Claims

1. An equipment anomaly detection device comprising:

a cascade of neural networks including a learning state and a learned state;

wherein, the cascade of neural networks receives and learns N nominal sensor event streams from N event stream input connections in the learning state based on online learning to form the learned state of the cascade of neural networks, wherein each of pulses in the sensor event streams is transmitted as an event;

the cascade of neural networks in the learned state receives N monitored sensor event streams from the N event stream input connections as input of the cascade of neural networks in an operation state, and outputs N monitored reconstructed event streams as output of the cascade of neural networks based on the N monitored sensor event streams, and the N monitored reconstructed event streams represent a reconstructed version of the N monitored sensor event streams; and

a detection module for calculating difference between the N monitored sensor event streams and the N monitored reconstructed event streams, wherein the detection module sends a detection trigger when the difference between N monitored sensor event streams and N monitored reconstructed event streams exceeds a threshold difference value.

2. The equipment anomaly detection device of claim 1, wherein the cascade of neural networks comprises:

an embedding network for receiving the N nominal sensor event streams from the N event stream input connections as input of the embedding network in the learning state, and outputting M nominal embedded encoding streams as output of the embedding network based on the N nominal sensor event streams, wherein the N is an integer greater than the integer M; and

a decoding network being a neural network for receiving the M nominal embedded encoding streams as input of the decoding network in the learning state, and outputting N reconstructed event streams as output of the decoding network based on the M nominal embedded encoding streams, wherein the decoding network learns to generate the output of the decoding network from the input of the decoding network and to form a trained decoding network state of the decoding network based on a rule to reduce difference between the N reconstructed event streams and the N nominal sensor event streams.

3. The equipment anomaly detection device of claim 2, wherein the embedding network learns to generate the output of the embedding network from the input of the embedding network and to form the trained embedding network state of the embedding network using spike-timing dependent plasticity.

4. The equipment anomaly detection device of claim 3, wherein the embedding network

comprises embedding neurons with a set of weights W_I, activity $y(t)$ represents output of the embedding network, activity $x(t)$ represents input of the embedding network, $y(t) = W_I \cdot x(t)$, Δw_{ij} represents an adjustment to weight w_{ij} in W_I,

$$\Delta w_{ij} = \eta \left(\int_{\Delta t} x_j(t) y_i(t)\, dt + \kappa \left(\int_{\Delta t} y_{tgt} - y_i(t)\, dt \right) w_{ij}^2 \right);$$

η represents a learning rate;

Δt represents relative timing between timing of a postsynaptic spike and timing of a presynaptic spike;

t represents time;

dt indicates an integral with respect to time;

$x_j(t)$ represents the pre-synaptic activity of neuron *j*;

$y_i(t)$ represents the post-synaptic activity of neuron *i;*

κ represents a post synaptic learning rate;

y_{tgt} represents a target activity for a post-synaptic neuron;

w_{ij} represents a weight applied to $x_j(t)$ for $y_i(t) = w_{ij} \cdot x_j(t)$.

5. The equipment anomaly detection device of claim 3, wherein the embedding network comprises embedding neurons with a set of weights W_I, activity $y(t)$ represents output of the embedding network, activity $x(t)$ represents input of the embedding network, $y(t) = W_I \cdot x(t)$, Δw_{ij} represents an adjustment to weight w_{ij} in W_I,

$$\Delta w_{ij} = \begin{cases} \eta e^{-w_{ij}+1} x_j(t) & if\ \Delta t > 0 \\ -\eta y_i(t) & if\ \Delta t < 0 \end{cases};$$

η represents a learning rate;

e represents Euler's number;

Δt represents relative timing between timing of a postsynaptic spike and timing of a presynaptic spike;

t represents time;

$x_j(t)$ represents the activity of pre-synaptic neuron *j*;

$y_i(t)$ represents the activity of post-synaptic neuron *i*;

w_{ij} represents a weight applied to $x_j(t)$ for $y_i(t) = w_{ij} \cdot x_j(t)$.

6. The equipment anomaly detection device of any of claims 1-5, wherein an output layer of the equipment anomaly detection device performs an absolute value operation using a pair of spiking neurons, to obtain a reconstruction loss.

7. The equipment anomaly detection device of any of claims 3-5, wherein the embedding network utilizes lateral inhibitory connections between embedding neurons of the embedding network to perform a first type of winner-takes-all algorithm; or the embedding network utilizes a population of inhibitory connections between embedding neurons of the embedding network to perform a second type of winner-takes-all algorithm.

8. The equipment anomaly detection device of claim 7, wherein the embedding network in the trained embedding network state outputs M monitored embedded encoding streams based on the N monitored sensor event streams; and

the decoding network in the trained decoding network state outputs the N monitored reconstructed event streams based on the M monitored embedded encoding streams.

9. The equipment anomaly detection device of claim 8, wherein the decoding network filters the M nominal embedded encoding streams to obtain a filtered version $\hat{y}(t)$ of the M nominal embedded encoding streams, filters the N nominal sensor event streams to obtain a filtered version $\hat{x}(t)$ of the N nominal sensor event streams, and generates N nominal reconstructed event streams $\hat{z}(t)$ as output of the decoding network based on a weighted combination of the filtered version $\hat{y}(t)$ of the M nominal embedded encoding streams, wherein $\hat{z}(t) = W_o \cdot \hat{y}(t)$.

10. The equipment anomaly detection device of claim 9, wherein the decoding network in the learning state performs a self-supervised learning process to adjust the weight W_o to reduce an error E.

11. The equipment anomaly detection device of claim 10, wherein the error E is $E = \|W_o \cdot \hat{y}(t) - \hat{x}(t)\|^2 + \lambda\|W_o\|^2$, and

wherein λ represents a regularization parameter for ridge regression.

12. The equipment anomaly detection device of claim 11, wherein the decoding network in the learning state uses a ridge-regression process to minimize the error E.

13. The equipment anomaly detection device of claim 9, wherein the decoding network utilizes exponential low-pass filters to filter the M nominal embedded encoding streams and the N nominal sensor event streams.

14. The equipment anomaly detection device of claim 9, wherein the decoding network in the trained decoding network state filters the M monitored embedded encoding streams to obtain a

filtered version $\hat{y}_m(t)$ of the M monitored embedded encoding streams, filters the N monitored sensor event streams to obtain a filtered version $\hat{x}_m(t)$ of the N monitored sensor event streams, and generates N monitored reconstructed event streams $\hat{z}_m(t)$ as output of the decoding network based on a weighted combination of the filtered version $\hat{y}_m(t)$ of the M monitored embedded encoding streams, and $\hat{z}_m(t) = W_o \cdot \hat{y}_m(t)$.

15. The equipment anomaly detection device of claim 14, wherein

the detection module filters the N monitored sensor event streams to obtain a filtered version $\hat{x}_m(t)$ of the N monitored sensor event streams; and

the detection module compares the reconstructed event streams $\hat{z}_m(t)$ against the filtered version $\hat{x}_m(t)$ of the monitored sensor event streams, to determine whether an anomaly is present or not.

16. The equipment anomaly detection device of claim 15, wherein the detection module comprises:

a subtraction calculator comprising a plurality of subtractors, wherein a subtractor selected from the plurality of subtractors calculates reconstruction induced difference between a monitored sensor event stream in a filtered version $\hat{x}_m(t)$ of the N monitored sensor event streams and a monitored reconstructed event stream in the N monitored reconstructed event streams $\hat{z}_m(t)$, such that the plurality of subtractors calculate reconstruction induced differences stream by stream between the filtered version $\hat{x}_m(t)$ of the N monitored sensor event streams and the N monitored reconstructed event streams $\hat{z}_m(t)$.

17. The equipment anomaly detection device of claim 16, wherein

the selected subtractor calculates an absolute difference $|\hat{z}_m(t) - \hat{x}_m(t)|$.

18. The equipment anomaly detection device of claim 16, wherein the detection module comprises:

a summation calculator for calculating summation of the differences between the filtered version $\hat{x}_m(t)$ and the N monitored reconstructed event streams $\hat{z}_m(t)$; and

a comparator for comparing the summation with a signal difference threshold, and outputting an alert signal representing anomaly of the N monitored sensor event streams when the summation exceeds the signal difference threshold.

19. The equipment anomaly detection device of any of claims 1-5, further comprising:

a signal conversion module for converting N nominal sensor signal streams into the N nominal sensor event streams, and N monitored sensor signal streams into the N monitored sensor event

streams.

20. The equipment anomaly detection device of claim 19, wherein the signal conversion module comprises a cascade of a bandpass filter, a low-pass filter, and a pulse-density modulator;

the bandpass filter is configured to perform bandpass filtering of signals received from the signal conversion module to select frequency components;

the low-pass filter is configured to rectify and smoothen the bandpass filtered signals; and

the pulse-density modulator is configured to encode the rectified and smoothened signals using pulse-density modulation.

21. The equipment anomaly detection device of claim 20, wherein the pulse-density modulator is a sigma-delta encoder.

22. The equipment anomaly detection device of any of claims 2-5, wherein the embedding network represents high-dimensional input singals in a lower-dimensional representation.

23. An equipment anomaly detection method comprising:

using an cascade of neural networks to receive and learn N nominal sensor event streams from N event stream input connections in a learning state base on online learning to form a learned state of the cascade of neural networks, wherein each of pulses in the sensor event streams is transmitted as an event；

using the cascade of neural networks in the learned state to receive N monitored sensor event streams from the N event stream input connections as input of the cascade of neural networks in an operation state, and output N monitored reconstructed event streams as output of the cascade of neural networks based on the N monitored sensor event streams, wherein the N monitored reconstructed event streams represent a reconstructed version of the N monitored sensor event streams; and using a detection module to calculate difference between the N monitored sensor event streams and the N monitored reconstructed event streams; and

the detection module sending a detection trigger when the difference between N monitored sensor event streams and N monitored reconstructed event streams exceeds a threshold difference value.

24. The equipment anomaly detection method of claim 23, wherein the cascade of neural networks comprises:

an embedding network for receiving the N nominal sensor event streams from the N event stream input connections as input of the embedding network in the learning state, and outputting M nominal embedded encoding streams as output of the embedding network based on the N nominal sensor event streams, wherein the N is an integer greater than the integer M; and

a decoding network for receiving the M nominal embedded encoding streams as input of the decoding network in the learning state, and outputting the N reconstructed event streams as

output of the decoding network based on the M nominal embedded encoding streams, wherein the decoding network learns to generate the output of the decoding network from the input of the decoding network and to form a trained decoding network state of the decoding network based on a rule to reduce difference between the N reconstructed event streams and the N nominal sensor event streams.

25. The equipment anomaly detection method of claim 24, wherein:

the embedding network in the trained embedding network state outputs M monitored embedded encoding streams based on the N monitored sensor event streams; and

the decoding network in the trained decoding network state outputs the N monitored reconstructed event streams based on the M monitored embedded encoding streams.

26. The equipment anomaly detection method of claim 24, wherein the embedding network learns to generate the output of the embedding network from the input of the embedding network and to form the trained embedding network state of the embedding network using spike-timing dependent plasticity with a symmetric learning window or spike-timing dependent plasticity with an asymmetric learning window.

27. The equipment anomaly detection method of claim 24, wherein the embedding network comprises embedding neurons with a set of weights W_I, activity $y(t)$ represents output of the embedding network, activity $x(t)$ represents input of the embedding network, $y(t) = W_I \cdot x(t)$, Δw_{ij} represents an adjustment to weight w_{ij} in W_I,

$$\Delta w_{ij} = \eta \left(\int_{\Delta t} x_j(t) y_i(t)\, dt + \kappa \left(\int_{\Delta t} y_{tgt} - y_i(t)\, dt \right) w_{ij}^2 \right);$$

η represents a learning rate;

Δt represents relative timing between timing of a postsynaptic spike and timing of a presynaptic spike;

t represents time;

dt indicates an integral with respect to time;

$x_j(t)$ represents the pre-synaptic activity of neuron *j*;

$y_i(t)$ represents the post-synaptic activity of neuron *i;*

κ represents a post synaptic learning rate;

y_{tgt} represents a target activity for a post-synaptic neuron;

w_{ij} represents a weight applied to $x_j(t)$ for $y_i(t) = w_{ij} \cdot x_j(t)$.

28. The equipment anomaly detection method of claim 24, wherein the embedding network

comprises embedding neurons with a set of weights W_I, activity $y(t)$ represents output of the embedding network, activity $x(t)$ represents input of the embedding network, $y(t) = W_I \cdot x(t)$, Δw_{ij} represents an adjustment to weight w_{ij} in W_I,

$$\Delta w_{ij} = \begin{cases} \eta e^{-w_{ij}+1} x_j(t) & if\ \Delta t > 0 \\ -\eta y_i(t) & if\ \Delta t < 0 \end{cases};$$

η represents a learning rate;

e represents Euler's number;

Δt represents relative timing between timing of a postsynaptic spike and timing of a presynaptic spike;

t represents time;

$x_j(t)$ represents the activity of pre-synaptic neuron *j*;

$y_i(t)$ represents the activity of post-synaptic neuron *i*;

w_{ij} represents a weight applied to $x_j(t')$ for $y_i(t') = w_{ij} \cdot x_j(t')$.

29. The equipment anomaly detection method of claim 23, wherein

the detection modulation utilizes a subtraction calculator to calculate differences between the N monitored sensor event streams and the N monitored reconstructed event streams;

wherein a subtraction calculator comprising a plurality of subtractors, wherein a subtractor selected from the plurality of subtractors calculates reconstruction induced difference between a monitored sensor event stream in a filtered version $\hat{x}_m(t)$ of the N monitored sensor event streams and a monitored reconstructed event stream in the N monitored reconstructed event streams $\hat{z}_m(t)$, such that the plurality of subtractors calculate reconstruction induced differences stream by stream between the filtered version $\hat{x}_m(t)$ of the N monitored sensor event streams and the N monitored reconstructed event streams $\hat{z}_m(t)$.

30. The equipment anomaly detection method of claim 29, wherein

a pair of spiking neurons are used to perform an absolute value operation, to obtain a reconstruction loss.

31. The equipment anomaly detection method of claim 29, wherein

the selected subtractor calculates an absolute difference $|\hat{z}_m(t) - \hat{x}_m(t)|$.

32. The equipment anomaly detection method of claim 24, wherein the embedding network utilizes lateral inhibitory connections between embedding neurons of the embedding network to perform a first type of winner-takes-all algorithm; or the embedding network utilizes a population

of inhibitory connections between embedding neurons of the embedding network to perform a second type of winner-takes-all algorithm.

33. The equipment anomaly detection method of any of claims 24-28, wherein the decoding network filters the M nominal embedded encoding streams to obtain a filtered version $\hat{y}(t)$ of the M nominal embedded encoding streams, filters the N nominal sensor event streams to obtain a filtered version $\hat{x}(t)$ of the N nominal sensor event streams, and generates N nominal reconstructed event streams $\hat{z}(t)$ as output of the decoding network based on a weighted combination of the filtered version $\hat{y}(t)$ of the M nominal embedded encoding streams, wherein $\hat{z}(t) = W_o \cdot \hat{y}(t)$.

34. The equipment anomaly detection method of claim 33, wherein the decoding network in the learning state performs a self-supervised learning process to adjust the weight W_o to reduce an error $E = \|W_o \cdot \hat{y}(t) - \hat{x}(t)\|^2 + \lambda\|W_o\|^2$, and wherein λ represents a regularization parameter for ridge regression.

35. The equipment anomaly detection method of claim 33, wherein the decoding network utilizes exponential low-pass filters to filter the M nominal embedded encoding streams and the N nominal sensor event streams.

36. A chip, comprising:

the equipment anomaly detection device of any of claims 1-22, or a processor configured to call and run a computer program stored in a memory, to cause a device in which the chip is installed to execute any of the methods of claims 23-35.

37. A computer readable storage medium, in which a computer program is stored, wherein the computer program causes a computer to execute any of the methods of claims 23-35.