sensors

Review

A Survey on Optimal Signal Processing Techniques Applied to Improve the Performance of Mechanical Sensors in Automotive Applications

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Abstract: In this paper a survey on recent applications of optimal signal processing techniques to improve the performance of mechanical sensors is made. Here, a comparison between classical filters and optimal filters for automotive sensors is made, and the current state of the art of the application of robust and optimal control and signal processing techniques to the design of the intelligent (or smart) sensors that today's cars need is presented through several experimental results that show that the fusion of intelligent sensors and optimal signal processing techniques is the clear way to go. However, the switch between the traditional methods of designing automotive sensors and the new ones cannot be done overnight because there are some open research issues that have to be solved. This paper draws attention to one of the open research issues and tries to arouse researcher's interest in the fusion of intelligent sensors and optimal signal processing techniques.

Keywords: smart sensors, optimal filtering, accelerometer, wheel speed sensor, strain gauge

1. Introduction

Today's industry is experiencing a continuous positive change from obsolete technologies of measuring or detecting physical quantities to the most advanced techniques that make use of the advances in microprocessor technology.

The reality is that, the advent of microprocessor technology initiated the requirement for sensors to have an electrical output that could be more readily interfaced to provide unattended measurement and control [1].

In short, a sensor is a device that is used to detect or measure a physical quantity and from this yield a measurable output. In addition, when the sensor is the basic element of a sensing system based on microcontroller, digital signal processor (DSP) or application-specific integrated circuit (ASIC) technologies that incorporate a certain amount of intelligence into the sensor itself, this device is called smart sensor. Also, the IEEE 1451.2 specification defines a smart sensor as a sensor that provides functions beyond those necessary for generating a correct representation of a sensed or controlled quantity [2].

Basically, what makes sensors important for us is what we do with the information coming from them. Furthermore, there are several areas where sensor technology is used. Among these areas, two of the most important ones are those aimed at using the sensors to gather information and to control systems.

On the one hand, according to Elgar [3], sensors used to gather information provide data for display purposes to give an understanding of the current status of system parameters. Also, they can be used for recording to provide a permanent account of performance or parameter variations.

On the other hand, in a control system sensors are used to measure the variables under control and the information coming from the sensors is sent to a controller, whose objective is to manipulate the input (or inputs) of the plant under control in order to make the output (or outputs) of the plant behave in a desired way.

However, in practice, the signals produced by sensors are frequently corrupted by noise that cause sensor operations to deviate from their true value, which causes an undesirable degree of uncertainty in the measurements carried out by the sensors. Therefore, in order to cancel the noise that corrupts the relevant information coming from the sensors, signal conditioning and signal processing stages are needed.

To this end, in the last decades, robust and optimal signal processing techniques have been gradually introduced in the design of smart sensors in order to transform the sensors into robust and optimal measuring systems able to perform satisfactorily in polluted environments. For example, among the worst applications for sensors are those of the automotive industry. In automotive applications, sensors have to endure dangerous chemical attacks, undesirably strong vibrations, electromagnetic interferences, high temperatures, high humidity, noise coming from other electromechanical or mechanical elements, and so on. For this reason, robustness, efficiency and reliability of sensors have been, and will continue to be, crucial for today's industry.

A number of well known and highly regarded textbooks are available in the area of optimal signal processing [4-7]. These books have a broad coverage and include the topics of filtering, linear systems, stochastic processes and models, Wiener filters, linear prediction, Kalman filters and adaptive filters, among others. Moreover, due to the continually growing need for better comfort and safety in today's cars, the applications of optimal filtering to improve the performance of the mechanical sensors have augmented quickly over the last few years. Examples of recent international publications in this area are the ones in [8-18], among others that will be discussed later in this paper.

The present paper is aimed at making a survey on the practical methods that today's automotive industry uses to suppress the noise that corrupts the relevant information coming from mechanical sensors used to measure motion, highlighting the performance of strain gauges, wheel speed sensors and accelerometers.

Here, the advantages and disadvantages of conventional signal treatment techniques are discussed, and the way the performance of mechanical sensors can be improved considerably by using robust and optimal signal processing techniques is discussed as well.

2.   Types of motion and displacement sensors

According to [19], motion sensors are designed to measure the rate of change of position, location, or displacement of an object that is occurring. If the position of an object as a function of time is *x(t)*, then the first derivative gives the speed of the object, *v(t)*, which is called the velocity if a direction is also specified, and if the speed of the object is also changing, then the first derivative of the speed gives the acceleration, *a(t)*.

The simplest type of displacement sensor is the potentiometer, and this device was already instrumental in electricity studies when W. Ohm presented his law in 1827. Since then, more variable resistance devices have been patented [20].

Potentiometers are often used where an electrical signal proportional to a displacement is required, costs should be kept low and high accuracy is not paramount [3]. However, potentiometers suffer from mechanical wear, friction in the wiper action, limited resolution in wire-wound units, and electrical noise. Also, they are only used in low frequency applications.

The most common signal conditioning stages used to carry out the treatment of the electrical signal coming from potentiometers are based on operational amplifier circuits. Examples of signal conditioning circuits for resistive sensors can be found in [3, 19, 20], among other international references.

In addition, the procedures of calibration of these sensors are very easy to carry out. Usually, such procedures of calibration are based on a comparison between the measurements carried out by the device under calibration and the measurements carried out by a working standard, which has been previously calibrated by another organization that is certified to calibrate the working standard you are using, in order to guarantee traceability. As mechanical engineers know, guaranteeing traceability is a key issue in the automotive industry.

As mentioned before, the accuracy of displacement sensors based on potentiometers is not high. Also, their uncertainty is not low. Therefore, they are not used for accurately measuring displacements.

Other types of displacement sensors are the capacitive, the inductive and the variable reluctance sensors. In the automotive industry there are many applications where these sensors can be found for the measure of linear and angular displacement. However, it is important to point out that the most commonly used sensors for accurately measuring displacements are the linear variable differential transformers (LVDTs). According to [19], a wide range of LVDTs is available with linear ranges at least from ±25 cm down to ±1 mm. In practice, LVDTs are forming part of systems which measure force, pressure and acceleration very often [3].

Most of the calibration procedures of these sensors are also based on the comparison of the measures taken by the sensors under calibration against the ones taken by working standards. The accuracy of these sensors is very high and their uncertainty is very low. Also, they are commonly used in feedback controlled systems where engineers use computer assistance to control mechanical machines. For example, in the automotive industry, they are used in apparatus to measure the deflection of bending beams, in position sensing in hydraulic cylinders, and in automotive suspension control, among other applications.

One particular useful sensor for measuring deformation of solid objects is the strain gauge. A resistive strain gauge consists of a conducting material in the form of a thin wire or strip which is bonded firmly to the object in which strain is to be detected [21]. There are many types of gauges and, in general, apart from measuring strain and displacement, they are also used as a secondary step in sensors to measure many other process variables such as pressure, force, and acceleration [19].

As a strain gauge exhibits a change in resistance when it is strained, it is necessary to transform such a change in resistance into an electrical signal. In spite of the fact that there are many ways of doing the aforementioned transformation, the most commonly used circuit for conditioning a strain gauge is the well-known Wheatstone bridge [22].

One particular calibration of strain gauges is that called Shunt Calibration, where a resistor of an unknown value is connected across one arm of the bridge (i.e., the Wheatstone bridge) creating a known arm resistance variation, then the bridge output is measured and compared against the expected voltage value. In this type of calibration, it is of paramount importance to have had calibrated the voltmeter before carrying out the calibration. Nevertheless, knowing the uncertainty of the resistor that is used in the calibration is not an important issue.

With regard to carrying out other kind of measurements, it is important to say that rotary potentiometers, optical encoders and tachometric generators are devices that are used to measure angular displacement. Information about the principles of these devices and their practical applications to the automotive industry can be found in [3, 21].

At this point, it should be highlighted that among the complete family of sensors for automotive safety, wheel speed sensors (WSS) and accelerometers stand out as two of the most important.

The electrical signals generated by the WSS used to measure the speed of rotation of the wheels of a car are regarded as one of the most important inputs to the Antilock Braking System (ABS), the Electronic Stability Program (ESP) and the Anti Slip Regulation system (ASR), among other systems that today's cars use to improve our road safety. In addition, other uses of the information from the rotational speed the car's wheels include: engine management, chassis control, transmission control and roll-over protection, among others.

Wheel speed sensors belong to the family of angular (or rotational) motion sensors, which are the perfect choice across the whole automotive applications spectrum [16]. This family of sensors consists of variable reluctance sensors, Wiegand effect sensors, Hall effect sensors, magnetoresistive sensors, anisotropic magnetoresistive sensors and giant magnetoresistive sensors. And they have many inherent advantages and sensing benefits. In short, their contactless operation, providing a long operating life and wear-free measurements and detection, high reliability, high sensitivity, unaffected by dirt or dust, relatively high operating temperature and relatively wide operating frequency range, among other

benefits, make them the best solution to carry out satisfactory measurements while working in hostile environments in automotive and industrial applications.

A detailed explanation of the principles and specific applications of the above mentioned angular motion sensors can be found in [16]. In addition, in [23] the reader can find a general explanation of the principles of these rotational motion sensors and their use in powertrain, chassis and body applications. Also, in [24] the reader can find general information about wheel speed sensors and their applications in today's cars, giving a large number of car's systems that use wheel-speed information, and some comments on the electrical circuits for both passive and active wheel-speed sensors are made. Furthermore, another reference where the reader can find general information on both linear and rotational velocity measurement is [25].

The most common and efficient way of calibrating WSS placed in a car is by making a comparison between the wheel speed indicated by the sensor under test and that indicated by a non-contact speed sensor appropriately placed in the same car. A very good example of placing and using a non-contact speed senor is the one given in [17], where a non-contact speed sensor was used as the fifth wheel of a car undergoing performance tests.

At this point, it should be pointed out that having a very low uncertainty of measurement of the WSS situated in cars is not a key issue for car manufacturers, because the exact value of any car's real-time speed depends strongly on the road coefficient of friction (μ) and this coefficient depends on many factors that do not depend on car manufacturers. For instance, μ depends on the road characteristics and on environmental factors, among others.

Finally, in the industrial world, the most common design of sensors to measure acceleration is the accelerometer design based on a combination of Newton's law of mass acceleration and Hooke's law of spring action. A number of highly regarded references are available in the area of mechanical sensors where the reader can find information about the principles of accelerometers and their applications [3, 19-21, 26, 27]. These references have a broad coverage and include traditional topics of accelerometers such as accelerometer principles and dynamics, types of accelerometers, applications, signal conditioning and classical filtering techniques applied to improve their performance.

With regard to the calibration of these sensors, it is important to say that their calibration procedures depend on the type of applications they are used in. For example, accelerometers used to measure static acceleration (e.g., gravity) have different calibration procedures from those used to measure dynamic acceleration (e.g., vibration). There is a wide variety of accelerometers that could be used in various applications depending on the requirements of range, natural frequency, damping, temperature, size, weight, hysteresis, low noise, and so on. Piezoelectric accelerometers, piezoresistive accelerometers, variable capacitance accelerometers, LVDTs, variable reluctance accelerometers, potentiometric accelerometers, gyroscopes used for sensing acceleration, strain gauges accelerometers, and microelectrical mechanical systems (MEMS), among others, are some of the numerous accelerometers. A very good calibration procedure of accelerometers is the one given in [13] and a modified version of it is given in [18].

3. Signal conditioning

In current literature on signal conditioning of mechanical sensors, the most common techniques that are used to transform a sensor output into a form necessary to interface with other elements of the process-control loop are those based on the common operational amplifier circuit configurations and, in some specific applications, the operational amplifier in conjunction with a Wheatstone bridge. In addition, in order to cancel the noise that corrupts the relevant information from the sensors, classical filtering techniques are used for analog signal conditioning and digital signal conditioning as well. The electrical circuits used by the authors in [3, 19-22, 24-28] to carry out the signal conditioning and treatment of mechanical sensors are clear examples of the above statement.

In practice, the sensors embedded in cars are buried in a broad-band noise background where we have little knowledge of the noise characteristics. Even worse is that in some cases the unwanted information and the relevant signal share the same or a very similar frequency spectrum. In these cases, the use of classical filters should be discarded [7].

Examples of mechanical noise sources are the following:

1. Vibrations of the framework, chassis, front axle, rear axle, and engine.
2. Noise generated by the vertical movement, yaw, pitch, roll, and forces and moments on each wheel.
3. Poor roads and environmental factors.
4. Driver distractions.

In addition, the mechanical vibrations have the following eigenfrequencies:

1. 1 Hz < eigenfrequencies < 3 Hz. Vibrations of the framework and the car sprung masses, vertical movement, yaw, roll and pitch.
2. 4 Hz < eigenfrequencies < 8 Hz. Vibrations of the wheels at low speed.
3. 10 Hz < eigenfrequencies < 20 Hz. Vibrations of the car sprung and unsprung masses at medium and high speed. Also, vibrations of the engine, framework, chassis, front and rear axle, etc.
4. eigenfrequencies > 20 Hz. Vibrations caused by direct actions, vibrations of the tires, etc.

Furthermore, in order to reflect real vehicle driving conditions, the variable road characteristics are treated as a random process. The above information was taken from [8-11, 13-18].

According to Anderson and Moore [7], the classical approach to filtering postulates that the useful signals lie in one frequency band and unwanted signals, normally termed noise, lie in another, though on occasions there can be overlap. Nevertheless, when there is overlap between the useful signals and the unwanted ones, it is very difficult to eliminate small-magnitude disturbance or interference, and the background noise causes serious difficulties, which is a serious drawback of classical filters.

Another disadvantage of using classical filtering techniques is that when the frequency band of the noise is close to the one of the relevant signal a very sharp cut-off region is needed, but sharp cut-off regions introduce problems such as additional delays, overshoots, undesirable amplification at some frequency range, and so on.

Butterworth, Chebyshev, Cauer (or elliptic-function) and Bessel filters are some of the landmarks in the body of classical filter design theory. A number of well known and highly regarded textbooks are available in the area of analog and digital filtering [29, 30]. In these books, the reader can find

information about the characteristics of these filters, their advantages and disadvantages, and their applications.

For those who are not electrical engineers or familiar with the classical filter design theory either, in order to understand the above three paragraphs, it is highly recommended that they read references [7, 29, 30]. The filter design theory is one of the most complex and active research area in Electrical Engineering and a scientific journal focused on Sensors is not the best place to look for information regarding the design of filters. However, in the next paragraphs, some important information about classical filters is given.

First of all, it should be mentioned that the term filter is used in many different ways in electrical engineering. An algorithm in a computer program that makes a decision on which commands and how certain commands are executed performs a filtering decision. A decision technique that estimates the input signal from a set of signals and noise is known as optimal filtering. In analog and digital signal processing, filters eliminate or greatly attenuate the unwanted portion of an input signal. Excellent information about the history of filters can be found in [29].

Second, there are two types of filter: passive filters and active filters. As we know, passive filters are limited to filters made of lossless elements: inductors, capacitors, and mutual inductances. On the other hand, active filters are superior to passive filters and the use active elements such as solid-state devices and technologies. However, both types of filters complement each other and have their places in electronic technology.

Third, in spite of the fact that active filters have proved to be practical and well-suited to solve many filtering problems, they have some limitations that make them not appropriate to cancel noise in some specific situations.

Generally speaking, the magnitude functions and the phase functions are usually dealt with separately, because the realization of a network function to achieve both a desirable magnitude function and a phase or delay function is a very difficult task. Even worse is that sometimes achieving this objective is mathematically impossible. Therefore, according to Su [29], in some applications the magnitude function is the only one that matters. Also, if both the magnitude and delay functions are important, designers usually prefer to implement the given magnitude function, as best they can, first.

The five ideal filter magnitude characteristics are the following: lowpass, highpass, bandpass, bandreject and allpass filters. The first four types of characteristics are used for their frequency-selective properties. On the other hand, the allpass filter is used mainly for its phase-linearization or delay-capabilities.

 Four, as the ideal characteristics are not realizable with finite networks, all filters can have only magnitudes that approximate the ideal characteristics. The study of methods of finding a real rational function in ω^2 to approximate an arbitrary magnitude or magnitude-square characteristic is a rather specialized area.

According to Su [29], numerous techniques using various criteria to achieve the approximation are available. Also, these general techniques are usually needed when the magnitude characteristics do not have any standard pattern, and the approximation of these general magnitude characteristics is more for general equalization purposes.

Finally, some of the best nonideal characteristics that are in common use in the classical filter design theory are the Butterworth, the Chebyshev, and the Cauer (or elliptic-function) magnitude

characteristics. They all have relative merits that make them suitable for some applications and unsuitable for others [29, 30]. Nevertheless, when what matters is the phase characteristic, Bessel-Thomson filter functions are the appropriate choice.

4.   Discussion of some practical examples of the current applications of classical filters to the automotive industry

At this point, it is important to point out that in spite of the fact that classical filters have the aforementioned problems, in many practical applications the filtering process is usually carried out by using a classical filter.

For example, in [26], it can be seen that car manufacturers usually use a 2- or 4- pole lowpass Bessel filter to suppress the noise that corrupts the information from the accelerometers. However, in [26], taking into consideration the comments made by the same author on the results of the filtering process, it cannot be said that they are 100% satisfactory. To be more specific, as mentioned by the author, there are cases in which the low-pass filter cannot suppress the noise and attenuates the relevant signal, causing serious distortions that affect the performance of crash-detection algorithms and decrease the signal-to-noise ratio (SNR) at the output of the sensing system.

To be more specific, today's cars use MEMS accelerometers for airbags. One of their advantages is the possibility of single-point sensing, reducing the system cost by removing some of the wiring and harnesses. A good example of an MEMS accelerometer is the Analog Devices ADXL50.

In this case of study, the required bandwidth of the signal does not have to be much greater than 400 Hz for impact applications or greater than 50 Hz for other applications.

In the current automotive industry [26], the worst problem that the practical accelerometer analog interface circuit design has is that when the sensor is subjected to a force greater than that of the output range, saturation occurs at both the input and the output of the lowpass Bessel filter they have. Therefore, the distorted waveform has odds harmonics and a dc component, if the signal is not centered perfectly at the input of the lowpass filter. So, the Bessel filter attenuates the fundamental and its entire harmonics, but cannot cancel the new dc component, appearing in the output of the filter.

The above distortion is a serious consideration in crass-detection algorithms causing such algorithms to work badly, which can cause traffic accidents. This problem is a safety-related problem that deserves our full attention.

In [27], readers can also find updated information about the practical signal conditioning circuits that today's industry uses top carry out the treatment of the information coming from them. From [27], it can be seen that such circuits are based on operational amplifier configurations, four-arms Wheatstone bridges and classical lowpass and bandpass filters. These filters have the drawbacks mentioned in this section and in the previous one.

Another important practical example that is worthy of consideration is the velocity measurement. From [24, 25], it can be seen that the real-world WSS placed in cars do not have advanced signal processing stages to suppress the noise. In fact, the noise they have is diminished in other stages added to the sensing systems, which are based on the well-known above-mentioned classical filters.

At the moment, cars do not have MEMS speed sensors embedded in their structure, but they use level comparators and microcontrollers, which allow car manufacturers to use intelligent monitoring

algorithms. As mentioned in Section 2, complete, excellent information about all the types of WSS that today's cars have embedded can be found in [16, 23, 24].

Finally, due to their good properties in terms of overshoot to a step function input while maximizing the rise and fall time, Gaussian filters are used in overshoot critical applications of force measurement in the automotive industry. Also, these filters do not introduce phase distortion.

However, the Gaussian filter has a drawback, it is sensitive to deviations due to peaks and valleys in the input signal, the mean line is perturbed by local peaks and valleys. But the automotive industry is currently trying to solve this problem by using a double-Gaussian filter.

Another application of Gaussian filters is in shaft lead detection (twist). Twist measurement is a new technique for assessing the surface lay on ground shafts. Information about this new technique can be found in [31].

5. Optimal filtering

Other filtering approaches that were introduced in the scientific community by Wiener and Kolmogorov in the 1940s [32, 33] were the statistical approaches to filtering.

In accordance with Anderson and Moore [7], the statistical approaches to filtering postulate that certain statistical properties are possessed by the useful signal and unwanted noise. And this postulate is one of the key issues of the optimal filtering theory.

In this theory, measurements are available of the sum of the signal and noise, and the task is still to eliminate by some means as much of the noise as possible through processing of the measurements by a filter.

The statistical ideas of Wiener and Kolmogorov were related to processes with statistical properties which do not change with time, i.e., to stationary processes. For such processes, it proved possible to relate the statistical properties of the useful signal and unwanted noise to their frequency domain properties [7]. Thus, there is a conceptual link with classical filtering.

A significant aspect of the statistical approach is the definition of measure of suitability or performance of a filter. In short, the best filter is that which, on the average, has its output closet to the relevant signal. By constraining the filter to be linear and formulating the performance measure in terms of the filter impulse response and the given statistical properties of the signal and noise, it generally transpires that a unique impulse response corresponds to the best value of the measure of performance [7].

However, the assumption that the underlying signal and noise processes are stationary is crucial to the Wiener and Kolmogorov theory. This assumption is a drawback of such a theory. The Wiener-Kolmogorov theory is inadequate to deal with problems in which the relevant signal and/or the noise are not stationary processes. But these are the kind of problems that engineers have to face in automotive applications. Automotive sensors have to work in environments in which neither the relevant signal nor the noise is a stationary process. For this reason, in the automotive industry there is no any application of Wiener filtering to solving noise canceling problems.

Fortunately, in order to deal with situations in which nonstationarity of the signal and/or noise is intrinsic to the problem, a new theory was developed in the late 1950s and early 1960s. This theory is

known as the Kalman filter theory [34-36] and with it the beginning of the modern era of control and filter theory became firmly established.

According to Haykin [5], a distinctive feature of the Kalman filter is that its mathematical formulation is described in terms of state-space concepts. Another novel feature of the Kalman filter (in contrast with all the filters mentioned so far in this paper) is that its solution is computed recursively, applying without modification to stationary as well as nonstationary environments. In particular, each updated estimate of the state is computed from the previous estimate and the new input data, so only the previous estimate requires storage. In addition to eliminating the need for storing the entire past observed data, the Kalman filter is computationally more efficient than computing the estimate directly from all of those data at each step of the filtering process.

In spite of the fact that the Kalman filter solved satisfactorily many problems that were considered as impossible to solve at the time it appeared, it has some drawbacks that make it unsuitable for some real-time automotive applications.

To be more specific, the Kalman filter is not robust. Its performance depends strongly on the mathematical modeling of the system (or plant) whose variables are being estimated recursively. Therefore, if the mathematical model of the plant is uncertain, then the Kalman filter does not work properly and its output is anything but a correct estimation of the relevant signals.

Excellent information about the Wiener filter theory and the Kalman filter theory can be found in [4-7]. Nevertheless, in the signal processing scientific literature there are few references addressing the problem of the lacking of robustness of the Kalman filter from the system theory point of view. For this reason, those engineers and scientists interested in having more information about the fact that the Kalman filter is an optimum filter (or optimum observer) but not a robust one are encourage to read Chapters 9, 10 and 11 of Friedland [37] and Chapter 14 of Zhou et al. [38].

The Kalman filter was the first in the family of recursive least-squares (RLS) filters, and a complete analysis of it provides a unifying framework for the derivation of this family. For filtering problems, a detailed explanation of the performance of this filter, its algorithm, and a very good application of it to automotive sensors can be found in [9]. In addition, for feedback controlled problems, a detailed explanation of this filter and its application to estimate unknown variables of a multivariable mechanical system consisting of automotive sensors can be found in [12].

Moreover, a discussion about recent applications of Kalman filters and adaptive filters to improve the performance of three of the most important mechanical sensors embedded in today's cars is given in the next section.

Finally, as introduced in the above paragraph it is important to define what an adaptive filter is. In short, an adaptive filter is a filter with a mechanism for adjusting its own parameters automatically by using a recursive algorithm at the same time that it is in active interaction with the environment. In addition, all this happens in such a way that the performance of the adaptive filter is continuously improved according to a specified performance criterion (or cost function) which has been previously established by the designer.

In spite of the fact that there is a wide variety of recursive algorithms in the scientific literature of adaptive filter theory, the choice of one algorithm over another is determined by one or more of the following factors [5]:

1. A fast rate of convergence.

2. A small amount of deviation of the final value from the minimum-squared error produced by the Wiener filter.
3. Very good tracking behavior.
4. Robustness against disturbances, internal or external to the filter.
5. Low computational requirements.
6. The structure of the algorithm should exhibit high modularity, parallelism or concurrency so that it is well suited for implementation using very large-scale integration.
7. Good numerical properties, numerical stability, numerical accuracy and numerically robust.

The study and design of adaptive filters is a very complex, active area of research. This area of research demands a great deal of team work between electrical engineers and mathematicians. And the worst drawback of these filters is that not all of them are robust. Therefore, when using them, designers should implement additional algorithms or signal conditioning circuits in order to guarantee robustness.

The applications of adaptive filters to improve the performance of automotive sensors have increased step-by-step from the last part of the last decade so far. Nevertheless, today's cars do not have implemented this type of filters yet. The applications of these filters to the automotive industry are still at a laboratory level.

6.   Recent applications of optimal filtering to improve the performance of mechanical sensors

At this point, it should be highlighted that applications of optimal signal processing techniques to improve the performance of mechanical sensors are many and that it is very difficult to discuss all of them in only one paper. However, it is also important to say that in spite of the fact that readers can find many applications of optimal filtering in the automotive industry, most of them are based on the same optimal filter; that is, are either based on the Kalman filter or based on the extended Kalman filter (EKF). But there are other filters, which are robust and less well-known than the Kalman filter and that perform better than it.

In [39], the vehicle motion and tire force histories are estimated from an incomplete, noise-corrupted measurement set using an EKF. In that paper, a nine degree-of-freedom vehicle model and an analytic tire force model are used to simulate true vehicle motion, and a five degree-of-freedom vehicle model is used in the estimator. There, the simulation of a simple slip control braking system using slip and slip angle estimates for feedback control demonstrated the effectives of the EKF for advanced control of ground vehicles.

In addition, in [40] the author carried out the estimation of motion, tire forces and road coefficient of friction by using an EKF and making Bayesian decisions. In that paper, the EKF estimated the motion and tire forces of an eight degree-of-freedom vehicle based on vehicle-mounted sensors. The methods used in [40] can find applications in both off-line construction of tire models and the development of vehicle control systems that requires the road coefficient of friction.

The key issue behind references [39] and [40] is that the real-time estimation of μ is a very difficult task, and only using optimum estimators can engineers have an estimation of the real time value of μ. Some mechanical engineers find the maximum value of μ by using a fifth wheel to register both the longitudinal force and the vertical force on the fifth wheel when the driver jammed on the brakes. But this kind is test is too expensive and it is not wise to implement this way of obtaining μ in cars.

Therefore, using an EKF is a good choice. More information about the above-mentioned mechanical test can be found in [41].

With regard to the system calibration, it is important to say that neither in [39] nor in [40] did the author calibrate the system.

In [9], a Kalman filter is used to cancel noise and interference corrupting the information from two accelerometers placed in a car undergoing performance tests. In that paper, a complete, detailed explanation of the Kalman filter algorithm is given and a satisfactory way of obtaining the SNR at the output of the filter is given as well. Also, in [9], in spite of the fact that the frequency bands of the signals of interests and the noise were not strongly mixed with each other, it was very difficult to diminish the noise by using classical filtering techniques. In that paper, a SNR improvement of 30 dB was achieved.

With regard to the system calibration in [9], it should be said that the new system was calibrated following the recommendations of the Guide to the Expression of Uncertainty in Measurement (GUM) [42-44] and the procedures of calibration in [45, 46]. In this case, the results of both the static calibration and the dynamic calibration were better for the sensors based on the Kalman filter than the ones for the sensor based on conventional filtering techniques.

In [47], an automotive radar tracking method for vehicle collision warning and collision avoidance (CW/CA) systems was proposed. In that paper, an algorithm that provided an optimal method to carry out the track-to-measurement data association was used.

The method proposed in [47] used a Kalman filter to estimate the track state vector of the system from a given sequence of measurement. In such a paper, the Kalman filter was an integral part of an order statistics probabilistic data association (OSPDA) algorithm, which constructs the order statistics based decision matrix using the association probabilities of the PDA filter to make an optimal data association between tracks and measurements.

Despite the fact that the authors in [47] did not show the way to implement the Kalman filter, the main idea of the implementation procedure of it is the same as the ones in [5-7, 9]. Furthermore, there is no any calibration procedure for the system proposed in this paper. Nevertheless, the experimental results are satisfactory.

Furthermore, in [48] a comparison is established among four observers of vehicle sideslip angle and lateral forces. To be more specific, in that paper a linear observer (i.e., a Luenberguer observer) and three nonlinear observers (i.e., an extended Luenberguer observer, an EKF and a sliding-mode observer) were used. In addition, the results of the study showed that observers are more accurate than simple models in order to estimate variables such as sideslip angles and transversal forces. Furthermore, the simulation results showed that the linear observer is least accurate and that the three nonlinear observers had a very similar performance. However, the EKF was the best among them all. As in [39, 40], the estimation of the sideslip angle is a very complex task and one of the most efficient ways of carrying out such an estimation is by using observers.

In [49], an approach for robust perception and risk assessment in highly dynamic environments is proposed. Such an approach was called Bayesian occupancy filtering and, basically, it combined a four-dimensional occupancy grid representation of the obstacle state space with Bayesian filtering techniques. There, the authors proposed a filtering algorithm that worked satisfactorily in a case under study in which the Kalman filter did not properly.

To be more specific, in [49] the assumption that the noise is Gaussian cannot be made, and the authors could not verify the required conditions to apply the Kalman filter. Therefore they developed a

new algorithm for which the assumption of Gaussian noise was not a basic requirement. The experimental results were satisfactory and the new approach can be seen as an alternative to complex multitarget tracking algorithms, which usually fail in situations involving numerous appearances, disappearances and occlusions of a large number of rapidly manoeuvring targets. It also brings a significant improvement to traditional approaches, by including a prediction step which allows us to make robust estimations relatively to temporary occlusions.

In spite of the fact that the new system was not calibrated, it was validated using an experimental car, a moving pedestrian and a parked car, which temporarily hid the pedestrian from the sensors of the experimental car.

Moreover, in [8] a recursive least squares (RLS) adaptive filter is used to estimate the relevant signal coming from an accelerometer placed in bus under performance tests. The bus in that paper, had just had an accident in Madrid, Spain, and by using a RLS adaptive filter to diminish the noise that corrupted the relevant information from the accelerometer placed in the bus, the tests carried out in the laboratory allowed mechanical engineers and crash experts to make a decision about what the causes of the accident were. In [8], a complete, detailed explanation of the RLS adaptive filter is given and a SNR improvement of 20 dB was achieved. Also, all the sensors involved in the performance tests were calibrated in accordance with [42-46].

In [10], an adaptive-line enhancer (ALE) based on a frequency-domain least-mean-squares (FDLMS) adaptive algorithm was used to predict the response of a WSS embedded in a car under performance tests. In [10], the ALE was used to predict the relevant signal from the WSS, which was buried in a broad-band, unknown noise background. Also, in [11] the response of a WSS was improved by using an adaptive noise canceller based on a FDLMS adaptive filter. There, a SNR improvement higher that 40 dB was achieved.

In both research [10] and [11], the WSS was a variable reluctance proximity sensor and it had to be placed very close to the car's wheels toothed wheels in order to produce an adequate output voltage. Also, the sensors suffered from a very high noise which at automobile speeds lower than 5 km/h corrupted the WSS electrical signal in such a way that a reliable measure at almost zero speed was impossible to achieve. Such a behavior is not appropriate for the cars' braking performance. For this reason the ABS of most of today's cars is disconnected at the end of the braking process and cars are finally braked but without the help of the electronic braking system, which is a safety-related problem.

The experimental results were satisfactory. Basically, it is impossible to achieve such a high SNR improvement (i.e., 40 dB) by using classical filters. Classical filters do not have the ability of self-adjustment. Therefore, at low car speed classical filters cannot differentiate the useful signal from the noise and, as a result, depending of the type of filter they either suppress both the noise and the useful signal or none of them.

The electronic systems designed in [10] and [11] were not calibrated. But a common procedure of calibration of these sensors is the one explained in Section 2.

In addition, in [50] an ALE system using a variable step-size affine-projection algorithm (VSS-APA) was designed. In that paper, the VSS-APA was used to improve both the convergence speed and the performance of the ALE system. Also, two practical applications were conducted to compare the performance of the proposed algorithm against traditional adaptive filtering algorithms based on the conventional LMS adaptive algorithm. The first application was aimed at improving the response of a WSS and the second one was aimed at reducing the background noise during rotating machinery fault diagnosis. Although the results of the experiments were satisfactory, there were no calibrations of the new electronic systems.

Generally speaking, according to the authors of [50]'s opinion, that research can be seen as a continuation of the work developed by the author of [8] and [10]. In [50], the authors developed an APA aimed at increasing the speed of convergence of the conventional LMS algorithm and described, in general terms, the proposed algorithm.

In spite of the fact that the results of [50] are satisfactory, a deeper mathematical analysis of the proposed algorithm is needed because although the conventional LMS algorithm has a lower rate of convergence than the conventional RLS algorithm, the first one is a robust algorithm but the second one is not a robust algorithm. Therefore, a question rises itself about the VSS-APA, is the new algorithm robust as it is the LMS algorithm?

Moreover, recent experiments (see [5]) have demonstrated that neither the LMS algorithm nor the RLS algorithm has a complete monopoly over a good tracking behaviour. It has been demonstrated that one or the other of these two adaptive filtering algorithms is the preferred algorithm for tracking a nonstationary environment, depending on the prevalent environmental conditions. But, what can be said about the tracking performance of the VSS-APA?

In [12] linear-quadratic optimal (LQR) control, Kalman filtering, linear-quadratic Gaussian (LQG) control and loop-transfer recovery (LQG/LTR) control techniques were used to shape the multi-input-multi-output (MIMO) loop transfer function (LTF) of a dynamic system whose state vector consisted of the displacement, the velocity and the acceleration of a car under performance tests. In [12], an LQG/LTR was used to estimate the response of both a WSS sensor and an accelerometer embedded in a car under performance tests. Other examples of this kind of application can be found in [37]. In both references [12] and [37], the authors described a real-world experiment and explained step-by-step the procedure to implement a robust controller based on optimum observers (i.e., Kalman filters).

In [13], a sensor to measure the rollover angle of a car was presented and a RLS lattice algorithm was used to suppress the noise that corrupted the information from that sensor. In that paper, a SNR improvement of 26.7 dB was achieved. Also, using a coverage factor of k = 2, an expanded uncertainty of 0.10^{o} was achieved. Complete information about the principles of the rollover sensor is given in that paper and its calibration was carried out in accordance with [42-46]. Also, detailed information about the RLS lattice algorithm is given in [13].

Also, in [14] a RLS lattice algorithm was used to improve the performance of a WSS placed in car. There, a SNR improvement of 30 dB was achieved. In addition, the optimal sensor designed in that paper is currently implemented in a driver drowsiness detection system for buses at the National Institute for Aerospace Technology, Madrid, Spain.

In order to apply optimal adaptive filtering techniques to improve the performance of other mechanical sensors than WSS and accelerometers, in [15] an adaptive noise canceller based on a RLS lattice algorithm was used to cancel the noise that corrupted the information from a load cell. In that paper, a SNR improvement of 27 dB was achieved. Also, as the load cell is currently operating in real-world industrial applications, it is calibrated once a year following the recommendations made in [42-46].

Moreover, in [17] a comparison was established between the performance of a 3-order lowpass digital Butterworth filter, which is one of the typical filters that today's cars use, and a RLS lattice adaptive filter used to improve the performance of an accelerometer placed in a car under performance tests. The results of the experiment showed that the SNR improvement achieved by using the optimum adaptive filter was 3.67 times better than the one achieved by using the classical filter, what clearly showed the superiority of optimum adaptive filters over classical filters.

Finally, in [18] an inverse square-root adaptive filtering algorithm for recursive least squares estimation (QR-RLS) was used to carry out the optimal estimation of the relevant information coming from a rollover sensor placed in car under performance tests. Complete information about the performance of the QR-RLS algorithm and its application to automotive sensors is given in [18].

In [18], a significant improvement of 45dB in the SNR at the system output was achieved and, using a coverage factor of k = 2, an expanded uncertainty of 0.09º was also achieved. The electronic system designed in that paper was calibrated following the recommendations made in [42-46].

7. Considerations and open research issues

In the previous section, several papers where optimal filtering techniques have been satisfactorily applied to improve the performance of mechanical sensors have been discussed. In addition, it is important to point out that in the cases where the research was conducted by using both classical and optimal filtering, the results of the experiment showed very clear that optimal adaptive filters are superior to classical filters. Nevertheless, most of today's cars use classical filtering to suppress the noise that corrupt the electrical signals from the sensors they have embedded.

However, it is important to point out that there is always a need for a minimal analog filtering stage for antialiasing avoidance. Therefore, practitioner engineers may not be induced to believe that no analog filtering is required when the noise filtering task relies on a highly efficient digital adaptive stage.

At this point, it should be highlighted that the cost of implementation of the different adaptive filters solutions pointed in this paper is affordable. Today's microcontrollers, DSPs and ASICs are low-cost, easy to program components, which makes the use of these technologies affordable to car manufacturers.

Furthermore, in order to reduce the cost of the systems and increase the miniaturization and integration of on-chip electronic intelligence, an important automotive sensor technology has being developed since the early 1980s. With micromachining, mechanical structures have been produced in silicon and this fact has greatly expanded the number and types of measurement that can be made [1]. This new technology is known as MEMS and, according to Fleming [23], MEMS manufacturing of mechanical sensors began in 1981 with pressure sensors for engine control, continued in the early 1990s with accelerometers to detect crash events for airbag safety systems [26] and in recent years has further developed with angular-rate inertial sensors for vehicle-stability chassis systems. Information about yaw-rate sensors, their applications, requirements and principles, and examples of MEMS that are single chip yaw-rate sensors with a wide operating range and a high resolution can be found in [51].

However, taking into consideration the experimental results obtained in the papers presented in the previous section, despite the astonishing advances made in microelectronics and MEMS over the last decade, there is still plenty of room for improvement in the numerical algorithms that MEMS and other sensors based on microcotroller, DSP or ASIC technologies use to cancel the noise that corrupts the relevant information from the sensors.

The above statement is an open research issue that has recently been under exploration during the last decade. Unfortunately, for many years, sensor manufacturers have only paid attention to the design

of sensors and their integration into miniaturized intelligent systems based on the fabrication of sensors and signal processing circuitry directly on the same chip. Also, since the started of the production of MEMS and intelligent sensors by several companies in the 1980s and 1990s, instead of using robust and optimal filtering and control algorithms, these sensors have been using the classical approach to filtering and control to deal with the consequences of the inevitable disturbances that corrupt the electrical signal generated by the sensors.

8. Conclusions

Automotive sensors have been in production for several decades and due to the advances in microelectronics, micromachining and microprocessor technologies, they are undergoing a soaring positive change from being simple devices used to generate a correct representation of a sensed or controlled quantity into very complex devices, with the ability to carry out very complex functions that allow them to make intelligent driving decisions that can save our lives in road accidents.

In this paper, a survey on recent applications of optimal signal processing techniques to the design of automotive sensors has been made. Here, a discussion of several research works focussed on specific applications of the Kalman filter, the EKF, the FDLMS adaptive filter, the RLS adaptive filter, RLS lattice filter and the inverse QR-RLS adaptive filter, among others, aimed at improving the performance of mechanical sensors have been made.

Furthermore, in this paper the performance of the above mentioned optimum filters was compared against the performance of the classical ones, making it clear that only by the fusion of robust and optimal signal processing techniques with microcontroller units, DSP and ASIC technologies can the designer find the appropriate way to build the intelligent (or smart) sensors that today's automotive industry needs.

Moreover, the results obtained in the references discussed in this paper have contributed positively to bridge the gap between intelligent signal processing techniques and the design of intelligent sensors for automotive applications.

Acknowledgements

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