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IoT Signal Procedures and Optimization

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Abstract
We develope efficient algorithms for the current estimation required for the torque control of electric power steering of motor vehicles connected via IoT. This makes it possible to validate the measured current with alternative (non-current) sensors, to test its plausibility, and to replace the meter in the event of a fault. Analytical redundancy makes this possible, as the current consumption can be estimated by measuring the phase voltages and speed - knowing the physical parameters of the motor.

Keywords: *IoT Optimization, Signal procedures, Convolution*

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I. INTRODUCTION

In a very wide range of technical creations, we observe the physical world around us with some kind of sensor / measuring system. With this information, either a person or an autonomous computer system makes decisions, and an embedded system intervenes in the host environment based on this. The Internet of Things (IoT), resp. in the world of cyberphysical systems, the devices are interconnected and solve complex tasks in a coordinated way (autonomous driving, adaptive traffic control, automatic swarming of vehicles, etc.). We need accurate information. The accuracy and quality of the decision and intervention is fundamentally influenced by the accuracy of the primary information about the physical world.

Nowadays, embeddedand cyber-physical systems process information digitally. However, the signaling pathway from physical quantity to digital information is affected by many distorting and confounding effects. In the framework of my research, we dealt with the improvement of the accuracy of the devices for monitoring the environment by digital signal processing (compensating the distortions of the signal path, reducing its disturbances).

II. METHODOLOGY

When observing a physical quantity according to Figure 1, we first assume a linear, time-invariant measuring system, the disturbances of which can be taken into account by an additive noise source that can be reduced to the output. Assuming sampled discrete signals as well as an input function and a finite sample register, the relation is a finite convolutional sum:

$$z(i) = \sum_{j=0}^{N_t-1} h(j)x(i-j) + n(i),$$

where x(i)the physical quantity to be measured (system input signal), h(i)the weight function of the measuring system, n(i)the noise register, z(i)the distorted and noisy response due to finite bandwidth. The task of inverse filtering (deconvolution) is to estimate the excitation of the system by knowing the transmission function and measuring the noisy and distorted output. The task is typically poorly conditioned, which means that even a small change in observation causes a very large difference in the estimator of the input signal [1]. Numerous solutions to reduce noise gain have been suggested in the literature (output smoothing [4], regularization operator [1], [5], Wiener filtering [6] [7], Kalman filtering [8] [9], signal model matching [10], neural networks). [11] etc.) Each of these attenuates the noise by distorting the useful signal as an additional error. One of the great challenges of the inverse filtering task is to find a compromise between noise pressure and distortion. The methods typically leave the user to find the amount of noise pressure. In the paperwe propose to automate this, so there is no need for a separate expert for the measurement, and we can also integrate the algorithm into autonomous systems.

2.1 Automatic optimization of several parameters

We developed an algorithm that automates the noise suppression of inverse filtering (deconvolution) methods in the case of parametric algorithms (inverse filtering algorithms that can be tuned with one or a few parameters). The advantage of this method compared to the algorithms found in the literature is that it minimizes the input error, it can handle several parameters, it can be calculated in a frequency range, thus eliminating computationally intensive matrix operations. The parameter optimization algorithm approximates the input error written in the frequency domain with signal models, where the models are automatically built from the measurements by the algorithm. The input error can be written as follows:

$$\begin{aligned}
\text{cost} = \quad & T_s \sum_{i=0}^{N_t-1} (x(i)-\hat{x}(i))^2 = \frac{T_s}{N_f}\sum_{k=0}^{N_f-1} |X(k)-\hat{X}(k)|^2 = \\
= \quad & \frac{T_s}{N_f}\sum_{k=0}^{N_f-1} |X(k)(1-H(k)K(k,\underline{p}))|^2 + \frac{T_s}{N_f}\sum_{k=0}^{N_f-1} |N(k)K(k,\underline{p})|^2 - \\
& -\frac{2T_s}{N_f}\sum_{k=0}^{N_f-1} |X(k)(1-H(k)K(k,\underline{p}))| \mid \underbrace{N(k)K(k,\underline{p})}_{A} \cos\left(\varphi_{AB}(k,\underline{p})\right) \\
= \quad & \text{cost}_{\text{bias}} + \text{cost}_{\text{noise}} + \text{cost}_{\text{bias noise}},
\end{aligned}$$

where x ˆ(i)the input estimate, T_sthe sampling time, the uppercase letters are discrete Fourier transforms of the corresponding signals. K(f,p)inverse filter transmission that can be optimized with the parameter set_pnegligible and the noise register or we proposed a model for the absolute value of the signal spectrum. WE assume white noise for the noise model and determine the noise level by evaluating the closing range in the observation spectrum. (If known, the color of the noise can also be modeled.) WE refine the model on the signal using an iterative algorithm. The initial models are:

$$|N_{\text{model}}(f)| = \text{const}, \quad |X_{\text{model}}(f)|_0 = \left|\frac{Z(f)}{H(f)}\right|.$$

If H(f)its absolute value were very close to zero anywhere, instead of the estimator (3), we apply a minimal regularization to the signal model, which is guaranteed not to cause any significant distortion in the signal (under-regularized with high certainty). With these estimators, the cost function can be calculated and pthe minimum can be determined as a function of the parameter set.

$$\text{cost}^* = \frac{T_s}{N_f}\sum_{k=0}^{N_f-1} |X_{\text{model}}(\text{k})|_0^2 \left|1-H(k)K\left(k,\underline{p}_0\right)\right|^2 + \frac{T_s}{N_f}\sum_{k=0}^{N_f-1} |N_{\text{model}}(\text{k})|^2 \left|K\left(k,\underline{p}_0\right)\right|^2$$

With this _p_0parameter, the signal spectrum model can be further refined:

$$|X_{\text{model}}(f)|_{m+1} = \left|Z(f)K\left(f,\underline{p}_m\right)\right|.$$

The iteration described in Equations (4) and (5) must be continued until the predefined stop condition is met. Experience shows that a few (5-10) iteration steps are sufficient. At the end of the iteration, the signal reconstruction can be obtained as follows:

$$\hat{x}(i) = \text{real}\left\{\text{IDFT}\left\{Z(f)K\left(f,\underline{p}_{\text{végleges}}\right)\right\}\right\},$$

where IDFT denotes the inverse discrete Fourier transform. With the above algorithm, the parameters of the inverse filter can be calculated automatically without user intervention. Wealso build the necessary models automatically from the spectrum of measurements.

2.2 Automatic inverse insertion of two-dimensional signals

WE also extended the method to the inverse filtering of two-dimensional signals (images) by parametric methods. In this case, the cost function shifts to a double sum corresponding to the two-dimensional spectrum:

$$\text{cost}^* = \frac{1}{N_k N_l}\sum_{k=0}^{N_k-1}\sum_{l=0}^{N_l-1} |X_{\text{model}}(k,l)|^2 |1 - H(k,l)K(k,l,\underline{p})|^2 + \\ + \frac{1}{N_k N_l}\sum_{k=0}^{N_k-1}\sum_{l=0}^{N_l-1} |N_{\text{model}}(k,l)|^2 |K(k,l,\underline{p})|^2.$$

2.3 Treatment of distortion and uncertainty for equivalent sampling systems

In the case of periodic signals during equivalent sampling, the signal is not scanned for adjacent samples, but the property that the signal has the same phase position in later periods due to periodicity is taken and the next sample is taken from a later period. This results in a very high apparent (equivalent) sampling frequency, but requires extra precise timing to determine the time of sampling and the actual execution of the sampling. This method is used in ultrafast sampling oscilloscopes.

WE have developed an algorithm that reduces the distortion caused by jitter (sampling time instant uncertainty) and gives the uncertainty caused by jitter as a time-dependent uncertainty band around the estimated signal.

The jitter can be modeled with a non-stationary additive noise (noise dependent on the derivative of the signal). WE took into account that the measurement is even loaded with a normally stationary noise component (quantization noise, electromagnetic interference, thermal noise, etc.). To reduce the effect of quantization noise, many periods are usually averaged, the effect of which can be described as a low-pass filter. The weight function describing the distortion is a function of the probability density of the time distribution of the jitter. This, in addition to non-stationary noise, also carries a jitter-dependent distortion in the signal. My goal is to reduce the distorting effect of jitter by deconvolution and to derive the uncertainty of compensation. The estimate can be written in the frequency range:

$$X_{\text{est}}(f) = X(f)H(f)H_j(f)K(f) + N_j(f)K(f) + N_s(f)K(f) = \\ = X(f) + \underbrace{X(f)\big(H(f)H_j(f)K(f) - 1\big)}_{\text{bias}} + \underbrace{N_j(f)K(f) + N_s(f)K(f)}_{\text{noise}},$$

where bias is the distortion, noise is the stochastic term. In the inverse filtering, WE consider the distortion effect of both the finite bandwidth and the jitter in the frequency range.

WE have developed an algorithm that WE can use to efficiently estimate the uncertainty caused by jitter. When estimating noise levels, WE assume a jump-like excitation. This is common when calibrating ultrafast oscilloscopes and other high frequency devices. After the settling time, the signal contains mostly stationary noise, the effect of jitter is negligible. The variance of stationary noise can be estimated by the corrected standard deviation of the (┤empirical std_ at a given point in time in this section ├ _s (t_"topline ")^2). The steep run-up of the jump section contains both stationary and jitter-dependent noise. The empirical standard deviation obtained from this section gives an estimate of the combined variance of the two noises (std_- n_o (t_"edge")^2). In both cases, the variance estimator is derived from a series of signals taken from different sample registers at a given time in the periodic signal. The two noises are independent of each other, so the following estimator can be given for the scatter of the amplitude noise caused by jitter:

$$std\_n_j\left(t_{edge}\right) = \sqrt{std\_n_o^2\left(t_{edge}\right) - std\_n_s^2\left(t_{topline}\right)} \quad ,$$

where t_"edge " the rising edge and t_"topline " post-settling roof line signal segments denote a given time instant, and std_n is the standard deviation estimator. (Here, WE estimate the scatter of the jitter noise to be zero if the scatter of the roof line were greater than that of the rising edge.) WE extrapolate the jitter noise over the time domain based on the derivative of the signal:

$$std\_n_j(i) = diff\ \{y_n(\mathrm{i})\}\frac{std\_n_j(t_{edge})}{diff\ \{y_n(i)\}|_{t_{edge}}},$$

where diff is the centrally calculated finite difference. The next step is to transform this standard deviation to the output of the inverse filter:

$$\text{std\_n}\ n_{s,invfit\ h} = std\_n_s\sqrt{\frac{1}{N_f}\sum_{k=0}^{N_f-1}} \ |K(k)|^2,\ \text{std\_n}\ n_{j,\,\text{inffit}}\,[i] = \sqrt{\text{std\_}n_j^2(i) * k^2(i)},$$

where k(i)denotes the weight function of the inverse filter and convolution. *Since the two noises are independent of each other, the standard deviations can be summed squared. Based on these, WE give the uncertainty band corresponding to the given confidence level with the following expression:

$$\text{uncert\_}\ x_{\text{est, invfitt}}\,(i) = b\sqrt{std\_n_{s,\,\text{invfit}}\ \ {}^2 + std\_n_{j,\,\text{invfit}}\,(i)^2},$$

where uncert_ x_"est,invflt " (i)is the uncertainty of the signal reconstruction, the bmultiplication factor carries the level of confidence to which the uncertainty band corresponds.

2.4 Application of inverse puncture for marker-based motion analysis for long exposure times

Many engineering tasks require measurement of position and orientation, such as motion analysis in sports or medical diagnostics, robot control, analysis of mechanical structures. One common method for this is marker-based optical measurement. One or more passive or active markers are placed on the object to be examined and the movement is monitored with a camera. Image of markers Spherical markers are preferably used on the camera sensor to examine circular motion in 3D. Its position is considered to be the center of the marker image, which is most often calculated with a geometric centroid. In poor lighting conditions, a long exposure time is required to achieve the correct signal level. In this case, depending on the speed of the movement, the marker image will blur and the marker will “pull”. For the blurred marker image, Wederived the error of the center estimate computed with the geometry centroid for both the point and extensive markers. Wehave shown that the distortion depends on the frequency of the movement. The distortion can be compensated if necessary:

$$H(f) = \frac{\sin(\pi f\tau)}{\pi f\tau}, \quad H_{inv}(f) = \begin{cases} \dfrac{\pi f\tau}{\sin(\pi f\tau)} & \text{ha } 0 < f < \dfrac{f_s}{2} \\ 1 & \text{ha } f = 0 \end{cases}$$

where τis the exposure time. Distortion is interpreted as the decrease in amplitude of the Fourier components of marker motion. The above relationship allows you to design the measurement (exposure time, aperture, ISO sensitivity adjustment) depending on the lighting conditions, the speed of movement, and the desired accuracy. Given that the distortion is known, we have the possibility to compensate for it (inverse filtering). Thesis 1 WE have developed methods for solving deconvolution problems. WE have provided an algorithm for the automatic setting of regularization parameters of parametric deconvolution methods. WE have provided a solution to compensate for frequency-dependent distortion caused by aperture jitter during equivalent sampling of ultra-fast sampling devices and to determine the uncertainty of the reconstruction. WE derived the error of marker-based position measurement for a long exposure time.

2.5 Deconvolution methods for system identification

System identification means the detection of signal path distortion during signal reconstruction. Nonparametric system identification determines the weight function of the linear and time-invariant system at each sampling time point. This, like signal reconstruction, is a deconvolution task. During the identification, the excitation of the system is controlled, the output is measured, and the weight function is estimated from it. If the shape of the excitation signal is not known with high accuracy or the stability of the signal generator is not ensured, the excitation signal must also be measured back. This measurement is an additional source of error that can be modeled with an input additive measurement noise. (Noise is only measurement noise, so the system is excited by the noise-free signal.)

Wealso derived the automatic parameter optimization of the deconvolution problem for the case of identification. To do this, we need to write a cost function according to (4), taking into account that both output and input measurement noise are burdened by the observation:

$$\begin{aligned}\text{cost}^* \quad &= \frac{T_s}{N_f}\sum_{k=0}^{N_f-1} |H_{\text{model}}(k)|^2 \left|1 - X_n(k)K\left(k,\underline{p}\right)\right|^2 + \\ &+ \frac{T_s}{N_f}\sum_{k=0}^{N_f-1} \left(\left|N_{y,\,\text{model}}(k)\right|^2 + \left|N_{x,\,\text{model}}(k)\right|^2 |H_{\text{model}}(k)|^2\right)|K(k,\underline{p})|^2,\end{aligned}$$

where |N_(x," model ") (f)|it describes the spectral model of X_n (f)the input, output noise, |N_(y," model ") (f)|the (noisy) measured excitation signal, K(f,p)the inverse filter. |H_"model" (f)|a model of the absolute value of the transfer function, which is continuously refined by an iterative algorithm as described in Thesis 1. The initial estimate |H_"model" (f)|_0=|Y_n (f)/X_n (f)|, or a minimally regularized version of it, is given by Y_n (f)the spectrum of the noisy output. The cost function (14) _pis minimized according to a set of parameters, which gives an estimate of the optimal regularization parameters of the weight function for given models. The absolute value of the Fourier transform of this weight function provides the model estimator for the next iteration step:

$$|H_{\text{model}}(f)|_{m+1} = \left|\frac{Y_n(f)}{X_n(f)} R\left(f,\underline{p}_m\right)\right|.$$

Here R(f,_p)=K(f,_p)X_n (f)is the regularizing function. The iteration is continued until the regularization parameters are set (typically steps 5-10). The stabilized parameters give the estimated optimum of the regularizing operators of non-parametric identification:

$$\widehat{H}(f) = Y_n(f)K\left(f,\underline{p}_{\text{final}}\right) = \frac{Y_n(f)}{X_n(f)} R\left(f,\underline{p}_{\text{final}}\right).$$

This can also handle the automatic parameter optimization of the deconvolution problem, which includes both output and input noise. The method is also suitable for modeling the uncertainty of the weight function assumed to be known in the case of a signal reconstruction task. Thesis 2 WE have developed a new method for parameter estimation of non-parametric identification regularization operators.

2.6 Signal model-based reconstruction

The efficiency of the signal reconstruction is increased if the excitation of the system can be written in the form of a finite parameter signal model. Immunity to noise during reconstruction is provided by the finite degree of the model. Such excitation signals can also be used for diagnostic purposes, where the properties of the system under test can be deduced from the distortion of the waveform.

One of the most common such test signals is the periodic signal, which can be detected by a few sinusoidal components (multisine). The harmonic components in the spectral range can be calculated using DFT. An alternative implementation of spectral resolution is the recursive Fourier analyzer based on observational theory [12], which can be effectively applied to implementation in embedded systems. Due to the recursive calculation, the structure requires little computation and is robust to disturbances and computational errors. Another advantage of DFT over its filter bank is that it can be freely tuned. This eliminates the need to ensure that the sampling frequency is set exactly to the fundamental harmonic of the signal. This is beneficial in several ways. On the one hand, in embedded systems (and other sampling systems as well), the sampling frequency cannot be tuned to arbitrarily fine resolution, thus ensuring leak f_s/N-free spectrum estimation with stepwise DFT. On the other hand, the frequency of the signal to be observed is not necessarily known in advance.

To tune to an unknown frequency, an estimate of the Fourier coefficient of the assumed fundamental harmonic channel must be observed. In the case of a frequency error, this complex revolves around a number plane. The rotation speed is proportional to the frequency error. Measuring this gives you the opportunity to retune the basic functions of the filter bank. This procedure is called the Adaptive Fourier Analyzer (AFA) [13]:

$$\omega_{1,n+1} = \omega_{1,n} + \frac{1}{N}\text{angle}\left(\hat{X}_{1,n+1}, \hat{X}_{1,n}\right)$$

where ω_(1,n)denotes the estimate of the circular frequency of the fundamental harmonic of the signal n. in step, X ̂_(1,n)denotes the output of the integrator of the channel corresponding to the fundamental and the angle (...) is the angle between the two complex numbers. The Adaptive Fourier Analyzer provides the ability to efficiently detect a multisine signal and measure its parameters at an unknown or slow-creeping frequency (short-term instability).

2.7 New frequency adaptation algorithm for the Adaptive Fourier Analyzer

Divides the correction of the frequency error into steps for immunity to noise .NThe following suggestions have been made in the literature for robust versions of this:

Robust AFA (rAFA): Divide the frequency error correction N·Q_"damp,AFA " stepwise.

Improved robust AFA (irAFA)Comparison of the mean of four consecutive Fourier components in the measurement of frequency error [14] [15].

comparison of spaced Fourier components when measuring frequency error [16].

As a combination of the above methods, WE proposed a new frequency adaptation algorithm that simultaneously introduces the previous methods:

Extended improved robust AFA (eirAFA):

$$\omega_{1,n+1} = \omega_{1,n} + \frac{1}{N \cdot P \cdot Q_{\text{damp},AFA}}\text{angle}\left(\hat{X}_{\text{aver}\,(1,n)}, \hat{X}_{\text{aver}\,(1,n-P)}\right), \quad \hat{X}_{\text{aver}\,(1,n)} = \frac{1}{B}\sum_{b=1}^{B} \hat{X}_{1,n+1-b}.$$

By tuning the three parameters $\left(P, B, Q_{\text{damp}}\right)$, different aspects can be emphasized.

2.8 Application of Adaptive Fourier Analyzer for testing AD converters

where τis the exposure time. Distortion is interpreted as the decrease in amplitude of the Fourier components of marker motion. The above relationship allows you to design the measurement (exposure time, aperture, ISO sensitivity adjustment) depending on the lighting conditions, the speed of movement, and the desired accuracy. Given that the distortion is known, we have the possibility to compensate for it (inverse filtering). Thesis 1 WE have developed methods for solving deconvolution problems. WE have provided an algorithm for the automatic setting of regularization parameters of parametric deconvolution methods. WE have provided a solution to compensate for frequency-dependent distortion caused by aperture jitter during equivalent sampling of ultra-fast sampling devices and to determine the uncertainty of the reconstruction. WE derived the error of marker-based position measurement for a long exposure time.

2.9 Application of inverse puncture for marker-based motion analysis for long exposure times

To determine the static and dynamic properties of AD converters, the system is excited by a high-purity sine signal. The properties of the measured signal are calculated from the deviation from the reference signal, where the reference signal is provided by sine fitting to the measured signal. The accuracy of the measurement can be increased by increasing the number of sampled points. For very long sample records (millions of samples), the parameter sensitivity of sinusoidal matching is greatly increased with respect to the initial frequency estimator. Therefore, instead of sinusoidal matching, wedeveloped an adaptation of the Adaptive Fourier Analyzer, which is able to indicate the short-term instability of the signal generator and to monitor and compensate it if required. The algorithm is summarized in Table I. The above features also allow the built-in AD converter of the microcontroller or DSP to be efficiently tested in embedded computer systems even when the short-term and / or long-term stability of the clock of the sampling timer rather than the signal generator is not ensured.

III. CONCLUSION

We developed efficient algorithms for the current estimation required for the torque control of electric power steering of motor vehicles. This makes it possible to validate the measured current with alternative (non-current) sensors, to test its plausibility, and to replace the meter in the event of a fault. Analytical redundancy makes this possible, as the current consumption can be estimated by measuring the phase voltages and speed - knowing the physical parameters of the motor.

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