

NEW SENSOR PARADIGM FOR FUTURE COMBAT SYSTEMS

J.I. Frankel*

Mechanical, Aerospace and Biomedical Engineering Department
University of Tennessee
Knoxville, TN 37996-2210

V. Protopopescu

Computer Science and Mathematics Division
Oak Ridge National Laboratory
Oak Ridge, TN 37831-6016

ABSTRACT

Highly sensitive and robust sensors are a fundamental component of modern science and engineering, with particular relevance to military applications. Stringent requirements posed by the Future Combat Systems (FCS) on real-time diagnostics from remotely sensed raw data, are only increasing the demand for fast, responsive, and accurate sensors. Basic to all measurement devices are inherent data errors associated with uncertainties and background noise. Turn-key, single-function sensors are designed to provide accuracy and repeatability for a specific, directly measured quantity. However, if these measurements are used to infer other physical quantities, special care must be taken. Indeed, in most applications, data differentiation is applied within the predictive process, sometimes even unbeknown to the user. Unfortunately, upon differentiation, the noise that affects all measured physical quantities is dramatically amplified. Refining the measurement (i.e. increasing the sample density) exacerbates the problem even further, because the increase in accuracy due to finer sampling is wiped out by the cumulative adverse effect of the numerical differentiation. In this paper, we propose the development and implementation of a new, rate-based sensors paradigm that would enhance and secure the US military strength.

1. INTRODUCTION

The generic problem is illustrated by the heat transmission in the half-space, whereby the goal is to predict the surface heat flux based on an embedded surface sensor. At the boundary of the medium the following integral relationships hold:

$$T_s(t) = \lambda \int_0^t \frac{q_s''(u)}{\sqrt{t-u}} du, \quad t \geq 0, \quad (1)$$

and

$$q_s''(t) = \frac{1}{\lambda\pi} \int_0^t \frac{dT_s(u)}{\sqrt{t-u}} du, \quad t \geq 0, \quad (2)$$

where $T_s(t)$ is the surface temperature, $q_s''(t)$ is the surface heat flux, and t is the time while the parameter λ is given as $\lambda = 1/\sqrt{\pi k \rho c_p}$, where k is the thermal conductivity, ρ is the density, and c_p is the heat capacity. These relations show that while the temperature at the boundary is expressed in terms of the heat flux, $q_s''(t)$, the latter is reconstructed from the heating/cooling rate, dT_s/dt . Thus the noise present in the temperature data emerges hugely amplified in the heat flux.

Figure 1 shows simulated temperature and heating/cooling rate data sets, containing M points, contaminated with different levels of white noise.

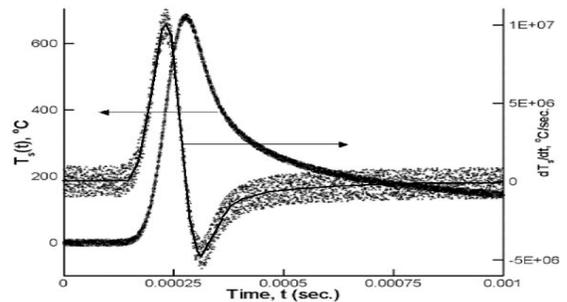


Fig. 1: Temperature, $T_s(t)$ (open circle-noisy data), and heating/cooling rate, dT_s/dt (open triangle-noisy data) when $M = 3000$ (solid line-exact).

Figure 2 displays the predicted heat flux based on $T_s(t)$ data and is clearly useless for real-time analysis.

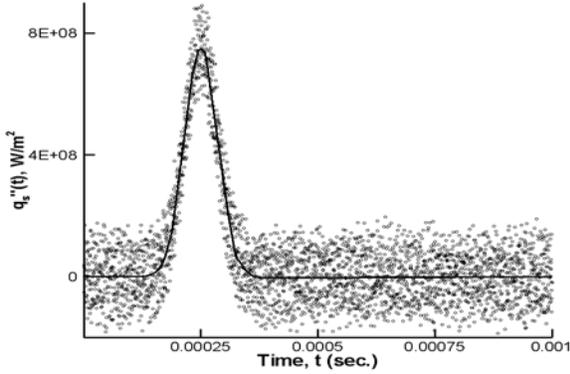


Fig. 2: Predicted heat fluxes, $q_s''(t)$ a) solid line-exact; b) dashed line-errorless data predictions (visually identical to (a)); and c) open triangle-noisy data predictions when $M = 3000$.

In contrast, Figure 3 displays the highly accurate and usable results for the predicted heat flux, based on the dT_s/dt data.

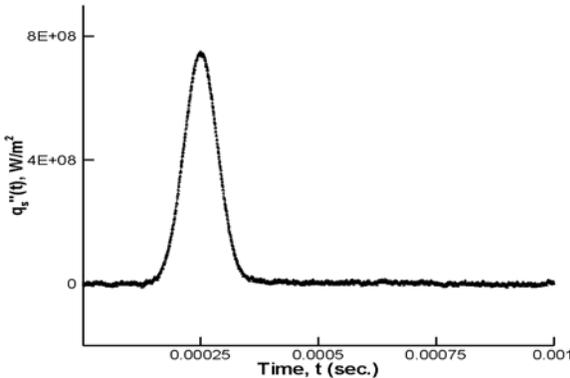


Fig. 3: Predicted heat fluxes, $q_s''(t)$ a) solid line-exact; b) dashed line-errorless data predictions (visually identical to (a)); and c) open triangle-noisy data predictions when $M = 3000$.

Figure 4 presents the predicted root-mean-square (RMS) heat flux error resulting from the data sets. The predicted RMS error of the heat flux based on dT_s/dt decreases as the sample density increases. Meanwhile, the predicted RMS error of the heat flux, based on $T_s(t)$, increases as the sample density M increases. Here, ϵ_j is a noise factor used in generating the white noise level.

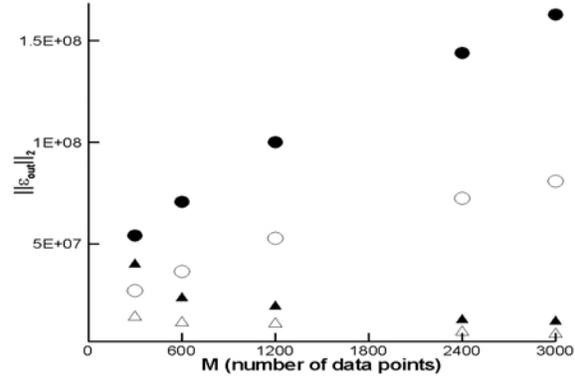


Fig. 4: Root-mean-square of the output error (W/m^2) over sample density (Temperature Data: open circle - $\epsilon_1 = 0.0125$, filled circle - $\epsilon_1 = 0.025$; and Heating/Cooling Rate Data: open triangle - $\epsilon_2 = 0.1$, filled triangle - $\epsilon_2 = 0.2$).

Thus, theoretical calculations and numerical simulations fully demonstrate the significantly increased accuracy, robustness, and implementation potential of our new rate-sensor based paradigm.

3. CONCLUSIONS

To date, direct rate sensors are available for a limited number of, mostly mechanical, physical quantities, but measuring rates of other important quantities, e.g., temperature, heat flux, concentration, etc., requires further investigation. Development of such active and/or passive sensors is in principle possible, by leveraging the theoretical ideas outlined here with the latest developments offered by the sensor industry. Military applications that could take advantage of this new technology include: thermal analysis in bores and breeches; ablators for bomblets and nose cones; directed energy weapons; nanomaterial propulsives and explosives; assessing strain in aging stored rockets and bombs; creep, fracture, and thermoelastic prediction.

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