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Sensor Fusion for Joint Kinematic Estimation in Serial Robots Using Encoder, Accelerometer and Gyroscope

Benigno Munoz-Barron · Jesus R. Rivera-Guillen · Roque A. Osornio-Rios · Rene J. Romero-Troncoso

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Abstract Open-chain manipulator robots play an important role in the industry, since they are utilized in applications requiring precise motion. High-performance motion of a robot system mainly relies on adequate trajectory planning and the controller that coordinates the movement. The controller performance depends of both, the employed control law and the sensor feedback. Optical encoder feedback is the most used sensor for angular position estimation of each joint in the robot, since they feature accurate and low noise angular position measurements. However, it cannot detect mechanical imperfections and deformations common in open chain robots. Moreover, velocity and acceleration cannot be extracted from the encoder data without adding phase delays. Sensor fusion techniques are found to be a good solution for solving this problem. However, few works has been carried out in serial robots for kinematic estimation of angular position, velocity and acceleration, since the delays induced by the filtering techniques avoids its use as controller feedback. This work proposes a novel sensor-fusion-based feedback system capable of providing complete kinematic information from each joint in 4-degrees of freedom serial robot, with the contribution of a proposed methodology based on Kalman filtering for fusing the information from optical encoder, gyroscope and accelerometer appended to the robot. Calibration and experimentation are carried out for validating the proposal. The results are compared with another kinematic estimation technique finding that this proposal provides more information about the robot movement without adding state delays, which is important for being used as controller feedback.

Keywords Kalman filters · Kinematics · Robot sensing systems · Sensor fusion · Motion measurement

B. Munoz-Barron · J. R. Rivera-Guillen · R. A. Osornio-Rios
HSPdigital-CA Mecatronica, Facultad de Ingenieria, Universidad Autonoma de Queretaro, Campus San Juan del Rio, San Juan del Rio, Qro., Mexico

B. Munoz-Barron
e-mail: bmunoz@hspdigital.org

J. R. Rivera-Guillen
e-mail: jrivera@hspdigital.org

R. A. Osornio-Rios
e-mail: raosornio@hspdigital.org

R. J. Romero-Troncoso (✉)
HSPdigital-CA Telematica, DICIS, Universidad de Guanajuato, Salamanca, Gto., Mexico
e-mail: troncoso@hspdigital.org

R. J. Romero-Troncoso
Facultad de Ingenieria, Universidad Autonoma de Queretaro, San Juan del Rio, Qro., Mexico

1 Introduction

Open-chain manipulator robots are widely used in many industrial applications, such as painting and welding. Those applications require high performance in the motion for increased quality in the manufactured products. The robotic system performance mainly relies on a good trajectory planning and efficient control. In the case of the trajectory planning, smooth movements are desired with constraints in speed acceleration and in some cases jerk [1]. Concerning to the motion controller, its performance depends of both the control law and the feedback system. Most of these feedback systems are based on optical encoder [2]. Usually, they are attached to servomotors that control the angular position of each joint in the robot [3]. Those sensors provide accurate information about the servomotor position; however, they cannot detect mechanical imperfections and deformations that are common in open chain robots [4]. In some cases, depending of the method used to extrapolate velocity, the control could decrease its performance at low-velocity movements due to the operating principle of optical encoders [5]. Several proposed techniques can extract the velocity an acceleration information from the encoder but at expenses of adding phase delays that prevent its use in the controller [6].

Related with robotic systems, in [7] a set of controllers featuring speed feedback for serial robots are proposed. The proposal is tested in a 2-DOF robot with fast movements. Results show the importance of having joint-speed measurement available for the controller. Also, in [8] a disturbance observer is proposed for improving the performance of a n-link Robot. It is mentioned that acceleration signal is required to perform the disturbance observer, but such measurement is a hard task in many robotic applications. Other work [9] proposes a robust control based on multivariable feedback and Lyapunov function. The proposal assumes that position, velocity and acceleration of the joints are available. In [4], a joint stiffness identification method for six-revolute serial robots is proposed. The mechanical problems common in serial robots are mentioned. They require translations and rotations measurements of the robot end effector. Also in [10] a filtering method is proposed for backlash estimation using accelerometer wrist torque torque sensor and position encoder information.

The mentioned works propose systems that attempts to improve the performance of motion controllers, also some works focuses on the estimation of mechanical imperfections in robots. However, most of the proposal assumes that velocity and acceleration feedback is available, which is a difficult task in real applications. Concerning to this problem, researches propose sensor fusion techniques that attempts to improve the controller feedback. In [11], encoder and accelerometer information is fused through a combined technique of oversampling and average decimation filtering. Angular position, velocity, acceleration and jerk are estimated for single joint in a serial robot. Due to the decimation stage, the sampling rate of the proposal decreases at each derivative. An efficient technique for machine dynamics estimation based on optical encoder measurements is proposed in [12]. It consists of an adaptive high-order finite impulse response (FIR) differentiator that is defined as two impulse window filter (TIWF), which minimizes the quantization noise generated by successive derivatives of encoder information. The method features low computation; yet, there are induced delays that depend on the adaptive algorithm. In [13] the encoder and accelerometer fusion by means of particle filtering (PF) is proposed. Simulations are carried out for a 3 Degree-Of-Freedom (DOF) robot. They mention that PF outperforms Extended Kalman Filter (EKF) but at the expense of increasing the computational cost. This disadvantage could be prohibitive in industrial robots with higher DOF. A review on the accelerometer and gyroscope fusion for joint angle estimation is presented in [14]. In that work several fusion methods are compared and validated in a 3-DOF robot. In addition, the good cost-performance relation that MEMS-based (Microelectromechanical Systems-based) sensors provide is commented, as well as the needing of reliable methods for increasing the accuracy of the measurement. In [15], the high accuracy of optical encoders and the measurement continuity that accelerometers provide are fused by means of KF technique for joint angular estimation. The proposal is validated in a 6-DOF PUMA robot. However, the proposed methodology is not valid for the first joint where the accelerometer does not provide attitude information. In addition, the variables of angular velocity and acceleration are not calculated since the information from the utilized sensors is not enough to obtain a good estimation of such parameters.

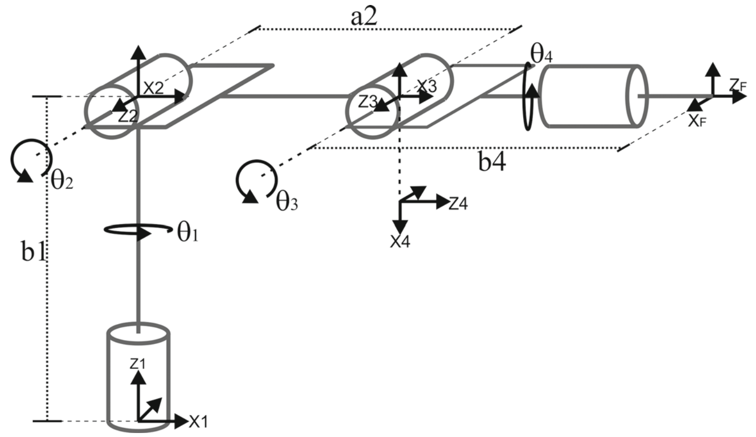

Fig. 1 Robot kinematics of a PUMA robot

The above mentioned techniques focus on providing accurate joint angle estimation in serial robots. Also, in some cases angular velocity is estimated. Nevertheless, only few works have been carried out for complete joint kinematics estimation, including angular acceleration, due to the fact that the accuracy in the measurement system decreases with the successive derivatives [6]. Some works attempt to propose filtering techniques to overcome those problems; however, the sampling rate is compromised, inducing delays that avoid their use in robotic systems. For this reason, it would be desired to have a feedback system capable of providing the robot kinematic information of angular position, velocity and acceleration in each joint in serial robots. Moreover, through the fusion of adequate primary sensors it would be useful to provide the kinematics information without state delays.

The novelty of this work is the design of a sensor-fusion-based feedback system capable of providing complete kinematics information from each joint in a 4-DOF robot, with the contribution of a proposed methodology based on KF technique to combine information from a set of primary sensors consisting of optical encoders, gyroscopes and accelerometers. The utilized kalman filter is a modified version that provides a filtered approximation of the derivative of the input. The proposed methodology allows the system to calculate the measurement of angular position, velocity and acceleration without induced state delays, and thanks to the sensor fusion approach, improve the overall estimation of the robot kinematics. A calibration procedure is utilized for validating the measurement system. Finally, a painting path is performed by the robot whereas the proposal provides complete kinematics information in each joint. The results are compared with the obtained when the technique reported in [12] is used.

2 Robot Kinematics

The kinematics of the PUMA (Programmable Universal Manipulation Arm) robot that is composed of 4 rotational joints is shown in Fig. 1.

where X_i, Y_i, Z_i are the axis name of each joint, θ_i is the angular position of each joint , it also denotes the rotation of the joint along Z axis, a_i is the distance between Z_i and Z_{i+1} axis, b_i is an offset measured along previous Z_{i-1} to the common normal. The robot is an open kinematic chain where each joint is controlled individually. From the diagram, the Denavit-Hartenberg (D-H) parameters are calculated and summarized in Table 1.

where α_i is the angle between Z_{i-1} and Z_i Such parameters are required to compute forward kinematics from the estimated angular positions of each

Table 1 D-H parameters for the robot

Joint i	a_i	b_i	α_i	θ_i
1	0	b_1	$\pi/2$	θ_1
2	a_2	0	0	θ_2
3	0	0	$\pi/2$	θ_3
4	0	b_4	0	θ_4

joint and obtain the position and orientation of each link in the robot. However, their joints are not completely rigid which limits their use in tasks demanding high-accuracy movements [4]. An efficient controller technique could minimize the mentioned problem; however, it mostly depends of the provided information of the instrumentation and measurement system used as a feedback. Some of the desired characteristics for joint measurement in serial robots are:

- Accurate angular position in each joint, for all the open kinematic chain.
- Continuous measurement provided from the sensors;
- The capability of providing angular velocity and acceleration.
- No delays induced by filtering or any kind of signal processing.

Considering those characteristics, a single-sensor feedback could not provide the required information for increasing the overall robot performance. For that reason, it is necessary to fuse the information of several sensors. In this work optical encoder, gyroscope and accelerometer are utilized as primary sensors. Their advantages and disadvantages are described next.

Optical encoders are the most utilized sensor in mechatronic applications, since they can provide noiseless and accurate information about angular position; however, the encoder measurement is quantized and the update rate of the measurement depends on the motor velocity; hence, at low-speed movements the poor information provided by the encoder does not allow to estimate velocity and acceleration without adding a filtering technique [12]. In contrast, gyroscopes can provide continuous angular velocity measurement, allowing to obtain continuous angular position using integration. However, the generated cumulative errors reduce the accuracy of the estimation along the time [16]. Finally, accelerometers are capable to provide information about the monitored robotic system in the form of linear acceleration, vibrations and attitude information using the constant gravity vector [11, 15, 18]. In all cases, optical encoders, gyroscopes and accelerometers have advantages and disadvantages for the information extraction from each joint in serial robots. In order to exploit all the benefits from each kind of sensor, a suitable robotic system is proposed.

3 Methodology

The methodology is summarized in two stages: instrumentation and measurement system. Following subsections describe those stages in detail.

3.1 Instrumentation

The instrumentation of the robot consist of four optical encoders attached to the servomotors, three 3-axis accelerometers and four 3-axis gyroscopes. In the case of gyroscopes only one axis per sensor is utilized. Also, there is no accelerometer in joint 1 since in its case it does not provide information about the angular position. Therefore, the system has to filter and fuse the information from 17 sensor measurements.

For each joint i, encoders directly measure angular position $\theta_{E\,i}$, gyroscopes provide information about the angular velocity $\omega_{G\,i}$ and accelerometers are used to determine the angular position $\theta_{A\,i}$ based on the measured acceleration in each axis $A_i = [A_{i\,X},\ A_{i\,Y},\ A_{i\,Z}]^T$.

3.2 Measurement System

The algorithm of the measurement system that computes the sensor fusion of three primary sensors is summarized in Fig. 2. The algorithm is repeated for each of the four robot joints. The inputs are angular position $\theta_{E\,i}$ obtained with the optical encoders, the accelerometer vector signal A_i , and the angular speed $\omega_{G\,i}$ from the gyroscope. The output of the methodology is the joint kinematics of angular position θ_i, angular velocity $\omega_i$and angular acceleration α_i.

From Fig. 2, it can be noted that the algorithm requires the present and the past state to estimate the angular position, velocity and acceleration. In other words, the induced delays are minimized compared with other techniques, such as the TIWF technique reported by [12] which use a FIR architecture with filter order bigger than 128.

In order to avoid the state delays generated by the FIR architecture, in this article an average recursive filter (ARF) is used. Its equation is shown in Eq. 1.

$$F_k = \frac{1}{N+1}\left(Z_k - F_{k-1}\right) \tag{1}$$

This technique allows to perform the average of the input signal (Z) recursively, with the advantage of

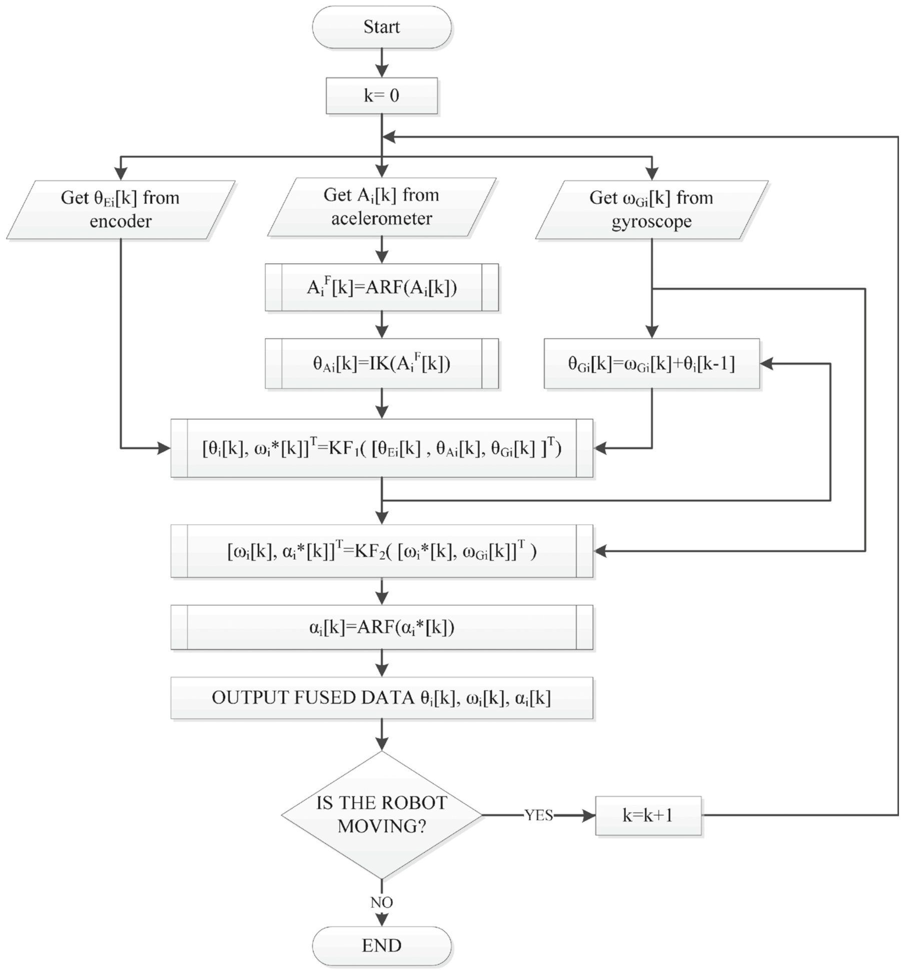

Fig. 2 Algorithm of the measurement system

using only the current measurement (Z_k) and the past filter output (F_{k-1}). N is the number of data being averaged. In the measurement system $N = 63$, for the reason that $N + 1$ becomes multiple of 2 and it simplifies the implementation of the division in the equation.

The subprocess Inverse Kinematics (IK) executes the gravity to inclination conversion from the filtered accelerometer signals $A_i^F = \left[A_{iX}^F, A_{iY}^F, A_{iZ}^F\right]$. This is summarized in Table 2 [15].

Concerning to the Kalman Filter (KF) subprocess, it is composed of the predict and the correct stages whose are summarized in the Eqs. 2 to 6[17].

Predict:

$$X_k^* = S\,X_{k-1} + B\,u_{k-1} \tag{2}$$

$$P_k^* = S P_{k-1} S^T + Q \tag{3}$$

where S matrix relates the previous state $X_{k-1}$and the estimated current state X_k^*, u is an optional control input and B defines the relation between u and X_k^*. Q is the signal covariance and P_k^* is the a priori estimated error covariance.

Table 2 Gravity to Inclination Conversion for Each Joint in the Robot

Joint i	ANGULAR POSITION (ACCELEROMETER) $\theta_{Ai}[k]$
1	–
2	$\pi - \tan^{-1}\left(A_{1y}^F[k]/A_{1z}^F[k]\right)$
3	$\tan^{-1}\left(A_{2x}^F[k]/A_{2z}^F[k]\right) + \theta_{A2}[k] - \pi$
4	$\pi - \tan^{-1}\left(A_{3x}^F[k]/A_{3z}^F[k]\right)$

Table 3 Sensor Characteristics of the Instrumentation

Sensor	Description	Features
Optical encoder	Embedded in a Carl Cloos 6342 Haiger Wire servomotor	Incremental encoder with 1000 counts/rev
Gyroscope	L3G4200D [20]	Digital three-axis gyroscope, up to 800 Hz user selectable bandwidth, user-selectable scale of ±250/500/2000 dps, a 16 bit rate value data output, 8.75 mdps/digit sensitivity and Communication protocol I2C and SPI
Accelerometer	LIS3L02AS4 [21]	Analog three-axis accelerometer, a bandwidth of 750 Hz, a user-selectable full scale of ±2 g/±6 g (g=9.81 m/s2), a 0.66 V/g sensitivity and a 5×10^{-4} resolution over a 100 Hz bandwidth

Correct:

$$K_k^* = P_k^* H^T \left(H P_k^* H^T + R \right)^{-1} \tag{4}$$

$$\begin{bmatrix} X_k \\ V_k^* \end{bmatrix} = \begin{bmatrix} X_k^* & K_k \\ 0 & K_k \end{bmatrix} \begin{bmatrix} 1 \\ Z_k - H X_k^* \end{bmatrix} \tag{5}$$

$$P_k = (I - K_k H)\, P_k^* \tag{6}$$

where R is the noise covariance from the sensor measurements, H relates the measurements Z_k with the current state X_k. $V_k$is an approximation of the derivative of X_k. K_k is a gain factor that minimizes the a posteriori estimated error covariance P_k. The inputs of KF are the measurement vector Z_k and the outputs are the result of Eq. 5. The required parameters to perform KF_1 and KF_2 are: $u = 0 \quad S = 1$, $B = 0$, Q is the covariance matrix of the signals required to filter and combine, R is a diagonal matrix with the noise covariance from each input sensor and $H = [1,\ 1,\ 1]^T$ in the case of KF_1 and $H = [1,\ 1]^T$ in the case of KF_2. It should be noted that the proposed techniques allow estimating angular position, velocity and acceleration without state delays, which is very important for online operation.

3.3 Sensor characteristics

The sensor characteristics are summarized in Table 3. Both encoder and gyroscope provide digital information. Conversely, accelerometer delivers analog measurement which is digitalized using an analog-to-digital converter (ADC) ADS7841 from Texas Instruments [19]. The ADC features four channels, 12-bit resolution and maximum sampling rate of 200kHz.

4 Calibration

In order to validate the performance of the proposed algorithm, a calibration process is proposed. The sensor fusion and the TIWF technique reported in [12] are compared. The TIWF technique is based on high-order adaptive FIR differentiator and takes as input the information provided by optical encoders attached to the servomotors. They are compared in performance, for estimating the position of the end effector in steady state after the robot had moved through a basic trajectory.

A dial indicator Starrett 25-441/5P is utilized as the reference instrument in the calibration procedure

[22]. According to the manufacturer, the dial indicator has an accuracy of ±0.001 inches and a precision of ±0.0005 inches. The calibration consists of the following steps:

- Step C1 To perform a square path in the robot whereas the set of sensors are monitored.
- Step C2 To measure the final position error of the movement by means of the dial indicator.
- Step C3 To estimate the final error using the proposed measurement system and the TIWF technique.
- Step C4 To repeat Step C1 to C3, 20 times and then go to Step C5.
- Step C5 To repeat Step C1 to C4 using a circle path and then go to Step C6.
- Step C6 To estimate the accuracy and the precision of the proposal.

The paths monitored by the sensor fusion-based approach are shown in Fig. 3. They are obtained through the application of forward kinematics to the angular position of the four monitored robot joints by means of the proposed methodology and, for comparing purposes, using TIWF technique in position. Only the error at the end of the movement is considered, since the reference sensor can only measure position statically. The obtained results show almost an identical behavior for both techniques, with differences smaller than 1 %. Through the calibration procedure of the proposed sensor fusion technique an average error of 0.5860 mm is obtained, as well as an accuracy of 0.0707 % and a precision of 0.0830 %. With the TIWF technique, the estimated average error is 0.5862 mm, an accuracy of 0.0707 % and a precision of 0.0832 %. Accelerometer and gyroscope sensors do not give significant information in steady state, for that reason the performance of the sensor fusion algorithm is alike to the TIWF technique. Therefore, the combination of several primary sensors does not affect the performance of the proposed method.

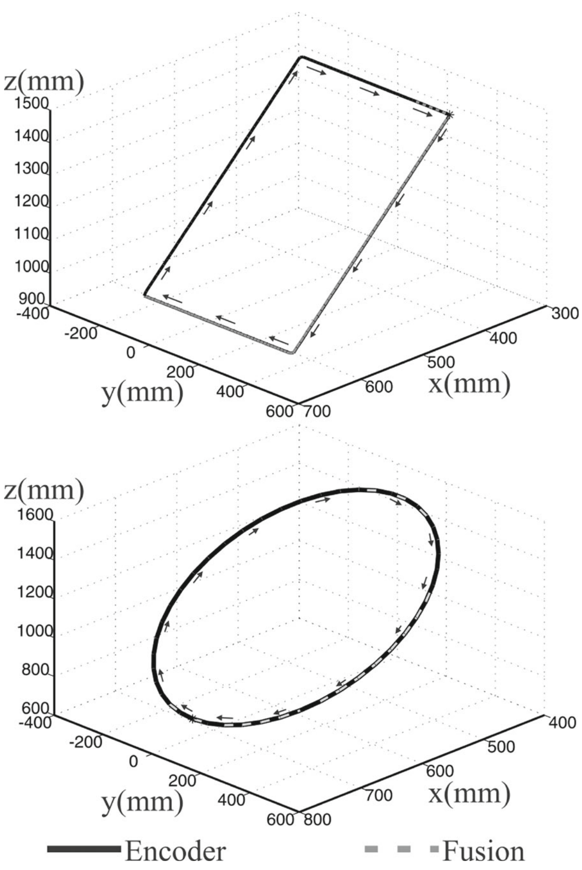

Fig. 3 Path performed by the robot for calibration purposes

5 Experimental Setup

The experimental setup is shown in Fig. 4. It consists of a PUMA robot instrumented with optical encoders, accelerometers and gyroscopes. A personal computer sends the desired trajectory to a multi-axis proprietary controller. The controller manages each joint utilizing as a feedback the optical encoders attached to each servomotor at a sampling rate of 1kHz. The movement is monitored through an FPGA-based data acquisition system since it allows processing all measurements from the sensor arrangement at the same sampling rate of the controller. Measurements are sent to the personal computer where the signal processing of the proposed measurement system is carried out.

In order to validate the proposed measurement system a painting path is performed in the robot since it is a repetitive task commonly used in the industry. During the robot operation the set of sensors are monitored and sent to a personal computer for their processing. The proposed measurement system extracts the information of angular position, angular velocity and angular acceleration for each joint. The results are compared with the TIWF technique.

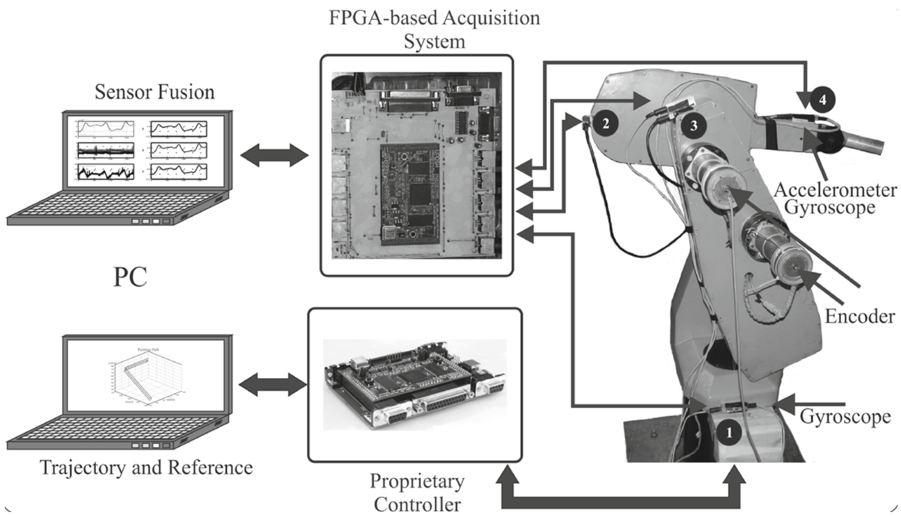

Fig. 4 Experimental setup

6 Results and Discussion

In Fig. 5 the robot tracking of the performed painting path is shown. The results obtained with the proposed methodology are compared to the results obtained using only the encoder information processed by TWIF technique. A particular analysis is carried in the second joint with the objective of show some characteristics of the results obtained. The results for the four joints are summarized and a discussion is presented.

As an illustrative example, the signal processing performed for joint 2 is seen in Fig. 6. The first column shows the primary sensors measurements for the input to the system. Second column shows three estimations

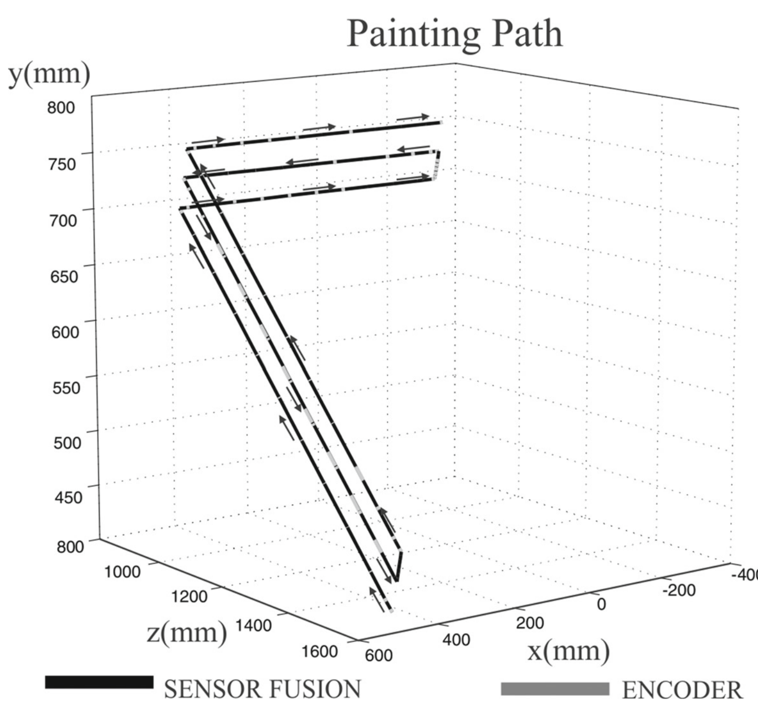

Fig. 5 Robot tracking of the painting path

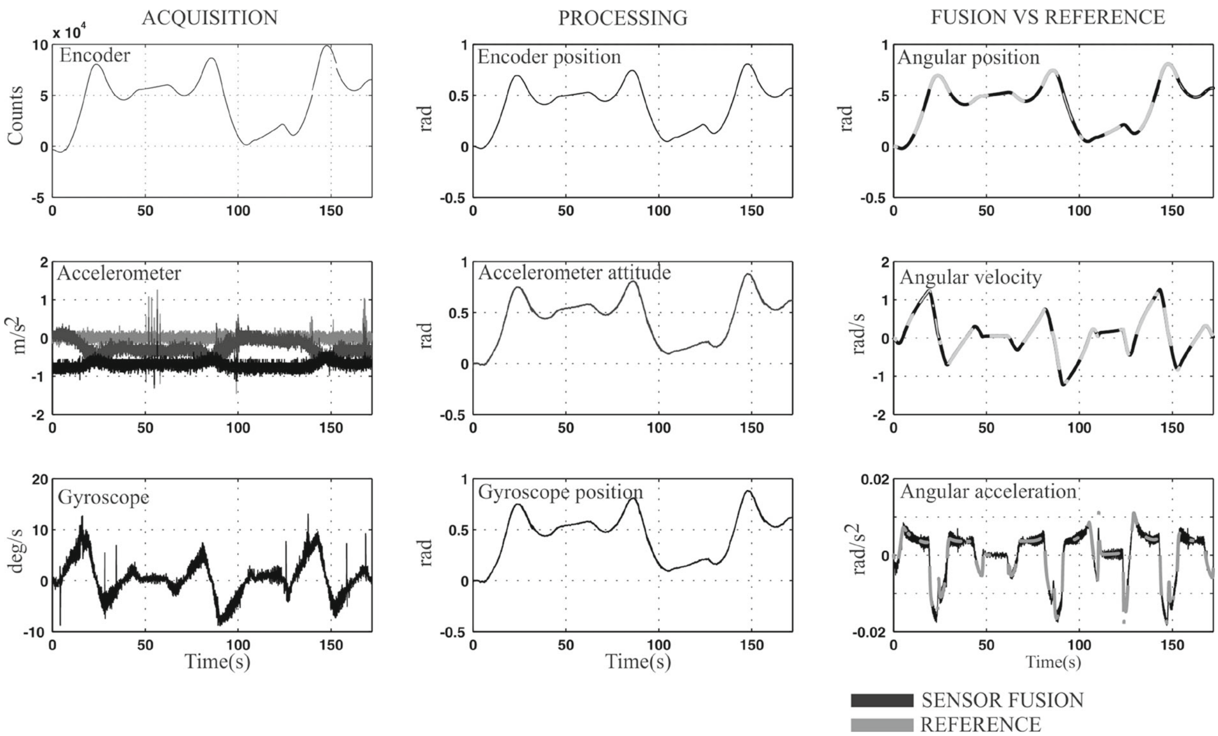

Fig. 6 Acquisition, processing and output for Joint 4

of angular position that are obtained through filtering and processing encoder, accelerometer and gyroscope signals. Third column consists of the output of the measurement system. The estimations of angular position, velocity and acceleration are compared with the ideal case.

Figure 7 shows an extensive analysis for the results obtained for the second joint. The plots in Fig. 7a show the theoretical reference, the kinematics estimation using the proposed method and the estimation using TIWF technique. In Fig. 7b a zoom of the indicated region is shown for a best appreciation. It can be observed that both methods are close to the reference; however, the TIWF technique, due to its auto-adjustable nature, adds some state delays that are more evident in the estimation of acceleration. Quantitatively, the filtered angular velocity using TIWF technique is delayed an average of 125 samples compared with the theoretical reference; in the case of angular acceleration, the delay is 170 samples. In the case of the proposed method, the delay is 27 samples for the angular velocity estimation and 56 samples delayed when angular acceleration is calculated. This means that the TIWF technique presents delays in the velocity estimation more than 4 times bigger than the proposed algorithm. Also, the delays in acceleration using the TIWF technique are 3 times bigger than the sensor fusion technique. The results give the importance of using several sensors, with different characteristics, to better estimate the angular position, velocity and acceleration in robots. Additionally, The proposed system based on the fusion of encoders, accelerometers, and gyroscopes features more information that could be owed to vibrations or other effects that encoder-only measurements cannot detect.

The controller errors calculated with the fused information of the primary sensors for strategic joints are shown in Fig. 8. For comparison purposes, the calculated errors using both the proposed method and the encoder are presented. In the case of joint 1, the fusion is carried out using encoder and gyroscope signal. In this case, the gravity vector obtained using accelerometer is orthogonal to the joint; hence, it does not provide a measurement utilizable in the fusion. For that reason, non significant improvement on position estimation is appreciated. For the joint 4, it can be seen that using only the encoder information, some

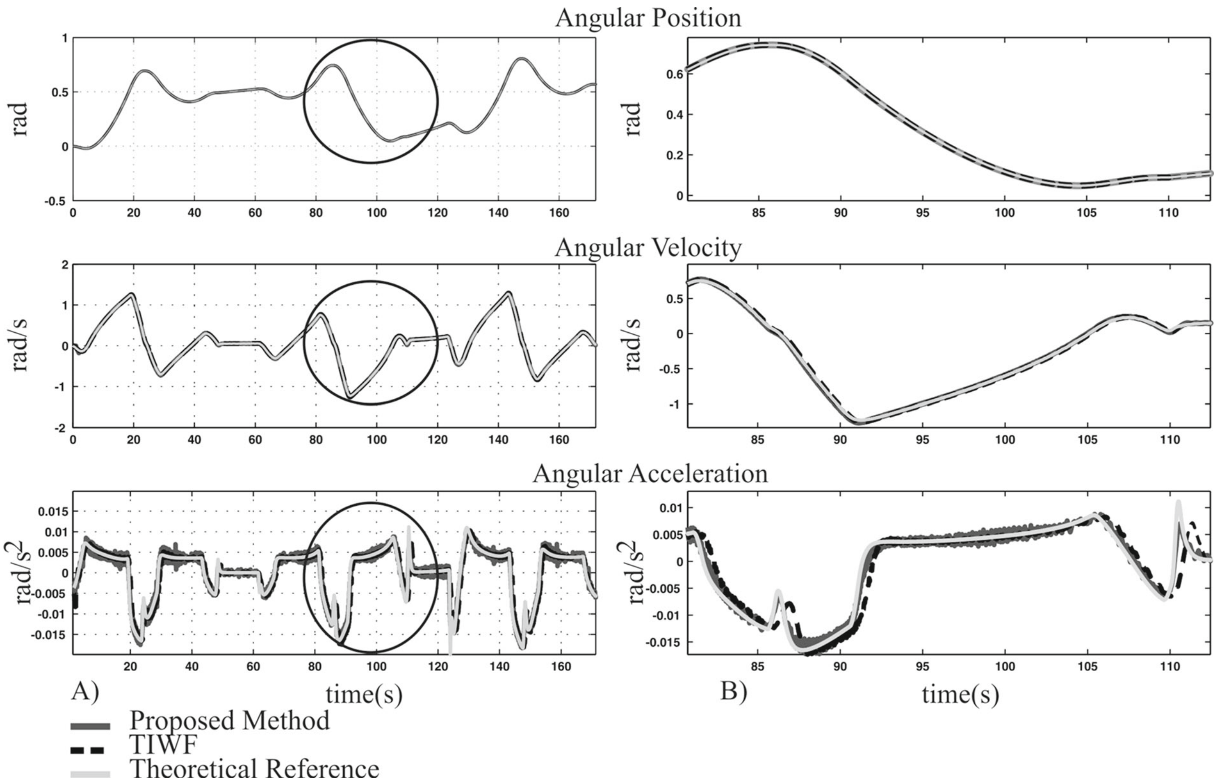

Fig. 7 Joint-2 kinematic estimation, A) comparative of methods, B) zoom to the circled region

errors, due to mechanical problems in the robot, cannot be detected. With the proposed methodology, the fusion is carried out using three different sensors. The measured errors are bigger than the obtained using encoder-only information. Meaning that, the proposed sensor fusion method detects some problems that encoder based system cannot visualize.

The robot controller have only encoder information as feedback. The controller tracking errors in angular position, velocity and acceleration are monitored by means of the sensor fusion algorithm and the TIWF technique, having as reference the theoretical motion profile. Summarized in Table 4, those monitored errors are calculated from the 4 joints of the robot. It can be observed that the monitored controller errors are very similar in both approaches. In some cases the TIWF technique measures lower controller errors, but as discussed previously in Fig. 8, a measurement using only encoder sensor cannot detect some errors owed to problems in the robot. On other side, the state delays in TWIF technique whose are shown and discussed in Fig. 7 are significant and they increase in each derivative, which can reduce the reliability of the error estimation in velocity and acceleration.

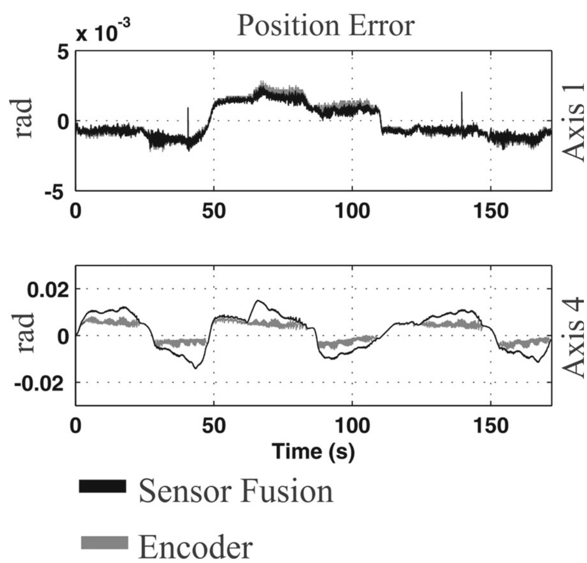

Fig. 8 Controller position errors obtained with the proposed method and the TIWF technique

Table 4 Mean Square Error of the robot controller

Variable	Technique	Joint i			
		1	2	3	4
Position (rad)	Kalman	0.0011	0.0015	0.0013	0.0080
	TIWF	0.0012	0.0006	0.0008	0.0044
Velocity (rad/s)	Kalman	0.0423	0.0716	0.8292	0.018
	TIWF	0.0048	0.1242	0.9307	0.015
Acceleration	Kalman	1.660	1.181	3.765	2.382
(rad/s^2 x10^{-4})	TIWF	0.108	1.895	2.999	0.2661

The importance of the results is that the proposed fusion technique measure errors that cannot be determined using only encoder information. Therefore, the proposal could be used as controller feedback in order to compensate the shown errors. Additionally, the low delays in the estimations using the proposed algorithm could allow to control not only angular position, but also angular velocity and acceleration.

Concerning the computational load of the proposed algorithm, it is required to perform approximately 434 operations. If it is considered an low-cost FPGA working at 48 MHz and a word size of 32 bits the maximum update rate of the proposed system should be approximately 110 kHz, covering the typical industrial applications requirements. Moreover, the cost of the utilized MEMS-based sensors are below 20 USD which converts the proposal in a low cost solution.

7 Conclusion

A system capable of providing complete joint kinematics is proposed and tested in a 4-DOF robot. The system is based on KF technique for fusing the measurements of three primary sensors: optical encoders, gyroscopes and accelerometers. The proposed measurement system takes the advantage of the high accuracy that optical encoders provide with added improvements, thanks to the fusion with gyroscope and accelerometer, such as the continuity in the measurement. The system is capable of providing complete kinematics in each joint (i.e. angular position, velocity and acceleration) without significant delays. The calibration procedure shows that the angular position error in the proposed sensor fusion technique is not affected by cumulative errors caused by using the gyroscope or the accelerometer information. Moreover, Same precision and accuracy is obtained against the technique developed in [12], meaning that the fusion of several primary sensors does not affect the performance of the measurement system in steady state. Dynamically, the performance of the proposed algorithm is measured by beans of the delays in the estimation. Finding that the proposed method is 4 times better in velocity and 3 time better in acceleration when compared with the TIWF technique. In other words, when the robot is moving the redundancy of information provided by the primary sensors and the proposed algorithm helps to estimate the robot angular velocity and acceleration without significant delays. Regarding to the controller errors, shown in Fig. 8, the angular position in each joint reveals some errors that could be due to mechanical imperfections or vibrations that the encoder could not detect. In the case of angular velocity the gyroscope sensor provides noisy error measurements while the sensor fusion improves the estimation. Finally, angular acceleration is also provided. Concerning to the profitability of implementation, the work reported in [15] shows that it is possible to implement KF technique in low-cost FPGA devices and reach the online operation (at least 1 kHz for industrial applications). Also, the utilized MEMS-based sensors in the robot instrumentation converts the proposal in a low-cost solution. It should be noted that the utilized sensors can be affected by changes in temperature. In the case of accelerometer, the change in temperature modifies the sensor bias. For this reason, in future studies, additional processing should be included to the proposed system in order to compensate those undesired effects such as the proposed by [23] where the gravity vector and the temperature values of the accelerometers are utilized for this purpose. Additionally, the system has to be tested as a feedback in motion controllers to quantify how much the robot overall performance is improved as proposed by [7–9]. Furthermore, the proposed methodology could be used as a feedback for some methods of parameter identification or calibration.

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