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A Bias Compensated Cross-Relation approach to Thermocouple Characterisation

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Abstract: The measurement of fast changing temperature fluctuations is a challenging problem due to the inherent limited bandwidth of temperature sensors. This results in a measured signal that is a lagged and attenuated version of the input. Compensation can be performed provided an accurate, parameterised sensor model is available. However, to account for the influence of the measurement environment and changing conditions such as gas velocity, the model must be estimated *in-situ*. The cross-relation method of blind deconvolution is one approach for *in-situ* characterisation of sensors. However, a drawback with the method is that it becomes positively biased and unstable at high noise levels. In this paper, the cross-relation method is cast in the discrete-time domain and a bias compensation approach is developed. It is shown that the proposed compensation scheme is robust and yields unbiased estimates with lower estimation variance than the uncompensated version. All results are verified using Monte-Carlo simulations.

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1. INTRODUCTION

Accurate measurement of temperature is necessary and in some cases, critical, in many industrial and scientific applications. In the automotive industry, for example, an accurate measurement of exhaust gas temperature is required for onboard diagnosis of catalyst malfunction (Kee et al., 2006), and to provide insight into engine combustion which can be used to evaluate performance. In this and other environments where the temperature is changing rapidly, fast temperature measurement can be performed using advanced techniques such as coherent anti-stokes spectroscopy, laser induced fluorescence, and infrared pyrometry. However, the instrumentation required for these is expensive, difficult to calibrate and maintain and is therefore not practical for general applications. Usually, thermocouples are used instead. These provide an inexpensive and robust method of measuring temperature over a wide range and at low cost. However, like all sensors, thermocouples have a limited bandwidth and are effectively low-pass filters. Their bandwidth is determined primarily by the wire diameter, and to a lesser degree, by the velocity of the surrounding gas (Kee et al., 2006). A consequence of this is that when the frequency of temperature fluctuations exceeds the bandwidth of the thermocouple, the measured output is an attenuated and delayed version of the input.

An obvious approach to reduce the measurement error is to make the wire diameter smaller, which in theory should increase the effective sensor bandwidth. Practically speaking, however, this is not a viable solution since it would result in a sensor that is mechanically fragile and unable to withstand harsh measurement environments. An alternative approach is to employ software-based compensation techniques. A requirement of this approach is that a dynamic model of the sensor is available and the sensor model parameters are known prior to compensation (Hung et al., 2005). Furthermore, the model estimation process should take the measurement environment into account and any other factors that influence the dynamic characteristics of the sensor.

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A loop current step response (LCSR) test is a generally accepted method to estimate the parameters of a sensor model *in-situ* (Hashemian and Petersen, 1992). However, it has some major disadvantages that render it unsuitable in certain applications. The most significant problem is that the test is intrusive and the relatively high levels of heating can potentially disrupt the process being measured (Tan et al., 2006). Furthermore, it is time consuming since the test must be regularly performed to adapt to changing conditions and can therefore represent significant set up time costs. Consequently, it is desirable to have a non-intrusive method to estimate the model parameters before compensating the sensor output. Since a measurable input signal is not available using a non-intrusive method, the model identification problem becomes one of identifying the model using only measured output data. This is known as a blind identification problem, or in this application, blind sensor characterisation.

In 1936, Pfriem, a German engineer proposed a solution to this problem (Pfriem, 1936). His solution specified the use of two sensors of known model structure, each with different dynamic characteristics and placed in the measurement environment such that they both experience the same thermal field. He then postulated that it would be possible to estimate both sensor models using only output measurements from the sensors. Since then, numerous approaches for two-thermocouple characterisation have been proposed based on the principle and assumptions of the approach proposed by Pfriem. A range of time-domain methods have been presented by Tagawa et al. (1998), Kee et al. (1999), O'Reilly et al. (2001) and Kar et al. (2004). Forney and Fralick (1994) and later Tagawa et al. (2003) then tackled the problem in the frequency-domain, thereby avoiding the numerical problems associated with estimating derivatives that were experienced in the time-domain. In recent years, with the growth and development in digital based instrumentation, a number of methods were developed in the discrete-time domain that take account of sampled data. The authors of Hung et al. (2005) were the first to cast the sensor characterisation problem in the system identification field and demonstrated an approach using difference equations that provides superior performance to other approaches in the literature. In an attempt to improve on the performance of the difference equation approach, Hung et al. (2007) proposed a new approach for sensor characterisation using a technique known as the cross-relation approach, initially proposed by Liu et al. (1993) for application to communication channel equalisation. The approach is based in the continuous-time domain and involves estimating the time constants of the sensor models directly by minimising an error cost function. For simulation purposes, the sensor models are represented as first-order continuous-time transfer functions and the output is computed by numerical integration. The main limitation of this approach is its limited resilience to high noise levels. The noise contribution has the effect of distorting the shape of the cost function around the local optimum in such a way that it becomes ill-posed as the noise level increases and characterisation is no longer possible. In addition, the distortion imposed on the cost function results in biased estimates.

In this paper, we present a methodology for advancing the work of Hung et al. (2007) by casting the problem explicitly in the discrete-time domain. In particular, we develop a novel bias compensation technique that yields unbiased parameter estimates and significantly improves the robustness of the method to measurement noise.

2. BLIND CHARACTERISATION

The cross-relation method proposed by Liu et al. (1993) is based on the principle of commutativity and the assumption that the systems to be identified are linear. A discrete-time formulation of the sensor characterisation problem using the cross-relation approach is illustrated in Fig. 1. Both sensors, which are represented by the transfer functions, G_1 and G_2, are assumed to experience the same input temperature, T_g^k and the outputs, T_{m1}^k and T_{m2}^k, where k is the sample instant, are linearly related by their responses, respectively. The sensor outputs are then collected and passed through the synthetic sensor models, $\hat{G}_2$ and $\hat{G}_1$ which are represented by discrete-time first-order transfer functions of the form

$$\hat{G}_1(z) = \frac{\hat{b}z^{-1}}{1-\hat{a}z^{-1}} \quad \text{and} \quad \hat{G}_2(z) = \frac{\hat{d}z^{-1}}{1-\hat{c}z^{-1}} \tag{1}$$

to produce the outputs T_{m12}^k and T_{m21}^k, respectively. Here, $\hat{G}_1$ and $\hat{G}_2$ are estimates of the corresponding true sensor transfer functions. The unknown model parameters to be estimated are

$$\hat{\boldsymbol{\phi}} = [\hat{a}, \hat{b}, \hat{c}, \hat{d}]. \tag{2}$$

By virtue of the commutative property of linear systems which states that, for noise free sensor outputs,

$$T_{m1} = T_g \otimes G_1 \quad \text{and} \quad T_{m2} = T_g \otimes G_2 \tag{3}$$

where $\otimes$ indicates convolution, it follows that when $\hat{G}_1 = G_1$ and $\hat{G}_2 = G_2$, then

$$G_1 \otimes \hat{G}_2 = G_2 \otimes \hat{G}_1. \tag{4}$$

Hence, the cross-relation method estimates the sensor models by adjusting $\widehat{\boldsymbol{\phi}}$ such that the difference between the outputs of the two signals paths in Fig. 1 is minimised. Assuming both sensors have been properly calibrated to have unity gain so that $b = 1 - a$ and $d = 1 - c$, a 2-D mean-squared-error (MSE) cost function, defined as

$$J_{CR}(\hat{a}, \hat{c}) = \frac{1}{N} \sum_{k=k_0+1}^{k_0+N} (e^k(\hat{a}, \hat{c}))^2, \ \forall \ \hat{a}, \hat{c}, \tag{5}$$

where N is the number of output samples and

$$e^k(\hat{a}, \hat{c}) = T_{m12}(\hat{c})^k - T_{m21}(\hat{a})^k, \tag{6}$$

can be minimised to give estimates of a and c. Since the initial conditions for the sensors are not known, the first k_0 data samples are omitted to avoid output mismatch due

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