Master of Science in Electronics and Information Technology Engineering

Project: Data Driven Fast Measurements (DDFM)

Ivan Markovsky
Vrije Universiteit Brussel

Abstract

Faster and more precise measurements would benefit all branches of science and technology. The speed and precision of a measurement device used in monitoring and control tasks determines the quality of the available data, which in turn limits the accuracy of models derived from the data. The model accuracy then limits the performance of monitoring or control system designed using the model.

Metrology—the science of measurement—is advancing by development of new measurement techniques and corresponding hardware. A given measurement technique, however, has fundamental speed and accuracy limitations. We overcome the hardware limitations by using a data driven signal processing method. The proposed method, called data driven fast measurement (DDFM) does real-time processing of the sensor's measurements. Contrary to sensor technologies, which are application specific, the DDFM algorithm is applicable to any sensor and can fuse measurements of multiple sensors.

Theoretical properties of the DDFM algorithm to improve sensors' speed and accuracy characteristics are established in the literature. This project aims to bridge the gap from the developed theory to the practice. We will implement the DDFM algorithm in a low-cost digital signal processor and demonstrate its benefits in real-life measurement test cases. The output of the project is a low-level C code implementation of the algorithm and prototypes for temperature and weight measurement.

Keywords: signal processing, system identification, metrology, dynamic measurements.

1 Problem formulation

Dynamic measurement

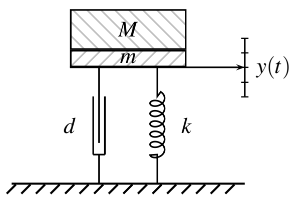
The measurement device, called the *sensor*, is modeled as a dynamical system with input—the to-be-measured value u (a constant)—and output—the sensor reading y (a function).

$$\begin{array}{c} \text{to-be-measured value } u \\ \text{(constant during measurement)} \end{array} \xrightarrow{\text{sensor}} \begin{array}{c} \text{measured value } y \\ \text{(exhibits transient response)} \end{array}$$

Example 1 (Temperature measurement). The sensor is a thermometer. The input is the environmental temperature, assumed constant for the measurement period. The output is the thermometer reading. The measurement process is described by Newton's law of cooling $\frac{\mathrm{d}}{\mathrm{d}t}y = a(u-y)$, where a is the heat transfer coefficient. The measurement process is a first order linear time-invariant (LTI) dynamical system.

Example 2 (Weight measurement). The sensor is a scale. The input is the measured mass M. The output is the scale reading y. The scale is modeled as a mass-spring-damper system, which has second order LTI dynamics

$$(M+m)\frac{\mathrm{d}^2}{\mathrm{d}t^2}y = -ky - d\frac{\mathrm{d}}{\mathrm{d}t}y - Mg.$$



Depending on the sensor and the environment, y exhibits longer or shorter transient. Physically, the transient represents the exchange of mass or energy, which takes place during the measurement process. Of interest in metrology is the steady-state value $y(\infty) = \lim_{t\to\infty} y(t)$, reached in theory only asymptotically. In practice, the measurement is taken after "sufficient decay" of the transient, *i.e.*, when the error $e(t) := \|y(\infty) - y(t)\|$ becomes "small". There is a *trade-off* between fast measurement (small measurement time t) and accurate measurement (small $e(t)$). This trade-off is a *fundamental limitation* of the measurement device determined by the physical laws on the basis of which the sensor is build.

> **The goal of this project is to achieve fast and accurate measurement by *predicting* the steady-state value $y(\infty)$ from data $y(t)$ collected over an interval $[0, T]$.**

The problem is referred to as *dynamic measurement* [1] and the solution is based on digital signal processing. The prediction algorithm, called *compensator*, is a dynamical system with input—the sensor output y—and output—the compensated sensor reading y_c.

$$\begin{array}{c} \text{sensor output signal } y \\ (\text{"long" transient response}) \end{array} \xrightarrow{\qquad\text{compensator}\qquad} \begin{array}{c} \text{compensated signal } y_c \\ (\text{"short" transient response}) \end{array}$$

Ideally, the compensator completely eliminates the transient. In practice, y_c still exhibits a transient. In addition, *disturbances and measurement noise* affect the sensor measurement y even in a steady-state.

> **The technological challenge of dynamic measurement is to design a compensator that achieves simultaneously short transient response and good disturbance and noise filtering.**

State-of-the-art: adaptive filtering for dynamic mass measurement

The *classical approach* in dynamic measurement (see [1] for a recent overview) assumes that the process dynamics is *known* and LTI. Consequently, the compensator is also an LTI system, designed by frequency or time domain de-convolution techniques. The assumption that the process dynamics is known, however, is often unrealistic. In the temperature measurement example, the process dynamics depends on the heat transfer coefficient, which may vary due to unpredictable factors. In the weight measurement example, the process dynamics depends on the unknown mass M. In general, the measurement process dynamics depends on the sensor, which is known, and on the environment or the measured quantity, which are unpredictable or unknown.

In order to deal with the issue of the unknown process dynamics, Shu proposed in [7] an adaptive compensator. Adaptive methods perform simultaneously online model identification and filtering. The method of [7] is specifically designed for weight measurement. It needs nontrivial modifications for other applications, in particular for applications with multiple sensors. Due to the online model identification, the adaptive methods are computationally expensive for implementation on a digital signal processor (DSP).

> **High computational cost for DSP implementation and nontrivial generalization to high-order multivariable processes prevent the widespread use of adaptive methods in metrology.**

The new idea: data driven dynamic measurement

The novel idea, pictorially shown in Figure 1, is to avoid the model identification step [4] in the classical methods. Both model-based and model-free (also called data driven) methods obtain (optimal) prediction or control signal from data. The model-based methods, however, compute as a byproduct a model of the plant.

A model-free signal processing method for dynamic measurement (abbreviated here DDFM) has been developed in the related ERC project [6, 5]. Similarly to the subspace methods in system identification [8], the DDFM method is based on projection operations. Instead of computing model parameters, however, DDFM computes directly an input estimate (see [6] for details). Theoretical analysis and validation of the DDFM

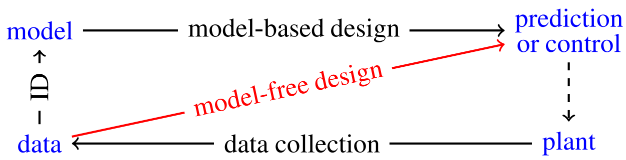


Figure 1: Model-based vs model-free design: the model-based approach requires identification (ID).

method on simulation examples shows improved computational efficiency and statistical accuracy in comparison with alternative methods [5].

> **Avoiding the explicit model identification step leads to a computationally fast method. Moreover, the DDFM method is applicable to high order multivariable systems.**

The aim of this project is to establish viability and overcome potential problems in the practical implementation of the DDFM method. The work plan includes implementation of the algorithm on a DSP and testing it on *real-life measurement* of temperature, weight, mechanical, and electrical quantities (see Section 2).

2 Plan of the activities

The aim of the project is *improvement of speed and accuracy characteristics of sensors by real-time signal processing*. We formalize this problem as an input estimation problem for a dynamical system with step input and use methods from model-free signal processing. The step level is the unknown (to-be-measured) quantity, the output is the known (measured) quantity, and the input-output relation represents the dynamics of the measurement process.

The problem is nontrivial because the measurement process dynamics is unknown. Adaptive filters estimate model parameters as well as the quantity of interest. Although the measurement process dynamics is not needed, it is estimated by the adaptive filter. An attractive feature of the DDFM method is avoiding the parameter estimation step. Moreover, the DDFM algorithm is applicable to general high-order multivariable measurement processes (multiple sensors).

Derivation and analysis of the method, Matlab implementation, and validation on simulated data are done in the related ERC starting grant [6, 5]. Stepping on these results, in the POC project, we will apply the DDFM method on real-life application and validate the theoretical framework as detailed below.

1. **Temperature measurement prototype** We will demonstrate the practical benefits of the DDFM method using low-cost hardware and open source software tools (see section "Equipment" below).
   (a) *Hardware setup:* familiarization with the DSP, the `sensors`, and the software; development of tools for real-time data acquisition and communication between the DSP and a PC.
   (b) *DDFM algorithm implementation:* the programming will be done in a C-like language called NXC, which supports IEEE double precision arithmetic and concurrent programming. The DDFM algorithm will be implemented as a process running in parallel with data acquisition and visualization processes.
   (c) *Tests with different temperature sensors under different operating conditions:* we will demonstrate the flexibility of the DDFM algorithm to use different sensors (*e.g.*, a thermo-couple and an infrared based ones) and operate in different environments (*e.g.*, air vs water) without ad-hoc parameter tuning.
2. **DDFM of other processes** This task demonstrates the flexibility of the algorithm.
   (a) *Weight measurement:* a mass-spring-damper setup with distance sensor will be build as a second real-life test bed for the DDFM algorithm.

(b) *Using multiple sensors in smoke detection:* we will test the algorithm on a smoke detection and localization problem, where an array of smoke concentration sensors are used and the source location is encoded in a multivariable input.

(c) *Battery state estimation:* we will test the DDFM algorithm on the problem of a battery state-of-charge estimation. If the simulation results are promising, we will test the algorithm on a real-life setup in the context of the BATTLE project at the VUB.

3. **Extensions** The assumptions of constant measured value and LTI process dynamics will be relaxed as detailed below. These extensions are also a way to mitigate risks in Tasks 1 and 2.

(a) *Tracking of a time-varying quantity* will be accommodated in the estimation by windowing the data and adding a forgetting factor. Practical questions to be addressed in this context are the choice of the window length and the forgetting factor. Tracking is needed in application for online *monitoring*.

(b) *Trends and periodic components:* Another interesting extension is to relax the assumption that the input is a constant to the assumption that it is a sum of damped exponentials or a polynomial. This would allow us to detect *trends and periodic components* of the measured variable.

Equipment

Software: Matlab with relevant toolboxes. Hardware: DSPs and sensors:

hardware	details
Lego NXT brick	ATmega48 microcontroller, 64KB RAM
Lego EV3 brick	AM1808 microcontroller, 64MB RAM
thermal sensor (three ranges)	0–50 / 50–100 / 100—150 C $\pm$0.1/0.5/2 C
thermal infrared sensor	$-$70–380 C $\pm$0.5 C
ultrasonic distance sensor	1–250 cm
infrared distance sensors	30–150 / 10–80 / 7–30 cm
accelerometer	
gyroscope	0–440 degrees/second
pressure sensor	0–500 kPa
currentmeter	0–12.5 A $\pm$1mA
voltmeter	0–26 V $\pm$1mV
total: 14 items	

References

[1] S. Eichstädt, C. Elster, T. Esward, and J. Hessling. Deconvolution filters for the analysis of dynamic measurement processes: a tutorial. *Metrologia*, 47:522–533, 2010.

[2] L. Ljung. *System Identification: Theory for the User*. Prentice-Hall, Upper Saddle River, NJ, 1999.

[3] I. Markovsky. An application of system identification in metrology. *Control Engineering Practice*, 43:85–93, 2015.

[4] I. Markovsky. Comparison of adaptive and model-free methods for dynamic measurement. *IEEE Signal Proc. Letters*, 22:1094–1097, 2015.

[5] W.-Q. Shu. Dynamic weighing under nonzero initial conditions. *IEEE Trans. Instrumentation Measurement*, 42(4):806–811, 1993.

[6] P. Van Overschee and B. De Moor. *Subspace identification for linear systems: Theory, implementation, applications*. Kluwer, Boston, 1996.