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Fredrik Gustafsson

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Fredrik Gustafsson, Rotational Speed Sensors: Limitations, Pre-processing and Automotive Applications, 2010, Instrumentation & Measurement Magazine, IEEE, (13), 2, 16-23.

<http://dx.doi.org/10.1109/MIM.2010.5438333>

Postprint available at: Linköping University Electronic Press

<http://urn.kb.se/resolve?urn=urn:nbn:se:liu:diva-55086>

Rotational Speed Sensors: Limitations, Pre-processing and Automotive Applications

Part 23 in a Series of Tutorials on Instrumentation and Measurement

Fredrik Gustafsson

Rotational speed sensors are used in a variety of applications and are known by many different names: tachometers, revolution-counters, RPM gauges, etc. There are two different principles, (i) *rotary encoders* that provide the absolute angle and (ii) *incremental rotary encoders* that give angular speed. The basic technology in such sensors is based on conductive tracks, optical reflections or magnetic field variation. The last two types are the most common today, where the latter is the dominant technology in rough environments such as automotive applications. The principle for rotational speed sensors is that a toothed wheel is attached to the rotating shaft. A magnet attached to one side causes a variation in the magnetic field that can be sensed by a Hall sensor, and the variation is converted to a square wave signal where each edge corresponds to one edge of the toothed wheel. The time between two or more edges is then registered and converted into angular speed.

Some applications, such as volume knobs in home audio equipment and speedometers, do not require particularly high resolution while other applications require varying degrees of accuracy. Examples include health condition monitoring, fault detection [1] and virtual sensors computing physical quantities such as tire-road friction and tire pressure [2], and yaw rate and absolute velocity [3]. In this paper, we will describe the computational process in more detail, with a focus on signal processing issues such as sampling, quantization effects, multi-domain signal processing aspects and the pre-processing needed to learn the manufacturing errors in the toothed wheel for very high accuracy applications.

For specific examples, our attention is directed to the particular rotational speed sensors found in cars equipped with ABS (Anti-locking Brake Systems). Since their introduction thirty years ago, these sensors have found many new applications such as Electronic

Fig. 1. Ideal toothed wheel (solid) has the angle $\alpha = 2\pi/N_{\text{cog}}$ radians between each cog. Real toothed wheels are always non-ideal with a small cog offset δ_i .

Stability Control (ESC), traction control systems, tire pressure monitoring systems (TPMS), and odometry (navigation system support) to mention a few. See the survey [4] for details and more examples.

Basic Functionality

The rotational speed sensor works as follows. A toothed (cog) wheel, see Figure 1, with N_{cog} cogs is mounted on a rotating shaft.

Initially we assume that the toothed wheel is ideal, so the angle between each tooth is $2\pi/N_{\text{cog}}$. The sensor gives a sinusoidal signal with varying amplitude and frequency, which is converted in a comparator to a square wave with constant amplitude. Each edge in this signal corresponds to an edge of a tooth. The time when tooth k is passing is denoted t_k . The corresponding angle is denoted $\varphi_k = k \frac{2\pi}{N_{\text{cog}}}$. The angle can also be given as a function of time $\varphi(t_k)$. Here, we encounter the problems of having two different domains: the angle domain and the time domain. Since the square wave is synchronized with the angle, the angle domain is to be preferred in many cases. One can say that the angle is sampled equidistantly in angle, where the *sample interval* is $\alpha = \frac{2\pi}{N_{\text{cog}}}$. The different domains are summarized in Table 1.

The angular speed $\omega(t_k)$ at time t_k can now be approximated as

$$\hat{\omega}_k = \frac{2\pi}{N_{\text{cog}}(t_k - t_{k-1})}. \quad (1)$$

This is the basic formula that will be analyzed in the following. Note that the absolute angular speed (the direction of rotation is not observable) is measured in the cog domain, not the time domain. The main computational problems that perturb the result are:

Table 1. Definitions of the different domains

Domain	Index	Angle	Angular speed	Index interval
Time	t	$\varphi(t)$	$\omega(t)$	—
Sample index	n	$\varphi(nT_s)$	$\omega(nT_s)$	T_s
Timer index	m	$\varphi(mT_c)$	$\omega(mT_c)$	T_c
Angle index	k	$k\alpha$	—	$\alpha = \frac{2\pi}{N_{\text{cog}}}$

- **Sampling time effects.** The sensor provides a square wave signal that corresponds to equidistant sampling in the angular domain. However, most applications are based on equidistant sampling in the time domain, defined by the sampling instants $t = nT_s$, where T_s is the sampling interval. Approximations are needed to convert from one domain to the other.
- **Quantization effects.** The exact times t_k cannot be determined. A counter based on a fast internal clock with cycle time T_c is used to approximate t_k with $m_k T_c$, where m_k is the number of clock cycles, but there is still a time jitter.
- **Non-ideal teeth.** As indicated in Figure 1, small manufacturing errors δ_i , $i = 1, 2, \dots, N_{\text{cog}}$, produce small angular deviations in the tooth positions that perturb the computed angular speed signal (1).

Sampling and Resampling

As noted previously, the basic expression (1) provides angular speed equidistantly in the angle domain. It is, however, in most cases more natural to interpolate the values to pre-specified points in other domains.

Interpolation and Resampling

First consider interpolation to the time domain. Any standard interpolation method can be used, such as linear interpolation

$$\hat{\omega}(t) = \frac{(t_{k+1} - t)\hat{\omega}_k + (t - t_k)\hat{\omega}_{k+1}}{t_{k+1} - t_k}, \quad (2)$$

where $t_k \leq t \leq t_{k+1}$. In particular, equidistant sampling is possible by letting $t = nT_s$, where T_s is the sampling interval. Note, however, that the sampling theorem requires the continuous time signal to be bandlimited to avoid aliasing. Even if the true $\omega(t)$ is bandlimited, the sampling process in (1) may induce aliasing. A remedy to this is given in Section *Integrated Sampling*.

Multi-Domain Signal Processing

There may be other domains of interest. For instance, shafts are often connected to other shafts through gears, and then there are at least two different angle domains. One should be careful when defining the time sequences for the cog events. We will use superindices to distinguish different cog domains, so $t_m^{(2)}$ denotes the time when the angle is $m\alpha^{(2)}$ in the second domain, corresponding to the m^{th} edge of the toothed wheel. If the sensor is located in one angle domain, samples equidistant

in this domain can be converted to the other one using the gearing ratio r and the formula

$$\varphi^{(2)}(t_m^{(2)}) = \varphi_m^{(2)} = m\alpha^{(2)}, \quad (3)$$

$$t_m^{(2)} = \frac{(m\alpha^{(2)} - kr\alpha^{(1)})t_{k+1}^{(1)} + ((k+1)r\alpha^{(1)} - m\alpha^{(2)})t_k^{(1)}}{\alpha^{(1)}}, \quad (4)$$

where k is chosen such as $kr\alpha^{(1)} \leq m\alpha^{(2)} \leq (k+1)r\alpha^{(1)}$. Now, the basic formula (1) can be applied using the time instants defined above.

Synchronous Averaging

Synchronous averaging is a technique to monitor vibrations in shafts. The idea is to average the angular speed over the revolutions. This can be done numerically in a simple way by putting the angular speeds in a matrix with N_{cog} columns, where each row corresponds to equidistant angular sampling of one complete revolution. By averaging over the rows, time-varying deterministic components and measurement noise will be attenuated, and only the superimposed vibration modes are left. This principle is described in [5]. Section *Fault Diagnosis* summarizes one application where a whole gear box is monitored for faults using one rotational speed sensor and the known gearing ratios.

Integrated Sampling

To elaborate on the idea, consider first a standard sampling example where a continuous time signal $y(t)$ is to be sampled to $y_k \leftrightarrow y(t_k)$ where $t_k = kT_s$. A standard sampler includes a hold circuit that integrates the signal over a short time Δ , so

$$y_k = \frac{1}{\Delta} \int_{t-\Delta}^t y(\tau) d\tau.$$

Integrated sampling, on the other hand, integrates over the whole sampling period,

$$y_k = \frac{1}{T_s} \int_{t-T_s}^t y(\tau) d\tau.$$

There are certain disadvantages with the latter from a sampling theory perspective, but there are obvious practical advantages. First, the averaging over the sampling interval corresponds to a (non-ideal) anti-aliasing filter, so the aliasing effect is (partially) mitigated automatically. Second, the integral can be recovered exactly

$$\int_0^{kT_s} y(\tau) d\tau = \sum_k y_k T_s, \quad (5)$$

which follows from the elementary properties of the integral. The most immediate drawback of integrated sampling is that it gives a positive bias if the signal is decreasing and a negative bias if it is increasing. If the signal is linearly increasing/decreasing in the sample interval, which constitutes a first order approximation, it can be written $y(t) = y((k-1)T_s) + (t - (k-1)T_s)\dot{\omega}$, where $\dot{\omega}$ denotes the true angular acceleration, and integrated sampling will give the value $y_k = y(kT_s) - \dot{\omega}T_s/2$.

For a rotational speed sensor, there is no way to include a continuous-time anti-aliasing filter, so integrated sampling is the only way to mitigate frequency folding. The basic formula (1) is then replaced with

$$\hat{\omega}(nT_s) = \frac{2\pi(k_n - k_{n-1})}{N_{\text{cog}}(t_{k_n} - t_{k_{n-1}})}, \quad (6)$$

where t_{k_n} denotes the time when the last cog k_n passed before time $t = nT_s$. The integral property (5) is preserved in this formula, which means that the angle can be recovered by summing $\hat{\omega}(nT_s)$ over time (except for the facts that the initial condition might not be known and the direction of speed might change unnoticed). All in all, integrated sampling should be preferred generally. We will return to the formula (6) in the next section.

Frequency Analysis

Frequency analysis is a classical tool in signal processing to detect resonances and dynamic effects in linear systems. The Discrete Fourier Transform (DFT) is the main tool here. For the computed wheel speed, it is defined as

$$\Omega_1(f) = \sum_{n=1}^N \hat{\omega}(nT_s) e^{-2\pi f n}, \quad f = i/(NT_s). \quad (7)$$

The advantage of this formulation is that the computationally efficient FFT (Fast Fourier Transform) algorithm can be used, and the minor drawback is that the integrated sampling principle has to be used. The alternative is to approximate the Fourier integral by a Riemann sum in the following way

$$\Omega_2(f) = \int \omega(t) e^{-2\pi f t} dt \quad (8a)$$

$$\approx \sum_{k=1}^N \hat{\omega}_k(t_k - t_{k-1}) e^{-2\pi f t_k} \quad (8b)$$

$$= \frac{2\pi}{N_{\text{Ncog}}} \sum_{k=1}^N e^{-2\pi f t_k}, \quad f = i/(NT_s), \quad (8c)$$

using $\hat{\omega}_k$ defined in (1). Note here that the integrand collapses since $\hat{\omega}_k(t_k - t_{k-1}) = 2\pi/N_{\text{Ncog}}$ by definition. Instead, the time indexes t_k enter the exponential function and thus propagate the frequency information.

In practice, the difference between (7) and (8) is small, and (7) is to be preferred in off-line applications due to the speed of the FFT algorithm while (8) is best in on-line applications due to its simplicity.

There is, however, an interesting definition of the DFT in the cog domain. The idea is to transform the time intervals

$$\Omega_3(f) = \sum_{k=1}^N (t_k - t_{k-1}) e^{-2\pi f t_k}, \quad f = i/(NT_s). \quad (9)$$

We will refer to the magnitude $|\Omega_3(f)|$ as the ‘‘cog spectrum’’. Note, that this definition is confusingly similar to (7) and (8) above, but its properties are different as will be demonstrated later on.

Fig. 2. Illustration of the different event domains: angle index k , sample index n and timer index m (dots on the line). When a new sample interval starts, the sensor waits for the next pulse from the cogs that defines time t_k and angle $\varphi_k = 2\pi k/N_{\text{cog}}$. The clock value is read as an approximation $\hat{t}_k$ of t_k . The rotational speed can then be computed according to (1).

Quantization Effects

We now focus on how the time in the basic expression (1) is measured and on the induced quantization effects.

Timer Clock

In practice the exact time instants t_k are not available. Instead, a counter triggered by a fast oscillator/clock is used to measure time. Let the duration of one clock cycle be T_c . To explain the quantization problems associated with this, consider Figure 2. As soon as a pulse is received at time $t_n \geq nT_s$, the value m_n of the clock counter is read. This value corresponds to cog number k_n . The cog time t_n is then approximated as $\hat{t}_n = m_n T_c$. Then, the computed angular velocity corresponding to integrated sampling in (6) is

$$\hat{\omega}(nT_s) = \frac{2\pi(k_n - k_{n-1})}{N_{\text{cog}}(\hat{t}_{k_n} - \hat{t}_{k_{n-1}})} = \frac{2\pi(k_n - k_{n-1})}{N_{\text{cog}}(m_n - m_{n-1})T_c}. \quad (10)$$

As a side note, one must treat counter overflow properly when evaluating $m_n - m_{n-1}$. The difference has to be taken modulo the maximum counter value. A further practical issue is to remove outliers due to missing or extra pulses, which can be done by monitoring the feasibility of the computed speed compared to the previous values.

Statistical Quantization Analysis

Formula (10) compared to (6) suffers from *quantization noise* due to clock jitter. We have

$$t_i - \hat{t}_i \in [0, T_c), \quad (11)$$

for $i = 1, 2$. It is reasonable to assume that the error is uniformly distributed between 0 and 1, that is

$$\frac{t_i - \hat{t}_i}{T_c} \in U(0, 1). \quad (12)$$

Since the difference $\hat{t}_k - \hat{t}_{k-1}$ contains the difference of two uniform distributions (an independence assumption is always justified in practice), it becomes an unbiased estimate of $t_k - t_{k-1}$ with triangular error distribution. The variance of $U(0, 1)$ is $1/12$, so the variance of the difference is twice that value, which implies

$$\text{Var}(\hat{t}_k - \hat{t}_{k-1}) = \frac{T_c^2}{6}. \quad (13)$$

It follows that the variance of the inverse angular frequency is

$$\text{Var}\left(\frac{1}{\hat{\omega}}\right) = \frac{T_c^2}{6} \left(\frac{N_{\text{cog}}}{2\pi(k_n - k_{n-1})}\right)^2 \approx \frac{T_c^2}{6\omega^2 T_s^2}. \quad (14)$$

The variance of $\hat{\omega}$ in (10) depends on its expected value. A first order Taylor expansion using the notation $\hat{\omega} = \omega + \tilde{\omega}$, where ω is the mean and $\tilde{\omega}$ is a zero mean stochastic variable, gives

$$\frac{1}{\hat{\omega}} = \frac{1}{\omega + \tilde{\omega}} = \frac{1}{\omega(1 + \frac{\tilde{\omega}}{\omega})} \approx \frac{1}{\omega} \left(1 - \frac{\tilde{\omega}}{\omega}\right) \Rightarrow \quad (15a)$$

$$\tilde{\omega} = \omega \left(\frac{1}{\hat{\omega}} - \frac{1}{\omega}\right) \quad (15b)$$

This first order expansion indicates that $\tilde{\omega}$ is zero-mean with variance

$$\text{Var}(\hat{\omega}) = \text{E}(\tilde{\omega})^2 = \omega^2 \text{Var}\left(\frac{1}{\hat{\omega}}\right) \approx \frac{T_c^2}{6T_s^2}. \quad (16)$$

The mean square error is a trade-off between bias and variance. We have

$$\begin{aligned} \text{MSE} &= \text{E}((\omega(nT_s) - \hat{\omega}(nT_s))^2) \\ &= (\omega(nT_s) - \text{E}[\hat{\omega}(nT_s)])^2 + \text{Var}(\hat{\omega}(nT_s)). \end{aligned} \quad (17)$$

Using the linear approximation

$\omega(t) = \omega((k-1)T_s) + (t - (k-1)T_s)\dot{\omega}((k-1)T_s)$ of the true signal, we get the concrete formula

$$\text{MSE} = \frac{\dot{\omega}^2 T_s^2}{4} + \frac{T_c^2}{6T_s^2}. \quad (18)$$

There is thus a trade-off between getting a small bias and small variance when choosing the sample interval T_s . A rule of thumb is thus that the sampling interval T_s should be small compared to the maximum rate of change of $\omega(t)$ to avoid a large bias, and the clock interval T_c should be small compared to T_s to avoid excessive variance. What “small” is quantitatively depends on the accuracy the application requires.

The bias and variance will propagate to all subsequently defined quantities, as for example the frequency domain expressions (7)–(9).

Saturation Effect

There is also an important *saturation effect* here. If the angular speed is too small compared to the sample interval, then (10) collapses, since no pulse will be available. The condition for

Fig. 3. Cog spectrum $\text{DFT}(t_k - t_{k-1})$ where the signal component from speed variations is concealed in the $2N_{\text{cog}}$ peaks caused by the cog errors. The lower plot shows the estimated cog errors $\hat{\delta}_i$, $i = 1, 2, \dots, 2N_{\text{cog}}$ as an error bar plot, where the standard deviation is shown for each cog error.

this not to happen follows from (10) setting $k_n - k_{n-1} = 1$ and using $(m_n - m_{n-1})T_c \approx T_s$ as

$$\omega \geq \frac{2\pi}{N_{\text{cog}}T_s}. \quad (19)$$

This gives a lower bound on the sampling interval for a given minimum speed. As a practical consequence of this, the ABS has to be turned off for low speeds. A remedy would be to sample the analogue sensor signal, rather than converting it to a square wave, and use the phase information, but this would affect the price of the sensor.

Cog Error Compensation

The wheel speed computed as in (10) is sufficient for most applications. However, in high-precision applications, where very accurate wheel speed information is needed, more sophisticated signal processing is required. The general principles are described below and are documented further in [6, 7].

Principles

The main reason for the limited precision in (10) is the cog errors $\{\delta_k\}_{k=1}^{2N_{\text{cog}}}$ illustrated in Figure 1. The true angle to the k^{th} edge on the toothed wheel can be written as $\frac{2\pi}{N_{\text{cog}}} - \delta_{k \bmod 2N_{\text{cog}}}$. Without compensation, the computed wheel speed would be

$$\hat{\omega}_k = \left(\frac{2\pi}{N_{\text{cog}}} - \delta_{k \bmod 2N_{\text{cog}}} \right) \frac{1}{t_k - t_{k-1}}. \quad (20)$$

A simple turn-around is to measure the time for one complete revolution,

$$\hat{\omega}_k = \frac{2\pi}{N_{\text{cog}}(t_k - t_{k-N_{\text{cog}}})}. \quad (21)$$

The idea is that the sum of errors $\sum_{i=1}^{N_{\text{cog}}} \delta_i = 0$ is zero and cancels out over one revolution. However, for a changing true speed, this introduces a significant bias that might not be tolerated in high-accuracy applications.

A better idea is to estimate the cog errors and replace $\delta_{k \bmod 2N_{\text{cog}}}$ in (20) with this estimate. Once the $\{\hat{\delta}_k\}_{k=1}^{2N_{\text{cog}}}$ sequence is estimated, the angular speed in (1) can be estimated by

$$\hat{\omega}_k = \left(\frac{2\pi}{N_{\text{cog}}} - \hat{\delta}_{k \bmod 2N_{\text{cog}}} \right) \frac{1}{t_k - t_{k-1}}. \quad (22)$$

An Example

Figure 3 illustrates the problem using time stamps t_k from an ABS sensor with $N_{\text{cog}} = 48$ cogs, where both edges are used and $T_c = 4 \cdot 10^{-7}$. The test drive was deliberately designed with almost constant speed. The upper plot shows the cog spectrum as defined in (9), where the bias (0 Hz) component corresponding to the speed has been removed. The spectrum shows various vibration modes as will be described in Section *Frequency Analysis*, but more importantly there are $2N_{\text{cog}}$ distinct strong peaks corresponding to the Fourier series of the sequence $\{\delta_k\}_{k=1}^{2N_{\text{cog}}}$. These dominate the rather weak signal components, and further frequency analysis clearly requires compensation. The possibility of highlighting cog errors is a key property of the cog spectrum in (9).

The lower plot in Figure 3 shows the estimated cog errors in an errorbar plot with standard deviations computed as the inverse Fourier series of the peaks in the upper plot. The standard deviation is much smaller (almost invisible

confidence interval), so the errors are significant. It should be remarked that this approach only works when the speed is constant. A better way to compute these errors is to use synchronous averaging as described in Section *Synchronous Averaging*.

Figure 4 shows the result of cog error compensation in the frequency domain. In this case, where the true speed is almost constant, the cog and time spectra look similar. However, the more the speed varies, the more important this pre-processing is.

Automotive Applications

Virtual Yaw Rate Sensor

A fundamental formula, used in odometry, for instance, computes the yaw rate $\dot{\psi}$ from the left and right wheel speed signal,

$$\dot{\psi} = \frac{\omega_l r_l - \omega_r r_r}{B}. \quad (23)$$

Here, ω_r denotes the right wheel speed, r_r the right wheel radius, similarly for the left side, and B is the wheel base. This

Fig. 4. (a) Cog spectrum as in Figure 3, where the time stamps are compensated with the estimated cog errors. (b) Spectrum of the speed estimate in (22).

Fig. 5. Speed on outgoing axle interpolated to the cog domain for an axle inside the gearbox. The upper plot shows the vibration for a fault free axle, and the lower plots the vibration for an axle with a faulty cog for two batches of data with different speeds. (The phase is not synchronized here, so the peak turns up at random places)

is a virtual yaw rate sensor, as an alternative to a gyroscope; see [4] for a derivation. Suppose the radii are the same, $r_r = r_t$. Then it is clear that the wheel speed difference loses many of its most significant digits. Intelligent pre-processing is clearly needed in order to make this virtual sensor useful. This virtual yaw rate sensor requires free-rolling wheels. In case of braked or driven wheels, one has to compensate for wheel slips, which further complicates the algorithm.

Health Monitoring and Imbalance Detection

The estimated sequence $\hat{\delta}_i$, $i = 1, 2, \dots, 2N_{\text{cog}}$ of cog errors illustrated in Figure 3 can be used for health monitoring of the shaft and its attached rotating parts (such as wheels). Any imbalance will show up as a low order trigonometric function in the lower plot in Figure 3. Conversely, it can be detected from significantly larger Fourier series peaks in the upper plot of Figure 3 for small indexes. For instance, attaching a single weight to a well balanced wheel would give a sinusoidal shape of the lower plot in Figure 3 and a clear peak at the first frequency of the upper plot in Figure 3. Statistical tests can be designed to detect if the first component is significantly larger

than the other ones. The threshold for this can be designed based on the variance of the quantization noise. The sensitivity to imbalance is another useful application of the cog spectrum in (9).

Frequency Analysis

Consider now the DFT expressions for the angular speeds in (7) and (8). First, the angular speed multiplied by the tire radius gives the absolute speed of that tire. The absolute speed is a low frequency component, and the high-frequency content is due to other phenomena. The tire dynamics can be modeled by three springs for torsional and radial forces in the tire rim and the radial forces in the tire tread. Table 2 indicates the three modes. There is also wide-band noise induced by the road surface and low-frequency disturbances from the spring-damper system. Further, narrow-band disturbances such as harmonics of the different rotating parts in the drive-line can sometimes be observed.

The lower plot in Figure 4 illustrates all of the noise components in Table 2 except for mode 3 which happens to be quite small for this tire.

Table 2. Frequency spectrum (7) (or (8)) for the wheel speed signal where different physical sources are given, with approximate limits in Hz. Here, mode refers to oscillation modes in the tire.

0–10	10–15	15–30	30–60	60–80	80–100	100–
Speed	Mode I	Noise	Mode 2	Noise	Mode 3	Noise
Damper	Narrow-band noise components					

Fault Diagnosis

We present an example of fault diagnosis with a result from [1] where synchronous averaging as described in Section *Synchronous Averaging* is used. This reference investigates fault detection in gear boxes for commercial vehicles after manufacturing and before installation. A certain test program is applied to all gear boxes, where the speed is changed and the gear is shifted in a pre-determined manner. An experienced human tester can generally detect a fault just by listening to the gear box. However, it is not always so easy to diagnose exactly which part in the gear box is broken. The principle of synchronous averaging is applicable here. The idea is to transform the measured speed signal to each angular domain in the gear box. There are seven axes in this gear box, thus seven transformations are needed. Figure 5 illustrates one domain. The upper plot corresponds to a fault-free gear box. The error signal is small, and as the histogram illustrates, the values are almost perfectly Gaussian distributed. A standard χ^2 test can thus be designed. The lower plots correspond to a faulty gear box. The short pulse disturbance indicates that one cog in the gearing is damaged, a fact that later was verified.

Summary

Rotational speed sensors are critical for all vehicular driver assistance systems and other applications such as engine control and robotics. For many embedded control systems, the accuracy of the computed speed needs to be high, and this puts special demands on the pre-processing of the sensor signal. In a wired centralized solution, the computational unit can get access to the raw square wave signal from the sensor. Without a dedicated wire, the sensor must include a timer, and the cog times t_k can be communicated to the processor. These cog times are the input to the algorithms described here, whose purpose is to calibrate manufacturing errors in the cog wheel and to interpolate the speed signal to the (usually time) domain of the application. A further purpose was to derive rules of thumb for how the sampling and quantization processes influence the bias and variance of the computed speed signal. Examples of applications to imbalance monitoring, frequency analysis applications, and fault detection were provided.

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Fredrik Gustafsson (fredrik@isy.liu.se) has been professor of Sensor Informatics in the Department of Electrical Engineering, Linköping University since 2005. He received the M.Sc. degree in electrical engineering in 1988 and the Ph.D. degree in Automatic Control in 1992, both from Linköping University. During 1992-1999 he held various positions in automatic control, and from 1999-2005 he had a professorship in Communication Systems. His research interests are in stochastic signal processing, adaptive filtering and change detection, with applications to communication, vehicular, airborne, and audio systems. His work in the sensor fusion area involves the design and implementation of nonlinear filtering algorithms for localization, navigation and tracking of all kinds of platforms, including cars, aircraft, spacecraft, UAV's, surface and underwater vessels, cell phones, and film cameras for augmented reality. He is a co-founder of the companies NIRA Dynamics (www.niradynamics.com) and Softube (www.softube.com) which develop signal processing software solutions for the automotive and music industries, respectively.

He was an associate editor for IEEE Transactions of Signal Processing from 2000-2006 and is currently an associate editor for EURASIP Journal on Applied Signal Processing and the International Journal of Navigation and Observation. In 2004, he was awarded the Arnberg prize by the Royal Swedish Academy of Science (KVA), and in 2007, he was elected member of the Royal Academy of Engineering Sciences (IVA).