Journal of Intelligent & Fuzzy Systems 29 (2015) 479–488
DOI:10.3233/IFS-141183
IOS Press

Attitude estimation using a Neuro-Fuzzy tuning based adaptive Kalman filter

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Abstract. This paper presents the development of a Kalman Filter with Neuro-Fuzzy adaptation (KF-NFA) which is applied in attitude estimation, relying on information derived from triaxial accelerometer and gyroscope sensors contained in an inertial measurement unit (IMU). The adaptation process is performed on the filter statistical information matrices R or Q, which are tuned using an Adaptive Neuro Fuzzy Inference System (ANFIS) based on the filter innovation sequence through a covariance-matching technique. The test results show a better performance of the KF-NFA when it is compared with a traditional Kalman Filter (T-KF). This work is being developed in the context of a Pedestrian Dead Reckoning (PDR) algorithm for localization based services (LBS), currently in progress.

Keywords: Kalman filter, ANFIS, IMU

1. Introduction

Pedestrian dead reckoning (PDR) is a navigation technique that provides and maintains the geographical position for a person travelling on foot by using self-contained sensors. The current advancements of personal mobile devices with low cost sensors such as accelerometer, gyroscope and magnetometer, have made PDR a relevant approach for the development of location based services (LBS) for indoor applications, where the GPS signal is unavailable. A fundamental component common to all LBS is the use of positioning technologies to track the movement of mobile users and to deliver information services on the move at the right time and right location [1].

In PDR techniques, each new position estimate is based on the previous estimate of the last step taking advantage of the sequential nature of pedestrian motion. In general, a PDR algorithm is composed of three parts: step detection, estimation of walking distance and tracking of sensor attitude. The accelerometer signals are used to detect steps and estimate step length, which in turn is calculated based on a walking step frequency. Attitude can be estimated by combining the measurement signals from the accelerometer, gyroscope and magnetometer included in an inertial measurement unit (IMU). On the one hand, low cost MEMS sensors used in PDR systems are affected by sensor noise and drift, which introduce errors in the displacement and relative attitude changes in the sensor´s frame of reference with respect to the human body [2].

On the other hand, PDR systems utilizing a magnetometer are not the best choice for indoor/urban navigation because magnetometers are subject to strong magnetic disturbances such as power lines, computers

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and different metal/steel objects. Therefore, if accurate navigation is required, the system has to rely on other means to determine attitude, such as gyros and accelerometers, according to the angle or position representation. Attitude estimation methods in pedestrian navigation are classified as quaternion method [3, 4], direction cosine matrix method [5, 6], or Euler angles method [7, 8].

The Euler angles method has the merit of being a more meaningful attitude expression than either the quaternion method or the direction cosine matrix method, and the user can recognize the attitude directly [9]. Kalman-based sensors fusion has been extensively used to pursue attitude estimation through inertial measurement units in navigation systems [10–12]. A problem with Kalman filter formulation is that it requires a priori knowledge of the process and measurement noise statistic. Furthermore, inadequate initial statistics of the filter will reduce the precision of the estimated states or will introduce biases to the estimates. Adaptive Kalman Filter (AKF) can be used to deal with such a problem [13–15].

Previous studies have investigated the fuzzy and neuro-fuzzy adaptation of Kalman filtering [9, 15–18], and they have used covariance-matching based approaches to perform the process of adapting the statistics of the filter in mobile applications. In [9], fuzzy adaptation based on the Takagi-Sugeno model is implemented to estimate humanoid robot attitude using the extended Kalman filter (EKF). The principal advantage is that EKF uses as inertial measurements only those provided by a gyroscope and an accelerometer. However, the approach only estimates three state variables, the roll, pitch and yaw angles, discarding the gyro bias, which is an important parameter because it could make the attitude error to diverge.

In [15] and [16] a fuzzy adaptive Kalman Filter algorithm is applied to an Attitude and Heading Reference System (AHRS). Usually, an AHRS consists of MEMS gyroscopes, accelerometers and magnetometers providing three axes signals. In [15] and [16] the authors use magnetometers to provide a measure of the attitude of the mobile device. By detecting the magnetic field information, they can compensate the errors of attitude caused by drifts of MEMS gyros and accelerometers. However, the use of magnetometers is not appropriate in PDR systems, where the indoor/urban navigation is essential and the magnetometers can be easily disturbed. In [17] the authors report a two-input ANFIS approach similar to our proposal, with the difference that they do not use inertial measurements, and therefore a bias correction is not required.

The main problem when using inertial sensors to obtain orientation information of a moving platform is the accumulation of errors due to the bias and offset inherently present in those sensors. As stated previously, several adaptive Kalman filter formulations can be found in the literature to deal with the orientation estimation problem. However, none of them seems to estimate the bias present in the inertial measurements. Therefore, the main purpose of this work is to develop an adaptive technique for the estimation and reduction of the inertial sensor bias. This in turns will reduce the error in the estimation of the orientation applied for pedestrian navigation. In previous works a fuzzy scheme for the adaptation of the filter has been proposed [9, 19]. The draw back of a fuzzy logic approach is the definition of the fuzzy sets used in the fuzzy rules. A neuro-fuzzy adaptation scheme offers the advantage of adjusting, in an automatic way, the fuzzy sets used in the fuzzy rules.

Therefore, in the present approach the attitude of a moving platform is estimated through a neuro-fuzzy tuned adaptive Kalman filter, which performs sensor fusion of gyroscope and accelerometer measurement signals. A Neuro-Fuzzy Inference System (ANFIS) is used to adaptively adjust the measurement noise statistical information for the Kalman filter based on the filter innovation sequence, aimed to cause a reduction of the error in the orientation estimation. The obtained results show an improvement in adaptation of the measurement noise covariance matrix performed by the Neuro-Fuzzy system, which was reflected in a better performance on the attitude estimation.

The organization of this paper is as follows: Section II describes the IMU data fusion methodology for attitude estimation through Kalman filtering. Section III describes the general scheme proposed to incorporate the Kalman filter with Neuro-Fuzzy adaptation into the attitude estimation algorithm, the related theory, and obtained results. Conclusions are presented in Section IV.

2. IMU data fusion for attitude estimation through Kalman filtering

Euler angles are defined as the rotation angles from the body frame to the navigation frame. Figure 1 presents the Euler angles: roll ϕ, pitch θ and yaw ψ. Euler angles can be derived from measurements

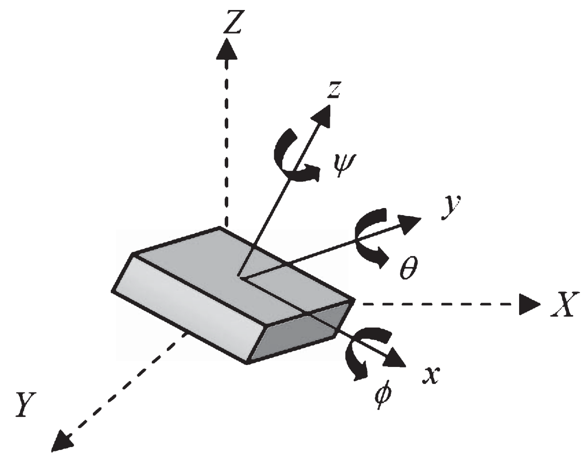

Fig. 1. Euler angles.

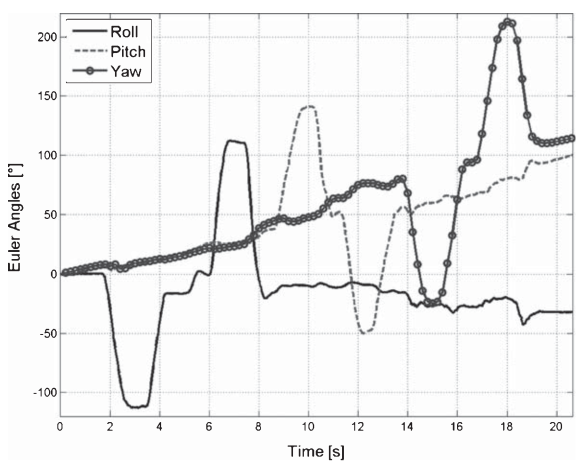

Fig. 2. Bias effect over the Euler angles obtained by integration of the gyro signal.

provided by inertial sensors such as gyroscopes and accelerometers. In a conventional inertial navigation system, the attitude is calculated by integrating the angular rate obtained from the gyroscope signals. However, the gyroscope signals undergo an effect called bias or drift, which is the average output from the gyroscope when it is not undergoing any rotation [20].

Accordingly, the angular rate integration is not appropriate for calculating the attitude of pedestrians because the bias makes the attitude error to diverge over time. The bias effect on the integrated signal of a triaxial gyroscope can be seen in Fig. 2, which presents the results from an experiment where the gyroscope was rotated from 90° to −90° arbitrarily on each axis from an initial position of 0°.

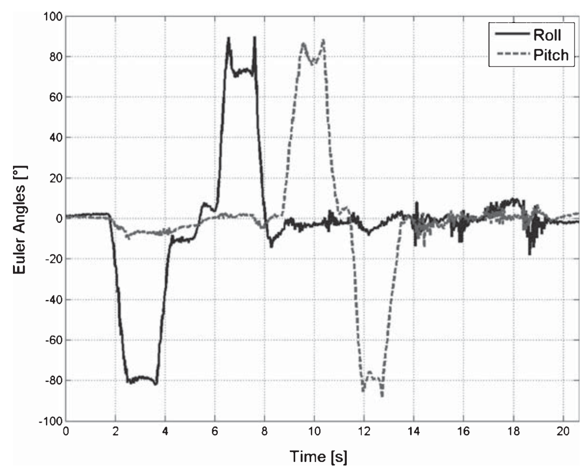

Fig. 3. Euler angles Roll and Pitch angles calculated by a triaxial accelerometer.

The roll and pitch angles can be estimated using a triaxial accelerometer $[a_x\ a_y\ a_z]$ through a geometric relation between the accelerations that act on each axis [21], according to the Equation (1) and Equation (2).

$$\phi = \tan^{-1}\left(\frac{a_y}{\sqrt{a_x^2 + a_z^2}}\right) \tag{1}$$

$$\theta = \tan^{-1}\left(\frac{-a_x}{\sqrt{a_y^2 + a_z^2}}\right) \tag{2}$$

The results of applying Equations (1) and (2) are shown in Fig. 3 following the same procedure described previously. It is observed that these angles are very noisy and the bias effect is lower in comparison to the angles calculated with the integration of gyro signals.

However, the principal disadvantage of this method is that the calculation of the angles could be affected by external accelerations [21]. In the case of the yaw angle, it can be calculated based on the roll and pitch values and the measurements from a triaxial gyroscope, as follows:

$$\dot{\psi} = -\omega_x \sin\theta + \omega_y \sin\phi\cos\theta + \omega_z \cos\phi\cos\theta \tag{3}$$

where ω_x, ω_y and ω_z are the angular rates along the three axis. Therefore, the yaw angle can be obtained by numerical integration of Equation (3), and it is shown in Fig. 4.

Kalman-based sensor fusion is a common approach to pursue attitude estimation in navigation systems. For that purpose, several tuning procedures based on the

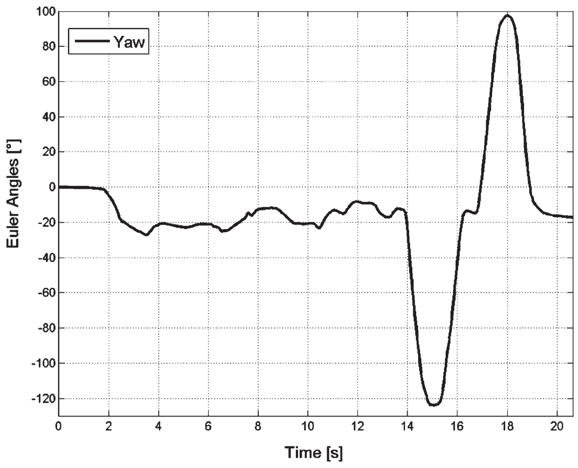

Fig. 4. Yaw angle calculated by a triaxial gyroscope and the pitch and roll angle.

innovation sequence have been proposed [18, 22]. In this work, the fusion of gyroscope and accelerometer measurements is carried out using the Kalman filter algorithm with a Neuro-fuzzy adaptive tuning procedure based on the innovation sequence. Figure 5 shows a block diagram of the scheme used to perform attitude estimation based on the IMU information.

2.1. Process model

The process model is represented by Equations (4–8), where the state vector is x_k, ϕ, θ and ψ are the estimated roll, pitch and yaw angles in degrees, respectively; b_ϕ, b_θ and b_ψ are the bias which are estimated by the filter in degrees per second, and u_k is the input vector containing the gyroscope raw data.

$$x_{k+1} = A \cdot x_k + B \cdot u_k \tag{4}$$

$$x_k = \left[\phi \; b_\phi \; \theta \; b_\theta \; \psi \; b_\psi\right]^T \tag{5}$$

$$u_k = \left[\omega_x \; 0 \; \omega_y \; 0 \; \omega_z \; 0\right]^T \tag{6}$$

$$A = \begin{bmatrix} 1 & -dt & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -dt & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -dt \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{7}$$

$$B = \begin{bmatrix} dt & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & dt & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & dt & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{8}$$

During the process, the angles ϕ, θ, ψ, are updated integrating the gyroscope raw data and performing a correction in order to eliminate the estimated bias.

$$\begin{aligned} \phi_{k+1} &= \phi_k + \left(\omega_{x_k} - b_{\phi_k}\right) \cdot dt \\ b_{\phi_{k+1}} &= b_{\phi_k} \end{aligned} \tag{9}$$

$$\begin{aligned} \theta_{k+1} &= \theta_k + \left(\omega_{y_k} - b_{\theta_k}\right) \cdot dt \\ b_{\theta_{k+1}} &= b_{\theta_k} \end{aligned} \tag{10}$$

$$\begin{aligned} \psi_{k+1} &= \psi_k + \left(\omega_{z_k} - b_{\psi_k}\right) \cdot dt \\ b_{\psi_{k+1}} &= b_{\psi_k} \end{aligned} \tag{11}$$

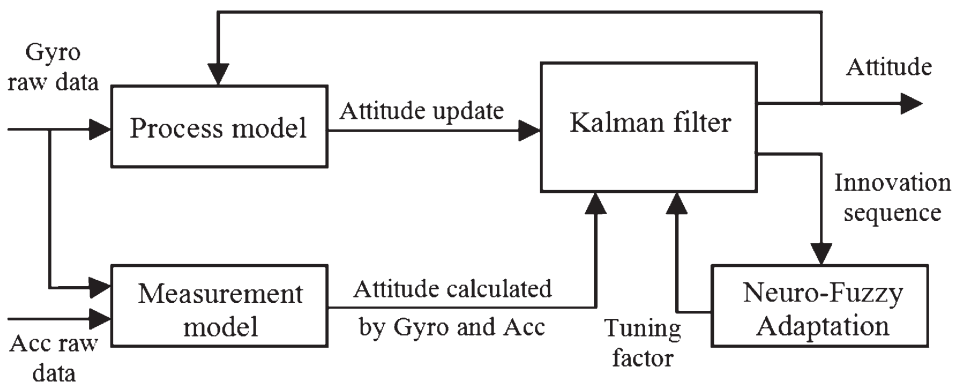

Fig. 5. Kalman filter structure for attitude estimation.

Table 1
Gyroscope measurement statistic moments

Parameter	X-axis	Y-axis	Z-axis	Units
mean (μ)	0.0130	-3.7636	4.7626	°/sec
var (σ^2)	0.0450	0.2270	0.2218	°/sec

Table 2
Accelerometer measurement statistic moments

Parameter	X-axis	Y-axis	Z-axis	Units
mean (μ)	15.4932	-6.5478	48.4429	Mg
var (σ^2)	3.6190	3.6278	5.1917	Mg

The measurement model uses the angles obtained from the triaxial accelerometer and the gyroscope, providing an estimation of the z_k vector:

$$z_k = H_k x_k \tag{12}$$

$$H_k = \begin{bmatrix} 1\,0\,0\,0\,0\,0 \\ 0\,0\,1\,0\,0\,0 \\ 0\,0\,0\,0\,1\,0 \end{bmatrix} \tag{13}$$

Noise arising from angular velocities measurements affects the process model as they are governing the general behavior of the process, whereas measurements obtained from inertial sensors are subject to measurement noise. These noise signals are assumed to be uncorrelated zero-mean Gaussian white noise sequences, with covariance matrices Q and R, representing process noise and measurement noise covariance matrices, respectively.

The Kalman filter formulation requires statistical information of matrices Q and R. In this work the values of Q and R matrices were acquired experimentally by maintaining the inertial module iNEMO® [23] to stand for one week in a vibration free environment. Tables 1 and 2 show the statistic moments obtained from the experiment. The process noise and measurement noise covariance matrices are then represented as expressed in Equations (14) and (15):

$$Q = \mathrm{diag}\left[\sigma^2_{\omega_x}\ \sigma^2_{b_{\omega x}}\ \sigma^2_{\omega_y}\ \sigma^2_{b_{\omega y}}\ \sigma^2_{\omega_z}\ \sigma^2_{b_{\omega z}}\right] \tag{14}$$

$$R = \mathrm{diag}\left[\sigma^2_{acc_x}\ \sigma^2_{acc_y}\ \sigma^2_{acc_z}\right] \tag{15}$$

Optimal performance of Kalman filtering strongly depends of correct initial process and measurement noise statistic. Inadequate initial statistic would be reflected in inaccuracies of estimated states, or it would introduce undesired biases to the estimates, generating in extreme cases filter divergence. Adaptive filter formulation deals with the problem of having imperfect a priori information and provides an improvement in performance over the fixed filter approach.

3. Attitude estimation using Neuro-Fuzzy adaptive Kalman filtering

There are two approaches to the adaptive Kalman filtering problem: innovation-based adaptive estimation (IAE) and multiple-model-based adaptive estimation (MMAE) [24]. In IAE the adaptation is carried out on the covariance matrices of measurement and/or process noise, based on the changes in the innovation or residual sequences.

In MMAE a bank of Kalman filters runs in parallel with different models for satisfying filter's true statistical information. MMAE has been used in several applications such as positioning systems [25] and attitude determination systems in microsatellites and spacecraft [26, 27], with good results, however a drawback is its processing time and computational complexity. The work presented in this paper is based on an IAE approach.

The IAE approach is based on the improvement of the filter performance through the adaptive estimation of the filter statistical information, the matrices Q and/or R. The innovation sequence is the difference between the actual measurement vector and its estimate:

$$Inn_k = z_k - H_k x_k^- \tag{16}$$

The innovation sequence represents the additional information available to the filter as a result of a new measurement z_k. For this reason the innovation sequence represents the information content in the new observation and is considered the most relevant source of information for the filter adaptation. The occurrence of bad data first shows up in the innovation vector. In this way the innovation sequence reports the discrepancy between predicted and actual measurement.

For an optimal filter, the innovation sequence is a linear combination of independent Gaussian random variables. Therefore, the innovation is a white Gaussian sequence of mean zero and covariance:

$$S_k = H_k P_k^- H_k^T + R_k \tag{17}$$

By checking whether the innovation sequence indeed possess their theoretical statistical properties the performance of the Kalman filter can be assessed. In this

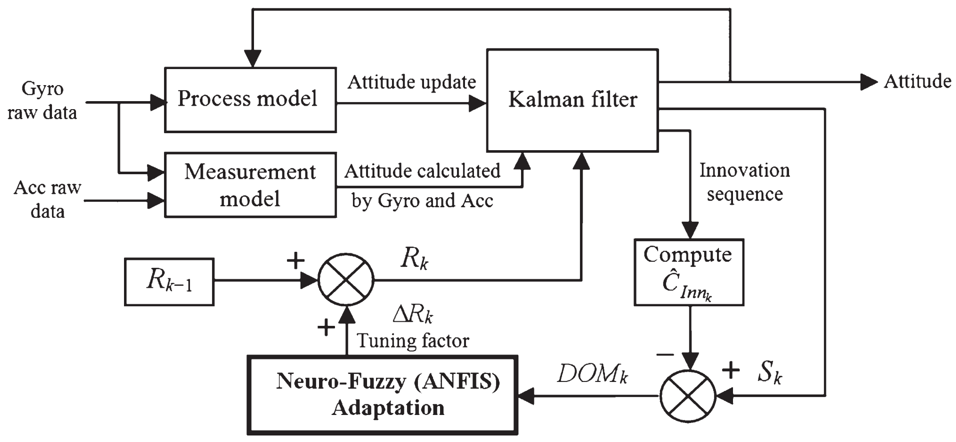

Fig. 6. Attitude estimation based on Neuro-Fuzzy adaptive Kalman filter.

work, an IAE scheme based on a neuro-fuzzy system is used to carry out the adaptation process on the statistical information contained in matrix *R*. The general idea behind this technique is that the actual value of the covariance of the residuals matches with its theoretical value.

When the statistical values of the innovation sequence show discrepancies between the theoretical and actual covariance values, then a Neuro-Fuzzy inference system (FIS) adjusts a tuning factor applied to the matrix *R* causing a reduction in the discrepancy [18, 22].

3.1. Adaptive adjustment of the measurement noise covariance matrix R with Q known

The adaptation process is carried out through the adjustment of the measurement noise covariance matrix R with Q known. Figure 6 shows a block diagram which schematically describes the whole process. The covariance matrix R represents the accuracy of the measurement instrument. Assuming that the noise covariance matrix Q is known, an IAE approach employing the principles of fuzzy logic is used to adaptively adjust the matrix R.

This adaptation is carried out in three steps. First, the theoretical covariance of the innovation sequence is obtained from the Kalman filter algorithm by the Equation (17). Second, the actual covariance $\hat{C}_{Inn_k}$ is defined as an approximation of the Inn_k sample covariance through averaging inside a moving estimation window of size M:

$$\hat{C}_{Inn_k} = \frac{1}{M} \sum_{i=i_0}^{k} Inn_i Inn_i^T \tag{18}$$

where $i_0 = k - M + 1$ is the first sample inside the estimation window. Third, if it is found that the actual value of the covariance $\hat{C}_{Inn_k}$ has a discrepancy with its theoretical value S_k, then an adaptation algorithm derives adjustments based on the size of this discrepancy. The covariance matching technique is employed by the adaptation algorithm. Hence, a new variable called Degree of Matching (*DoM*) is defined to indicate the degree of discrepancy between S_k and $\hat{C}_{Inn_k}$; this is expressed as:

$$DoM_k = S_k - \hat{C}_{Inn_k} \tag{19}$$

Note that an increment in R will increment S, and vice versa. Then the basic idea of the adaptation is to adjust R_k to vary S_k in accordance with the value of DoM_k, in order to reduce the discrepancy between S_k and $\hat{C}_{Inn_k}$. The adaptation of the (i,i) element of R_k is performed in accordance with the (i,i) element of DOM_k using the following general rules:

1. IF S and $\hat{C}_{Inn_k}$ match almost perfectly ($DoM \cong 0$) THEN keep R unchanged.
2. IF S is greater than its actual value $\hat{C}_{Inn_k}$ ($DoM > 0$) THEN decrease R.
3. IF S is smaller than its actual value $\hat{C}_{Inn_k}$ $DoM < 0$) THEN increase R.

Therefore, R is adjusted as follows:

$$R_k(i,i) = R_{k-1}(i,i) + \Delta R_k \tag{20}$$

An Adaptive Neuro Fuzzy Inference System (ANFIS) is used to generate the tuning factors ΔR_k for the diagonal elements of R_k, as represented in the block diagram shown in Fig. 6.

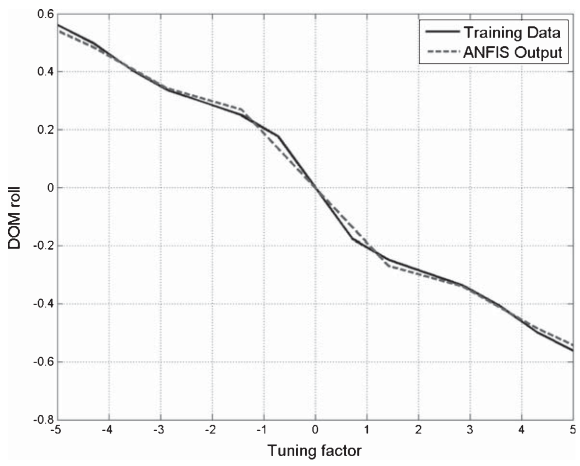

Fig. 7. Output and the transition function.

ANFIS combines the learning capabilities of neural networks with the approximate reasoning of fuzzy inference systems. One of the advantage of ANFIS over fuzzy systems is the use of a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. The optimization method used for training the FIS membership function parameter is a combination of the least-squares estimation with the backpropagation gradient descent algorithm [28, 29].

In this work, the ANFIS architecture is the foundation to build the previous collection of IF-THEN rules with the appropriate membership functions to model a set given input-output data. The input-output pair is comprised of DoM_k (i,i) as the input linguistic variable and ΔR_k as the output variable.

4. Results

The proposed system was implemented in MATLAB using the ANFIS model included in the fuzzy logic toolbox. Figure 7 presents the obtained transition function corresponding to input DOM_k related to the output ΔR_k, for the case of the roll (ϕ) angle. Note how the ANFIS output follows the transition function. Figure 8 shows the Gaussian membership functions for the input DOM_k that resulted from the training of the ANFIS. The number of membership functions was established empirically.

Figures 9, 11 and 13 present a comparison between the actual innovation covariance $\hat{C}_{Inn_k}$ and its theoretical value S_k, obtained when both Q and R are maintained fixed. Figures 10, 12 and 14 present the comparison

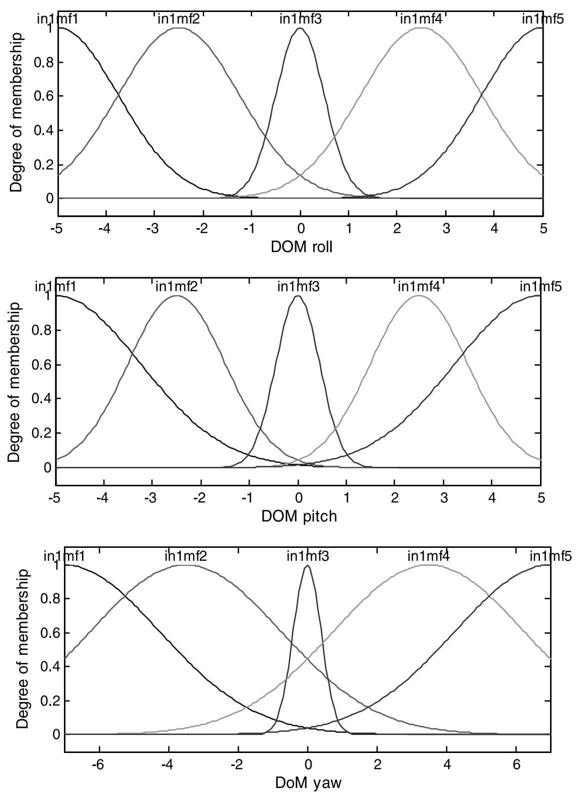

Fig. 8. Gaussian membership functions corresponding to the input *DOM*.

between the actual innovation covariance $\hat{C}_{Inn_k}$ and its theoretical value S_k, resulted when R is adjusted using the proposed neuro-fuzzy system. It can be noticed that S_k and $\hat{C}_{Inn_k}$ remain almost equal, *DoM* is around zero and R oscillates around its true value. This situation arises due to the continuous adjustment of the values in the main diagonal of R, produced by the Equation (20).

In order to demonstrate the efficiency of the Kalman filter with Neuro-Fuzzy adaption (KF-NFA) for attitude estimation, an experiment where the gyroscope was rotated from 90° to -90° on each axis from an initial position of 0° was performed. For comparison purposes, Figs. 15, 16, 17 and 18 present the attitude obtained using KF-NFA, the traditional Kalman filter (T-KF), and the attitude obtained from the gyroscope integration. Figure 16 shows a zoom of the roll angle in the interval where the sensor record an approximate rotation of -90°. The KF-NFA output is closer to -90°; hence a filter performance improvement is pointed out.

In previous work [19] the authors reported a fuzzy scheme for the adaptation of the Kalman filter (KF-FLA). The drawback of a fuzzy logic approach is the

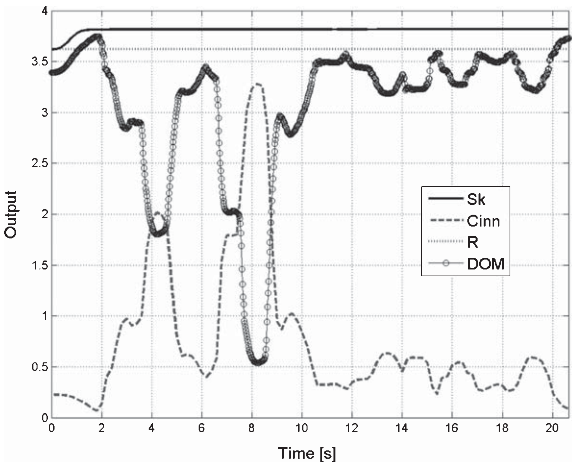

Fig. 9. Kalman filter without adaptation at roll angle.

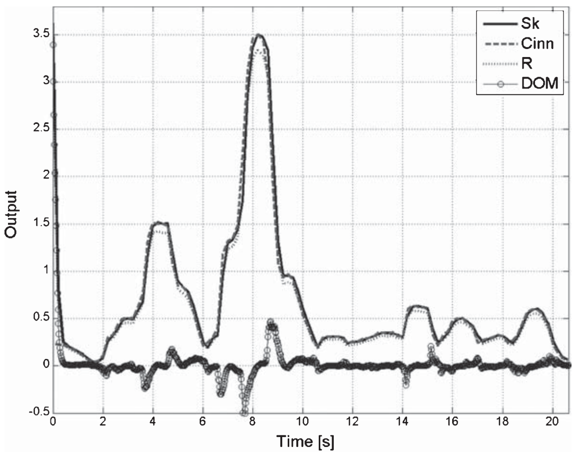

Fig. 10. Kalman Filter whit Neuro-Fuzzy adaptation at roll angle.

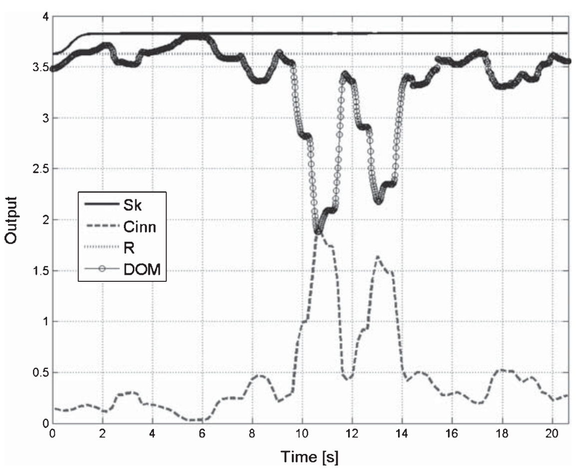

Fig. 11. Kalman filter without adaptation at pitch angle.

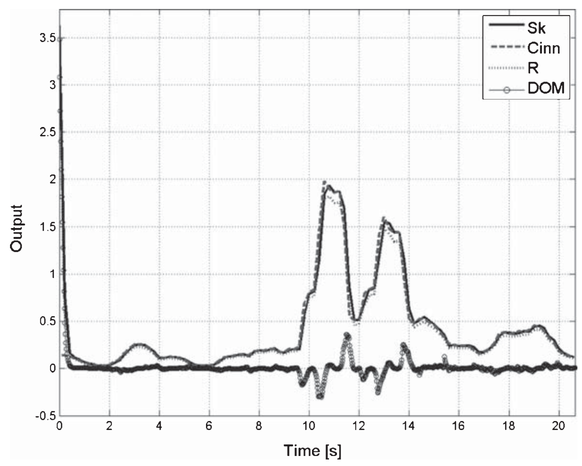

Fig. 12. Kalman Filter whit Neuro-Fuzzy adaptation at pitch angle.

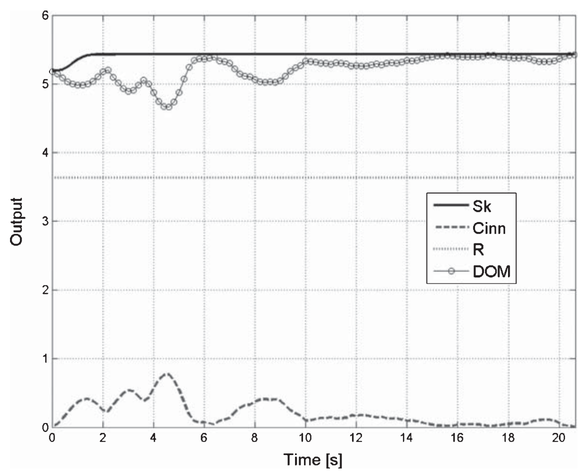

Fig. 13. Kalman filter without adaptation at yaw angle.

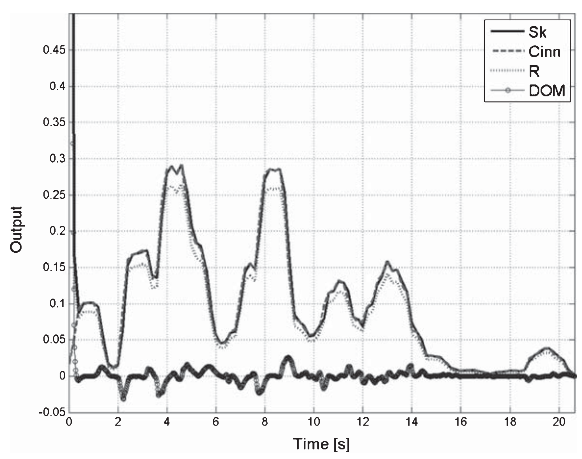

Fig. 14. Kalman Filter whit Neuro-Fuzzy adaptation at Yaw angle.

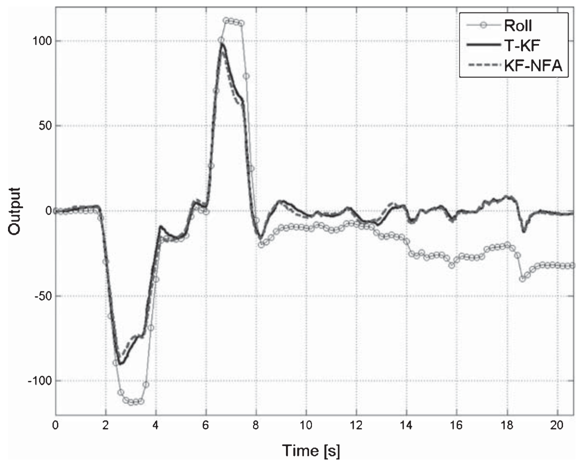

Fig. 15. Roll angle results.

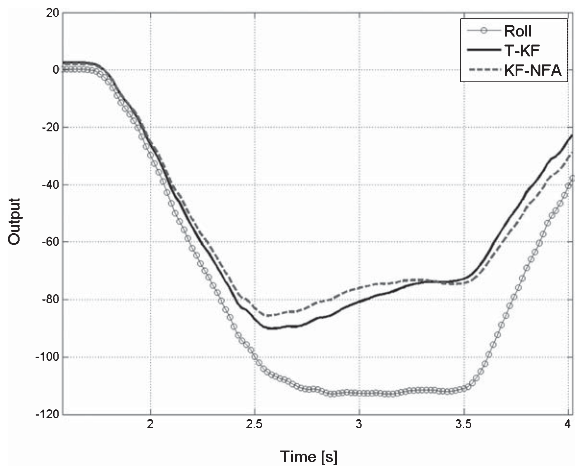

Fig. 16. $-90°$ Roll angle.

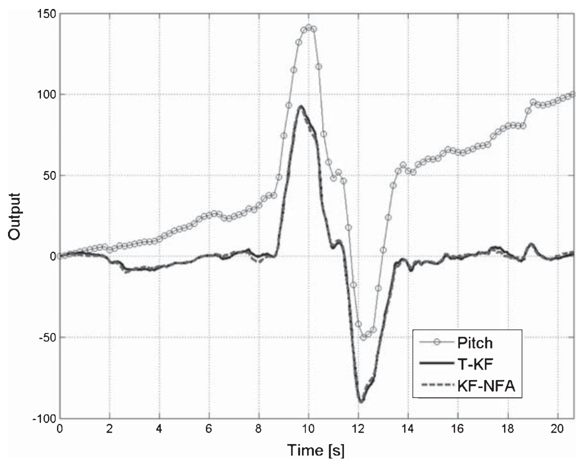

Fig. 17. Pitch angle results.

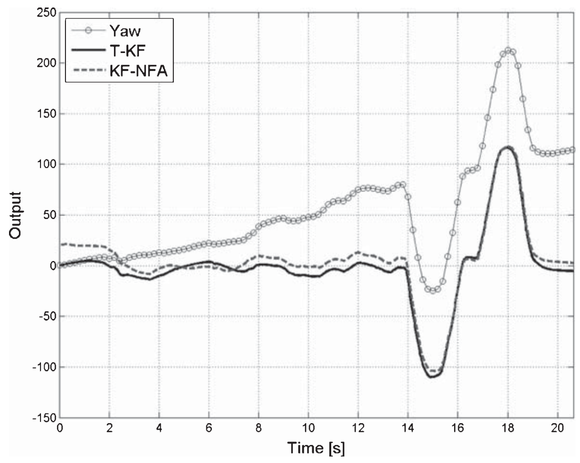

Fig. 18. Yaw angle results.

Table 3
% MSE measured in the different adaptations

	Roll	Pitch	Yaw
T-KF	8.9977%	7.9327%	29.9536%
KF-FLA	8.3975%	7.9145%	16.5305%
KF-NFA	8.3880%	7.7953%	16.5296%

definition of the fuzzy sets used in the fuzzy rules. A neuro-fuzzy adaptation scheme offers the advantage of adjusting, in an automatic way, the fuzzy sets used in the fuzzy rules. A Neuro-Fuzzy Inference System (ANFIS) is used to adaptively adjust the measurement noise statistical information for the Kalman filter based on the filter innovation sequence, which performs sensor fusion of gyroscope and accelerometer measurement signals. A comparison on percent mean square error (MSE) measured in each case indicates an improvement when ANFIS-based adaptation (KF-NFA) is used, as indicated in Table 3.

5. Conclusions

In this paper a Kalman filter with Neuro-Fuzzy adaptation (KF-NFA) for attitude estimation has been presented. The KF-NFA estimates and corrects the Euler angles trough the fusion of inertial measurements from a triaxial accelerometer and gyroscope. The comparison of the results obtained with the Neuro-Fuzzy adaptation, the Fuzzy logic adaptation and the traditional Kalman filter shows an improvement in adaptation of the measurement noise covariance matrix performed by the Neuro-Fuzzy system, which was reflected in a better performance on the attitude estimation. Obtained results shows in average an error decreasing of 6.77%, 1.73% and 44.8%, in roll, pitch, and yaw angles, respectively. Integration of the proposed method in a Pedestrian Dead Reckoning (PDR) system for attitude estimation is currently in progress.

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