

Brief Industry Paper: HDAD: Hyperdimensional Computing-based Anomaly Detection for Automotive Sensor Attacks

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Hyperdimensional Computing

- **Hyperdimensional computing** (HDC) is an emerging computing scheme that leverages the abstract patterns and mathematical properties of vectors in high dimensional space, inspired by human brain functionality.
- HDC works with hypervectors (HV), which are high dimensional (e.g., 10000), holographic vectors with i.i.d.
- There're three **basic operations**, **Addition**, **Multiplication** and **Permutation** and three **core modules** **Encoding**, **Training** and **Inference** in HDC.

Basic operations:

Addition: perform element-wise add between two HVs

$$\vec{H}_p + \vec{H}_q = \langle h_{p1} + h_{q1}, h_{p2} + h_{q2}, \dots, h_{pn} + h_{qn} \rangle$$

Multiplication: perform element-wise multiply between two HVs

$$\vec{H}_p * \vec{H}_q = \langle h_{p1} * h_{q1}, h_{p2} * h_{q2}, \dots, h_{pn} * h_{qn} \rangle$$

Permutation: perform a circular shifting over a HV

$$\rho_1(\vec{H}) = \langle h_n, h_1, h_2, \dots, h_{n-1} \rangle$$

Core Modules:

Encoding: Project feature data into hyperdimensional space

$$\vec{H} = E(\mathcal{R}, \vec{F}) = E(\mathcal{R}_1[f_1], \mathcal{R}_2[f_2], \dots, \mathcal{R}_m[f_m])$$

Training: Aggregating HVs with same label to build a classifier

$$\mathcal{A} = \{\vec{A}^1, \vec{A}^2, \dots, \vec{A}^k\} = \{\sum \vec{H}^1, \sum \vec{H}^2, \dots, \sum \vec{H}^k\}$$

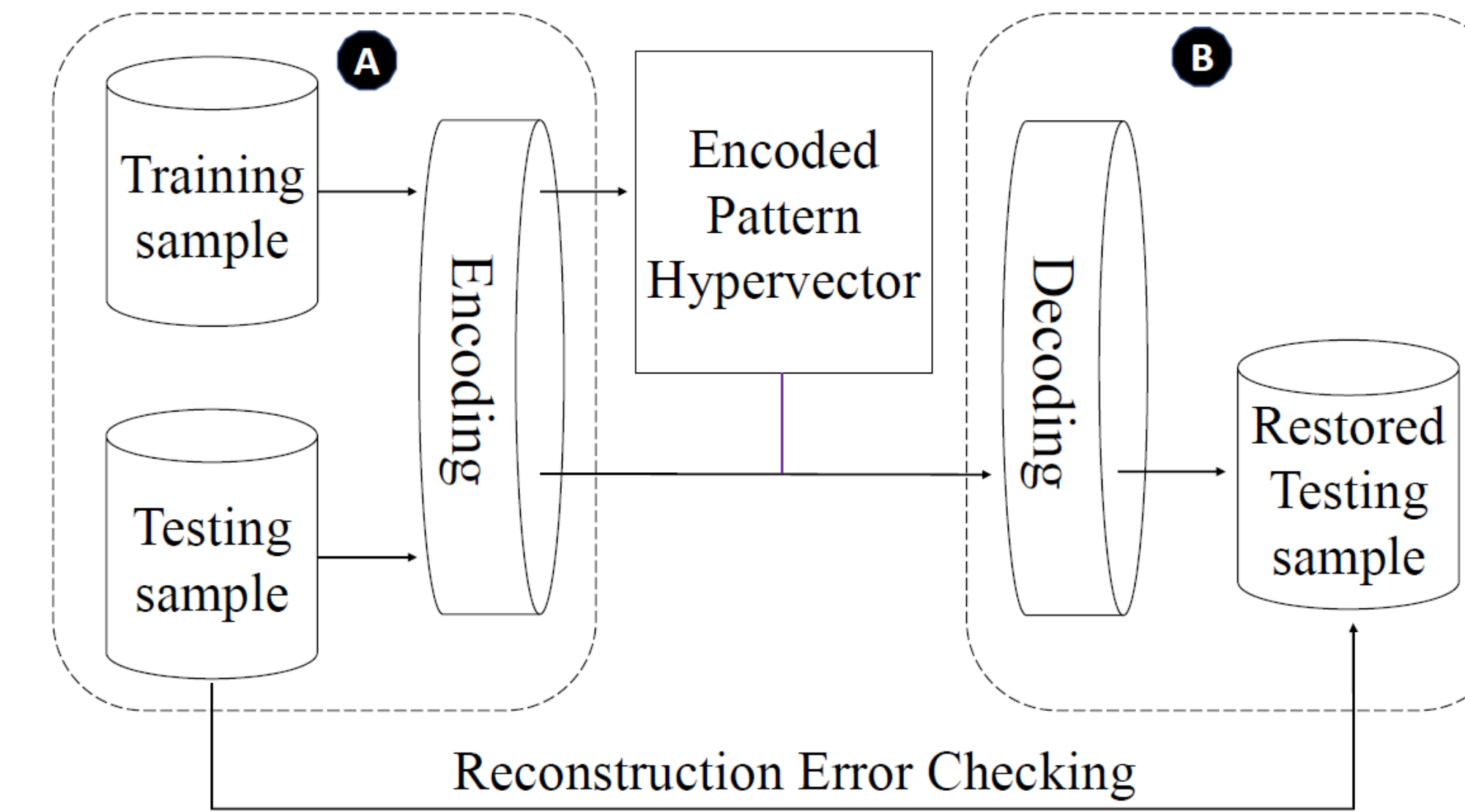
Inference: Deploy similarity check to determine the prediction result

$$l = \operatorname{argmax}(\{\delta(\vec{H}_q, \vec{A}^1), \delta(\vec{H}_q, \vec{A}^2), \dots, \delta(\vec{H}_q, \vec{A}^k)\})$$

Motivation

- Potential security vulnerabilities have been exposed since the growing connectivity and autonomy of modern vehicles.
- Multiple sensors on a vehicle can simultaneously respond to the same physical feature in a correlated manner. Meanwhile, the inherent correlation neither depends on the background knowledge nor has the cost increased by redundant sensors.
- Based on the observation, we propose to identify the consistency embedded in correlated data and use it for anomaly detection.
- **HDAD:** hyperdimensional computing (HDC)-based anomaly detection method

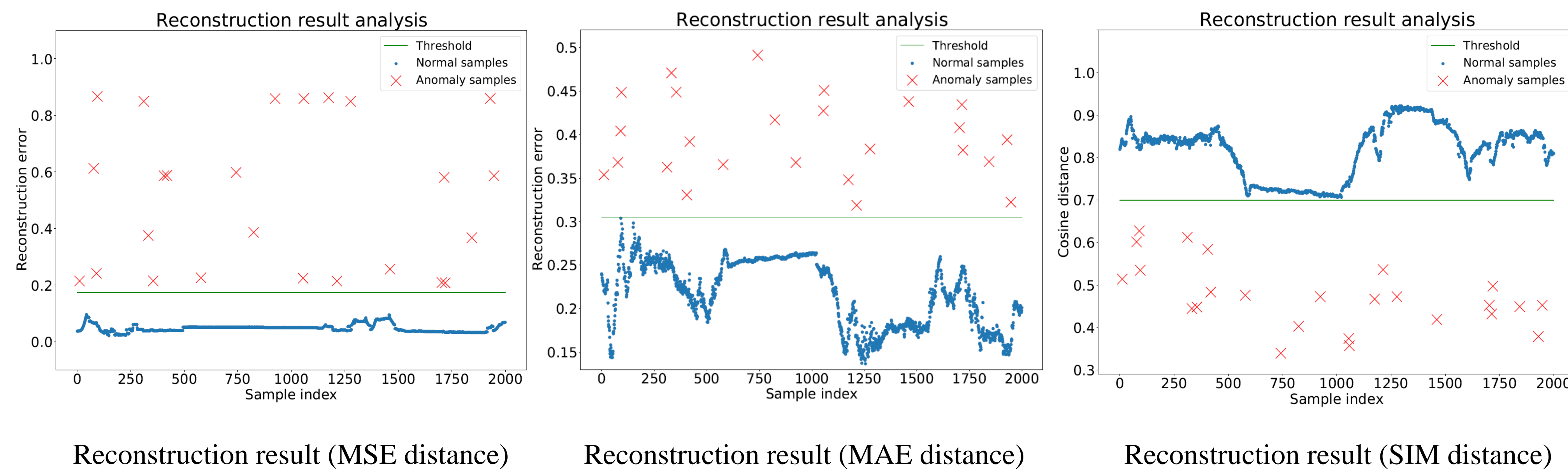
HDAD Structure Overview



HDAD anomaly detection with two key phases:

- **Pattern encoding**, where we encode training samples into hypervectors (HVs) for the pattern learning purpose.
- **Pattern decoding**, where we decode the HVs and reconstruct them to the original samples.
- After we finishing decoding, we do a reconstruction error check, where we check the reconstruction error between original and reconstructed sample.

Experiment Results & Analysis



The anomaly detection result are shown as above. For the First observation, we find all three distance models can achieve 100% anomaly detection accuracy, as all the anomaly samples and normal samples can be clearly separated by the calculated threshold.

For MSE-based and MAE-based models, the reconstruction errors of all anomalous samples, are higher than the calculated threshold. And for the cosine similarity-based detection, with a predefined threshold of 0.7, all the reconstructed anomaly samples have smaller similarity to their original patterns, but all the normal samples have higher similarity to their original patterns.

Conclusion & Future Works

- This paper presents HDAD, an anomaly detection approach based on the emerging HDC
- **This paper presents the first effort in using HDC for anomaly detection** and the promising result opens the door for this potential research direction. In our approach, **HDAD can achieve 100% detection accuracy** on a real-world vehicle sensors reading dataset.
- Our future work will consider using HDC for sample clustering or feature extraction and even use it for anomaly detection under more complected scenarios.