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Optimised temperature modulation of metal oxide micro-hotplate gas sensors through multilevel pseudo random sequences

A. Vergara [a], E. Llobet [a,*], J. Brezmes [a], P. Ivanov [a], X. Vilanova [a], I. Gracia [b], C. Cané [b], X. Correig [a]

[a] *Department of Electronic Engineering, Universitat Rovira i Virgili, Avda. Països Catalans, 26, 43007 Tarragona, Spain*
[b] *Department of Microelectronics and Silicon Technologies, Centre Nacional de Microelectrònica, Barcelona, Spain*

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Abstract

We show how it is possible to optimise a multi-frequency signal to be used in the modulation of the operating temperature of an integrated gas sensor microarray. In the first step, a multilevel pseudo random sequence (ML-PRS), which allows for modulating the operating temperature of the sensors in a wide frequency range, is used to obtain an estimate of the impulse response of each microsensor-gas system. ML-PRS are interesting because they help to reduce the effects of noise and non-linearity as experienced with gas sensors. In the second step, by analysing the spectral components of the impulse response estimates, the modulating frequencies that better help in discriminating and quantifying the gases and gas mixtures considered are found. Finally, by selecting a subset of the best modulating frequencies, an optimised multi-frequency temperature-modulating signal can be synthesised. The method is illustrated by analysing different concentrations of NH_3, NO_2 and their mixtures using a microarray of WO_3-based gas sensors, but it can be further applied to any given gas analysis problem.

Keywords: Multilevel pseudo random sequence; Micro-hotplate gas sensor; System identification; Temperature modulation; Variable selection; Quantitative gas analysis

1. Introduction

Although metal oxide gas sensors are inexpensive and very sensitive to different toxic species, they still suffer from serious shortcomings such as poor selectivity and response drift.

Among the different strategies used to improve selectivity and fight drift, the modulation of the operating temperature of metal oxide gas sensors has been remarkably successful in many applications [1–4]. With the development of microsystem technology, the availability of micromachined substrates for metal oxide gas sensors implied that sensors had their operating temperature modulated in a more efficient way. In micro-hotplate gas sensors, the active film lays on a thin membrane with a thermal response in the range of milliseconds, which compares favourably with the thermal response of seconds found in conventional sensors. Many authors have introduced different methods to process the multivariate information from temperature-modulated micro-hotplate sensors [5–13]. Although the results reached are very promising, the selection of the modulation frequencies used in all these previous works are based on a trial and error procedure, and there is no way to ensure that the frequencies used are the optimal for each application considered.

In a previous work [14], we reported a systematic method to choose the modulation frequencies of micro-hotplate gas sensors based on pseudo random binary sequences of maximum length. Since these signals have a flat power spectrum (i.e. like white noise) in a wide frequency range, an estimate of the impulse response of each gas–sensor pair can be computed by the cross-correlation of excitatory and response sequences. Studying the impulse response estimates, the set of modulating frequencies that are useful to discriminate between different gases and to estimate gas concentration, is obtained in a systematic way.

In this paper, an evolved method to modulate the working temperature of metal oxide micro-hotplate gas sensors in a wide frequency range is presented, based on maximum

* Corresponding author. Tel.: +34 977 558 502; fax: +34 977 559 605.
E-mail address: ellobet@etse.urv.es (E. Llobet).

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length multilevel pseudo random sequences. One of the main reasons for considering multilevel signals instead of binary signals is that the former can provide a better estimate than the latter of the linear dynamics of a process with non-linearities. And it is well known that temperature-modulated metal oxide gas sensors present non-linearity in their response.

The method described in this paper enables each gas–sensor system to be identified and to find, in a systematic way, a reduced set of modulation frequencies that are important to discriminate between different gases and to estimate gas concentration. Its usefulness is demonstrated by the analysis of different concentrations of ammonia and nitrogen dioxide using tungsten oxide based micro-hotplate gas sensors.

The organisation of the paper is as follows: Section 2 describes how multilevel pseudo random sequences can be generated, used to identify systems and how the method can be extended to systematically study temperature-modulated gas sensors. Section 3 describes the sensors used, the experimental set-up and the measurements performed. Finally, in Section 4 the results are presented and discussed.

2. Multilevel pseudo random sequences and temperature-modulated sensors

2.1. Generation of multilevel PRS signals

The theory behind the generation of multilevel pseudo random sequences (ML-PSR) based on multilevel maximum length signals is well developed. As in binary pseudo random sequences, ML-PRS are periodic, deterministic signals and have an autocorrelation function similar to white noise. ML-PRS exist for the number of levels, q, equal to a prime or a power of a prime $p(>1)$, i.e. for $q = 2, 3, 4, 5, 7, 8, 9, 11, 13, \ldots$ [15,16]. The length of such a sequence $\{x_r\}$ is $q^n - 1$, where n is an integer. After $q^n - 1$ digits, the sequence repeats itself. ML-PRS signals are generated in a similar manner that the binary ones using a shift register and modulo addition. Fig. 1 shows the shift register configuration for the generation of ML-PRS signals. The sequences can be generated by a q-level shift register with feedback to the first stage consisting of the modulo q sum of the outputs of the other stages multiplied by coefficients $c_1, \ldots, c_n$, which are integers that lie in the range $[0, q-1]$. For ease of reference, the important properties of q-level maximum length signals are summarised below:

- Basic signals comprise the integer elements 0, 1, 2, …, $q-1$.
- Each cycle has $(q^n - 1)$ digits, where n is an integer $(n > 1)$ corresponding to the number of stages in the equivalent q-level feedback shift register (FSR) generator.
- The number of zeros is in each cycle is $(q^{n-1} - 1)$.
- The number of each of the non-zero elements in a cycle is q^{n-1}.

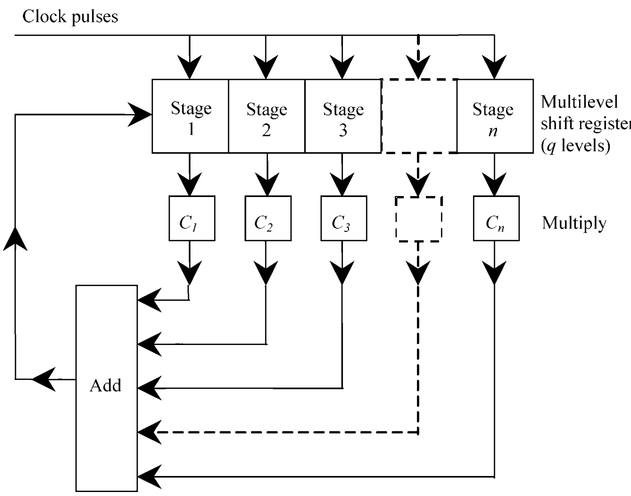

Fig. 1. A generator of a q-level pseudo random binary sequence using a shift register and modulo q addition.

- Each cycle comprises $(q-1)$ sequential 'blocks' of digits of length $(q^n - 1)/(q-1)$ digits, and hence $(q-1)$ is always a factor of $(q^n - 1)$ for all q and n.
- From any reference point in the cycle, the block comprising the subsequent $(q^n - 1)/(q-1)$ digits can be derived by multiplying (modulo q) all digits in the preceding block of length $(q^n - 1)/(q-1)$ by a primitive element g of the Galois field of q elements GF(q).
- As for the generation of binary sequences, the feedback configuration corresponds to a primitive polynomial, modulo q. A list of primitive polynomials can be found in [17].
- If the polynomial $a_n x^n + a_{n-1} x^{n-1} + \ldots + a_1 x + a_0$ is primitive, modulo q, then, in a similar manner to the binary case [16], the logic connections to the first stage are given by:

$$a_0 X = -a_1 DX - \ldots - a_{n-1} D^{n-1} X - a_n D^n X \pmod{q} \tag{1}$$

where X is the input sequence to the shift register and $D^i X$ the output at the ith stage of the register, $a_0 = 1$ and the remaining coefficients $a_1, \ldots, a_n$ have integer values in the range $[0, q-1]$.

2.2. System identification using ML-PRS

The impulse response, $h(t)$, is the main descriptor of a linear invariant system. Among the different strategies to estimate impulse response, noise methods allow for exciting the system under study during enough time to supply it with the necessary energy to obtain a good estimate of $h(t)$. Exciting with white noise signals ensures a homogeneous distribution of the energy over a large frequency range. Since ML-PRS signals have a low crest factor (i.e. low peak-to-average factor) they minimise the risk of saturating the system under study. In practice, this means that the signals contain energy enough to obtain a good signal-to-noise ratio in a wide frequency range (i.e measurement with high dynamic range)