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Design and Experimental Development of Wireless Iterative Learning Fault Estimation Algorithm With Quantization and Packet Losses

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ABSTRACT In this paper, a wireless iterative learning fault estimation algorithm (WILFEA) is proposed and validated experimentally with the aim to achieve perfect tracking of a prescribed reference trajectory for systems with packet losses and quantizer measurements that operate repetitively. First, state variables, Markov chain process of random packet losses, and a logarithmic quantizer are considered to establish an extended-state-space system model. Next, based on this model, sufficient conditions for linear repetitive processes are developed with the Lyapunov-Krasovskii technique and H_∞ approach is applied to calculate the observer gain and the learning gain. Then, WILFEA based fault estimation is constructed. Compared with the existing methods, the proposed WILFEA improves the fault estimation performance in the current iteration by consider both state error and fault estimation error. Finally, the simulation and experimental results are used for DC-Servomotor system to illustrate the effectiveness of the proposed approach using Matlab/simulink software, LabVIEW Software, ZigBee Xbee and Arduino board.

INDEX TERMS Iterative learning algorithm, quantiser measurements, random packet losses, fault estimation.

I. INTRODUCTION

Networked Control Systems (NCSs) are usually composed by continuous-time plants, controlled by digital controllers where the sensors and control signals are transmitted over user-selected communication network. In this context, the controller-to-actuator and sensors-to-controller channels make the overall control signals sampled before being transmitted with communication delays. NCSs provide many technological advantages, regarding to traditional point-to-point continuous time control approaches, from the use of networked data transmission between the plant to be controlled and the control components, such as a reduced installation costs, better maintainability and greater flexibility [1]–[4]. Moreover, with the growing development of the network access technologies, NCSs are now being much more displayed in many real control systems, for example in wide area plant automation, in intelligent transportation systems, or in smart grids [3]–[6]. However, compared to traditional point-to-point continuous-time control approaches, the closed-loop NCS dynamics is strongly affected by the sampled-data nature of the control signals and the network-induced delays, which may lead to degrade the closed-loop performances or in the worst-case to make the closed-loop NCS unstable. Network induced packet losses can cause the delay [7], [8], even lead to loss and error of system information, thus increasing the complexity of the system. These factors will affect the reliability of the system, and cause the system performance decline. In order to improve the reliability and security of the system, the NCSs fault diagnosis (FD) of the problem is crucial. Therefore, it is of great significance to study FD of NCSs. Many FD schemes have been introduced in the literatures. For example, in [9], the problem of observer-based FD for a class of NCSs with random time-delays is studied. In [10], the FD problem for non-linear NCSs with packet dropout and delay is investigated. A co-design approach of time variant residual generator and threshold is proposed in [11], with the aim to improve the dynamic and the

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sensitivity of the FD system to the faults. Considering the presence of signal quantization, such as digital computers with Analogue-to-digital and digital-to-analogue converters, the presence of access network medium with limited capacities may cause low resolution of the transmission of data and large quantization errors. Whereas the negative effects of quantization errors, [12] propose fault estimation (FE) problem for a class of non-linear quantitative measurement systems. Over the past decades, considerable attention has been devoted to the theoretical research on the FE problem, a few researchers have considered the FE problem for repetitive systems [13]–[16]. For estimating the fault in a class of linear systems with sensor random packet losses, time-varying delays, limited communication and actuator failure. In [13], an networked iterative learning (IL)-based FE approach is proposed. Refs. [17]–[19] proposes different solutions to the problem of stabilization of systems with quantized signals. By considering dynamic quantization, a combined framework was presented in [20] for the analysis of NCSs via a mixed system approach. However, varying transmission delays and packet loss were ignored in the analysis. A LMI-based time-triggered algorithm was provided in [4] via the approach of time delay for NCSs with dynamic quantization and network-induced delays, this algorithm is proposed in terms of sampling instants at the sensors. By considering logarithmic quantiser of output signals and the number of quantization levels of output signals, an iterative learning observer for nonlinear systems is provided in [21]. For describe the time-varying parametric uncertainties, an adaptive iterative learning control method for switched nonlinear continuous-time systems with time-varying parametric uncertainties is has been investigated in [22]. However, packet loss was not taken into account. In [21], the fault estimation problem is investigated for a class of non-linear systems with quantized measurement. A sensor fault estimation scheme-based iterative learning observer is proposed for non-linear repetitive system [23]. Some iterative learning algorithms based fault estimation have been developed for non-linear systems [21], [23]–[25], but they are restricted to NCSs [26]–[28]. The discussions above motivate us to develop a wireless iterative learning algorithm (WILA) based fault estimation for systems with packet losses and quantizer measurements. The goal of this paper are highlighted as follows:

1) A new dynamic model of NCSs is constructed, random sensor-controller channels packet losses and quantized measurement are considered in a unified framework.
2) A new relaxed stability is proposed, the Lyapunov function is presented to verify the stability of state estimation error system and robust monotonic trial to trial convergence and satisfy H_∞ performance, and the optimal function is designed to guarantee the iterative tracking error convergence.
3) The designed WILA is robust against quantizer measurements and packets losses, and it realizes better tracking performance in fault signal tracking. Finally, to evaluate the performance of presented iterative learning scheme based fault estimation method, the proposed method is compared with the existing iterative learning scheme results [21], [28], the results demonstrate that the proposed method realizes a short running iteration index and satisfactory tracking performance in fault signal tracking.
4) Experimental test bench for validation of designed wireless iterative learning scheme based fault estimation method is proposed.

The remainder of this paper is organized as follows: The next section introduces the problem statement and preliminaries, in this section the model of quantized NCSs and Markov chain process of packet loss are established. The design of the proposed WILFEA is developed in section III. Section IV presents, the experimental setup of WILFEA and discusses the simulation and experimental results. Finally, a conclusion is provided, including some perspectives of this work.

II. SYSTEM DESCRIPTION AND PRELIMINARIES

The following continuous-time linear repetitive systems with system fault is considered:

$$\begin{aligned} x_k(t+1) &= Ax_k(t) + Bu(t) + F_f f_k(t) \\ y_k(t) &= Cx_k(t), \quad 0 \le t \le \mathrm{T_c} \end{aligned} \tag{1}$$

where k denotes the iteration index, $k \geq 0$, t is the time index, $\mathrm{T_c}$ is the iteration length; $x_k(t) \in R^n$, $u_k(t) \in R^p$ are the system state vector and control input vector respectively, $f_k(t) \in R^q$ is fault system. The matrices A, B, C, and F_f are real constant matrices with approximate dimensions. The initial condition is given by $x_k(0) = x_0$.

We consider quantized measurements as in [20]

$$q(y_k(t)) = (I + \delta_q(t))y_k(t), \tag{2}$$

After each transmission and reception, the values in $q(y_k(t))$ are updated with the newly received values after each iteration.

If $\delta_q(t) = 0$, the system output is not affected by data quantization.

where

$$\delta_q(t) = \begin{pmatrix} \delta_q^1(t) & 0 & \cdots & 0 \\ 0 & \delta_q^2(t) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \delta_q^n(t), \end{pmatrix}, \tag{3}$$

with $\left|\delta_q^i(t)\right| < \theta, i \in [1, 2, \cdots n]$,

$q(.)$ denotes the logarithmic quantizers, and satisfies

$$q(\sigma) = \begin{cases} \varsigma_\tau & \dfrac{1}{1+\theta}\varsigma_\tau < \sigma < \dfrac{1}{1-\theta}\varsigma_\tau \\ 0, & \sigma = 0 \\ -q(-\sigma) & \sigma < 0 \end{cases} \tag{4}$$

where $\theta = \dfrac{1-\rho}{1+\rho}$, $\varsigma_\tau = \rho^\tau$, $\tau = \{0, \pm 1, \pm 2, \cdots\}$.

Assuming that random packet losses exist in the sensors-to-controller link. The following equation describe this phenomena [10]:

$$\bar{y}_k(t) = \begin{cases} y_k(t-1), & \gamma(t) = 0 \\ y_k(t), & \gamma(t) = 1 \end{cases} \tag{5}$$

where $\gamma(t) = 0$ means that there exist packet losses; $\gamma(t) = 1$ indicates that the information transmission is successful in sensors-to-controller link, $\bar{y}_k(t)$

The stochastic variable $\gamma(t)$ which satisfy the Markov chain process. The Markov chain process considered in this paper is established as follows

$$\begin{cases} p_{ij} = Prob\{\gamma(t+1) = j \mid \gamma(t) = i\} \\ \sum_{j=0}^{1} p_{ij} = 1, \ \forall i, j \in \{0, 1\}, p_{ij} > 0. \end{cases} \tag{6}$$

where p_{ij} denotes the transition probabilities.

Substituting (5) into (1), we can get

$$\begin{aligned} x_k(t+1) &= Ax_k(t) + Bu(t) + F_f f_k(t) \\ \bar{y}_k(t) &= C\Psi(t)\bar{x}_k(t), \quad 0 \le t \le \mathrm{T_c} \end{aligned} \tag{7}$$

with

$$\Psi(t) = \begin{bmatrix} 1-\gamma(t) & 0 \\ 0 & \gamma(t) \end{bmatrix} \text{ and } \bar{x}_k(t) = \begin{bmatrix} x_k(t) \\ x_k(t-1) \end{bmatrix},$$

Then, from (7) and (2), the resulting dynamic augmented system with random packet losses and quantised measurements can be rewritten as

$$\begin{aligned} x_k(t+1) &= Ax_k(t) + Bu(t) + F_f f_k(t) \\ \widetilde{y}_k(t) &= (I + \delta_q(t))C\Psi(t)\bar{x}_k(t), \quad 0 \le t \le \mathrm{T_c} \end{aligned} \tag{8}$$

III. ITERATIVE LEARNING OBSERVER DESIGN

According to (8), the WNILA based fault estimation considered in this paper is proposed as

$$\begin{aligned} \hat{x}_k(t+1) &= A\hat{x}_k(t) + Bu(t) + F_f\hat{f}_k(t) \\ &\quad + K\left[\delta_q(t)\Psi(t)(y(t) - \hat{y}_k(t)\right]) \\ \hat{y}_k(t) &= C\hat{x}_k(t)) \end{aligned} \tag{9}$$

where $\hat{x}_k(t)$ and $\hat{y}_k(t)$ are the estimated state and estimated output at k iterations, respectively. The parameter matrix K is an appropriate gain matrix.

If we define the state estimation error in the k^th iteration as

$$\varepsilon_k(t) = x_k(t) - \hat{x}_k(t), \tag{10}$$

and the fault estimation error as

$$\eta_k(t) = f_k(t) - \hat{f}_k(t), \tag{11}$$

then the dynamic error system can be described by

$$\begin{aligned} \Delta\varepsilon(t) &= \varepsilon_k(t+1) - \varepsilon_k(t) \\ &= (A - I - KC\Psi(t))\varepsilon_k(t) + F_f\eta_k(t)) \\ &\quad - \delta_q(t)KC\Psi(t)\bar{x}_k(t) \end{aligned} \tag{12}$$

$$\Delta y_k(t) = y_k(t) - \hat{y}_k(t) \tag{13}$$

The wireless iterative learning scheme based on the fault estimating law is proposed as

$$f_{k+1}(t) = f_k(t) + \Gamma_1\varepsilon_k(t) + \Gamma_2\Delta\varepsilon_k(t) \tag{14}$$

In which, Γ_1 and Γ_2 represents gain matrices.
then, the dynamic error system can be described by

$$\begin{aligned} \eta_{k+1}(t) &= f_k(t) - \hat{f}_{k+1}(t) \\ &= \eta_k(t) - \Gamma_1\varepsilon_k(t) + \Gamma_2\Delta\varepsilon_k(t)\eta_{k+1}(t)) \\ &= -\left[\Gamma_1 + \Gamma_2(A - I - KC\Psi(t))\right]\varepsilon_k(t)) \\ &\quad + (I - \Gamma_2 F_f)\eta_k(t) + \delta_q(t)KC\Psi(t)\Gamma_2\bar{x}_k) \end{aligned} \tag{15}$$

IV. CONVERGENCE ANALYSIS

To guarantee the error extended system is asymptotically stable, following Lyapunov function is considered

$$V(t) = \varepsilon_k^T(t)P_1\varepsilon_k(t) + x_k^T(t)P_2x_k(t) \tag{16}$$

Let us consider the following optimal function to ensure the convergence of fault estimating law via H_∞ performance.

$$\mathbb{H}_k(t) = \sum_{t=0}^{T_d}\left[\eta_{k+1}^T(t)\eta_{k+1}(t) - \gamma^2\eta_k^T(t)\eta_k(t)\right] \le 0 \tag{17}$$

with $\gamma \in [0, 1]$.

Hence, system fault estimation can be achieved.

Theorem 1: Consider linear system (1). The sufficient condition of the error dynamic system (15), which satisfy asymptotically stable H_∞ performance and the fault estimation error convergence,if there exist positive-definite matrices $P_1 = P_1^T$, $P_2 = P_2^T$, gain matrix K, updating gain matrix Γ_1 and Γ_2 and scalars $\mu > 0$, $\lambda > 0$, set that $\bar{K} = P_1^{-1}K$, such that the following LMI holds:

$$\Xi = \begin{bmatrix} -I & 0 & \Xi_{13} & \Xi_{14} & -I & 0 & 0 \\ * & -P_1 & \Xi_{23} & \Xi_{24} & 0 & -P_1 & 0 \\ * & * & \Xi_{33} & 0 & 0 & 0 & 0 \\ * & * & * & -\mu^2 I & 0 & 0 & \Xi_{47} \\ * & * & * & * & 0 & 0 & 0 \\ * & * & * & * & * & \Xi_{66} & 0 \\ * & * & * & * & * & * & -\lambda I \end{bmatrix} < 0$$

$$\begin{aligned} \Xi_{13} &= -\Gamma_1 - \Gamma_2(A - I) \\ \Xi_{14} &= I - \Gamma_2 F_f \\ \Xi_{23} &= P_1 A - \delta_q(t)\bar{K}C \\ \Xi_{24} &= P_1 F_f \\ \Xi_{33} &= -P_1 + C^T C \\ \Xi_{47} &= \delta_q(t)C^T\bar{K}^T \\ \Xi_{66} &= A^T P_2 A - P_2 + \lambda\theta^2 C^T C \end{aligned} \tag{18}$$

where $(*)$ denotes de the symmetric term.

In which $\bar{K} = P_1^{-1}K$, then $K = P_1\bar{K}$

Proof: Consider the Lyapunov function as

$$V_k(t) = \varepsilon_k^T(t)P_1\varepsilon_k(t) + x_k^T(t)P_2x_k(t) \tag{19}$$

According to (12), the derivative time of (19) is given as:

$$\begin{aligned}\Delta V_k(t) = {}& \varepsilon_k^T(t)\left[(A-LC)^T P_1(A-LC)-P_1\right]\varepsilon_k(t)) \\ &+\eta_k^T(t)F_f^T P_1 B_f \eta_k(t)x_k(t)) \\ &\times\left[(LC\delta_q(t))^T P_1 LC\delta_q(t)+A^T P_2 A-P_2\right]x_k(t)) \\ &+2\eta_k^T(t)F_f^T P_1(A-L_1C)\varepsilon_k(t)) \\ &+2\eta_k^T(t)(LC\delta_q(t))^T P_1(A-L_1C)\varepsilon_k(t)) \\ &+2x_k^T(t)(LC\delta_q(t))^T P_1(A-L_1C)\varepsilon_k(t)) \\ &+2x_k^T(t)(LC\delta_q(t))^T P_1 F_f\eta_k(t) \\ &+2u_k^T(t)B^T P_2 A x_k(t)+2f_k^T(t)F_f^T P_2 A x_k(t)) \\ &+2f_k^T(t)F_f^T P_2 Bu(t)+2u(t)B^T P_2 Bu(t)) \\ &+f_k^T(t)B_f^T P_2 F_f f_k(t))\end{aligned} \tag{20}$$

Meanwhile, Equation (20) satisfy the following assumptions:

Assumption 1: The input vector satisfy $\max_{1\le k\le n}\|u(t)\|\le\bar{u}$.

Assumption 2: The intermittent fault signal $f_k(t)$ *satisfy* $\max_{1\le k\le n}\|f_k(t)\|\le\bar{f}$.

According to the assumptions, the derivative time of (19) is rewritten as:

$$\begin{aligned}\Delta V_k(t) \le {}& \varepsilon_k^T(t)\left[(A-LC)^T P_1(A-LC)-P_1\right]\varepsilon_k(t)) \\ &+\eta_k^T(t)F_f^T P_1 B_f \eta_k(t)x_k(t)) \\ &\times\left[(LC\delta_q(t))^T P_1 LC\delta_q(t)+A^T P_2 A-P_2\right]x_k(t)) \\ &+2\eta_k^T(t)F_f^T P_1(A-L_1C)\varepsilon_k(t)) \\ &+2\eta_k^T(t)(LC\delta_q(t))^T P_1(A-L_1C)\varepsilon_k(t)) \\ &+2x_k^T(t)(LC\delta_q(t))^T P_1(A-L_1C)\varepsilon_k(t)) \\ &+2x_k^T(t)(LC\delta_q(t))^T P_1 F_f\eta_k(t) \\ &+2\bar{f}_k\left\|BF_f^T\right\|\|P_2\|\,\bar{u}) \\ &+2\bar{u}^2\|B\|^2\|P_2\|) \\ &+\|f_k(t)\|^2\left\|B_f P_2 F_f\right\|)\end{aligned} \tag{21}$$

Then, (21) can be re-written as:

$$\Delta V_k(t) \le \begin{bmatrix}\varepsilon_k(t)\\ \eta_k(t)\\ x_k(t)\end{bmatrix}^T \Pi_1 \begin{bmatrix}\varepsilon_k(t)\\ \eta_k(t)\\ x_k(t)\end{bmatrix} \tag{22}$$

with

$$\Xi_1 = \begin{bmatrix} -I & 0 & \Xi_{1,13} & I-\Gamma_2F_f & 0 \\ * & -P_1 & \Xi_{1,23} & P_1F_f & 0 \\ * & * & \Xi_{1,33} & -\gamma^2 I & 0 \\ * & * & * & 0 & 0 \\ * & * & * & * & 0 \end{bmatrix},$$

$$\Xi_{1,13} = -\Gamma_1-\Gamma_2(A-I)+\Gamma_2P_1^{-1}\bar{K}C,$$

$$\Xi_{1,23} = P_1A-KC,$$

$$\Xi_{1,33} = -P_1+C^TC+\lambda I,$$

Based on Lyapunov stability theory, we can rewrite the inequality (19) as follow:

$$\Xi_1 < 0 \tag{23}$$

According to (17), The optimal function $\mathbb{H}_k(t)$ is re-written as follow

$$\mathbb{H}_k(t) = \sum_{t=0}^{T_d}\left[\begin{bmatrix}\varepsilon_k(t)\\ \eta_k(t)\\ x_k(t)\end{bmatrix}^T \Xi_2 \begin{bmatrix}\varepsilon_k(t)\\ \eta_k(t)\\ x_k(t)\end{bmatrix}\right] \le 0 \tag{24}$$

with

$$\Xi_2 = \begin{bmatrix} -I & 0 & \Xi_{2,13} & I-\Gamma_2F_f & 0 \\ * & -P_1 & \Xi_{2,23} & P_1F_f & 0 \\ * & * & \Xi_{2,33} & -\gamma^2 I & 0 \\ * & * & * & 0 & 0 \\ * & * & * & * & 0 \end{bmatrix},$$

$$\Xi_{2,23} = P_1A-\delta_q(t)KC,$$

$$\Xi_{2,33} = -P_1+C^TC+\lambda,$$

$$\Xi_{2,14} = I-\Gamma_2F_f,$$

Let us denote $\bar{K} = P_1K$, then the following inequalities holds

$$\Xi_1 = \Xi_2+\Xi_3 < 0$$

$$\Xi_3 = \begin{bmatrix} 0 & 0 & \delta_q(t)\Gamma_2P_1^{-1}\bar{K}C & 0 & 0 \\ * & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 \\ * & * & * & * & 0 \end{bmatrix}, \tag{25}$$

The matrix Ξ_1 is well extracted into the summation of the constant term. $\left|\delta_q(k)\right| \le \theta$,

Moreover, if and only if there exist *delta* > 0, then the inequality (25) holds, such that

$$\Xi_4 = \begin{bmatrix} -I & 0 & \bar{\Xi}_{13} & \bar{\Xi}_{14} & 0 & \Gamma_2 & 0 \\ * & -P_1 & \bar{\Xi}_{23} & \bar{\Xi}_{24} & -\bar{K} & 0 & 0 \\ * & * & \bar{\Xi}_{33} & 0 & 0 & 0 & \bar{\Xi}_{37} \\ * & * & * & -\gamma^2 I & 0 & 0 & 0 \\ * & * & * & * & -\delta I & 0 & 0 \\ * & * & * & * & * & 0 & 0 \\ * & * & * & * & * & * & \bar{\Xi}_{77} \end{bmatrix}$$

$$\begin{aligned}&\bar{\Xi}_{13} = -\Gamma_1-\Gamma_2(A-I) \\ &\bar{\Xi}_{14} = I-\Gamma_2F_f \\ &\bar{\Xi}_{23} = P_1A-\delta_q(t)KC \\ &\bar{\Xi}_{24} = P_1F_f \\ &\bar{\Xi}_{33} = -P_1+C^TC \\ &\bar{\Xi}_{37} = \delta_q(t)C^T\bar{K}^T \\ &\bar{\Xi}_{77} = -\gamma_2P_1\end{aligned} \tag{26}$$

In which $\bar{K} = P_1^{-1}K$, then $K = P_1\bar{K}$.

This completes the proof.

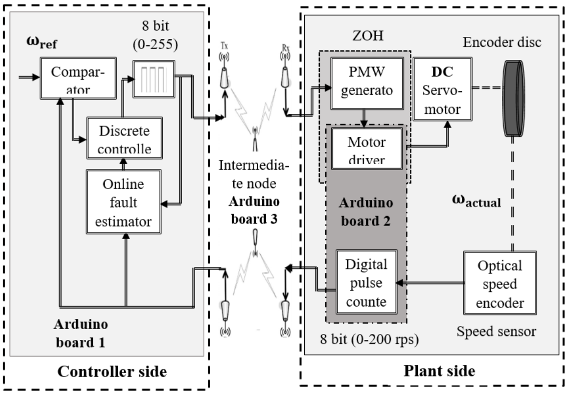

FIGURE 1. Experimental setup of wireless NCS using *ZigBee Xbee* modules for wireless communication, LabVIEW software and Arduino board and DC servo motor.

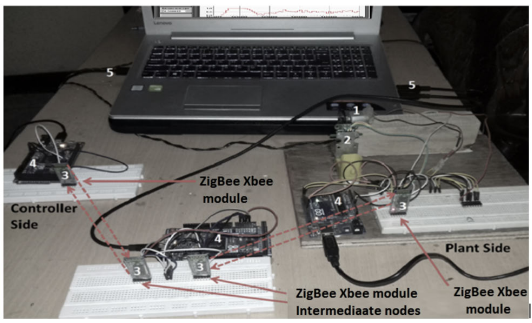

FIGURE 2. Real setup of the experiment.

TABLE 1. Technical specifications of ZigBee [29].

Specifications	Description
Frequency	$2.4\,GHz$ (Home automation)
Communication range	10 to 100 $meters$ (line of sight)
Data rate	20 $kbps$ to 50 $kpbs$
Network type	Device to device communication

TABLE 2. Specifications of *HC-020k* [30].

Specifications	Description
Measurement frequency	$100\,KHz$
Encoder resolution	20 $lines$
Voltage range	$4V - 5V$

V. EXPERIMENTAL AND SIMULATION RESULTS

A. EXPERIMENTAL SETUP

The experimental setup of wireless NCS using *ZigBee Xbee* modules for wireless communication, LabVIEW software, Arduino board, and DC servo motor is depicted schematically in Figure(1), and the real setup of the experiment as shown in Figure(2).

The technical specifications of ZigBee is depicted in the Table (1). The speed sensor module used in this works is an *HC-020k* optical speed encoder, the technical specifications of HC-020k is shown in Table(2).

The speed rate of DC servo-motor is 200 rps and rated voltage is $3V - 5V$. The DC servo-motor is coupled to the drive motor, the motor driver is an *L293D* driver *IC* of Texas Instrument.

Table(3) shows the specifications of *L293D*.

TABLE 3. Specifications of L293D [30].

Specifications	Description
Voltage range	$4.5V - 36V$
Output current	$600\,mA$
Peak output current	$1.2A$
Speed controller	PWM

TABLE 4. Parameters of simulations cases.

Case	Quantization density	Observer gain K	Gain matrices
1	$\rho = 0.88, \theta = 0.024$	$K = 0.77$	$\Gamma_1 = 0.62, \Gamma_2 = 0.54$
2	$\rho = 0.99, \theta = 0.008$	$K = 0.86$	$\Gamma_1 = 0.78, \Gamma_2 = 0.88$
3	$\rho = 0.75, \theta = 0.15$	$K = 0.72$	$\Gamma_1 = 0.69, \Gamma_2 = 0.72$

Arduino board used is an Arduino Uno R3 based on Atmel Atmega 328 microcontroller and has a speed of clock of 16 MHz. The rate speed of DC motor is of 200 rps and he rate voltage of $3V - 5V$.

B. SIMULATION RESULTS

The transfer function of the model of DC servo-motor is identified using System Identification Tool:

$$G(s) = \frac{4.67}{1.02s + 3.99} \tag{27}$$

By choosing a sampling frequency as $f_s = 1/T_s = 200\,Hz$, a discrete time equivalent of this plant can be obtained:

$$G(z) = \frac{0.08864}{z - 0.9247} \tag{28}$$

The state-space model matrices is obtained as

$$\begin{aligned} x_k(t+1) &= 0.9247x_k(t) + 0.2500u(t) \\ y_k(t) &= 0.3546x_k(t), \end{aligned} \tag{29}$$

with $A = [0.9247]$, $B = [0.2500]$, and $C = [0.3546]$. $f(t)$ is considered as intermittent fault signal and is defined as: $f(t) = \begin{cases} f(t) = 0.41(t-80) & 80s \leq t \leq 90s \\ f(t) = 0.45(t-75.7) & 90s \leq t \leq 115s \\ f(t) = 0 & 115s \leq t \leq 130s. \end{cases}$

In simulation, we are choosing the initial state of dynamic model of the system as $x_0 = [0.1]$ and $f(0) = 0$. The range of input control current of servo-motor is set as $3.5mA$, the reference input speed is set as $y_r(t) = 60rps$. The transition probabilities according to Markov chain process are given as $p_{00} = 0.55$, $p_{01} = 0.45$, $p_{10} = 0.2$, and $p_{11} = 0.8$.

We presume that DC servo-motor system accomplish the same assignment above a finite time repetitively, the length is $T_e = 130s$. The following three cases of quantization density are considered in this simulation. Table. 4 shows the observer gain K obtained for deferments quantization density in accordingly Theorem 1.

The distribution of packet losses are depicted in Figure (3).

The actual speed and estimated speed of DC-Servomotor subject to packet losses are shown in Figure (4). From this figure, it is clear to happen that the stability of the system will be slowly reduced. The proposed scheme takes into account the negative effect induced by packet loss.

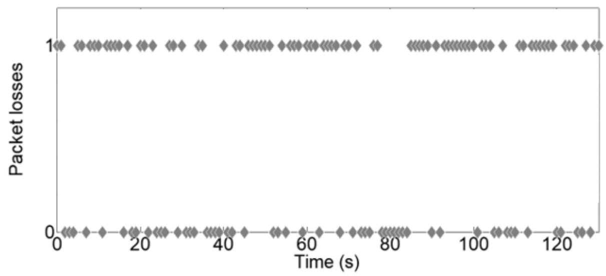

FIGURE 3. The distribution of packet losses (1 means packet received, 0 means packet lost).

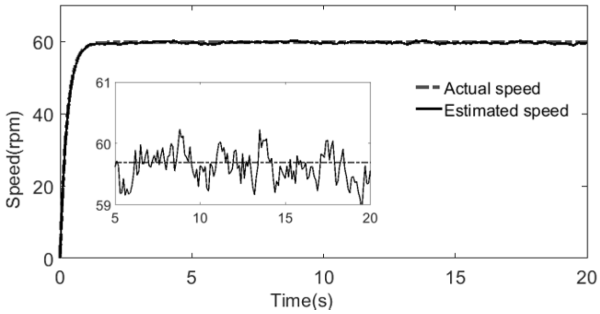

FIGURE 4. Actual speed and estimated subject to packet losses.

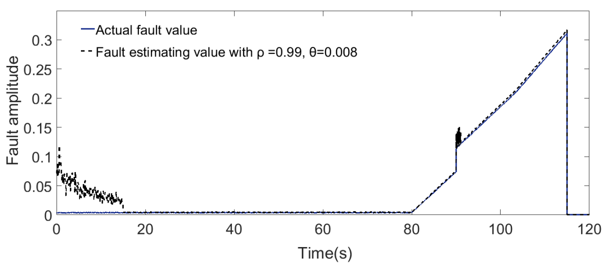

FIGURE 5. Actual fault and estimated fault.

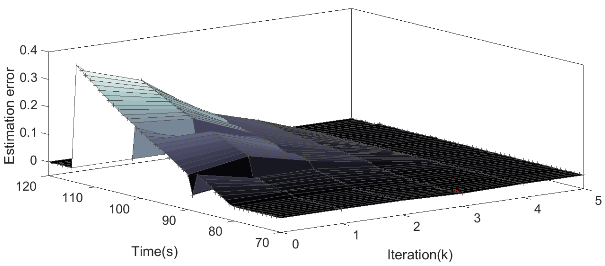

FIGURE 6. Fault estimating error with ($\rho = 0.88, \theta = 0.034$).

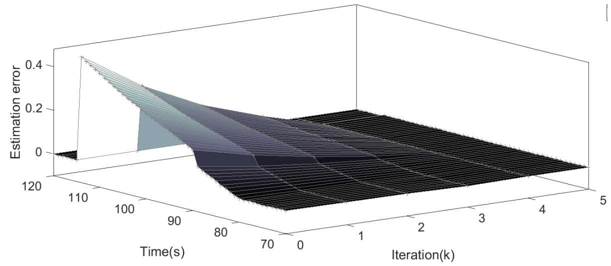

FIGURE 7. Fault estimating error with ($\rho = 0.99, \theta = 0.008$).

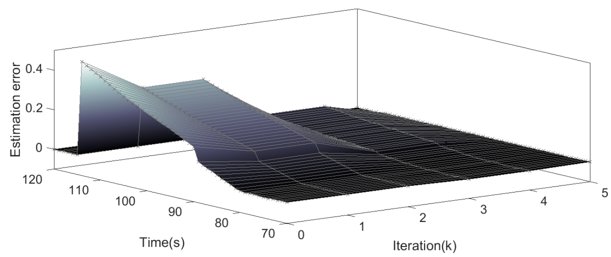

FIGURE 8. Fault estimating error with ($\rho = 0.75, \theta = 0.15$).

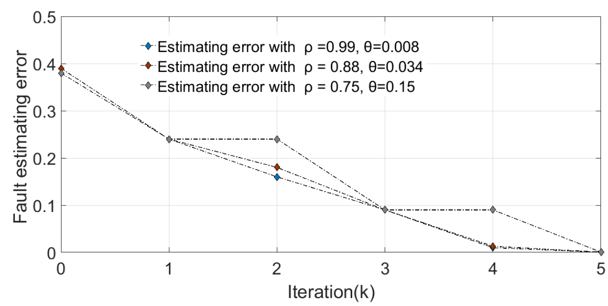

FIGURE 9. Tracking trajectory in different iterative index.

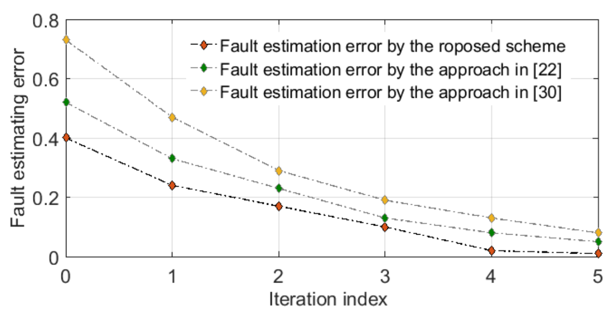

FIGURE 10. Fault estimating error with ($\rho = 0.75, \theta = 0.15$).

The estimated fault signal and actual fault signal at the 3^{rd} iteration is shown in Figure(5). We can obtain that when iterative index increases, the estimating of fault achieve better result.

Figure (6), Figure (7) and Figure (8) present the tracking trajectory in different iterative index for three cases.

The tracking error Figure (9) decreases according to quantization density. It is clear that tracking error is provided by reached quantisation.

To improve illustration of the superiority of proposed scheme, Figure(10) depict the expectations of tracking trajectory along the iterative index. Compared with the approach proposed in [21] and [28], the proposed method has good achievement in fault tracking and a better performance.

C. EXPERIMENTAL RESULTS

In addition, the algorithm for fault estimation for DC servo-motor is depicted in Table (4). Figure(11) and Figure(12) show the experimental results. The evolution of the tracking trajectory of speed are presented at 1^{st} iteration and 3^{rd} iteration, the random packet losses control input and are induced through the network via a code running in speed

TABLE 5. Algorithm.

Algorithm
Set parameters $y_r, T_d, K, \Gamma_1, \Gamma_2, x_0$
While Serial:available() do
Receive signal $y_k(t)$
Register signal $y_k(t)$
Estimate $y_k(t)$ using rules in Section(3)
Compute $\Delta y_k(t) = y_k(t) - \hat{y}_k(t)$,
for $k = 1, ..., T_d$
do (10)-(12)
end for
Apply (14) and update Γ_2 based on (14)
$Drive = \Delta y_k(t)$
if $Drive > actuatorsaturation$ then
set $Drive = constraint(Drive, 0 - 255)$
end if
Send $DRIVE$ signal
if sensor data are received ($\delta_q(t) = 0$)
Compute $DRIVE$ signal using (2)
else
Go to (12)
end if
Return $y_k(t)$,

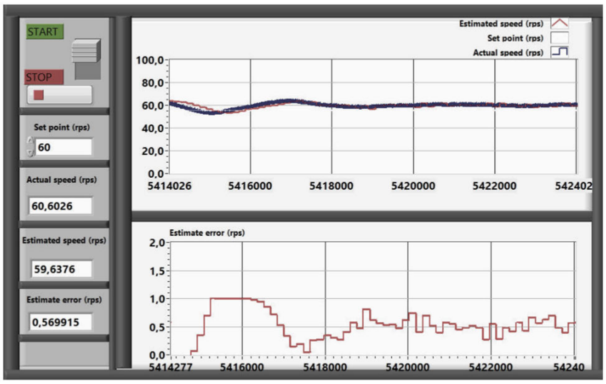

FIGURE 11. LabVIEW interface display for the monitoring of DC servo-motor (Experimental result at 1st iteration).

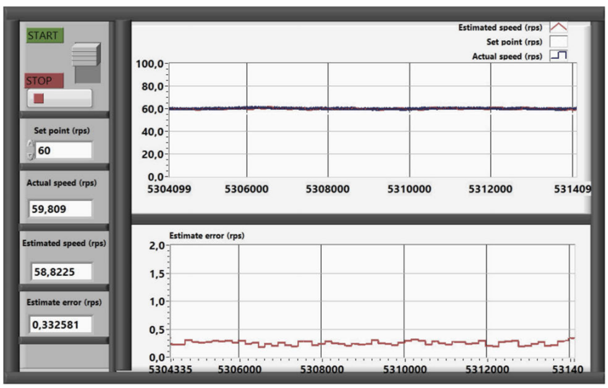

FIGURE 12. LabVIEW interface display for the monitoring of DC servo-motor (Experimental result at 3rd iteration).

sensor. It can be seen from Figure(11) and Figure(12) that the estimating results based on WNILA have good performance.

VI. CONCLUSION

In this paper, wireless networked iterative learning algorithm (WNILA) based fault estimation has been proposed for a class of systems with packet losses and quantizer measurements. Lyapunov function is introduced to prove the stability of fault estimation error and the optimal function is developed to guarantee the iterative tracking error trial to trial convergence, and satisfy H_∞ performance. LMIs is used to obtain the practicable solution of learning gain matrices and observer gain matrix. Compared with the existing methods, the proposed WILFEA in this paper realizes a short running iteration index and satisfactory performance in fault signal tracking. The simulation and experimental results show that the proposed WNILA achieves better fault estimation performance under packet losses and quantizer measurement.

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