. This study is of help to better assess the improvement in gas identification and quantification obtained by an optimized modulation of the sensors' operating temperature.

Identification and quantification tasks were attempted using the steady-state value of the normalized resistance change, $\Delta R/R_0$, experienced by the sensors in the presence of gases or gas mixtures. A fuzzy ARTMAP classifier, which used as inputs the steady-state response of the sensors within the array was built and validated using the leave-one-out approach. Gases and gas mixtures could be identified with a 81% success rate, which is significantly worse than the identification rate reached when transient information was used (e.g. 100% when using multi-sinusoidal temperature modulation). The building of PLS calibration models was also envisaged. Like in previous cases, specific calibration models for every gas or gas mixture were built and validated. The process employed to determine the number of latent variables to be used and the validation procedures are identical to the ones described above. Table 3

summarizes the validation results for the different PLS models built. These results show that the concentration of the different gases can not be accurately estimated when using the steady-state sensor response only.

Table 2. Validation results for the specific PLS calibration models. (Information from sensors A, B and C was used). Number of LV used, slope (m) and correlation coefficient (r) of the linear regression between real and predicted concentrations and root mean square error of cross-validation (RMSECV).

Gases/mixture models ↓	Cross-validation results			
	LV#	m	r	RMSECV
Acetaldehyde	5	0.999	0.999	0.92
Ethylene	10	0.954	0.978	0.61
Ammonia	6	0.999	0.998	0.99
Ethylene + Acetaldehyde	9	0.936	0.945	12.13
		0.959	0.980	7.29
Ethylene + Ammonia	5	0.952	0.973	8.52
		0.981	0.985	3.58
Acetaldehyde + Ammonia	6	0.982	0.990	2.81
		0.968	0.985	3.57

Table 3. Validation results for the specific PLS calibration models. The steady-state sensor response was used.

Gases/mixture models ↓	Cross-validation results			
	LV#	m	r	RMSECV
Acetaldehyde	3	0.90	0.90	8.2
Ethylene	3	0.86	0.89	16.2
Ammonia	3	0.93	0.91	6.36
Ethylene + Acetaldehyde	2	0.22	0.44	33.05
		0.86	0.92	14.00
Ethylene + Ammonia	3	0.81	0.89	16.60
		0.83	0.90	8.86
Acetaldehyde + Ammonia	3	0.82	0.88	9.17
		0.37	0.57	16.81

These results prove that optimizing the temperature-modulation frequencies of metal oxide sensors is essential if quantitative gas analysis is to be performed. The reader with sensing capability shows promising potential for fruit monitoring.

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