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ONLINE HEALTH MONITORING OF ELECTRONIC COMPONENTS SUBJECTED TO REPEATED HIGH-ENERGY SHOCK

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ABSTRACT

Electronic components that undergo shock and vibration are susceptible to failure caused by damage in the base printed circuit board that makes up the substrate of these systems. In certain applications, it may become paramount to know in real-time if the electronic components are damaged to enable a next-generation active system to take immediate responses. Broad examples of such systems include blast mitigation systems or safety systems in car accidents. These systems on classified under the term “high-rate” as they experience high shock levels on short time scales. This work proposes a long short-term memory neural network to enable real-time damage detection and assessment of electronic assemblies subjected to shock. The long short-term memory neural network is able to infer the state of the structure in approximately 4 milliseconds following the impact. The model obtains perfect classification results at 4 milliseconds for the data used in this work. This work is supported by experimentation that indicates damage to electronic packages can be quantified through the in situ monitoring of the impedance of electrical connections. Changes in impedance correlate to alterations in the physical properties of electronic components which indicate the occurrence of damage. On this basis, a comprehensive dataset is created to monitor the impedance changes of a daisy-chained connection through repeated high-energy shocks. Meanwhile, the shock response of the electronic components is captured using an accelerometer, enabling a detailed analysis of the effects of high-rate shock on the components’ performance. A dataset is developed to encompass 30 repeated impacts experiencing 10,000 g_n during impact with an average half-sine time of 322 microseconds. The paper outlines the proposed real-time machine learning framework while performance metrics are presented and discussed in detail.

INTRODUCTION

Electronics experiencing high-rate dynamic events, such as shock, can lead to adverse effects on the internal microstructures and delicate contacts, ultimately compromising the overall performance of electronic systems. Structures that experience shock loads leading to accelerations exceeding 100 Gs in under 100 milliseconds fall under the category of high-rate dynamics [1]. The technical field of high-rate structural state estimation is foundational for creating high-speed control systems for context-aware control systems experiencing high levels of shock [1, 2]. Context-aware real-time control of active structures could be leveraged for next-generation orbital infrastructure, hypersonic vehicles, systems designed to penetrate hardened targets, and blast mitigation mechanisms, which all function within environments characterized by high-rate dynamics [2]. The highly variable and uncertain conditions of these environments necessitate updating the estimated state of these systems in less than a millisecond. By reducing the delay in state estimation processes, next-generation context-aware control schemes can achieve quicker reaction times, which are vital for the efficiency of control mechanisms operating at high rates.

Potential failures in electronic components resulting from shock and vibration can be classified into solder-joint failures, pad cratering, chip-cracking, copper trace fracture, and underfill fillet failure [3]. There is a direct correlation between the duration of shock loading and the resulting damage to electronic components [4]. Studies present a wide range of approaches to quantify induced damage in electronic components under vibration and shock loading [5]. Hardware solutions such as damping putty and shock-resistant packaging are also found to be effective in reducing the transmissibility of shocks and oscillations to delicate electronic components, further providing physical protection [6]. The paper by Liu et al. [7] investigates the deformation and stress distribution of printed circuit boards (PCBs) with varying thicknesses and materials under shock loading conditions. This study provides valuable insights for designing PCBs with enhanced durability and reliability for applications in harsh environments, suggesting that both thickness and material composition are crucial factors for optimizing PCB performance under shock loading. Vibration control systems have also been studied for mitigating the damage caused by shock and vibrations. For example, Esser and Huston demonstrated mass damping of electronic circuit boards [8]. Active damping using strategically placed piezoelectric force transducers has been demonstrated. For example, Chomette et al. used active modal damping, instead of the traditional isolation approach to obtain a damage reduction factor within the second mode of 255 [9]. Software-based error handling algorithms within the system that are held by the PCB (i.e. the computer) are, in theory, capable of detecting and mitigating anomalies caused by vibration-induced noise, ensuring data integrity and minimizing the impact of disturbances.

This study explores the feasibility of real-time damage detection in electronic components during impact events through online high-rate structural health monitoring. It involves predicting the damage state of a given system as a shock event occurs, based on the temporal response of the system. To support this investigation, a dataset was created featuring a ball grid array chip subjected to repeated shocks. This dataset captures both the signal integrity, as measured by impedance, and the acceleration responses to these shocks. A model employing long short-term memory (LSTM) neural networks was developed to distinguish between damaged and undamaged chips. This model successfully identified the health status of the chips solely from their acceleration responses, showcasing the effectiveness of online high-rate damage detection algorithms. Both the dataset and the training approach are made publically available [10, 11].

The contributions of this work are two-fold. First, a data-driven methodology for training an online state estimating algorithm using LSTM networks is proposed. Second, a dataset of electronic components subjected to repeated high-energy shock is provided. This dataset serves as a valuable resource for researchers and engineers in the field of fault detection and mitigation. This methodology enables the prediction of the health state of electronic circuits, enhancing their survivability when exposed to high-rate dynamic events.

METHODOLOGY

This section explains the experimental setup and machine learning model developed for this work

Experimental setup

Preliminary investigations have indicated that damage to electronic contacts can be quantified through the in situ monitoring of the impedance of the electric connections. It is assumed that changes in impedance correlate to alterations in the physical properties of electronic components which can indicate the occurrence of damage. On this basis, a comprehensive dataset was created to monitor the impedance changes following repeated high-energy shocks. Figure 1 shows the electronic component used in this work whereas Figure 1(a) details the connections of the printed circuit board (PCB) and chip circuit. A ball grid array (CABGA_36 from Amkor Technology) is arranged with a daisy-chain connection attached through the PCB and chip at multiple points. The daisy-chained array was designed to maximize the potential of solder-joint failures which can be detected using a single impedance measurement. As shown in Figure 1(b), the dataset also captures the shock response of the electronic components using two accelerometer sensors, one mounted to the shock mass and another attached to the PCB. The shock mass acceleration is taken to be the input acceleration signal and the PCB acceleration is taken to be the response acceleration signal.

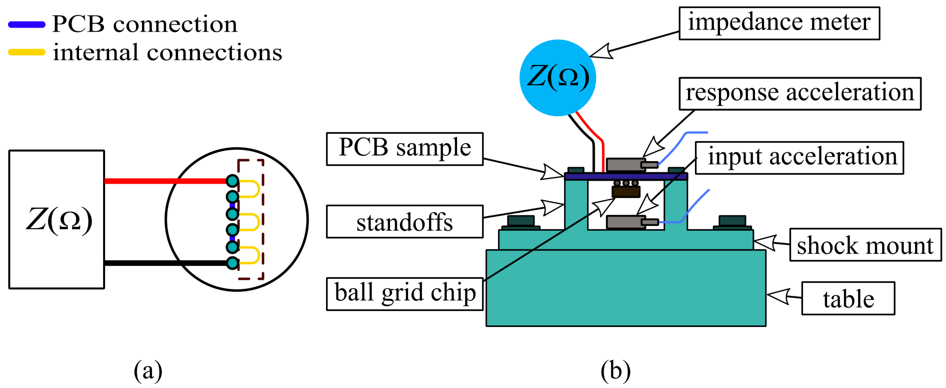

FIGURE 1. Experimental setup comprising of two parts: (a) a circuit diagram illustrating the impedance measurement from a daisy-chained ball grid electronic chip, and (b) the shock test configuration with labeled key components.

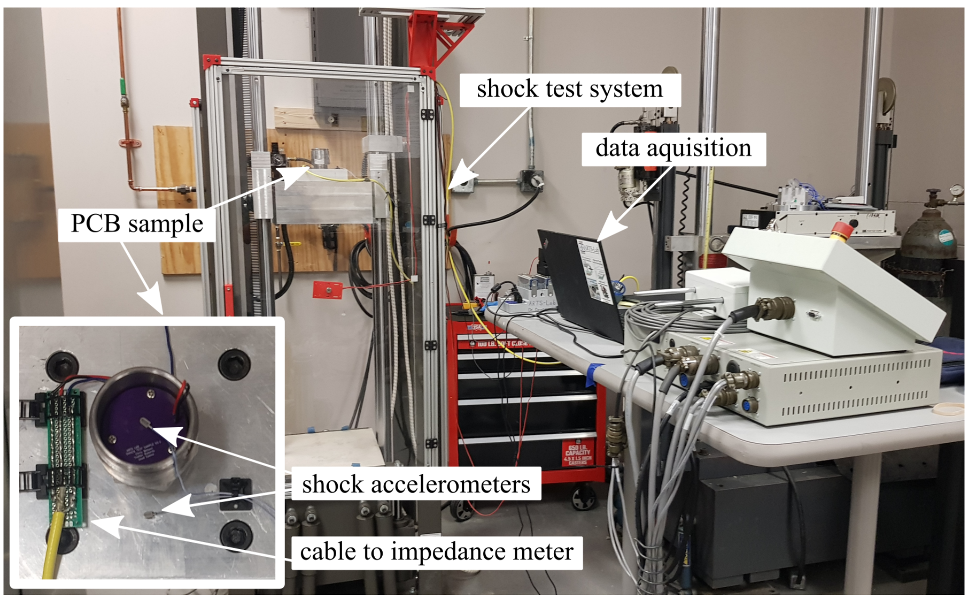

FIGURE 2. The shock test system, as well as impedance data acquisition, with key components annotated.

This setup enables a detailed analysis of the effects of high-rate dynamic environments on the components' performance.

Figure 2 shows the shock test system experimental setup where the PCB sample is the test component shown in figure 1(b). The PCB sample was subjected to 30 repeated impacts with an average maximum acceleration of 39046 m/s^2 and an average half-sine time of 322 µs. Figure 3 shows the time and frequency domain responses of a single impact. As can be seen in figure 3(b), the modal resonance of the PCB is around 4000 Hz.

The development of the experimental setup is motivated by the intuition that alterations to the geometry of the ball grid chip due to damage can be quantified by measuring impedance. When examining the magnitude of impedance in figure 4(a), a large drop occurred after 10 impacts. It's assumed that change in electrical impedance is due to a failure in the ball grid chip (i.e. solder, die, packaging). To support the assumption, various time and frequency domain metrics were obtained for the time-series acceleration data acquired from the PCB-mounted accelerometer for each impact test. The metrics used in this work have been found to be applicable to the high-rate challenge [12]. The results are presented in terms of percent deviation in figure 4(b) which shows that most metrics drift away from the initial value during testing. This seemed to indicate that structural damage in the PCB occurred continuously with each impact. This is in contrast with the impedance data that indicates damage in the electrical connections manifests itself only after impact 11. The acceleration response metrics indicate that the first ten impacts

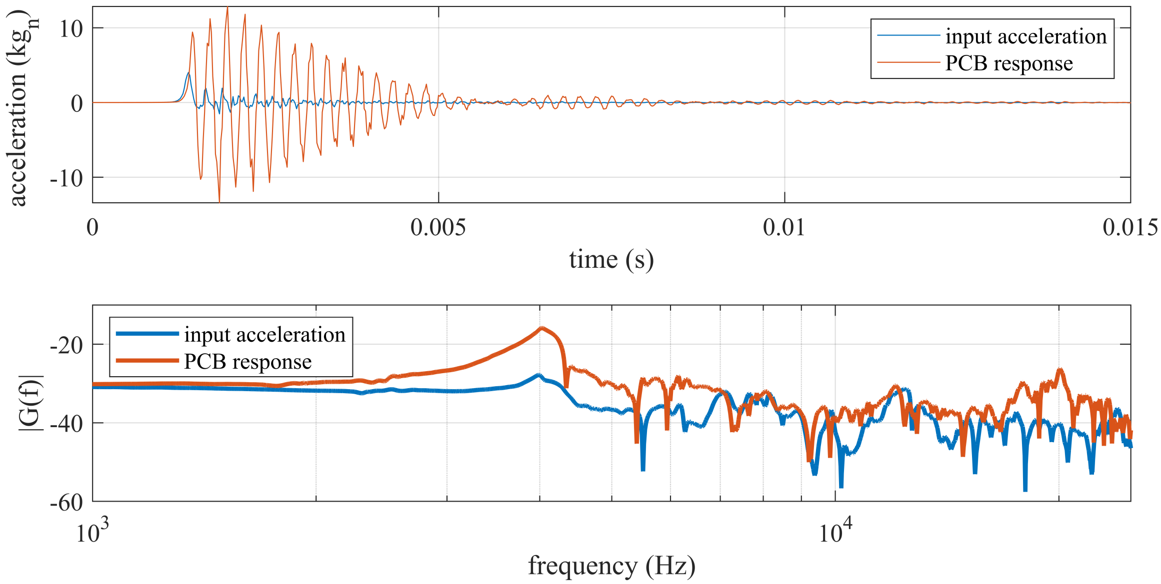

FIGURE 3. Shock response of the PCB experimental setup including (a) time domain, and (b) frequency domain response.

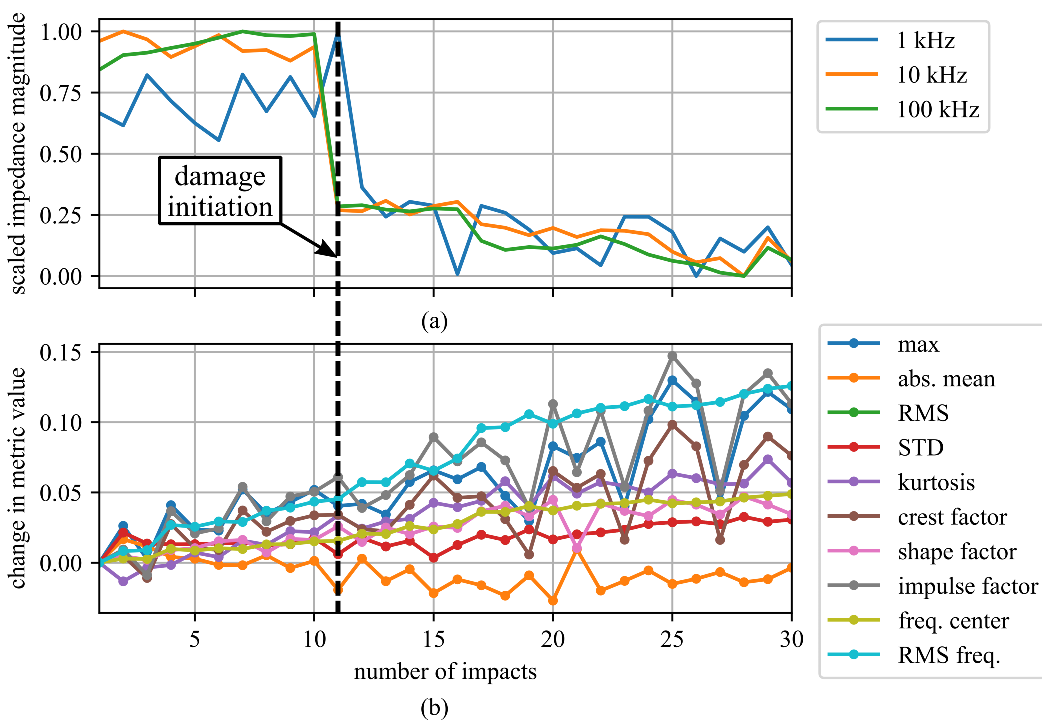

FIGURE 4. Preliminary experimental results with (a) impedance measurements, and (b) features extracted from the shock response of the ball grid chip conducted over 30 impacts.

are self-similar and so were categorized as healthy. Then, the final ten impacts were taken to represent an unhealthy chip, with the middle ten impacts being discarded as an equal number of labeled healthy and damaged datasets were desired. Moreover, discarding the middle third of impacts, we hoped to produce a clear demarcation between healthy and unhealthy responses.

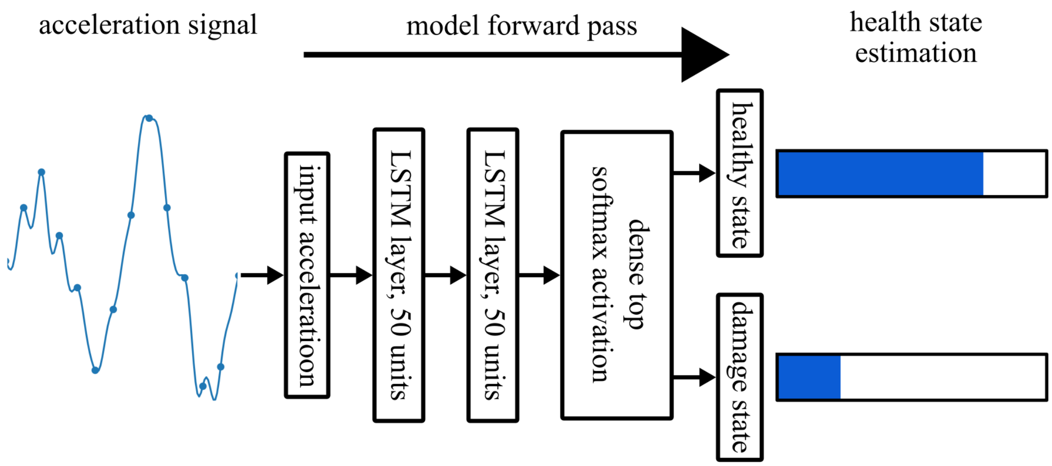

FIGURE 5. Online health state estimator taking in accelerometer signal and predicting the health of electronic components.

Model development

Recurrent neural networks (RNNs) are a class of neural networks which process time-sequence data. Computation occurs at each timestep, where the RNN transforms an input vector and a state vector into an output vector and updated state vector. Long short-term memory (LSTM) networks are a type of recurrent neural network that excel in modeling sequential data and are well-suited for time-series analysis. Equations 1-6 show the forward pass calculations of an LSTM cell for one timestep. Here, c_t and h_t are the state vectors and h_t is returned as the output vector.

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{1}$$

$$i_t = \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right) \tag{2}$$

$$o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right) \tag{3}$$

$$\tilde{c}_t = \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right) \tag{4}$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \tag{5}$$

$$h_t = o_t \circ \tanh\left(c_t\right) \tag{6}$$

An LSTM layer outputs a vector with *units* dimensionality, where *units* controls the size and shape of the vectors and weight matrices, and roughly measures the complexity of the layer.

In this work, an LSTM model is developed to estimate the electric component's health and trained using a supervised learning procedure. Training is done offline and optimized using the backpropagation through time (BPTT) algorithm, which solves the effects of recurrence in the error gradient of the model's weights. Figure 5 shows the architecture of the model used in this paper. Two stacked LSTM layers with 50 *units* perform the recurrent computation. The dense layer after the final LSTM layer transforms the output of the LSTM layer into a two-element vector with each element corresponding to a predicted health state. The SoftMax activation function of the dense layer scales elements of the output to be positive and sum to one. The output can be taken as the model's certainty of the health state. For online prediction updating, the LSTM model takes the acceleration time series data as input and produces a health state estimate for each timestep as indicated in Figure 5. The training was performed as a sequence-to-sequence problem. The training process incentivizes the model to develop a rapid prediction of the chip's health state and update this prediction as more information is revealed through the signal. Training used the Adam optimizer with learning rate $1e-6$, $\beta_1 = 0.9$, and $\beta_2 = 0.99$. Training occurs over 1000 epochs, with all tests computed in one batch, so that weight updating occurs once per epoch.

Results

Figure 6 shows the input and resulting model output for one impact in the undamaged set and one in the damaged set. In subfigure (a), the acceleration response data are overlaid to show the difference between the two signals. As shown in subfigure

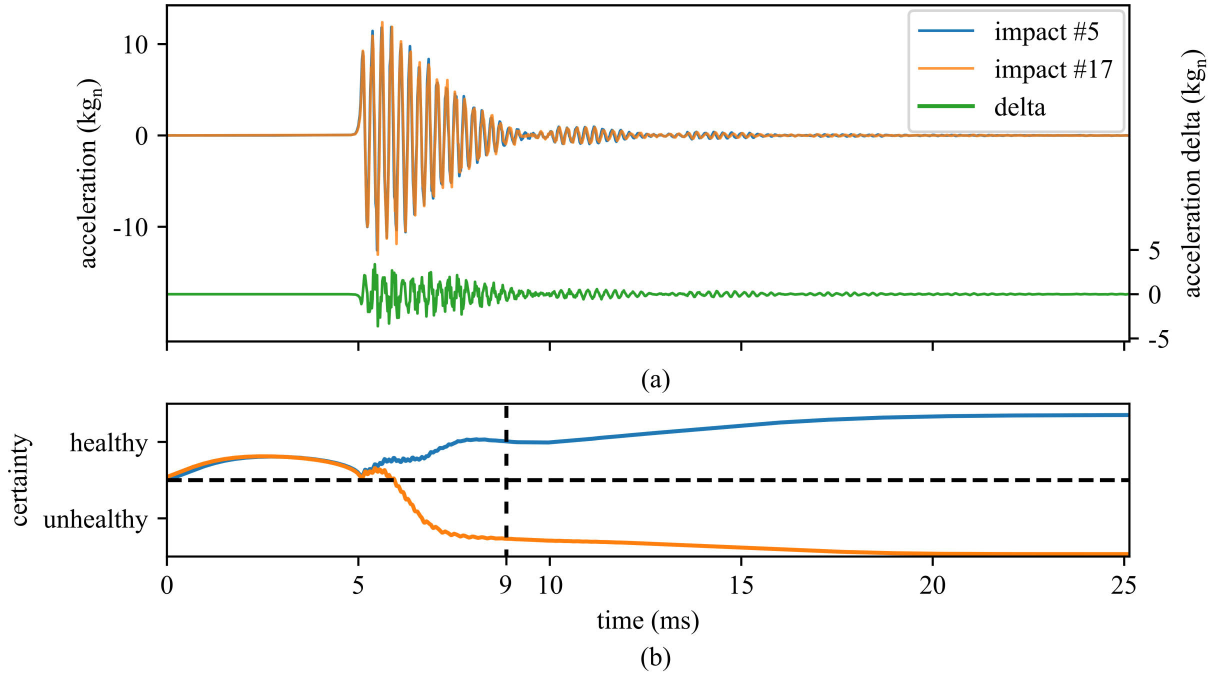

FIGURE 6. Data of a healthy and damaged drop test showing: (a) impact acceleration; and; (b) model estimation through the impact.

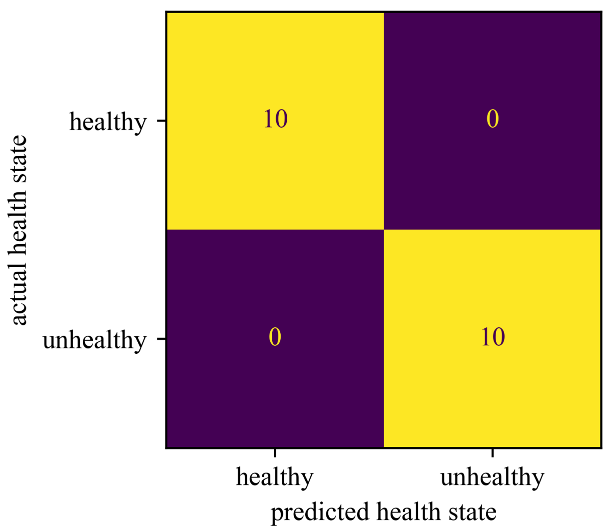

FIGURE 7. Confusion matrix indicating perfect classification of the model.

(b), the model prediction follows the same profile until the impact occurs at 5 ms. From 800 µs after the impact, the model predictions have differentiated and correctly predicted the health state. Throughout the rest of the impact, the model predictions gain certainty and then plateau after reaching high certainty.

For purposes of the analysis, we take the greater state prediction at 4 ms after impact as the model's classification prediction. As shown in figure 7, the model perfectly classifies all impacts in the dataset. These results indicate that the approach developed in this paper can achieve high accuracy in classifying the health state of electronic components.

CONCLUSION

This paper investigated the proposed LSTM-based network for making online inferences about the health of the electronic system during impact. An LSTM-based network was developed to infer the health state from the component's response during impact. The contributions of this work are two-fold. First, a dataset of electronic components subjected to repeated high-energy shock is provided. This dataset serves as a valuable resource for researchers and engineers in the field of fault detection and mitigation. Second, a data-driven methodology for training an online state estimating algorithm using LSTM networks is proposed. This methodology enables the prediction of the health of electronic circuits under repeated shock, enhancing the survivability of electronic systems exposed to high-rate dynamic events.

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