Multi-Channel Encoding in HTM-Based Anomaly Detection

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1 Introduction

This project is based on Roman Malits' work on online anomaly detection using an HTM model[1]. In his work, he details an HTM and TSSE encoder based online anomaly detection system that is specialized to the SWaT dataset. The SWaT dataset is a fully operational six-stage scaled-down water treatment plant resembling real plants found in cities, with the primary purpose of enabling experimentally validated research in the design of security and safety of cyber-physical systems. This time series dataset has 11 days of data at a frequency of 1 HZ, comprising of 25 sensors (continuous data) and 26 actuators (discrete data), of which the last four days have 36 attacks.

Malits' anomaly detection system uses a hierarchical approach. The first level aims to detect anomalies at a single channel level (L1), and higher levels are intended to detect cross-channel anomalies and tune system-wide anomaly detection performance to meet the desired anomaly detection sensitivity. L1 uses a separate encoder and HTM network for each channel, specifically for continuous channels, L1 uses Malits' newly proposed TSSE encoder. Temporal SDR sequence encoder (TSSE) is designed to allow an HTM to learn the semantic properties of slowly changing signals in a way that will enable efficient memory use, good prediction, and anomaly detection performance. The basic idea is to encode a time series of SDRs into a single SDR that represents the temporal pattern. See Malits' paper for more details on TSSE.

Building on Malits' work, this project focuses on extending the anomaly detection system by exploring different methods to encode data from multiple channels. Code can be found at github.com/TamirOffen/HTM_multi_channel.

[1] The use of HTM and TSSE Encoder for Online Anomaly Detection In Industrial Cyber-Physical Systems

2 Multi-channel Encoding Methods

Given $\mathtt{n}_{\geq 2}$ continuous channels, our goal is to encode their data into a single SDR that can be input into an HTM. This representative SDR should effectively capture both the instantaneous patterns at the current timestamp and the temporal patterns evolving over time. Each channel has their own SDR and window size parameter. The SDR size is the total number of bits in the encoded representation of a channel's value, and the window size refers to the number of previous values used by each channel's encoder to generate its encoding. To achieve an effective multi-channel encoding, we explored four methods for combining data from the channels: Timestamp TSSE, Spatial Encoding, Temporal Encoding, and Combined Encoding.

2.1 Timestamp TSSE

For every timestamp: encodes each channel's value using channel specific encoders and applies TSSE to combine the encodings into a unified multi-channel representation. Note: for channels with different SDR sizes, we pad the shorter encoding with zeros to match the length of the longest encoding. This can cause larger channels to dominate the shorter ones because the larger channels contribute more active bits to the final encoding, giving them disproportionate influence in the pattern recognition process.

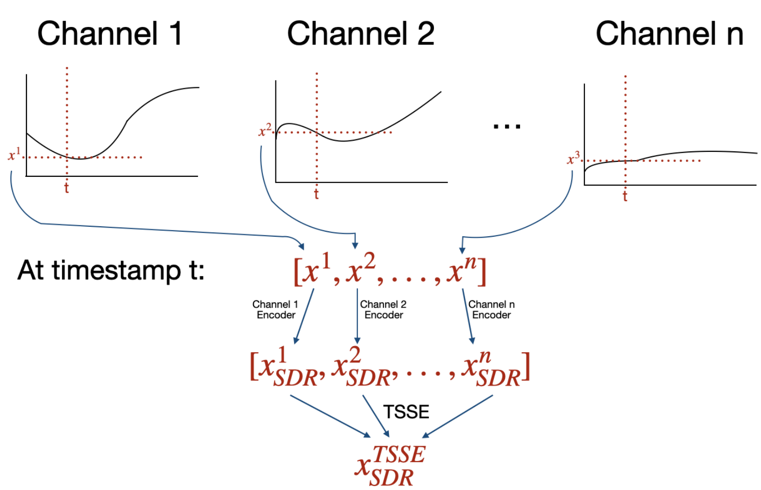

Figure 1: Timestamp TSSE Visualization

2.2 Spatial Encoding

This encoding method is taken from this paper on encoding data[2].
The spatial encoding approach concatenates individual channel encodings into a single, wider SDR that preserves each channel's "spatial location" in the final representation. For every timestamp: encodes each channel's value using channel specific encoders and concatenates individual encodings into a single spatial representation.

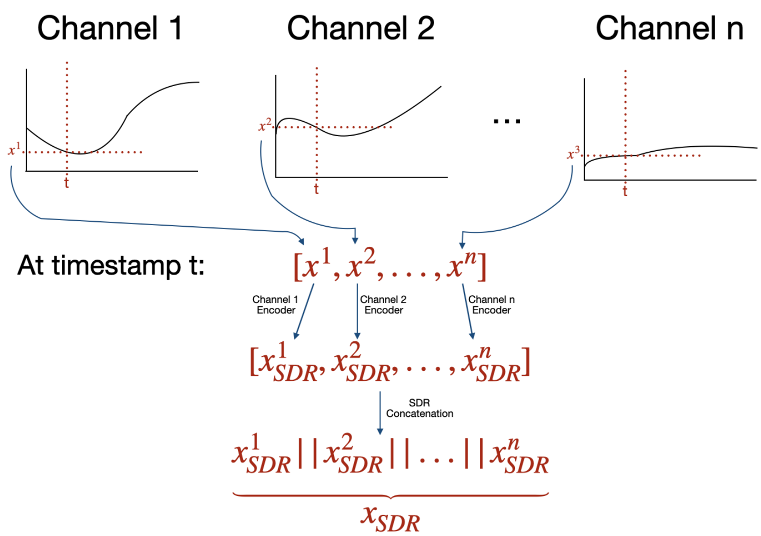

Figure 2: Spatial Encoding Visualization

Note: as highlighted in the encoding paper[2], it is crucial to maintain a consistent number of active bits across all channels when concatenating SDRs. The sizes of the SDRs, however, can vary as needed.

We decided to maintain consistent active bit count across all channel encoders by adjusting each channel's sparsity. Specifically, we:

1. Find the largest SDR size among all channels
2. Calculate target active bits as 2% of the largest SDR size
3. Adjust each channel's sparsity to achieve this target active bit count, using:

```
channel_sparsity = target_active_bits/channel_sdr_size
```

[2] Encoding Data for HTM Systems

For example: If the input SDR sizes of a 3 channel combination are $[1024, 512, 256]$, then the channel's adjusted SDR sparsity will be $[0.02, 0.04, 0.08]$.
This ensures that regardless of different SDR sizes, all channels contribute the same number of active bits to the final encoding.
Spatial encoding is called "spatial" because it preserves the spatial relationships between channels at a single point in time by concatenating their encodings side by side in space. Unlike TSSE which combines encodings through overlapping patterns, spatial encoding maintains clear spatial boundaries between channels while ensuring each channel contributes an equal number of active bits to the final representation.

2.3 Temporal Encoding

The temporal encoding approach is named for its emphasis on time-based patterns rather than just immediate states. It accepts a parameter `b` for buffer size and it works by:

1. Creating a buffer of spatial encodings from multiple consecutive timestamps
2. Applying TSSE to this buffer to capture temporal relationships

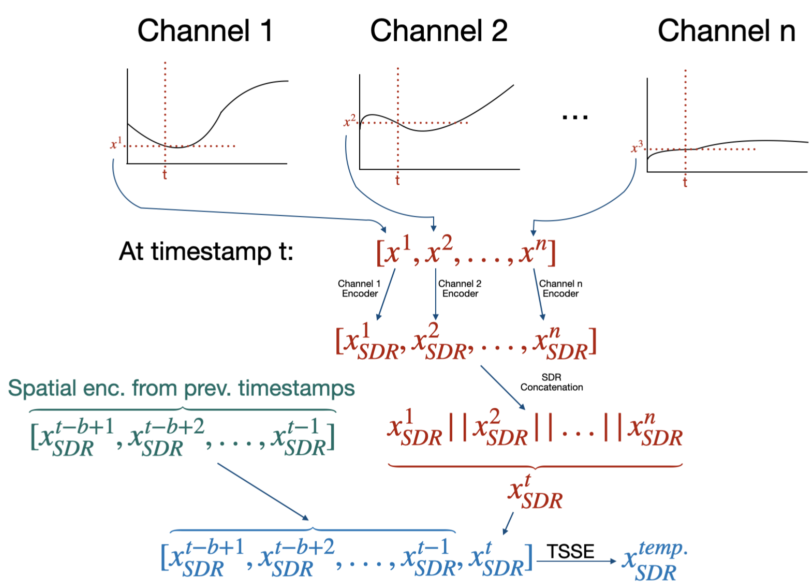

Figure 3: Temporal Encoding Visualization

The key distinction is that while spatial encoding captures relationships between channels at a single timestamp, temporal encoding captures how these relationships evolve over time.

2.4 Combined Encoding

The combined approach aims to capture both immediate state relationships and temporal patterns. It accepts three parameters:

- `b` - buffer size: controls temporal pattern length
- α - spatial weight: emphasizes immediate states
- β - temporal weight: emphasizes sequence patterns

and works by:

1. Processing spatial and temporal encodings in parallel
2. Using separate Temporal Memory instances, one for spatial and one for temporal.
3. Computing final anomaly score through a weighted average

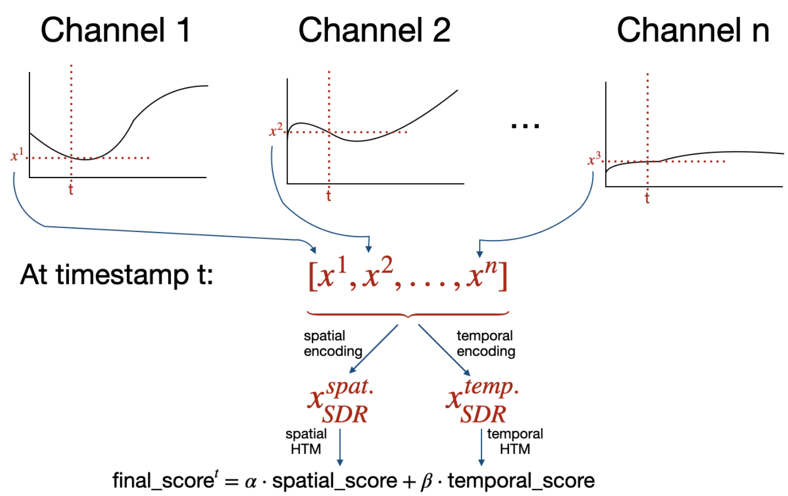

Figure 4: Combined Encoding Visualization

3 Experiments and Results

In order to evaluate the effectiveness of each of the proposed multi-channel encoding methods, we ran a series of experiments on the SWaT dataset. The objectives of these experiments were to evaluate the anomaly detection performance of each encoding method and to determine whether multi-channel combinations can detect anomalies missed by the single-channel approach, while maintaining a low rate of false positives.

Initially, we tested channel combinations within each stage, with one exception: stages 1 and 6 each had only one continuous channel, so they were excluded from the tests. Next, we explored channel combinations that we believed were interconnected and likely to produce meaningful results. For reproducibility, refer to the `multi_channel_runner` folder, which contains the batch files. The labels that were detected using a multi-channel approach, but were not using a single-channel approach, are marked in green. The results are as follows:

Table 1: Multi-Channel combinations within the same stage showing FP, TP, and detected labels.

Single-Channel				**Multi-Channel**				
Stage 2								
	FP	TP	Detected Labels		Enc. Type	FP	TP	Detected Labels
AIT202	2	1	26	AIT202 and FIT201	TSSE	52	14	1, 2, 6, 7, 8, 11, 16, 17, 21, 22, 23, 24, 26, 30
					Spatial	0	2	2, 26
FIT201	0	4	2, 26, 28, 30		Temporal (b = 3)	28	6	2, 7, 8, 11, 17, 21
					Combined (b=3, $\alpha = 0.7$)	16	4	2, 7, 8, 17
Stage 3								
	FP	TP	Detected Labels		Enc. Type	FP	TP	Detected Labels
DPIT301	13	4	8, 23, 28, 35	DPIT301 FIT301 LIT301	TSSE	92	13	2, 3, 7, 8, 21, 23, 26, 28, 32, 35, 36, 37, 41
FIT301	0	1	28		Spatial	0	1	23
					Temporal (b = 3)	133	16	2, 3, 6, 8, 11, 19, 21, 23, 26, 28, 32, 33, 35, 36, 37, 41
LIT301	1	8	7, 16, 25, 26, 28, 32, 35, 41		Combined (b=3, $\alpha = 0.7$)	5	5	2, 8, 23, 26, 32

Stage 4								
	FP	TP	Detected Labels		Enc. Type	FP	TP	Detected Labels
AIT402	8	5	11, 22, 28, 38, 40	AIT402 FIT401 LIT401	TSSE	148	19	3, 8, 10, 11, 17, 20, 22, 23, 25, 27, 28, 30, 31, 32, 37, 38, 39, 40, 41
FIT401	1	7	10, 11, 22, 28, 37, 39, 40		Spatial	0	4	11, 22, 28, 40
LIT401	3	5	8, 11, 25, 27, 31		Temporal (b = 3)	0	5	11, 22, 28, 38, 40
					Combined (b=3, $\alpha = 0.7$)	0	5	11, 22, 28, 38, 40

Stage 5								
	FP	TP	Detected Labels		Enc. Type	FP	TP	Detected Labels
AIT501	58	8	19, 20, 21, 22, 24, 25, 30, 40	AIT501 AIT502 AIT503 AIT504 FIT501 FIT503 FIT504 PIT501 PIT503	TSSE	0	2	20, 28
AIT502	7	5	11, 22, 28, 38, 40		Spatial	2	4	11, 20, 22, 28
AIT503	18	1	20		Temporal (b = 8)	0	0	
AIT504	0	3	11, 22, 40		Combined (b=8, $\alpha = 0.7$)	2	4	11, 20, 22, 28
FIT501	0	6	10, 11, 22, 28, 37, 40					
FIT503	0	0						
FIT504	0	1	28					
PIT501	0	1	28					
PIT503	0	0						

Table 2: Multi-Channel combinations within the same stage showing RE, PR, F1.

Single-Channel || **Multi-Channel**

Stage 2

Single-Channel:

	RE	PR	F1
AIT202	0.03	0.33	0.06
FIT201	0.125	1.0	0.22

Multi-Channel:

	Enc. Type	RE	PR	F1
AIT202 and FIT201	TSSE	0.44	0.21	0.29
	Spatial	0.06	1.0	0.12
	Temporal (b=3)	0.19	0.18	0.18
	Combined (b=3,$\alpha = 0.7$)	0.125	0.2	0.15

Stage 3

Single-Channel:

	RE	PR	F1
DPIT301	0.125	0.24	0.16
FIT301	0.03	1.0	0.06
LIT301	0.25	0.89	0.39

Multi-Channel:

	Enc. Type	RE	PR	F1
DPIT301 FIT301 LIT301	TSSE	0.41	0.12	0.19
	Spatial	0.03	1	0.06
	Temporal (b=3)	0.5	0.11	0.18
	Combined (b=3,$\alpha = 0.7$)	0.16	0.5	0.24

Stage 4

Single-Channel:

	RE	PR	F1
AIT402	0.38	0.16	0.22
FIT401	0.22	0.88	0.35
LIT401	0.16	0.625	0.25

Multi-Channel:

	Enc. Type	RE	PR	F1
AIT402 FIT401 LIT401	TSSE	0.59	0.11	0.19
	Spatial	0.125	1.0	0.22
	Temporal (b=3)	0.16	1.0	0.27
	Combined (b=3,$\alpha = 0.7$)	0.16	1.0	0.27

Stage 5								
	RE	PR	F1		Enc. Type	RE	PR	F1
AIT501	0.25	0.12	0.16	AIT501 AIT502 AIT503 AIT504 FIT501 FIT503 FIT504 PIT501 PIT503	TSSE	0.06	1.0	0.12
AIT502	0.16	0.42	0.23					
AIT503	0.03	0.05	0.04		Spatial	0.125	0.67	0.21
AIT504	0.09	1.0	0.17					
FIT501	0.19	1.0	0.32		Temporal (b=8)	0	0	0
FIT503	0	0	0					
FIT504	0.03	1.0	0.06		Combined (b=8,$\alpha = 0.7$)	0.125	0.67	0.21
PIT501	0.03	1.0	0.06					
PIT503	0	0	0					

Table 3: Multi-Channel experiments results showing FP, TP, and detected labels.

Single-Channel

Channel	FP	TP	Detected Labels
LIT301	1	8	7, 16, 25, 26, 28, 32, 35, 41
FIT301	0	1	28

Multi-Channel

Channels	Enc. Type	FP	TP	Detected Labels
LIT301 and FIT301	TSSE	138	16	2, 3, 7, 8, 17, 19, 23, 26, 28, 32, 33, 35, 36, 37, 38, 41
	Spatial	0	1	26
	Temporal (b = 3)	82	11	2, 3, 6, 8, 23, 26, 28, 32, 35, 36, 37
	Combined (b=3, $\alpha = 0.7$)	6	4	2, 8, 26, 37

Single-Channel

Channel	FP	TP	Detected Labels
LIT101	2	8	1, 3, 21, 26, 28, 30, 33, 36
AIT202	2	1	26

Multi-Channel

Channels	Enc. Type	FP	TP	Detected Labels
LIT101 and AIT202	TSSE	38	13	1, 2, 3, 6, 7, 8, 16, 21, 22, 26, 30, 33, 36
	Spatial	0	1	26
	Temporal (b = 2)	4	7	1, 2, 6, 7, 21, 26, 30
	Temporal (b = 3)	9	7	1, 2, 6, 7, 8, 21, 26
	Temporal (b = 5)	30	9	1, 2, 6, 7, 8, 11, 16, 21, 26
	Temporal (b = 8)	38	11	1, 2, 6, 7, 8, 11, 16, 17, 21, 22, 26
	Combined (b=3, $\alpha = 0.7$)	0	6	1, 2, 6, 7, 21, 26

Single-Channel

Channel	FP	TP	Detected Labels
LIT401	3	5	8, 11, 25, 27, 31
FIT401	1	7	10, 11, 22, 28, 37, 39, 40

Multi-Channel

Channels	Enc. Type	FP	TP	Detected Labels
LIT401 and FIT401	TSSE	8	11	8, 10, 11, 17, 22, 25, 28, 37, 38, 39, 40
	Spatial	0	6	10, 11, 22, 37, 39, 40
	Temporal (b = 2)	16	10	10, 11, 22, 23, 25, 28, 37, 38, 39, 40
	Temporal (b = 3)	35	12	8, 10, 11, 17, 22, 23, 25, 28, 37, 38, 39, 40
	Temporal (b = 5)	74	15	8, 10, 11, 17, 22, 23, 25, 27, 28, 31, 32, 37, 38, 39, 40
	Temporal (b = 8)	114	19	1, 8, 10, 11, 16, 17, 22, 23, 25, 27, 28, 30, 31, 32, 37, 38, 39, 40, 41
	Combined (b=3, $\alpha = 0.7$)	2	8	10, 11, 22, 25, 37, 38, 39, 40

	FP	TP	Detected Labels		Enc. Type	FP	TP	Detected Labels
LIT101	2	8	1, 3, 21, 26, 28, 30, 33, 36	LIT101 LIT301 LIT401	TSSE	97	27	1, 2, 3, 6, 7, 8, 11, 16, 17, 21, 22, 23, 25, 26, 27, 28, 30, 31, 32, 33, 35, 36, 37, 38, 39, 40, 41
LIT301	1	8	7, 16, 25, 26, 28, 32, 35, 41		Spatial	0	5	21, 26, 30, 33, 36
LIT401	3	5	8, 11, 25, 27, 31		Temporal (b = 3)	26	15	1, 2, 3, 7, 8, 11, 16, 17, 17, 21, 26, 30, 33, 35, 36
					Combined (b=3, $\alpha = 0.7$)	0	7	1, 8, 21, 26, 30, 33, 36

	FP	TP	Detected Labels		Enc. Type	FP	TP	Detected Labels
LIT401	3	5	8, 11, 25, 27, 31	LIT401 AIT502 FIT501 FIT601	TSSE	207	27	1, 2, 3, 6, 8, 10, 11, 16, 17, 19, 21, 22, 23, 25, 26, 27, 28, 30, 32, 33, 35, 36, 37, 38, 39, 40, 41
AIT502	7	5	11, 22, 28, 38, 40		Spatial	0	1	11
FIT501	0	6	10, 11, 22, 28, 37, 40		Temporal (b=3)	0	1	11
FIT601	3	2	8, 28		Combined (b=3, $\alpha = 0.7$)	0	1	11

	FP	TP	Detected Labels		Enc. Type	FP	TP	Detected Labels
LIT101	2	8	1, 3, 21, 26, 28, 30, 33, 36	LIT101 AIT202 LIT301 FIT301	TSSE	16	4	2, 3, 8, 11
AIT202	2	1	26		Spatial	0	0	
LIT301	1	8	7, 16, 25, 26, 28, 32, 35, 41		Temporal (b=3)	48	7	2, 3, 6, 8, 11, 17, 19
FIT301	0	1	28		Combined (b=3, $\alpha = 0.7$)	7	3	2, 8, 11

Table 4: Multi-Channel experiments results showing RE, PR, F1.

<table>
<tr><th colspan="4">Single-Channel</th><th colspan="5">Multi-Channel</th></tr>
<tr><th></th><th>RE</th><th>PR</th><th>F1</th><th rowspan="5">LIT301 and FIT301</th><th>Enc. Type</th><th>RE</th><th>PR</th><th>F1</th></tr>
<tr><td rowspan="2">LIT301</td><td rowspan="2">0.25</td><td rowspan="2">0.89</td><td rowspan="2">0.39</td><td>TSSE</td><td>0.5</td><td>0.1</td><td>0.17</td></tr>
<tr><td>Spatial</td><td>0.03</td><td>1</td><td>0.06</td></tr>
<tr><td rowspan="2">FIT301</td><td rowspan="2">0.03</td><td rowspan="2">1.0</td><td rowspan="2">0.06</td><td>Temporal (b=3)</td><td>0.34</td><td>0.12</td><td>0.18</td></tr>
<tr><td>Combined (b=3,$\alpha = 0.7$)</td><td>0.13</td><td>0.4</td><td>0.19</td></tr>
<tr><td rowspan="4">LIT101</td><td>RE</td><td>PR</td><td>F1</td><td rowspan="8">LIT101 and AIT202</td><td>Enc. Type</td><td>RE</td><td>PR</td><td>F1</td></tr>
<tr><td rowspan="3">0.25</td><td rowspan="3">0.8</td><td rowspan="3">0.38</td><td>TSSE</td><td>0.41</td><td>0.26</td><td>0.31</td></tr>
<tr><td>Spatial</td><td>0.06</td><td>1.0</td><td>0.12</td></tr>
<tr><td>Temporal (b=2)</td><td>0.22</td><td>0.64</td><td>0.33</td></tr>
<tr><td rowspan="4">AIT202</td><td>RE</td><td>PR</td><td>F1</td><td>Temporal (b=3)</td><td>0.22</td><td>0.44</td><td>0.29</td></tr>
<tr><td rowspan="3">0.03</td><td rowspan="3">0.33</td><td rowspan="3">0.06</td><td>Temporal (b=5)</td><td>0.28</td><td>0.23</td><td>0.25</td></tr>
<tr><td>Temporal (b=8)</td><td>0.34</td><td>0.23</td><td>0.27</td></tr>
<tr><td>Combined (b=3,$\alpha = 0.7$)</td><td>0.19</td><td>1.0</td><td>0.32</td></tr>
</table>

Sensor	RE	PR	F1
LIT401	0.16	0.63	0.25
FIT401	0.22	0.88	0.35

Sensors	Enc. Type	RE	PR	F1
LIT401 and FIT401	TSSE	0.34	0.58	0.43
	Spatial	0.19	1.0	0.32
	Temporal (b=2)	0.31	0.39	0.35
	Temporal (b=3)	0.38	0.26	0.3
	Temporal (b=5)	0.47	0.17	0.25
	Temporal (b=8)	0.59	0.14	0.23
	Combined (b=3,$\alpha = 0.7$)	0.25	0.8	0.38

	RE	PR	F1
LIT101	0.25	0.8	0.38
LIT301	0.25	0.89	0.39
LIT401	0.16	0.625	0.25

Sensors	Enc. Type	RE	PR	F1
LIT101 LIT301 LIT401	TSSE	0.84	0.22	0.35
	Spatial	0.16	1.0	0.27
	Temporal (b=3)	0.47	0.37	0.41
	Combined (b=3,$\alpha = 0.7$)	0.22	1.0	0.36

	RE	PR	F1
LIT401	0.16	0.625	0.25
AIT502	0.16	0.42	0.23
FIT501	0.19	1.0	0.32
FIT601	0.06	0.4	0.11

Sensors	Enc. Type	RE	PR	F1
LIT401 AIT502 FIT501 FIT601	TSSE	0.84	0.12	0.20
	Spatial	0.03	1.0	0.06
	Temporal (b=3)	0.03	1.0	0.06
	Combined (b=3,$\alpha = 0.7$)	0.03	1.0	0.06

	RE	PR	F1
LIT101	0.25	0.8	0.38
AIT202	0.03	0.33	0.06
LIT301	0.25	0.89	0.39
FIT301	0.03	1.0	0.06

	Enc. Type	RE	PR	F1
LIT101 AIT202 LIT301 FIT301	TSSE	0.125	0.2	0.15
	Spatial	0	0	0
	Temporal (b=3)	0.22	0.13	0.16
	Combined (b=3, $\alpha = 0.7$)	0.09	0.3	0.14

4 Discussion

From the results, we observe distinct patterns in the performance of different multi-channel encoding methods. Timestamp TSSE consistently achieves the highest TPs but also suffers from a high rate of FPs, likely due to its lack of emphasis on balancing channel contributions as was mentioned in section 2.1. Spatial encoding, on the other hand, maintains the lowest FP and TP rates, suggesting it excels in precision but often misses subtle anomalies due to its static nature. Temporal encoding provides a middle ground, capturing temporal patterns effectively, resulting in a moderate FP and TP rate albeit still high FP rate. Combined encoding balances these trade-offs, achieving a reduced FP rate compared to Timestamp TSSE while maintaining reasonable TP detection, that is consistently able to detect anomalies that were not detected in single-channel. Moreover, increasing the temporal buffer size (`b`) in Temporal and Combined encodings improves TP rates but also leads to a proportional rise in FPs, emphasizing the importance of tuning this parameter for specific use cases. Although testing wasn't done on the trade off of temporal/spatial weight (α, β) and FP rate, it can be reasoned that a decrease in α will lead to an increase in FPs and TPs because of the larger emphasis on temporal encoding.

We noticed that increasing the number of channels generally led to worse performance. For instance, combining all channels in stage 4 yielded poorer results compared to using a subset (LIT401 and FIT401). The subset detected all anomalies found by the full set, plus three additional ones, while only adding two false positives. Similarly, combining all nine channels in stage 5 resulted in significantly worse performance compared to using a single channel. This decline in performance with larger channel combinations might be attributed to the increasing complexity and potential noise in the multi-channel encoded representation, which can dilute the impact of individual anomalies.

Taking channel combinations from different stages yielded good results in our experiments. For example, the combinations LIT101 and AIT202, as well as LIT101, LIT301, and LIT401, performed well, achieving high F1 scores and maintaining a low rate of false positives. These results suggest that selecting channels across different stages may introduce complementary information, enabling the detection of anomalies that might otherwise be missed.

Hyperparameter tuning significantly impacted performance, as the SDR size, window size for each channel, temporal buffer size, and temporal/spatial weights all needed careful adjustment in order to maximize performance. These hyperparameters offer numerous combinations, and due to time constraints, we estimated values for each multi-channel combination in our experiments that we though would yield best results. We always took the same window size from the single channel case. We sometimes kept the same SDR size from the single channel case, when we saw we got good results. If we did not get good results, we adjusted the SDR sizes accordingly. Specifically, channels we wanted to prioritize were assigned smaller SDR sizes. As explained in Section 2.2, smaller SDR sizes result in a higher density of active bits, making these channels more dominant in the combined encoding. For instance, if a particular channel produced a high number of FPs in the single-channel case and continued to do so in the multi-channel case, we increased its SDR size. This adjustment reduced the density of active bits, making the channel's encoding sparser and less sensitive to noise, ultimately lowering the FP rate in the multi-channel scenario.

5 Conclusion and Future Work

In this project, we extended Roman Malits' HTM-based anomaly detection system by developing and evaluating several multi-channel encoding methods to enhance anomaly detection in cyber-physical systems. Our work demonstrated that multi-channel combinations, when encoded effectively, can detect anomalies that single-channel methods miss, particularly when channels from different stages are combined. However, our results also highlighted the challenges of increasing the number of channels, as larger combinations tended to dilute anomaly signals due to increased complexity and noise. Among the encoding methods, Combined Encoding showed the most promise by balancing temporal and spatial relationships, achieving reasonable detection rates with reduced false positives compared to the other methods.

This project can be expanded upon by:

1. Additional Multi-Channel Encoding Methods and Refinements: Explore encoding methods beyond the four proposed approaches. Additionally, refine the existing methods to address limitations, such as balancing channel contributions or reducing FPs in Timestamp TSSE and Temporal Encoding.

2. Runtime Optimization: The current implementation is empirically slow. Leveraging tensor operations and GPU supported libraries could significantly enhance performance and scalability.

3. Comprehensive Hyperparameter Search: With improved runtime, conducting an extensive hyperparameter search could lead to optimized anomaly detection results.

4. Exploring Additional Channel Combinations: Investigate which combinations of the four continuous channel types (LIT, FIT, PIT/DPIT, AIT) yield the most meaningful multi-channel encoding and anomaly detection outcomes.

5. Dynamic Channel Selection: Develop a model capable of dynamically selecting the most relevant channels during system operation, adapting to changing conditions in real-time.

6. Integration of Discrete Channels: This project focused solely on continuous channels. Future work could explore incorporating discrete channels into multi-channel encodings.