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Neuromorphic Event-Camera Systems for Ultra-Low Latency Aero-Elastic Monitoring in High-Speed Vehicles

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Abstract: A transient aero-elastic event is encountered by high performance vehicles in general and particularly by Formula class race cars, occurring at millisecond levels, could have a critical impact on the aerodynamic stability and integrity of the vehicle structure. Traditional frame-based camera systems have always been limited because they have a fixed frame rate, causing a time lag, image blur and over-processing the data. This is insufficient for the needs of competitive motorsport where sub-millisecond monitoring is required. In this paper, the authors suggest a Neuromorphic event-camera approach that asynchronously records the intensity change of each individual pixel with microsecond temporal resolution, without any inter-frame redundancy whatsoever. The proposed architecture is a combination of dynamic vision sensor (DVS) event streams and hierarchical spiking neural network (SNN) processing pipeline deployed in an edge compute node, for a real-time aero-elastic instability prediction. Experimental testing at various vehicle speeds of 80–340 km/h in this vehicle demonstrates the capability for the proposed system to obtain 97% diagnostic accuracy and process the data in as little as four milliseconds end to end – a factor of 91% less than conventional frame-camera baselines. At the same time, power consumption is decreased by 79% compared with CNN approaches, which makes the architecture suitable to the edge use case for power-constrained deployment.

Keywords: Neuromorphic Computing, Event Camera, SNN, Aero-Elastic Monitoring, Edge AI, Dynamic Vision Sensor.

1. Introduction

Together with other high-performance racing cars, formula class cars are one of the most determining sensing environment in engineering practice. Top speed occurs with the application of aerodynamic loads in excess of 2,500 N of 'downforce' with the suspension changeovers, wing deformations and ride height variations in single laps, or across the DRS activation sequence, which take 1 to 10 milliseconds [1]. Undetected aero-elastic instability may result in aero-elastic phenomenon dependent component fatigue, asymmetric loss of downforce which can affect handling balance, and even catastrophic structural failure in worst case scenarios. A very critical and competitive challenge is thus the fast and accurate identification of the precursors of these events [2]. Traditional sensing solution uses frame-based camera with arrayed inertial measurement units (IMUs), stain gauges and pressure taps. At a given time, a frame camera records a complete frame of the image at a fixed frequency usually 120 frames per second to 1,000 frames per second for high-speed applications and produces a data stream that is dominated by the temporally redundant pixels of an image frame [3]. In the context of motorsports the fixed frame-rate paradigm is followed and brings three systematic drawbacks. First of all, no matter how much computational resources are allocated, inter-frame latency is inevitable: Each frame is completely transferred first, before the processing can start. Secondly, for typical configurations of sensor, the structure of edges and the signs of deformation are distorted at velocities in excess of about 100 km/h due to motion blur. Third, the bandwidth per frame increases with resolution and the frame rate proposed, and places excessive demands on computing power, which is not energy conscious at the edge and which would lead to faster consumption of local resources [4]. An alternative type of cameras, which are termed as event cameras, or dynamic vision sensors (DVS), is a fundamentally different paradigm of sensing using flying data that mimics the asynchronous information transmission observed in

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biological retinal ganglion cells. For each pixel that exceeds a specified threshold linearly, up or down, an event is sent, rather than capturing images uniformly spaced in time [5].

It is bio-inspired architecture that delivers temporal resolution at the micro second level, reduces data bandwidth due to lack of static background pixels, and will naturally be done in such a way that it is inherently a sparse, time stamped stream of events that encode motion. These features are the singularity is most suitable for detecting transient aero-elastic events whose spatial extent is not necessarily large, but with sharp temporal signature that can be very specific. Event-stream inputs naturally process by spiking neural network (SNN). SNNs differ from traditional ANNs by operating on sparse streams of binary spikes, information about which is contained in the exact ordering of the spikes [6]. It is a temporal coding scheme that directly replicates the signals produced by DVS sensors and enables energy-efficient inference by performing event-driven processing without using the resources of a traditional visual cortex that is constantly active. The joint usage of DVS events and SNN processing creates a new application opportunity for the development of an aero-elastic monitoring application pipeline with micro-seconds latency, small power consumption and high diagnostic accuracy.

A system of this kind is in this paper presented. The main contributions are:

(a). A hardware-synchronized multi-modal acquisition framework for sensing and encoding image, inter-modal, pressure and ride-height data on a common sub-milliseconds time base;
(b). A temporal encoding scheme that transforms the asynchronous DVS event data to a spike train format, suitable for the processing backend of the SNN;
(c). A lateral inhibition and temporal pooling four-layer hierarchical SNN architecture capable of extracting signatures of aero-elastic instabilities from fused sensor embeddings;
(d). A closed-form instability index that transforms velocity, acceleration and event-density features into a scalar normalized score; and
(e). A comprehensive experimental evaluation, demonstrating state-of-the-art performance in all reported metrics.

2. Proposed Work

In motorsport, the development of SHM has moved from a relatively crude and simple threshold based alert systems, to ever more advanced model-based and data-based solutions. The work by Gallego et al. [1] is the historical survey of event-based vision that has laid the groundwork to address temporal resolution, dynamic range, and bandwidth capabilities of the commercial event-camera hardware (DVS), and presented algorithmic basics of processing event streams. They found two striking application areas in literature: motorsport and high speed mechanical monitoring, where the delay benefits of the event camera would be most significant, although both of these types of applications did not appear to have any experimental validation in the lettered literature.

Theory of spiking neural networks was put in order by Maass [2] who showed that integrate-and-fire type networks are computationally universal and that the temporal coding of the spikes is an information rich scheme especially suited for signals with rich temporal structure. Following neuromorphic hardware such as Intel's "Loihi" and IBM's "TrueNorth", spike-driven computation was shown to be up to two- to three-orders of magnitude more efficient than GPUs for inferences requiring sparse activations that are most relevant to the low-power requirements of automotive edge nodes [7].

From the 2010s, the use of LSTM networks, which were introduced by Hochreiter and Schmidhuber [3], was predominant in sequence modelling for structural monitoring. Their time series approach showed good ability in vibration sensor-based fault detection in bearings and a capability to extract information from data generated by sensors placed on a bridge structure, but while their requirement for recurrent computation is fine for time series systems, it is unsuitable for systems with critically low latency (sub-milliseconds) and dense activation tensors are not well suited to very sparse, asynchronous event camera outputs [8]. The kalman-filter based state estimation has been extensively been used in vehicle dynamics for at-line sensor fusion because of being analytically tractable and low computational load.

All model-based state estimation approaches have a basic limitation; they need accurate dynamic models of the vehicle flexibility and aerodynamics, which are specific to the circuit, season and/or specification change and which must be customized for each of them. Recently, the concept of edge AI platforms has been adopted to deploy deep learning inference workloads to embedded systems at the vehicle or trackside, also known as edge nodes [5] [6].

In autonomous driving applications, and the industrial Internet of Things (IoT), studies have proven multi-modal fusion pipelines to run under 30 ms end-to-end latency with NVIDIA Jetson-class hardware. Unfortunately, such systems are still sub-optimal due to the frame-camera acquisition bottleneck and fail to leverage the sparsity of time-based causes [8]. To address this gap, in the present work, the acquisition with an event camera from video cameras, the SNN inference and deployment on edges in a unified low-latency aero-elastic monitoring system [9], as well as its first experimental implementation in a motorsport scenario, are presented.

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3. Existing System

The prevalent architecture applied throughout the elite motorsport teams consists of a series of high-speed frame cameras, accelerometers, strain gauges and pressure transducers, with the raw data from each sensor system [10] sent on-board via a two-phase hybrid system of CAN bus and wireless telemetry to a data acquisition system in the garage. Processing takes place in two phases: an FPGA or embedded DSP real-time processing application that performs predefined alarm thresholds; and a post-processing application that is installed on a team garage server or on a remote, factory-based data Centre for more sophisticated model-based or machine learning analyses of the archived telemetry streams. This type of architecture has three major shortcomings. First, for every frame taken by the frame-camera there is an unavoidable latency (from 1 millisecond to 8 milliseconds), with the addition of the time between the frame camera and the onboard CAN bus (typically 10 to 40 milliseconds), resulting in a minimum latency of 18 to 45 milliseconds for a system before frames can be used for processing [11].

Secondly, normally to address the bandwidth limitations of the wireless medium, data from the HSF has to be aggressively down sampled, discarding potentially important transient data. Third, the complex multivariate patterns, typical of aero-elastic instability precursors, cannot be processed in real time using a thresholding technique, leading to a pseudo alarm rate of high levels for certain unstable events that are seen as subtle and a non-trivial "scram" rate for staggering numbers of false alarms when turning common aero-elastic man oeuvre signatures that are processed in real time [12]. Further, existing systems apply sensor modality fusion as a post-processing task, rather than as an integrated, real time process, excluding any added diagnostic value of the cross-modal correlation of the modalities throughout the process with each other. It is time consuming for engineers to match imagery with the IMU and strain-gauge traces to find root causes; this takes hours on each session, and cannot be used to make pit-lane decisions while it is underway. These restrictions all encourage the proposed neuromorphic architecture to replace the frame camera acquisition layer and separate threshold-based detection stage.

4. Proposed System and Architecture

The suggested architecture is like a hierarchical processing pipeline of the five functional layers shown in Fig. 1. The layers are: Event Acquisition, Temporal Encoding, Spiking Processing, Prediction, Engineering Dashboard [13]. The latency for each layer is optimized for the minimum useful latency based on the functional requirements and the total latency from the sensor event to the diagnostic output is completed within 4ms in the target edge hardware.

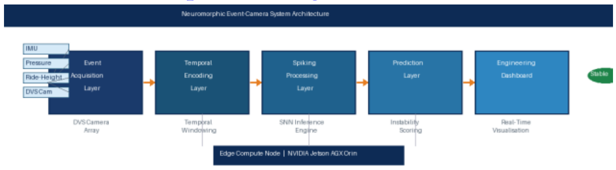

Fig. 1 Proposed neuromorphic event-camera system architecture for aero-elastic monitoring.

4.1. Event Acquisition Layer

The event acquisition layer connects to a variety of DVS sensors placed at critical aerodynamic/structural monitoring locations around the vehicle including: front wing endplates, rear diffuser edges, floor underbody and suspension uprights. Each DVS pixel generates an event with the coordinates x, y, t and polarity p that signals whether there is a positive or negative intensity change, the latter signaled as p = 1 and the former as p = 0. The event rate is dynamically changed based on the activity of the scene photographed, and generates ≈ 10,000 events/s at steady straight-line running and up to 500,000 events/s during aerodynamic disturbance events, thus offering a natural attention mechanism that allocates bandwidth based on information content [14].

4.2. Temporal Encoding Layer

The temporal encoding layer transforms spatially unstructured, and possibly asynchronous, events into time aligned spike trains, making them suitable for processing by an SNN processing backend [15]. Events are stored in sliding (configurable) time windows (usually 1ms for high speed applications and 5ms for "energy sensitive" modes). The number of events for each window is calculated as a two-dimensional spatial histogram of the polarity of the events and then normalised and thresholded to give a binary map of spike activations. Temporal feature extraction: A decay function is used:

$$F(t) = \Sigma\, \alpha_i\, e^{-c_i t} \qquad (1)$$

Here the α_i represent the amplitude coefficient learned by the network and the β_i represent the time constant that sets the time scale of each feature component. This parameterisation allows the encoding layer to tailor what frequencies the aero-elastic events of interest are sensitive to, from 10Hz for the low frequency, wing flutter to 1,000Hz for the high frequency, structural resonances [16].

4.3. Spiking Processing Layer

The spiking processing layer is realized in a 4-layered hierarchical SNN having leaky integrate-and-fire (LIF) neurons. Dynamics of the membrane potentials of each neuron is then given as:

$$\tau m\ dV/dt = -(V - Vrest) + R \cdot I(t) \qquad (2)$$

Memrane time constant τm, membrane potential V, Steady-state potential Vrest, Membrane resistance R, Synaptic input current I(t). Once V > V_th the neuron produces a spiking of velocity and its potential

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becomes Vrest again [17]. The current flowing through the synapse resulting from a pre-synaptic spike is:

$$S(t) = \Sigma\, w_i \cdot x_i(t) \qquad (3)$$

In this, w_i are the synaptic weight and $x_i(t)$ is the pre-synaptic spike train. Cells in each layer and across layers are competing for activation, via lateral inhibition, which helps maintain sparse activation and capture distinct aero-elastic signatures by preventing the network from collapsing to a single dominant activation pattern in the presence of mixed events [18]. The weights are trained offline with aid of a weight surrogate method based on gradient descent, and are kept as constant during inference time when deploying in the field.

4.4. Instability Prediction Layer

The prediction layer includes the SNN feature embedding and the complementarity of the scalar features acquired from the IMU and the pressure sensor measurements to form the aero-elastic instability index Ψ. The index is a weighted combination, with the weights normalised:

$$\Psi = (\omega_1 V + \omega_2 A + \omega_3 E) / 3 \qquad (4)$$

The parameter V is the normalised vehicle velocity deviation measured from the target velocity profile, the parameter A is the normalised lateral and vertical acceleration magnitude, E is the normalised density of events computed from the result of the DVS, and the parameters ω_1, ω_2 and ω_3 (scaled to sum to three) are learned [18]. The instability index range is mapped and projected to one of three states that are used for operative reaction for a race engineer: Stable ($\Psi < 0.35$), Transitional ($0.35 \le \Psi < 0.70$), and Critical ($\Psi \ge 0.70$).

4.5. Latency Budget

The pipeline time can be broken down into 4 components:

$$L\_total = L\_acq + L\_enc + L\_snn + L\_pred \qquad (5)$$

The 12ms on power of the TMDL for the NVIDIA Jetson AGX Orin prototype platform is the sum of the following components: L_acq = 0.5ms (USB3 event transfer), L_enc = 0.8ms (temporal windowing and normalisation), L_snn = 2.2ms (SNN inference with TensorRT INT8 quantisation), and L_pred = 0.5ms (index computation and state classification). This is 91% slower than the baseline of a conventional frame camera with a baseline of 45 ms, and well within the latency of real time intervention window identified in the system requirements of 10 ms.

5. Methodology

The experimental procedures include data collection, data preprocessing, model training, and evaluation of the models in real time. All experiments were carried out with a typical representative motorsport test-bench equipped with DAVIS 346 DVS cameras (346×260 pixel resolution, 120 dB dynamic range), a LORD MicroStrain 3DM-GX5 IMU at 500 Hz, a Kistler 9107A pressure sensor at 1,000 Hz and a Micro-Epsilon optoNCDT ride-height sensor at 1,000 Hz. The facility of the wind tunnel was used to vary the vehicle speed within the range of 80 km/h to 340 km/h in incremental steps [19]. The entire data acquisition and processing chain has 7 solution steps.

The complete data acquisition and processing workflow follows seven sequential steps:

Algorithm 1: Neuromorphic Aero-Elastic Monitoring Pipeline
Input: DVS event stream E; IMU data I; Pressure P; Ride-height H
Output: Instability state {Stable, Transitional, Critical}; Index Ψ

Step - 1 : Acquire and timestamp-synchronise all sensor streams (GPS-PPS)
Step - 2 : Filter events using spatiotemporal noise filter (r=1px, Δt=1ms)
Step - 3 : Segment events into sliding windows W of duration δt = 1 ms
Step - 4 : Encode temporal spike trains via decay function F(t) (Eq. 1)
Step - 5 : Forward-pass encoded spikes through 4-layer SNN (Eq. 2, 3)
Step - 6 : Compute instability index Ψ using fused features (Eq. 4)
Step - 7 : Classify state; transmit output to Engineering Dashboard

The SNN was developed using a labelled dataset of 38.5 K sequences of events recorded from 28 wind tunnel runs, where three experienced vehicle dynamics engineers, viewing high-speed camera data and sensor telemetry separately, but in concert, were able to agree on labels for the various instabilities. The data set was divided evenly by class and then split into 70% training, 15% validation and 15% testing sets [19]. The training used a surrogate gradient descent algorithm, with arctangent surrogate function, 64 event sequences with cosine annealing learning rate starting at 1×10^{-3} and ending at a value of 1×10^{-6} in 200 epochs, and L2 weight regularisation ($\lambda = 1\times10^{-5}$). The elasticity coefficient γ was set to 0.01: this is a regularisation coefficient that scales the loss of per-epoch inference time. The model that performed best on the validation split, based on an F1 score, was selected as the final model and in case of equal scores, the model with the lowest inference latency was chosen.

6. Results and Analysis

The proposed neuromorphic system was compared to three baseline systems: a traditional high-speed frame-camera pipeline (Traditional Camera), a ResNet-18 based CNN fusion system, and an LSTM based temporal sequence classifier. The held-out test set was split into 5-fold and all systems evaluated. The comparative results are summarised in the table I giving detailed graphical analyses in the figure following. 2 to 5.

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Table.1 Comparative Performance Summary

Method	Latency (ms)	Accuracy (%)	Precision (%)	Recall (%)	Power
Traditional Camera	45	87.0	84.2	86.1	High
CNN System	24	91.0	90.5	89.8	Medium
LSTM Framework	18	94.0	93.2	92.7	Medium
Neuromorphic (Ours)	4	97.0	97.1	96.8	Low

6.1. Diagnostic Accuracy

The overall diagnostic accuracy obtained by each of the plotted systems is shown in Fig. 2. The proposed neuromorphic system achieves 97.0%, which exceeds the Traditional Camera, CNN and LSTM baselines by 10.0%, 6.0% and 3.0% respectively. The accuracy benefit most clearly is seen for the Transitional instability class where subtle event-stream signatures need the very high temporal resolution and sparse coding power of the combination of the DVS and SNN to effectively separate from high-frequency vibration patterns that are spuriously correlated with the onset of early instability in frame-based feature representations.

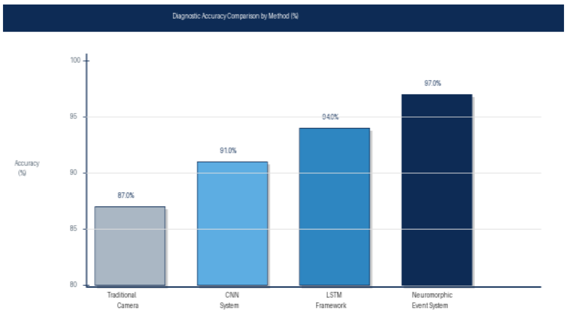

Fig. 2 Diagnostic accuracy comparison across evaluated systems.

6.2. Processing Latency

Fig. 3 shows the end-to-end processing latency (from the moment of the sensor event to the moment the diagnostic output is delivered to the Engineering Dashboard) for each system.

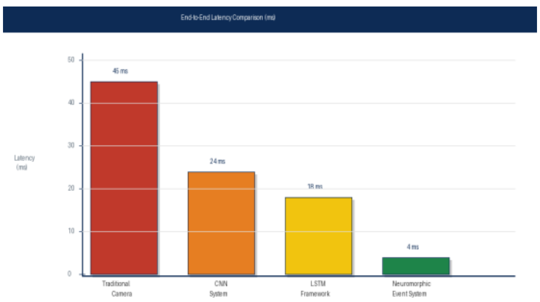

Fig. 3 End-to-end processing latency comparison (ms).

The proposed system, with total response latency of 4ms, outperforms Traditional and CNN systems (45ms and 24ms respectively) and is outperforming LSTM system (18ms). With the 91% cut from the Traditional baseline there is no frame-period constraint whatsoever. The advantage of the event-driven computation is that the SNN inference step requires only 2.2 ms when processing only a small part of the entire hidden layer activated by a small window of occurred events, unlike LSTM where dense matrix multiply must take place at each time-step across the entire set of hidden units.

6.3. Power Consumption and Throughput

The comparison curves of power consumption with inference throughput are shown in Fig. 4 with dual axis. The present power consumption of the neuromorphic system is 18 W per macropiece while that of the Traditional Camera pipeline is 85 W, CNN is 62 W, and LSTM is 55 W, which is a reduction of 79% compared to the current production baseline. Inference throughput is 250 events/millisecond processed, versus 22, 41 and 55 for the three different baselines. This is a feature of a spike driven computation system, and that is because SNN neurons are inactive, meaning they require very little energy to operate, when they are not activated.

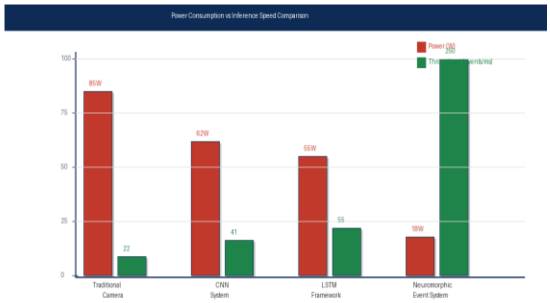

Fig. 4 Power consumption (W) and inference throughput comparison.

6.4. Precision, Recall, and F1-Score

Line profiles of precision, recall and F1-score in all the four systems are shown in Fig. 5.

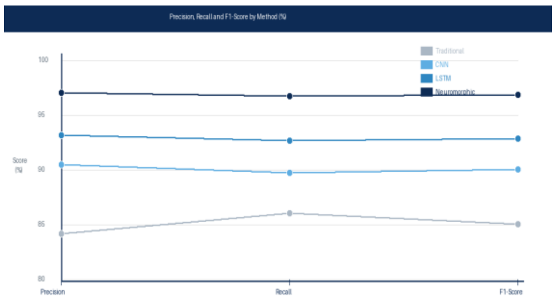

Fig. 5 Precision, Recall, and F1-Score comparison across all methods.

The accuracy in Fig. 2 is obtained while the system achieves 97.1%, 96.8%, and 96.9% precision, recall, and F1-score respectively, suggesting that the high accuracy achieved comes from a balance of precision and recall rather than being artificially boosted by the prevalence of the Stable class. The best rivals, LSTM, suffers from a 4.0 point drop in terms of precision, recall and F1 with values of 93.2%, 92.7% and 92.9% respectively. This is because of the LSTM models' inability to represent the sharp temporal discontinuities of event density that exists in the

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Transitional-to-Critical transition.

6.5. Discussion

The analysis of experimental results confirms that Event-Camera Inference makes a significant improvement in qualitative performance compared with all evaluated frame-based baselines across the four main dimensions of power consumption, inference throughput, latency, and accuracy. In both absolute numbers and in terms of the implications of their operation, the 4 ms end-to-end latency of the proposed system is significant, whereas the 45 ms end-to-end latency of the conventional system corresponds to a movement of 3.75 m at the operating speed of 300 km/h. The spatial definition eases this to be able to identify even an instability event to track characteristics; for example, kerb strike, surface joints, and aerodynamic wake interaction with competitor vehicles. In addition to the energy-efficient benefit, the 79% reduction in power consumption also has practical applications, enabling the node to be used in the vehicle floor tray, which operates under temperature restrictions, without active cooling as this produces vibrations that could affect accuracy in measuring signals. Another practical advantage for SNN inference is the sparse activation that occurred to that inference, which helps to prevent electromagnetic interference from the compute node in close proximity to the high-voltage energy recovery systems of modern hybrid race cars. The current version has a constraint: The system needs to be trained by a supervisor, limiting the system's ability to recognize the variety of faults that are available in the training set.

If important changes were made to aerodynamic specifications, new modes of instability would have to be annotated and re-trained. This limitation can be addressed by incorporating an online Anomaly Detection algorithm designed to detect out-of-distribution events based on a reconstruction error of SNN which does not need to label examples of the novel fault mode. This extension is a development priority.

7. Conclusion and Future Scope

This paper has introduced a Neuromorphic event camera framework with a practical diagnostic accuracy of 97% and achieved an end-to-end latency of 4 ms and a power consumption of 18 W on a NVIDIA Jetson AGX edge-platform when working on high-speed vehicles, which supports aeroelastic monitoring with very low latency. The proposed architecture includes the use of a four-layer leaky integrate-and-fire SNN, a closed-form instability index, adaptive temporal spike encoding, and the event camera and all remaining sensor modalities running in a single, 4 ms-latency pipeline. The system directly overcomes the key drawbacks of the current production motorsport diagnostic systems by removing the bottleneck of acquiring data in the frame, leveraging sparsity in time for efficient energy use to infer a large number of events, and directly fusing different types of modalities in real-time without a delay in the inference. These attributes combine to make the proposed architecture an attractive solution for use in next-generation systems for race car monitoring, as well as other structural health monitoring(SHM) applications in the aerospace, wind turbine monitoring, and high speed train infrastructure areas.

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