Event-Triggered Based State Estimation for Autonomous Operation of an Aerial Robotic Vehicle

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Abstract: In this article the problem of event-triggered (ET) state estimation for autonomous navigation of an aerial vehicle is investigated numerically. The aerial vehicle is considered as a general example of a nonlinear non-Gaussian system for state estimation under process and measurement noise. The motivation behind the problem is the conditions that the aerial vehicles are facing in extreme and hazardous environments due to constant exposure of the sensors and actuators to the high frequency process and measurement noises. Here we consider autonomous operation of a quadcopter for mapping of a radioactive environment, where the quadcopter may subject to radiations and non-Gaussian noises. Autonomous operation of the aerial vehicle with a limited available energy and for a longer period of time, demands an efficient management of the energy sources. Therefore, in this study we take the first step towards this goal by studying an event triggering strategy in which the data measured by the sensors is transmitted to the processing unit only if certain events happen. The sensor employed for navigation purpose is the inertial measurement unit, including accelerometers and gyroscopes, used to estimate the quadcopter states only when their measurements are informative. An event-triggered particle filtering (PF) state estimation technique is adopted for this application. The choice of particle filter as state-estimator is inevitable not only because of nonlinear and non-Gaussian nature of the system, but also because of non-Gaussianity of the conditional distribution of the posteriori probability density function resulting from the event triggering. In the proposed method, it is proved that particles are weighted differently in the case of event triggering and no triggering. The numerical results for robust nonlinear attitude stabilization of the quadcopter in the presence of event-triggered particle filter state estimation confirm the efficiency of the proposed method.
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Keywords: Event-triggering (ET), Multichannel Sliding Mode Control, Quadcopter, Particle filtering (PF), Inertial sensors.

1. INTRODUCTION

The quadcopters are increasingly used in various applications, particularly for search and rescue, surveillance and exploration under extreme conditions such as fire, earthquake, flood, and radiation conditions [2]. Of specific importance is nuclear decommissioning in which robotics and autonomous systems have opened their ways in such applications recently. For example, in [3, 4] the problem of dynamic modelling and parameter estimation of a hydraulically actuated seven degree of freedom manipulator for nuclear decommissioning applications is investigated. Although the developed mechanistic model is useful to predict the dynamic behaviour of the robot, optimisation techniques such as the one proposed in [14, 15] are used to tune the parameters of the developed gray-box model. The proposed approach relies on the so-called multi-objectivisation and resulted in a significant improvement in calibration of the hydraulic robotic arm [3, 4]. Alternatively, the use of quadcopter for can be used directly for radiation mapping of the nuclear environment [5, 6], or it is useful to improve the situational awareness of the robotic manipulator working in the same environment [7]. The main advantage of using quadcopter in the nuclear environment is its ability to accurately manoeuvre in a complex industrial setting and navigate deeply inside an unknown hazardous environment. To achieve this performance, finding the exact position and orientation of the quadcopter is crucial while it is equipped with navigation sensors, which are able to communicate with the central computing unit. The remote computing machine is usually able to facilitate calculations relating to the navigation problem of the vehicle. Such systems are referred to as cyber-physical systems in which the sampled measurements are transferred to a digital processor via wired/wireless communication networks. Although in such applications, the central processing unit is well equipped, sensors have limited energy resources, which should be saved as far as possible for autonomous operation of the vehicle. Moreover, there are restrictions in the communication channels, limiting the amount of data transferred by the sensors. To overcome this problem, an event based sampling strategies have attracted extensive attentions during the past two decades. The basic idea behind such a strategy is that the data is transmitted from sensors to the central processing units only if certain events are happening [1].

The problem of state (attitude and position) estimation in a quadcopter UAV has been investigated in several valuable research works [5]. For example, [2] presents an Extended Kalman Filter (EKF) based quadrotor state estimation in which the data coming from the sensors is noisy and intermittent. The EKF filter provides the estimated information for the missing timestamps. An optimal Kalman Filter (OKF) has been used in [8] to estimate the system state vector of a small quadcopter with internal disturbances including the white Gaussian and measurement noises. However, the problem of event triggered state estimation has not been investigated so far for control and navigation problem of the quadcopters.

Although in an event triggered state estimation problem the sensors measuring the outputs of the system at every sampling instant, the measured data are only sent to the estimator when a certain event happens. In this framework, once the measurements are received by the estimator, it updates the estimated states and when it is not received, the estimator selects a predefined value [1].

Generally speaking, the quadcopter operating in the nuclear environment may be a nonlinear non-Gaussian system, and due to the non-Gaussianity of the conditional (posteriori) distribution as a result of event triggering, it is possible to apply the event triggered particle filtering (PF) similar to [1] for the quadcopter system proposed in this paper. The main feature of the proposed method is that, in the case of event triggering and no triggering, that particles are weighted differently. After this introduction, the paper is organized as follows. The system and measurement models of the quadcopter are presented in section 2. Section 3 provides information about the event triggered particle filtering approach. Simulation results are provided in section 4, and the paper is concluded in section 5.

2. QUADCOPTER MATHEMATICAL MODEL

2.1 System model

A quadrotor includes four rotors that generate propeller forces. The propellers are in cross-shaped frame as illustrated in Fig. 1. Variations on the forces and moments by proper adjustment of the rotors speeds produces the attitude changes in the quadrotor. The quadrotor attitude dynamics can be written in the following form [6]:

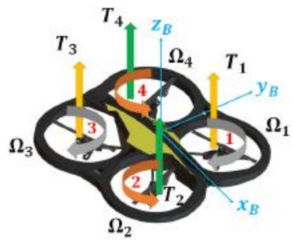


Fig. 1. Schematic of quadrotor with coordinate axes.

$$\ddot{\phi} = \frac{I_{yy} - I_{zz}}{I_{xx}} \dot{\theta}\dot{\psi} - I_r \Omega_r \frac{\dot{\theta}}{I_{xx}} + \frac{u_1}{I_{xx}} + \omega_{\dot{\phi}} \tag{1-1}$$

$$\ddot{\theta} = \frac{I_{zz} - I_{xx}}{I_{yy}} \dot{\phi}\dot{\psi} + I_r \Omega_r \frac{\dot{\phi}}{I_{yy}} + \frac{u_2}{I_{yy}} + \omega_{\dot{\theta}} \tag{1-2}$$

$$\ddot{\psi} = \frac{I_{xx} - I_{yy}}{I_{zz}} \dot{\phi}\dot{\theta} + \frac{u_3}{I_{zz}} + \omega_{\dot{\psi}} \tag{1-3}$$

where, ϕ, θ, ψ are Euler angles which are respectively known as roll (rotation around x-axis), pitch (rotation around y-axis) and yaw (rotation around z-axis). The inertia parameters around three axes are represented with I_{xx}, I_{yy} and I_{zz}, and u_1, u_2 and u_3 are roll, pitch and yaw moments acting on the quadrotor system in the body frame respectively. Moreover, I_r is the inertia of the propellers and Ω_r describes the relative speed of the propeller. Also, the parameters $\omega_{\dot{\phi}}$, $\omega_{\dot{\theta}}$ and $\omega_{\dot{\psi}}$ are roll, pitch and yaw process noises which are zero mean non-Gaussian random processes with known probability density functions and variances of $\sigma^2_{\dot{\phi}}$, $\sigma^2_{\dot{\theta}}$ and $\sigma^2_{\dot{\psi}}$ respectively.

Now, by changing the variables of the model presented in (1) in the standard state-space form

$$x_1 = \phi,\ x_2 = \dot{\phi}, \tag{2}$$

$$x_3 = \theta,\ x_4 = \dot{\theta}, \tag{3}$$

$$x_5 = \psi,\ x_6 = \dot{\psi}, \tag{4}$$

the following compact nonlinear model of the system will be achieved

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)) = \begin{bmatrix} x_2 \\ \frac{I_{yy} - I_{zz}}{I_{xx}} x_4 x_6 - I_r \Omega_r \frac{x_4}{I_{xx}} + \frac{u_1}{I_{xx}} \\ x_4 \\ \frac{I_{zz} - I_{xx}}{I_{yy}} x_2 x_6 + I_r \Omega_r \frac{x_2}{I_{yy}} + \frac{u_2}{I_{yy}} \\ x_6 \\ \frac{I_{xx} - I_{yy}}{I_{zz}} x_2 x_4 + \frac{u_3}{I_{zz}} \end{bmatrix} + \boldsymbol{\omega}(t) \tag{7}$$

where,

$$\mathbf{x} = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 & x_6 \end{bmatrix}^T,$$

$$\mathbf{u} = \begin{bmatrix} u_1 & u_2 & u_3 \end{bmatrix}^T$$

$$\boldsymbol{\omega} = \begin{bmatrix} \omega_{\phi} & \omega_{\dot{\phi}} & \omega_{\theta} & \omega_{\dot{\theta}} & \omega_{\psi} & \omega_{\dot{\psi}} \end{bmatrix}$$

It is worth mentioning that, $\mathbf{x} \in \mathbb{R}^6$ is the state vector with an initial value $\mathbf{x}(0)$, which is generally non-Gaussian with known probability distribution and mean value vector $\boldsymbol{\mu}_0$, and covariance matrix $\mathbf{P}_0$, $\mathbf{u} \in \mathbb{R}^3$ is the input vector, and $\mathbf{f} \in \mathbb{R}^6 \times \mathbb{R}^3 \rightarrow \mathbb{R}^3$ is the nonlinear system function. Furthermore, $\boldsymbol{\omega} \in \mathbb{R}^6$ is the process noise vector which is a zero mean non-Gaussian random process with known probability density function and the covariance matrix $\mathbf{Q} = diag\left(\sigma_\phi^2, \sigma_{\dot{\phi}}^2, \sigma_\theta^2, \sigma_{\dot{\theta}}^2, \sigma_\psi^2, \sigma_{\dot{\psi}}^2\right)$. After discretizing the model of equation (7), the following general discrete nonlinear model is obtained

$$\mathbf{x}_{k+1} = \mathbf{f}_k\left(\mathbf{x}_k, \mathbf{u}_k\right) + \boldsymbol{\omega}_k, \tag{8}$$

where the parameters are the discretized version of the one introduced in the continuous model in (7).

2.2 Measurement model

The employed sensors in this paper are inertial sensors including gyroscopes and accelerometer. Three orthogonally aligned gyroscopes, sensing the angular rate of rotation about the three axes and are corrupted with the measurement noises. The gyroscope measurement model can be written as [10]

$$\mathbf{w}_m = \mathbf{w} + \nu_w, \tag{9}$$

where, $\mathbf{w} = \begin{bmatrix} w_x & w_y & w_z \end{bmatrix}^T$ is a 3×1 angular velocity in the body frame $\mathbf{B}$ defined relative to the world frame $\mathbf{E}$, and ν_w is zero mean 3×1 measurement noise vector with known probability density function and covariance matrix $\mathbf{Q}_w$.

3. EVENT TRIGGERED BASED PARTICLE FILTERING

In this section, a summary of the event-triggered method proposed in [1] is presented to establish the theoretical framework required to apply the technique to the quadcopter system presented in section 2.

3.1 Triggering condition

In order to schedule the data sent by the sensors, a triggering index γ_k, is introduced. Here $\gamma_k = 0$ means no measurement is transferred to the estimator and $\gamma_k = 1$ defines the transmission of measurements from sensors to the estimator.

The event-triggering strategy is presented as

$$\gamma_k = \begin{cases} 0 & \varphi\left(\mathbf{y}_k, \mathbf{y}_{k-l}\right) \geq \zeta_k \\ 1 & otherwise \end{cases} \tag{10}$$

where $\varphi(.)$ is the triggering probability function which determines the information available to the estimator at the no-event instants ($\gamma_k = 0$), and ζ_k is also considered as a random variable with a uniform distribution over $\begin{bmatrix} 0 & 1 \end{bmatrix}$. Besides, $\mathbf{y}_{k-l}$ is the measurement vector sent by the sensors at time the instant $k-l$ which is the last information received by the estimator. The triggering condition here is defined by the probability of no-event given $\mathbf{y}_k$ and $\mathbf{y}_{k-l}$ are known as

$$\Pr\left(\gamma_k = 0 \middle| \mathbf{y}_k, \mathbf{y}_{k-l}\right) = \varphi\left(\mathbf{y}_k, \mathbf{y}_{k-l}\right) \tag{11}$$

where $\varphi(.)$ is the probability kernel with corresponding probability density function $p_\varphi(.)$ and is a function of $\mathbf{y}_k$ and $\mathbf{y}_{k-l}$, generally speaking. Different functions can be defined for $\varphi(.): \mathbb{R}^n \rightarrow \begin{bmatrix} 0 & 1 \end{bmatrix}$. For example, considering a stochastic send-on-delta with a Gaussian kernel we will have

$$\varphi\left(\mathbf{y}_k, \mathbf{y}_{k-l}\right) = \exp\left\{-\frac{1}{2}\left(\mathbf{y}_k - \mathbf{y}_{k-l}\right)^T \mathbf{Y}\left(\mathbf{y}_k - \mathbf{y}_{k-l}\right)\right\}, \tag{12}$$

where $\mathbf{Y}$ is a non-singular positive definite weighting matrix that determines the shape of the Gaussian kernel. The measurement information received by the estimator is denoted as

$$\mathcal{Y}_k = \begin{cases} \mathbf{y}_k & \text{if} \quad \gamma_k = 1 \\ \mathcal{Y}_{k-1} & \text{if} \quad \gamma_k = 0 \end{cases} \tag{13}$$

Accordingly, the measurement history, which is a combination of a set of point-valued measurement is given by

$$\mathbf{I}_k := \left\{\mathcal{Y}_1, \mathcal{Y}_2, \ldots, \mathcal{Y}_{k-1}, \mathcal{Y}_k\right\} \tag{14}$$

3.2 Event-triggered Based Particle Filtering

The MMSE estimate is the mean of $\mathbf{x}_k$ given all combined (set and point valued) information obtained from the event-triggered scheme, that is, the measurement history $\mathbf{I}_k$ as

$$\hat{\mathbf{x}}_k = E\left(\mathbf{x}_k \middle| \mathbf{I}_k\right) = \int_{\mathbb{R}^n} \mathbf{x}_k\, p\left(\mathbf{x}_k \middle| \mathbf{I}_k\right) d\mathbf{x} \tag{15}$$

Since the quadcopter system may be a highly nonlinear and non-Gaussian system in general, it is impossible to obtain an analytical solution for $\hat{\mathbf{x}}_k$ similar to KF or EKF methods. That is due to the fact that the Gaussian assumption does not hold anymore. To overcome this problem, we employ particle filter, in which the probability density function of $p\left(\mathbf{x}_k \middle| \mathbf{I}_k\right)$ is approximated in real-time using the importance sampling with a set of particles generated using system dynamics. According to the Sequential Importance Sampling with Resampling (SISR) method ([11], [12], and [13]), the particles are resampled using their corresponding weights obtained through measurement probability density function such that more important ones are selected amongst others.

The posteriori probability density function, $p\left(\mathbf{x}_k \left|\mathbf{I}_k\right.\right)$ is giving the available hybrid information in two different cases of no triggering ($\gamma_k = 0$) and triggering condition ($\gamma_k = 1$):

No Triggering when $\gamma_k = 0$:

$$p\left(\mathbf{x}_k \left|\mathbf{I}_k\right.\right) = p\left(\mathbf{x}_k \left|\gamma_k = 0, \mathbf{I}_{k-1}\right.\right) \tag{16}$$

which gives [1]:

$$p\left(\mathbf{x}_k \left|\mathbf{I}_k\right.\right) \simeq \frac{1}{N}\sum_{i=1}^{N}\omega_i \delta\left(\mathbf{x}_k - \mathbf{x}_k^{i-}\right) \tag{17}$$

$i = 1, 2, ..., N$

where $\omega_i = \dfrac{p\left(\gamma_k = 0 \left|\mathbf{x}_k^{i-}, \mathbf{I}_{k-1}\right.\right)}{p\left(\gamma_k = 0 \left|\mathbf{I}_{k-1}\right.\right)}$ is the weight corresponding to the i^{th} particle and $\mathbf{x}_k^{i-}$ is the i^{th} generated new particle using the system model, and $\mathbf{x}_{k-1}^{i+}$ is the i^{th} resampled particle at the time instance $k-1$. Also, N is the number of generated particles.

After weight normalization we will have

$$\omega_i^* = \frac{\omega_i}{\sum_{j=1}^{N}\omega_j} = \frac{p\left(\gamma_k = 0 \left|\mathbf{x}_k^{i-}, \mathbf{I}_{k-1}\right.\right)}{\sum_{j=1}^{N} p\left(\gamma_k = 0 \left|\mathbf{x}_k^{j-}, \mathbf{I}_{k-1}\right.\right)} \tag{18}$$

where $p\left(\gamma_k = 0 \left|\mathbf{x}_k^{i-}, \mathbf{I}_{k-1}\right.\right)$ is approximated by $\varphi(.)$ as

$$p\left(\gamma_k = 0 \left|\mathbf{x}_k^{i-}, \mathbf{I}_{k-1}\right.\right) \simeq \varphi\left(\mathbf{y}_k, \hat{\mathbf{y}}_k^{i-}\right) \tag{19}$$

$\hat{\mathbf{y}}_k^{i-} = \mathbf{g}\left(\mathbf{x}_k^{i-}\right)$ is the output predicted by the i^{th} particle of the estimator.

Triggering when $\gamma_k = 1$:

$$p\left(\mathbf{x}_k \left|\mathbf{I}_k\right.\right) = p\left(\mathbf{x}_k \left|\mathbf{y}_k, \mathbf{I}_{k-1}\right.\right) \tag{20}$$

In this case, $p\left(\mathbf{x}_k \left|\mathbf{I}_k\right.\right)$ is approximated with an equation similar to (15) with $\omega_i = \dfrac{p\left(\mathbf{y}_k \left|\mathbf{x}_k^{i-}, \mathbf{I}_{k-1}\right.\right)}{p\left(\mathbf{y}_k \left|\mathbf{I}_{k-1}\right.\right)}$. The normalized weights are then computed as

$$\omega_i^* = \frac{\omega_i}{\sum_{j=1}^{N}\omega_j} = \frac{p\left(\mathbf{y}_k \left|\mathbf{x}_k^{i-}, \mathbf{I}_{k-1}\right.\right)}{\sum_{j=1}^{N} p\left(\mathbf{y}_k \left|\mathbf{x}_k^{j-}, \mathbf{I}_{k-1}\right.\right)} \tag{21}$$

It is worth mentioning that in both cases the normalized weights $\omega_i^*, i = 1, 2, ..., N$, are then employed for importance resampling (IR) in the particle filter algorithm.

4. SIMULATION RESULTS

In this section, the simulation results using MATLAB software for the event-triggered tracking of the quadcopter system is presented. Here the quadcopter is stabilized using a nonlinear robust sliding mode control technique presented in [5, 6].

Physical parameters of the quadcopter which is an AR Drone Parrot 2.0 are measured [4, 5] and considered as $I_{xx} = 7.72\times10^{-2}$ kg m^2, $I_{yy} = 7.64\times10^{-2}$ kg m^2, $I_{zz} = 0.1031$ kg m^2, $I_r = 1.8\times10^{-5}$ kg m^2 and m=2.5 kg.

Figure 3 (a)-(c) illustrates the estimated and real values of the quadcopter roll, pitch and yaw angles when the triggering weighting matrix is selected as $\mathbf{Y} = I_{3\times3}$, where $I_{3\times3}$ is a 3×3 identity matrix. Variation of the triggering index γ_k is also depicted in Fig. 2. Here, the number of particles selected for calculations is $N = 1000$. Furthermore, a Gaussian send-on-delta event trigger condition with different weighting matrices, $\mathbf{Y}$, is considered. The weighting matrix determines the sensitivity to the triggering error and affects the communication rate. The estimation results are compared through root mean square error (RMSE) criterion when different triggering rates are considered. In Table 1, RMSE and percentage of reduction in the communication rate for different weighting matrices are summarized. As can be seen from table for the system considered here, with 83.86% reduction in the communication rate, it is still possible to have a good estimation of the system states with the level of accuracy comparable to 3.2% reduction in the communication rate.

Table 1. Comparing RMSE and communication rate reduction for different weighting matrices

Weighting Matrix ($\mathbf{Y}$)	RMSE	Communication Rate Reduction (percentage)
$\mathbf{Y} = 1000 I_{3\times3}$	3.7488×10^{-5}	3.2119%
$\mathbf{Y} = 200 I_{3\times3}$	5.4712×10^{-5}	26.6255%
$\mathbf{Y} = 100 I_{3\times3}$	7.3402×10^{-5}	53.2729%
$\mathbf{Y} = 50 I_{3\times3}$	9.6105×10^{-5}	83.8603%
$\mathbf{Y} = 10 I_{3\times3}$	1.0112×10^{-4}	99%

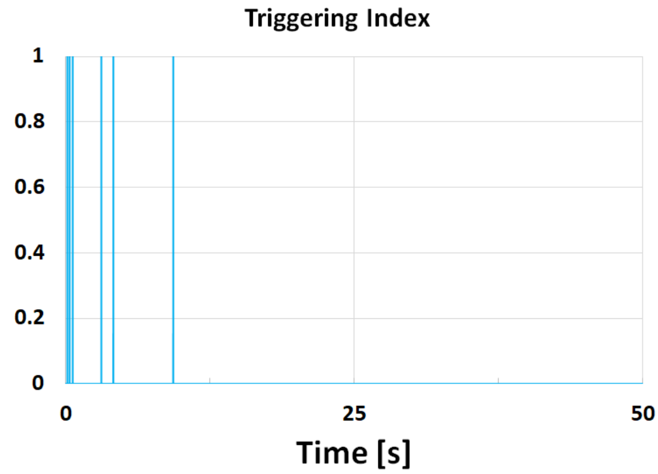
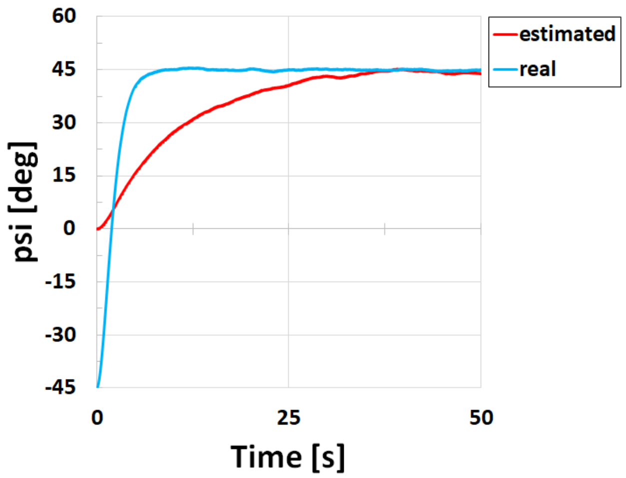
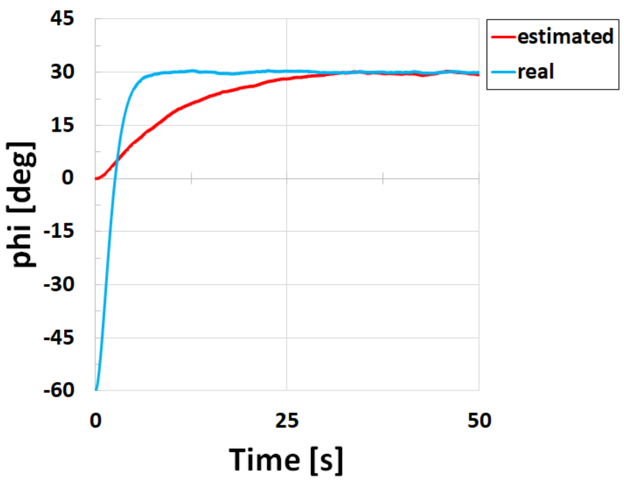


Fig. 2. Triggering index for $\mathbf{Y} = I_{3\times3}$.

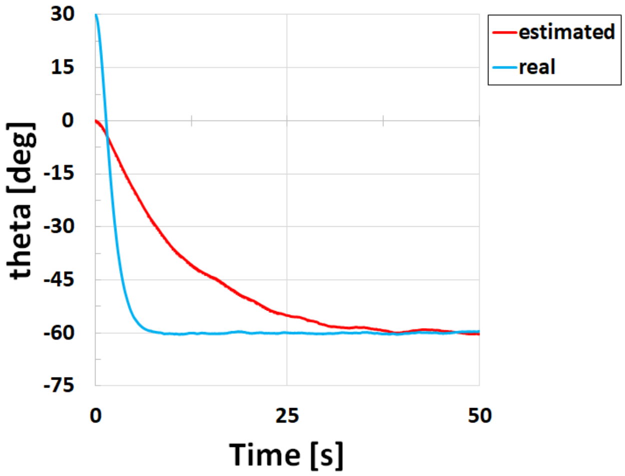


(c) yaw angle (ψ)

Fig. 3. Estimated versus the real values of the quadcopter Euler angles for $\mathbf{Y} = I_{3\times3}$.



(a) roll angle (ϕ)



(b) pitch angle (θ)

5. CONCLUSIONS

In this paper, the problem of event-triggered (ET) state estimation (navigation) for a quadcopter UAV is studied. Here the model of the quadcopter is modelled as a general nonlinear non-Gaussian system on which particle filter is used for state-estimation. The sensors employed for navigation and tracking control problem of the quadcopter are inertial measurement sensors, including accelerometers and gyroscopes which are transmitting the data to the estimator only in the occasions when the measurements are informative. The developed event triggered particle filtering (PF) method proposed in [1] has been employed for state estimation problem of the nonlinear quadcopter system. In the proposed method, the particles are weighted differently in the case of event triggering and no triggering, as proved in [1]. The simulation results demonstrates the efficiency of the proposed method for the quadcopter system to be used in extreme environments, especially for nuclear decommissioning applications.

6. ACKNOWLEDGEMENT

The work is supported by the Engineering and Physical Sciences Research Council (EPSRC), grant number EP/R02572X/1, and National Centre for Nuclear Robotics. The authors are grateful for the support of the National Nuclear Laboratory (NNL) and the Nuclear Decommissioning Authority (NDA).

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