Cross-Layer Control Adaptation for Autonomous System Resilience

(Invited Paper)

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***Abstract*—The last decade has seen tremendous advances in the transformation of ubiquitous control, computing and communication platforms that are anytime, anywhere. These platforms allow humans to interact with machines through sensing, control and actuation functions in ways not imaginable a few decades ago. While robust control techniques aim to maintain autonomous system performance in the presence of bounded modeling errors, they are not designed to manage large multi-parameter variations and internal component failures that are inevitable during lengthy periods of field deployment. To address the trustworthiness of autonomous systems in the field, we propose a cross-layer error resilience approach in which errors are detected and corrected at appropriate levels of the design (hardware-through software) with the objective of minimizing the latency of error recovery while maintaining high failure coverage. At the control processor level, soft errors in the digital control processor are considered. At the system level, sensor and actuator failures are analyzed. These impairments define the health of the system. A methodology for adapting the control procedure of the autonomous system to compensate for degraded system health is proposed. It is shown how this methodology can be applied to simple linear and nonlinear control systems to maintain system performance in the presence of internal component failures. Experimental results demonstrate the feasibility of the proposed methodology.**

***Index Terms*—System resilience, error tolerance, checksum encoding, autonomous systems**

I. Introduction

Intelligent autonomous systems are emerging as promising technological marvels to improve human life. The electronics industry is investing significant resources in the pursuit of enabling autonomous driving systems. However, the inherent disconnect between the electronics and control industries is raising valid questions about the safety and reliability of these systems since the control designers assume that the underlying digital, mixed-signal and electro-mechanical systems operate reliably and safely. Recent accidents on trial deployment of self-driving cars [1–4] have generated serious doubts about the successful deployment of these vehicles in the commercial arena due to the possibility of life-threatening consequences in presence of malfunctions in the electrical and electronic sub-systems. To ensure reliable and dependable operation of autonomous systems, robust cross-layer (digital, mixed-signal and control) error resilience methods need to be developed that deliver ultra-high levels of dependability (equal to safety/dependability of aircraft and space travel), on a per-system basis to thousands of autonomous systems for the technology to ever become commercially successful on a massive scale. The primary objective of this research is to address the trustworthiness of these systems by proposing a real-time cross-layer control adaptation where an error-checking scheme detects performance deviations due to varied failure mechanisms and extracts key diagnostics about the root-cause of underlying failures to update the control law for satisfying the system objective with high coverage and low cost.

The idea of implementing failure tolerance through checksums was the fundamental concept behind algorithm-based fault tolerance (ABFT) [5; 6] and further used for error resilience in complex signal processing algorithms [7] and linear state variable systems [8; 9]. While error detection could be performed with low overhead in [8], error correction incurred large overheads both in area and time using the proposed algorithms. To resolve this, probabilistic and guided error compensation schemes were proposed in [10–13]. The present research employs similar encoding techniques in control systems and propose real-time error resilience techniques for online detection and correction of faults in systems operating under arbitrary failure mechanisms. Here, the errors are detected in the stage where the errors has happened and the control law has been adjusted to correct the error quickly in the next stage.

In this paper, we briefly describe the proposed methodology of real-time cross-layer control adaptation in Section II. The error resilience is demonstrated on three different test cases in Sections III, IV and V. Finally we conclude in Section VI.

II. Proposed methodology: Real-Time Cross-Layer Control Adaptation

The proposed methodology is applicable to any nonlinear real-time dynamical system that is represented by the state-space equations:

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{f}(t, \mathbf{x}, \mathbf{u}) \\ \mathbf{y} &= \mathbf{h}(t, \mathbf{x}, \mathbf{u})\end{aligned} \tag{1}$$

where, $\mathbf{x} \in \mathbb{R}^n$ is the state variable, $\mathbf{u} \in \mathbb{R}^m$ and $\mathbf{y} \in \mathbb{R}^q$ are the inputs and outputs of the system and $\dot{\mathbf{x}} = \frac{d\mathbf{x}}{dt}$. The appropriate control input $\mathbf{u}$ is computed by the designed control law from the user input r and output $\mathbf{y}$. The core contribution of the proposed research is demonstrated in Figure 1.

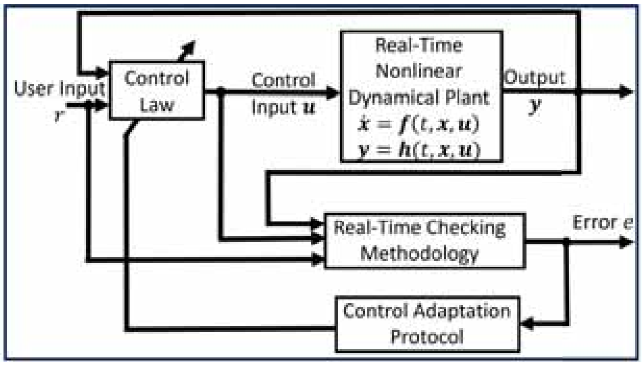

Fig. 1. Overview of real-time control adaptation methodology

The real-time checking methodology encodes the system dynamics and creates a single error signal e from the inputs $\mathbf{r}$, $\mathbf{u}$ and $\mathbf{y}$. In case of linear systems, the system in 1 simplifies to $\dot{\mathbf{x}} = A\mathbf{x} + B\mathbf{u}$ where A and B are system and input matrices. A single checksum e is computed by encoding the matrices A and B through a coding vector as discussed in [14; 15]. In contrast, for nonlinear systems, the error e is computed through nonlinear mapping functions that encode the system dynamics $\mathbf{f}(.)$ and $\mathbf{h}(.)$ as described in [16]. The error e stays within a pre-computed threshold while the system operates in a fault-free manner. In presence of faults (parametric failures, soft errors, computational mistakes, mixed-signal system degradation or environmental anomalies), the error e crosses the threshold, indicating the presence of errors.

It has been demonstrated for both linear [15] and nonlinear [17] systems that the transient waveform of error e contains diagnostic information about the underlying cause of failures and has strong correlation with the parameters of the optimal control strategy. The control adaptation protocol shown in Figure 1 is trained in pre-deployment stage to predict the optimal control parameters from the transient error waveform through diagnostic analysis of the root cause of the failure mechanisms. In the post-deployment stage, the trained control adaptation protocol is invoked in the digital controller stage in presence of faults when the error e crosses the threshold and the nominal control law is modified to satisfy the system objective in real-time with low latency.

III. Test-Case I: Real time diagnosis and correction in DC motor

In this research, the real-time error detection and correction is demonstrated on a DC motor. The faults injected in the system are multi-parameter perturbations in coefficient of armature reactance L_a, moment of inertia J, torque constant K_e, and armature resistance R_a. Injection of faults generates a non-zero checksum error signal $e(t)$ indicating the presence of failure modes in the system.

Pre-deployment training: In the pre-deployment phase, 400 parameter-perturbed DC motor systems were created in MATLAB simulation framework. The checksum error signals for each of the systems were sampled at 100 samples per second. 200 system instances were selected in random to train a Multivariate Adaptive Regression Spline (MARS) model with the perturbed parameter set as target output. After training, a MARS model was obtained with 14 basis functions.

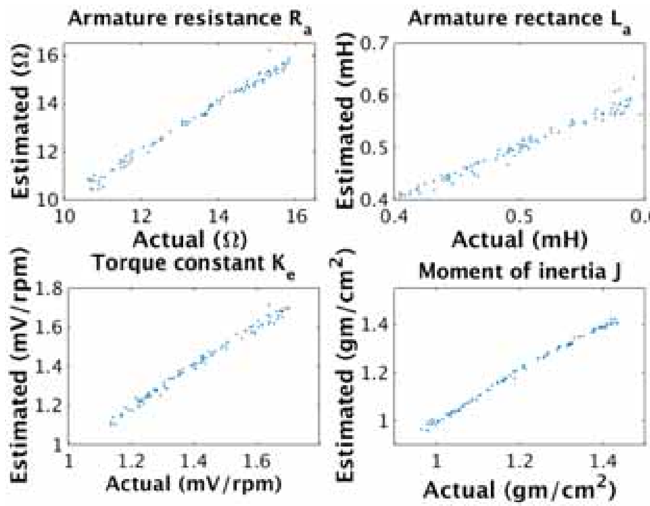

Fig. 2. Estimated vs Actual parameter of DC motor with control

The trained model is tested for validation by the remaining 200 system instances. The strong correlation between the actual and estimated values of the different parameters are shown in Figure 2, thus demonstrating that the error e contains crucial information about the failure modes. Next, a neural network model is trained with the error signal $e(t)$ and the corresponding input stimulus as inputs and the different plant parameters as target outputs. The simulation data from 128 systems along with a nominal PID controller designed to satisfy certain specifications such as % overshoot of 5% and rise time of 100 μs, are used to train the neural network.

Post-deployment control adaptation: In this test-case two checksums are implemented - $e_{system}(t)$ that is used to detect errors and trigger error correction and $e_{plant}(t)$ that is used to estimate system parameters. The transient waveforms of system output ω (angular velocity of motor), $e_{plant}(t)$ and $e_{system}(t)$ for a fault-injected system are shown in Figure 3. Around 10 ms, $e_{system}(t)$ crosses the detection threshold indicating performance deviations. The input and $e_{plant}(t)$ are recorded from 10 ms to 12.5 ms and system parameters are predicted from pre-trained neural network model. Using these parameters as starting conditions, a Levenberg-Marquardt optimization algorithm improves the accuracy of the estimated parameters by 15 ms. The PID controller parameters and the checksum $e_{system}(t)$ are updated, thus restoring the system specifications of overshoot from 1.1% to 3.1% and rise time of 102 μs to 99.6 μs.

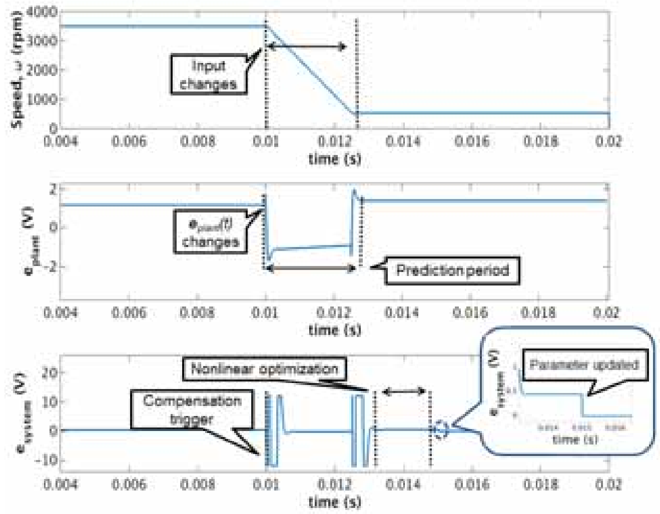

Fig. 3. Estimated vs Actual parameter of DC motor with control

IV. Test-Case II: Kalman filter

Kalman filter is typically used to predict the entire statistics (mean and covariance) of system states from noisy measurements of a limited subset of the system states. The exertion of optimal control depends on the accuracy of the predicted state values. The goal of this research is to detect errors in any underlying arithmetic computation (e.g. addition/multiplication) involved in the operation of the Kalman filter and to correct the errors in real-time.

Error detection: For error detection, two separate linear encodings are developed - the state and covariance checks. These checks are designed to ensure the correctness of the update operation of the state and covariance functions in the Kalman filter algorithm. With concurrent execution of these two check states, errors in all the arithmetic computations of the Kalman filter are detected with high coverage and low cost.

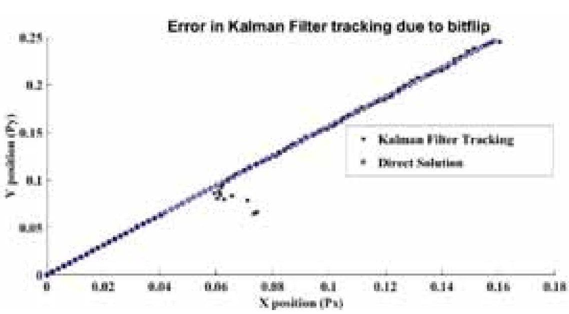

Fig. 4. Deviation in trajectory due to bit error

Error correction: On error detection, the system states are restored from the last known error-free time step of operation and all control/filtering operations are continued as normally performed. This method is capable of correcting the errors in any step of filtering operation that are caused by transient bit-

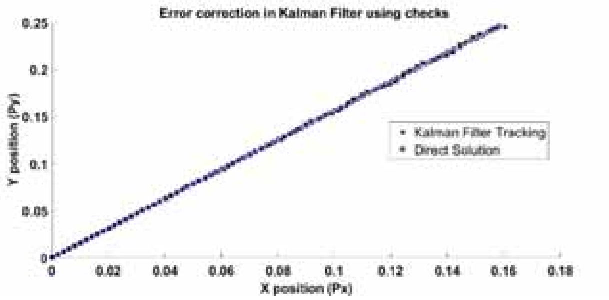

Fig. 5. Error correction using the checks

flips in the underlying digital processor. The error detection and correction capabilities in a particle trajectory tracking problem using Kalman filter is shown in Figures 4 and 5.

V. Test-Case III: Brake-by-wire System

We consider a brake-by-wire (BBW) system as our third test case. These systems are replacing the mechanical and hydraulic braking systems in modern automobiles. Details about the system and dynamics are available in [16; 18].

Pre-deployment training: In this research, a reinforcement learning algorithm is used for online adaptation of the control law in presence of failures. The correlation between the critical system parameters and the transient error waveform is exploited to choose optimal starting conditions for the reinforcement learning algorithm to minimize the online adaptation time. The nominal control law is implemented with an actor-critic network [17] with 500 episodic simulations of the vehicle dynamics along with different applied pedal forces. The transient error data from 500 systems with degradation of brake shoes and wheel velocity sensors is used to train a MARS regression model for predicting the system parameters. In addition, a PNN classifier is also trained to cluster the 500 systems into different clusters based on learning performance of the nominal controller and separate reinforcement learning weights are optimized for each cluster and stored.

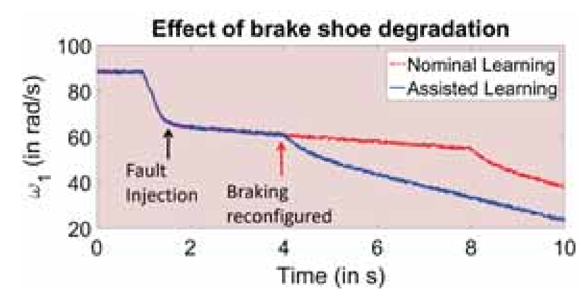

Fig. 6. Real-time control law adaptation with diagnostics-assisted reinforcement learning

Post-deployment control adaptation: Figure 6 illustrates the real-time control law adaptation in a braking situation with a degraded brake shoe. On initiation of braking at $t = 1s$, the wheel angular velocity drops uniformly till $t = 1.8s$ when a brake shoe degradation of 10% is injected. Due to the reduction in applied braking force, the rate of deceleration reduces indicating potential hazards. From $t = 1s$ to $t = 3.2s$, the error signal is recorded and the trained MARS model estimates the perturbed parameter values from the transient waveform. The reinforcement learning parameters are updated according to the stored actor-critic weights from the corresponding cluster to which the predicted parameter set belongs. It is seen that exploiting the diagnostics-assisted reinforcement learning partially recovers the braking performance at $t = 3.9s$ compared to $t = 8s$ for the usual reinforcement learning algorithm, thus demonstrating that the proposed scheme can restore system performance under non-catastrophic actuator degradations with low latency enabling uninterrupted system operation.

VI. Conclusion

In this paper, a cross-layer adaptation for linear and nonlinear systems is presented. The effectiveness of the proposed methodology has been demonstrated through error resilience results from different linear and nonlinear control systems where it is shown that system performance is restored in presence of parametric perturbations and component degradations with low latency. Simulation data from three different systems strongly corroborate the efficacy of the proposed technique. Endeavors in this area will pave the way for future self-healing autonomous systems.

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