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Data Standardization in Positioning: The Role of Large Language Models

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For the most accurate and detailed information, please refer to the published paper.

Sensor Fusion?

GSM/3/4/5G

Indoor GNSS

UWB

GNSS

Ultrasound

Image SLAM

Radio AM&FM

Accelerometer

BLE

Visual Positioning System (VPS)

Radar

NFC

WLAN

LiFi

WiFi

Theodolites

TV

Gyroscope

Imagemarkers

Contactless cards

Pressure

LiDAR

Bar codes

Cospas Sarsat, Argos

Magnetometer

Opportunity radio signals

Any Trouble?

> **Inconsistent Data Format**

- Variety of **formats**, **units**, or **conventions**
  - UTC time or Local time?
  - UNIX or YYYY-MM-DDTHH:mm:ss.sssZ?
  - Degree or Radian?
  - Cartesian or Polar Coordinate?

> **Which can lead to**

- Error during execution
- Incorrect state estimates

> **Current Solutions**

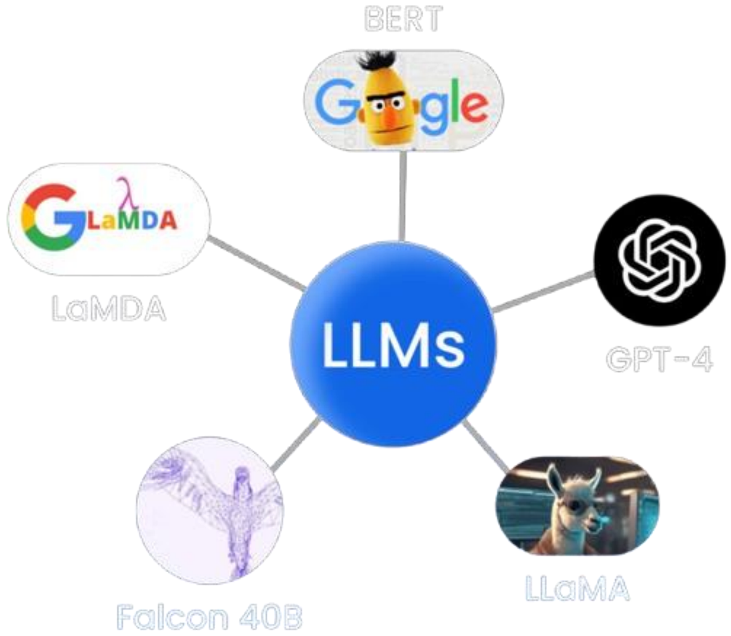
- Sensor Calibration and Preprocessing Pipelines
- Manual Unit Conversions
- Manual Coordinate Transformations

> **Drawbacks**

- High **complexity** and **maintenance** cost
- Manual **errors** -> error propagation
- Limited **flexibility** & **scalability**
- Compromised **real-time** performance

Can LLMs Help?

> **LLMs as a Solution**
- Contextual Understanding of Diverse Data
- Automatic Detection and Standardization
- Adaptability to New Sensors
- Reduction of Manual Effort and Error



Complexity

Flexibility

Errors

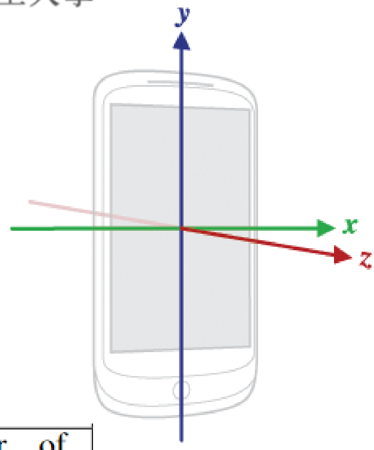
Computational cost

Scalability

Real-time performance

Schema

The Pre-defined Schema



- The schema is based on common inputs to the Kalman filter for sensor fusion
- Assumption: Coordinate System is Android or WGS84/HK1980 format

Sensor Type	**Required Fields**	**Values Object Properties**	**Description**
Magneto-meter	name, time, values	x (µT), y (µT), z (µT)	Measures magnetic field strength along x, y, and z axes in microteslas (µT).
Gyro-scope	name, time, values	x (rad/s), y (rad/s), z (rad/s)	Measures angular velocity along x, y, and z axes in radians per second (rad/s).
Accelero-meter	name, time, values	x (m/s²), y (m/s²), z (m/s²)	Measures acceleration along x, y, and z axes in meters per second squared (m/s²).
Gravity	name, time, values	x (m/s²), y (m/s²), z (m/s²)	Measures gravity effects along x, y, and z axes in meters per second squared (m/s²).
Ultra-Wideband (UWB)	name, time, values	x (m), y (m), z (m)	Determines spatial position in meters (m).
Bluetooth	name, time, values	x (m), y (m), z (m)	Determines spatial position in meters (m).
Pedometer	name, time, steps	steps (count)	Tracks the number of steps taken (count).
Ori-entation	name, time, values	qx, qy, qz, qw	Provides orientation details in quaternion format.
Baro-meter	name, time, values	relative altitude (m), pressure (mBar)	Measures relative altitude in meters (m) and atmospheric pressure in millibars (mBar).
Location	name, time, values	latitude (°), longitude (°), altitude (m), speed (m/s), speed accuracy (m/s), horizontal accuracy (m), vertical accuracy (m)	Provides comprehensive location data including coordinates (degrees), speed (meters per second), altitude (meters), and accuracies (meters).
Image	name, time, image	image (data)	Provides image data in binary format.

The Pre-defined Schema

Sensor Type	Required Fields	Values Object Properties	Description
Magneto-meter	name, time, values	x (μT), y (μT), z (μT)	Measures magnetic field strength along x, y, and z axes in microteslas (μT).
Gyro-scope	name, time, values	x (rad/s), y (rad/s), z (rad/s)	Measures angular velocity along x, y, and z axes in radians per second (rad/s).
Accelero-meter	name, time, values	x (m/s^2), y (m/s^2), z (m/s^2)	Measures acceleration along x, y, and z axes in meters per second squared (m/s^2).
Gravity	name, time, values	x (m/s^2), y (m/s^2), z (m/s^2)	Measures gravity effects along x, y, and z axes in meters per second squared (m/s^2).
Ultra-Wideband (UWB)	name, time, values	x (m), y (m), z (m)	Determines spatial position in meters (m).
Bluetooth	name, time, values	x (m), y (m), z (m)	Determines spatial position in meters (m).
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Ori-entation	name, time, values	qx, qy, qz, qw	Provides orientation details in quaternion format.
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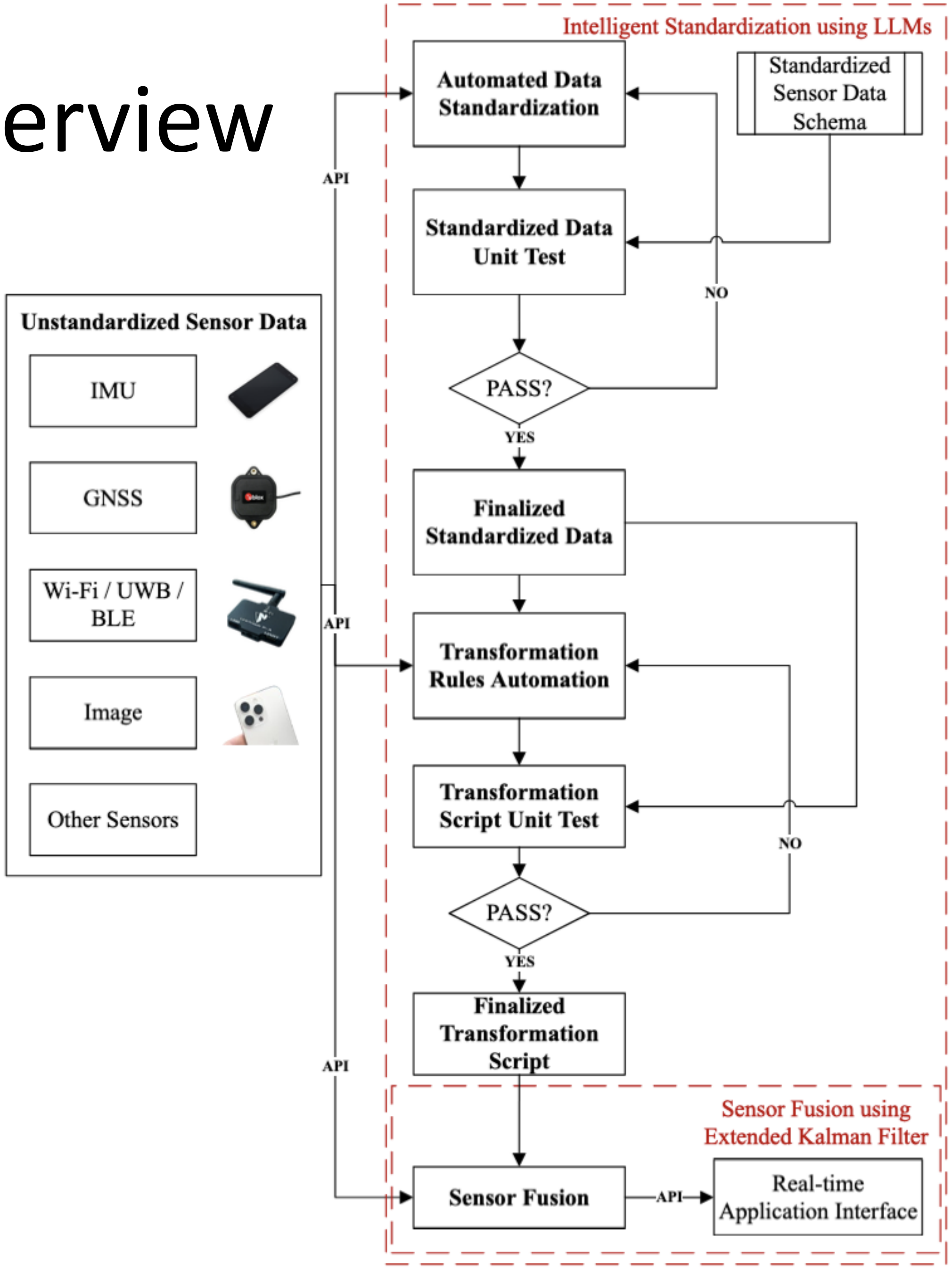
Location	name, time, values	latitude (°), longitude (°), altitude (m), speed (m/s), speed accuracy (m/s), horizontal accuracy (m), vertical accuracy (m)	Provides comprehensive location data including coordinates (degrees), speed (meters per second), altitude (meters), and accuracies (meters).
Image	name, time, image	image (data)	Provides image data in binary format.

Framework

Framework Overview

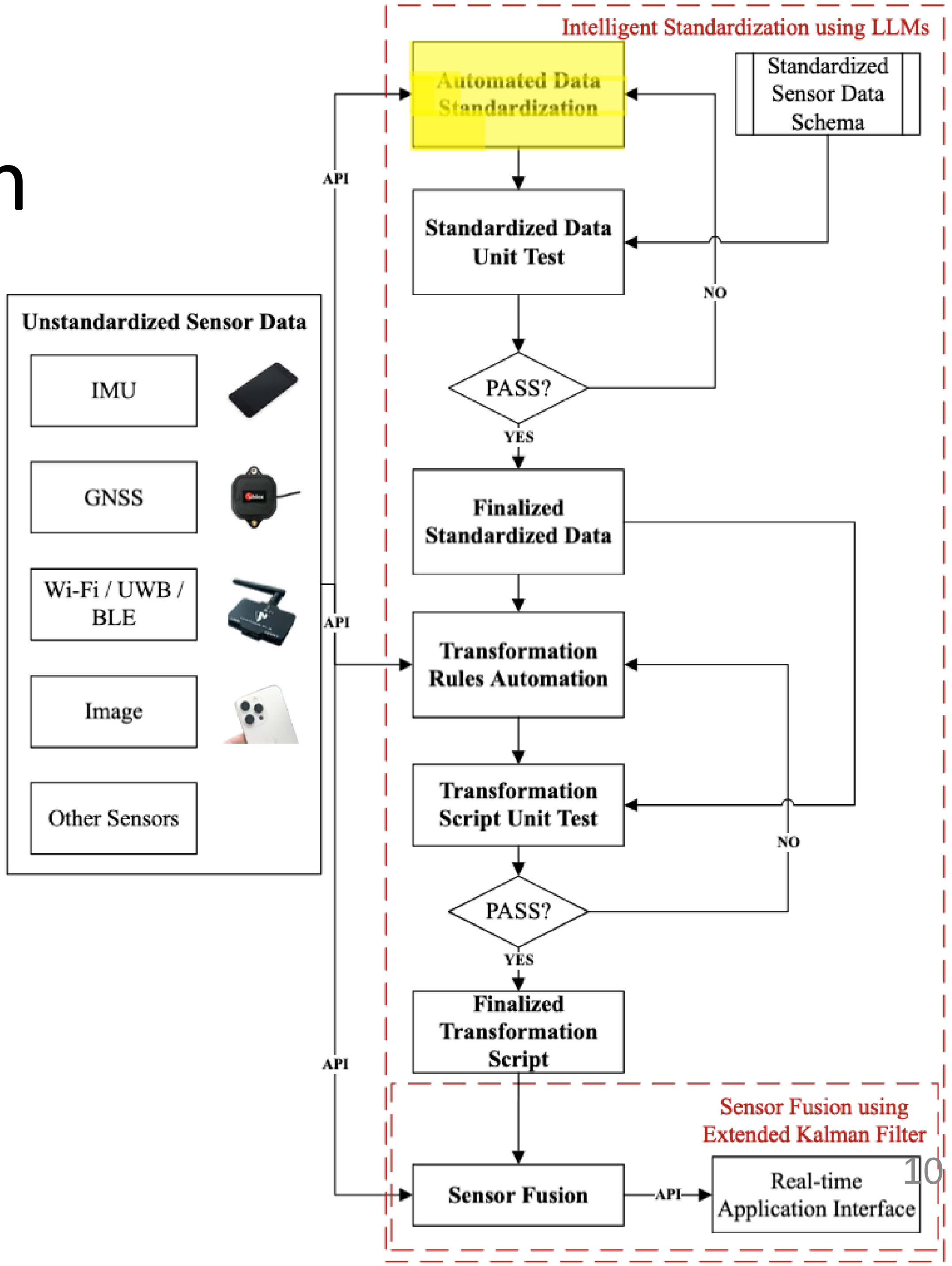


Automated Data Standardization

> **Overview**
- The standardization module leverages **GPT-4-0613** for standardizing sensor data.
- Trained Sensors: Pedometers, Magnetometers, Orientation Sensors, Gyroscopes, Accelerometers, Gravity Sensors, Barometers, GNSS Receivers, Bluetooth, and UWB

> **Data Standardization Process**
- Input Data: $\mathcal{D} = \bigcup_{i=1}^{n} d_i$
- Standardization Process: $\mathcal{S} = \mathcal{F}_{\text{ADS}}(\mathcal{D}) = \bigoplus_{i=1}^{n} \phi(d_i)$

> **Fine-Tuning & Training**
- Dataset: 100 training + 30 test pairs
- Structure: JSON-like format.



Automated Data Standardization – Training

> **Training Loss**

- Decreased from **0.3484** loss to near zero by step **27**.

> **Training Accuracy**

- Increased from **93.38%** to **100%** by step **14**.

> **Validation Loss**

- Started at **0.1724**, briefly increased to **0.6984** at step **2**, then declined to nearly zero by step **27**.

> **Validation Accuracy**

- Increased from **96.14%** to near **100%** by step **27**.

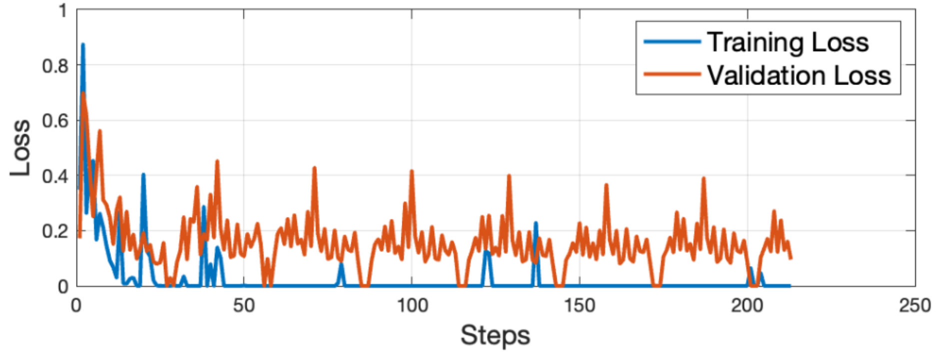


Fig. 2. Training and Validation Loss of the LLM over Steps.

Fig. 3. Mean Token Accuracy of the LLM over Steps.

Automated Data Standardization – Example

Unstandardized Data


```
{
     "time": {
         "time": "Saturday, 04
May 2024 14:00:00 GMT"
     },
     "acc": {
         "x": 0.456,
         "x": 0.123,
         "z": 0.789,
     },
     "mag": {
         "x": -24.321,
         "y": -12.849,
         "z": -0.233,
     },
     "gyro": {
         "x": -0.654,
         "y": 1.234,
         "z": 2.931,
     }
}
```


Converted Data

- Timestamp Format
- Sensor Data Labels
- Data Structure
- Correction of Axis Labels
- Etc.

Automated Data Standardization →

Standardized Data


```
[
    {
        "name": "Accelerometer",
        "time": 1714831200000,
        "values": {
            "x": 0.456,
            "y": 0.123,
            "z": 0.789
        }
    },
    {
        "name": "Magnetometer",
        "time": 1714831200000,
        "values": {
            "x": -24.321,
            "y": -12.849,
            "z": -0.233
        }
    },
    {
        "name": "Gyroscope",
        "time": 1714831200000,
        "values": {
            "x": -0.654,
            "y": 1.234,
            "z": 2.931
        }
    }
]
```

Standardized Dataset **Unit Tests**

> **Overview**

- Validate compliance of sensor data with **predefined JSON schemas**.

> **Validation Function**

$$(\nu, e) = \mathcal{V}_{\text{ADS}}(\mathcal{S}, \sigma) = \begin{cases} 1, & \text{if schema}(\mathcal{S}) \equiv \sigma \\ 0, & \text{otherwise} \end{cases}$$

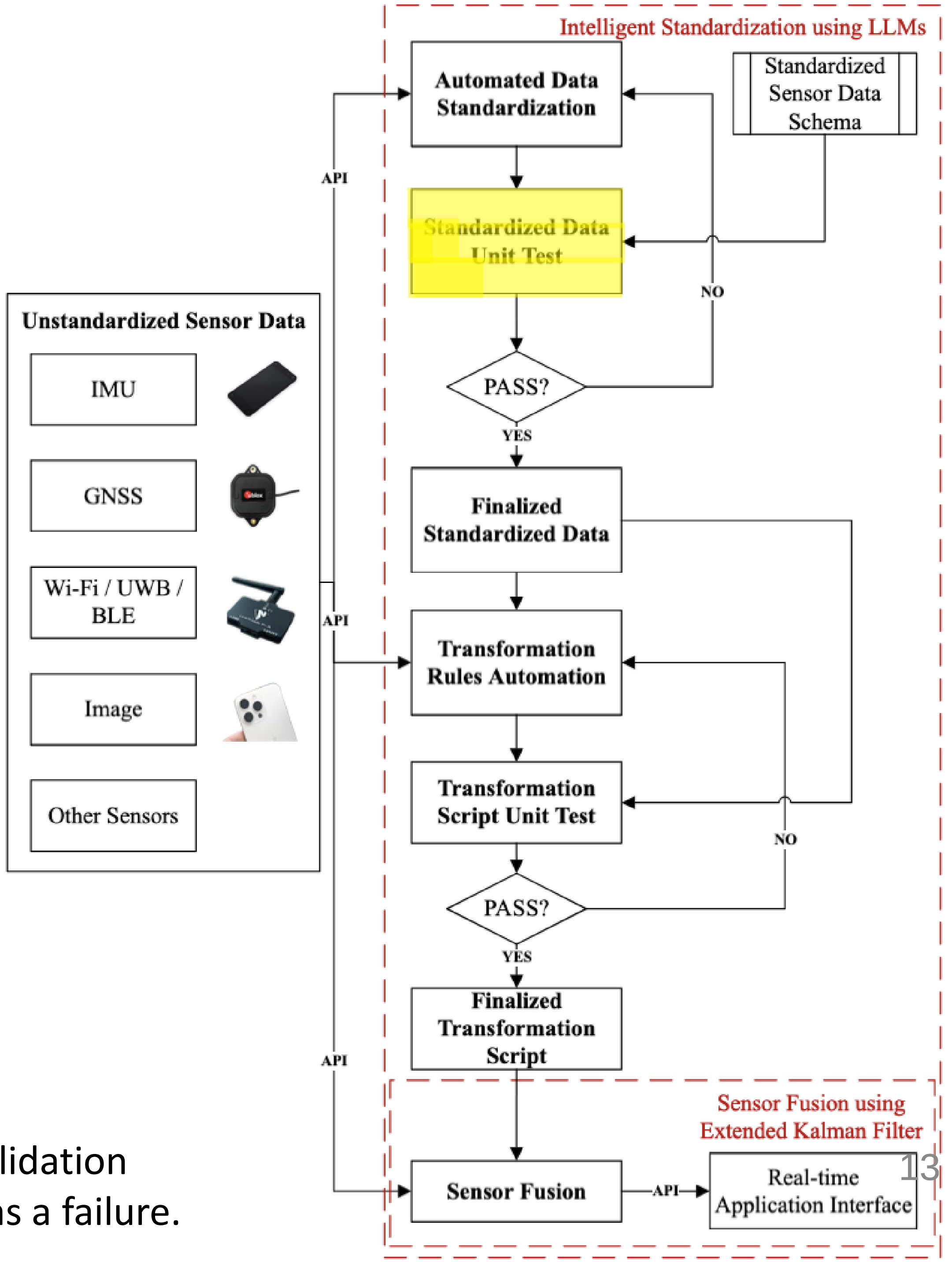
- If errors are detected ($e \neq \emptyset$), these errors are fed back into the transformation function:

$$\mathcal{S} = \mathcal{F}_{\text{ADS}}(\mathcal{D}, e) = \bigcup_{i=1}^{N} \text{adjust}(\mathcal{D}_i, e_i)$$

> **Validation Process**

- Library Used:
  - JSON Schema
- Checks Performed:
  - Correct Data Types
  - Required Fields

Most datasets (24 out of 30) required only **one iteration** for successful validation
The process typically completes in **5 iterations**; otherwise, it is regarded as a failure.



Standardized Dataset **Unit Tests** – Edge Cases

Edge Case	Expected Outcome	Example Adjustments	Success Rate (%)
Non-uniform Units	Accurately convert various input units to predefined standard units.	Input units successfully standardized to meters and Unix nanoseconds.	89.47
Missing Entries	Appropriately handle missing data using default values.	Missing data entries were identified and marked as Null.	82.35
Unstructured Data	Correct non-conforming data structures to fit expected formats.	Unstructured data was reorganized to desired JSON format.	100.00
Data Type Mismatches	Convert various inputs into their corresponding numerical data types.	Textual strings were accurately converted and formatted as numerical data.	100.00

Transformation Rules Automation

> Overview

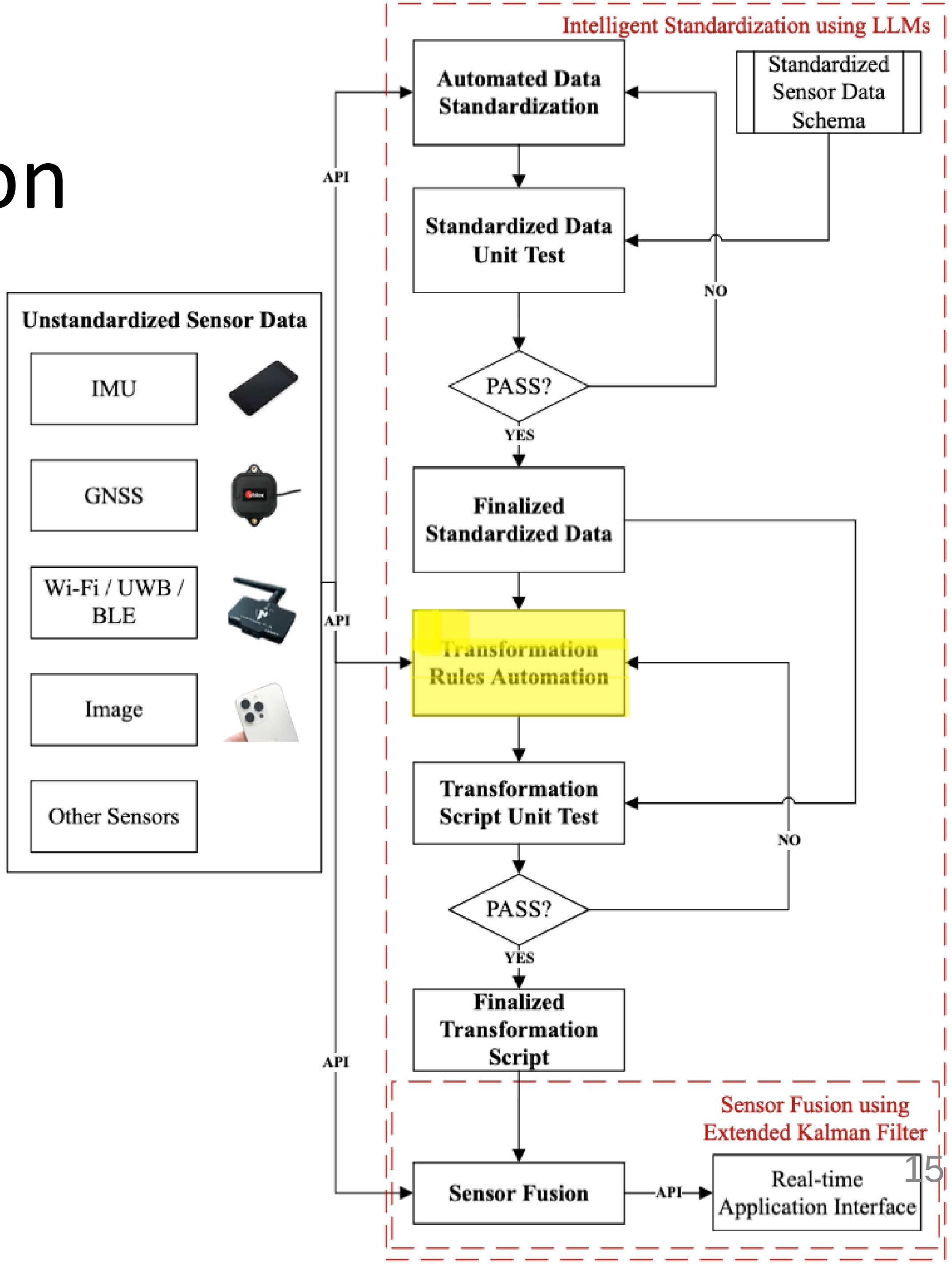
- TRGM leverages **GPT-4-0613** to generate transformation script for standardization

> Transformation Process

$$\mathcal{T} = \mathcal{F}_{\text{TRA}}(\mathcal{S}, \mathcal{D}) = \bigcup_{i=1}^{M} \text{transform}(\mathcal{S}_i, \mathcal{D}_i)$$

> Transformation Rules

Field Name	Data Type	Description
inputPath	String	JSONPath expression pointing to the source field in the input JSON structure.
outputPath	String	JSONPath expression pointing to the target field in the output JSON structure.
transformation	Function	A function or expression used to transform the input data before mapping it to the output path.
Example		
inputPath	String	$.sensor_data.Accelerometer.timestamp
outputPath	String	$[?(@.name == ’Accelerometer’)].time
transformation	Function	float(re.search(r’[-+]?*?+’, value).group(0))



Transformation Script **Unit Tests**

> **Overview**

- Ensure accuracy and functionality of transformation scripts generated by LLMs.
- Scripts convert input JSON data (I) into the standardized format (S).

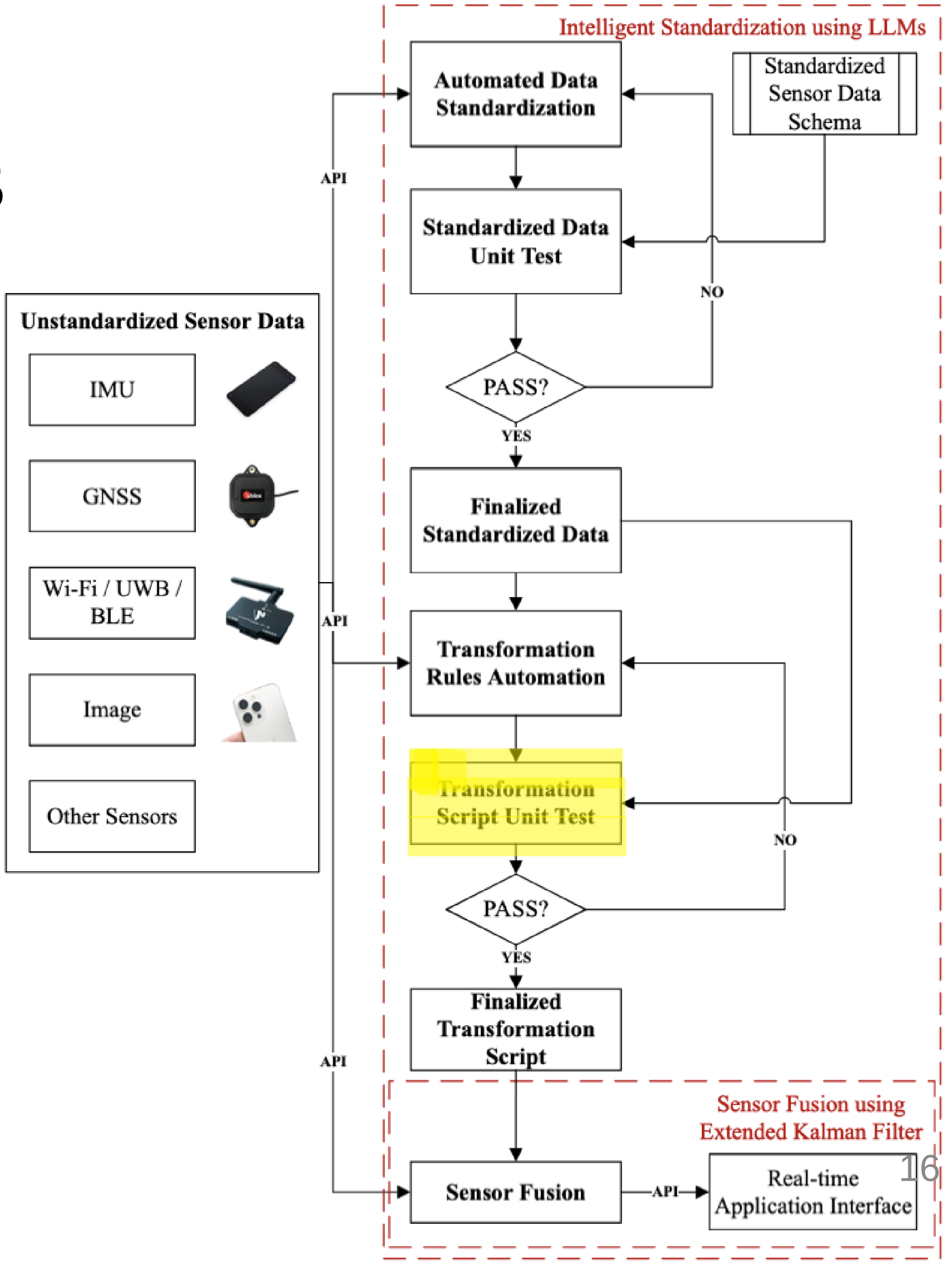
> **Validation Function**

$$(\nu, e) = \mathcal{V}_{\text{TRA}}(\mathcal{T}(\mathcal{D}), \mathcal{S}) = \begin{cases} 1, & \text{if compare}(\mathcal{T}(\mathcal{D}), \mathcal{S}) \\ 0, & \text{otherwise} \end{cases}$$

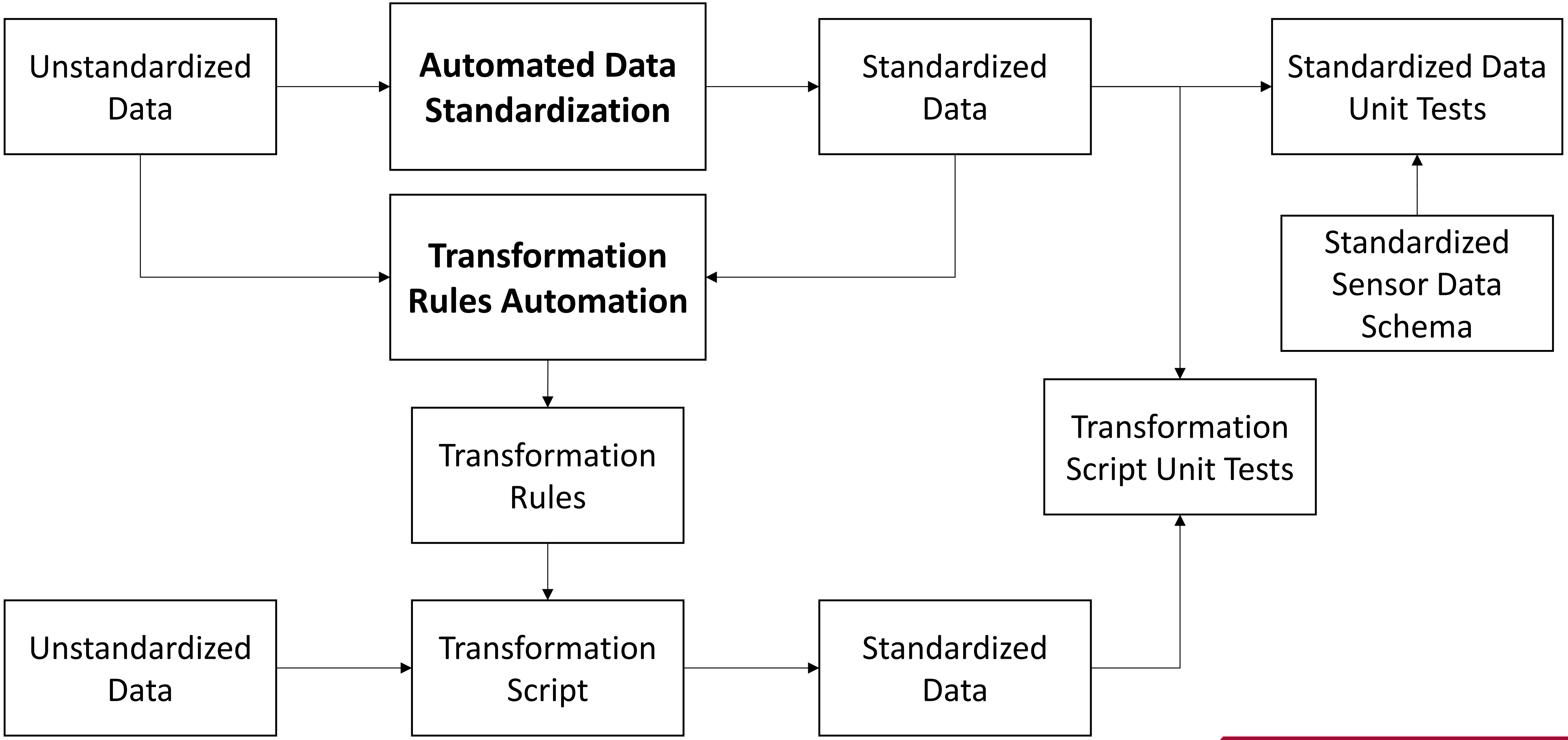
- If discrepancies or errors ($e \neq \emptyset$) are identified, these errors are fed back into the transformation function:

$$\mathcal{T} = \mathcal{F}_{\text{TRA}}(\mathcal{S}, \mathcal{D}, e) = \bigcup_{j=1}^{P} \text{modify}(\mathcal{S}_j, \mathcal{D}_j, e_j)$$

Process repeats until no errors are detected ($\nu = 1$ & $e = \emptyset$).



Proposed Framework



Unstandardized Data


```
{
  "sensor_data": {
    "Accelerometer": {
      "timestamp": 1683302400000,
      "readings": {
        "x": 9.81,
        "y": 0.02,
        "z": -0.03
      }
    },
    "Magnetometer": {
      "timestamp": 1683302400000,
      "accuracy_level": 2,
      "coordinates": {
        "x": 0.012,
        "y": -0.030,
        "z": 0.022
      }
    },
    "Gyroscope": {
      "timestamp": 1683302400000,
      "axis": {
        "x": 1.23,
        "y": 0.45,
        "z": -0.67
      }
    }
  }
}
```


Standardized Data


```
[
  {
    "name": "Accelerometer",
    "time": 1683302400000,
    "values": {
      "x": 9.81,
      "y": 0.02,
      "z": -0.03
    }
  },
  {
    "name": "Magnetometer",
    "time": 1683302400000,
    "accuracy": 2,
    "values": {
      "x": 0.012,
      "y": -0.030,
      "z": 0.022
    }
  },
  {
    "name": "Gyroscope",
    "time": 1683302400000,
    "values": {
      "x": 1.23,
      "y": 0.45,
      "z": -0.67
    }
  }
]
```


Transformation Rules


```
{
  "rules": [
    {
      "inputPath": "$.sensor_data.Accelerometer.timestamp",
      "outputPath": "$[?(@.name == 'Accelerometer')].time"
    },
    {
      "inputPath": "$.sensor_data.Accelerometer.readings.x",
      "outputPath": "$[?(@.name == 'Accelerometer')].values.x"
    },
    {
      "inputPath": "$.sensor_data.Magnetometer.timestamp",
      "outputPath": "$[?(@.name == 'Magnetometer')].time"
    },
    {
      "inputPath": "$.sensor_data.Magnetometer.coordinates.x",
      "outputPath": "$[?(@.name == 'Magnetometer')].values.x"
    },
    {
      "inputPath": "$.sensor_data.Gyroscope.timestamp",
      "outputPath": "$[?(@.name == 'Gyroscope')].time"
    },
    {
      "inputPath": "$.sensor_data.Gyroscope.axis.x",
      "outputPath": "$[?(@.name == 'Gyroscope')].values.x"
    }
  ]
}
```

Transformation Rules

Generic Transformation Script

```
def apply_transformation(input_JSON, transformation_rules):
    """Applies transformation rules to input JSON and produces output JSON."""
    output_JSON = {}

    for rule in transformation_rules["rules"]:
        # Convert inputPath to list of keys for dictionary access
        input_keys = rule['inputPath'].replace('$.', '').split('.')
        value = get_from_dict(input_JSON, input_keys)

        # Check if a transformation is needed and apply it
        if "transformation" in rule:
            transformation_code = rule["transformation"]
            value = eval(transformation_code)

        # Convert outputPath to list of keys and set value in output JSON
        output_keys = rule['outputPath'].replace('$.', '').split('.')
        set_in_dict(output_JSON, output_keys, value)

    return output_JSON
```

"speed": "1.5 m/s"

Transformation Rules

```
{
"rules": [
{"inputPath": "$.name", "outputPath": "$.name"},
{"inputPath": "$.time", "outputPath": "$.time"},
{"inputPath": "$.values.latitude", "outputPath": "$.values.latitude"},
{"inputPath": "$.values.longitude", "outputPath": "$.values.longitude"},
{"inputPath": "$.values.altitude", "outputPath": "$.values.altitude"},
{
"inputPath": "$.values.speed",
"outputPath": "$.values.speed",
"transformation": "float(re.search(r'[-+]?\\d*\\.?\\d+', value).group(0))"
},
{"inputPath": "$.values.speedAccuracy", "outputPath": "$.values.speedAccuracy"},
{"inputPath": "$.values.bearingAccuracy", "outputPath": "$.values.bearingAccuracy"},
{"inputPath": "$.values.horizontalAccuracy", "outputPath": "$.values.horizontalAccuracy"},
{"inputPath": "$.values.verticalAccuracy", "outputPath": "$.values.verticalAccuracy"},
{"inputPath": "$.values.bearing", "outputPath": "$.values.bearing"}
]
}
```

Change in Location

Change in Value

Extended Kalman Filter (EKF)

> **Method:**

- The standardized data is passed to the Extended Kalman Filter (EKF) for sensor fusion.

> **Outcome:**

- The EKF integrates data from multiple sensors (GNSS, UWB, IMU, BLE…) to provide real-time positional and velocity estimates.

> **State Transition Matrix & State Vector**

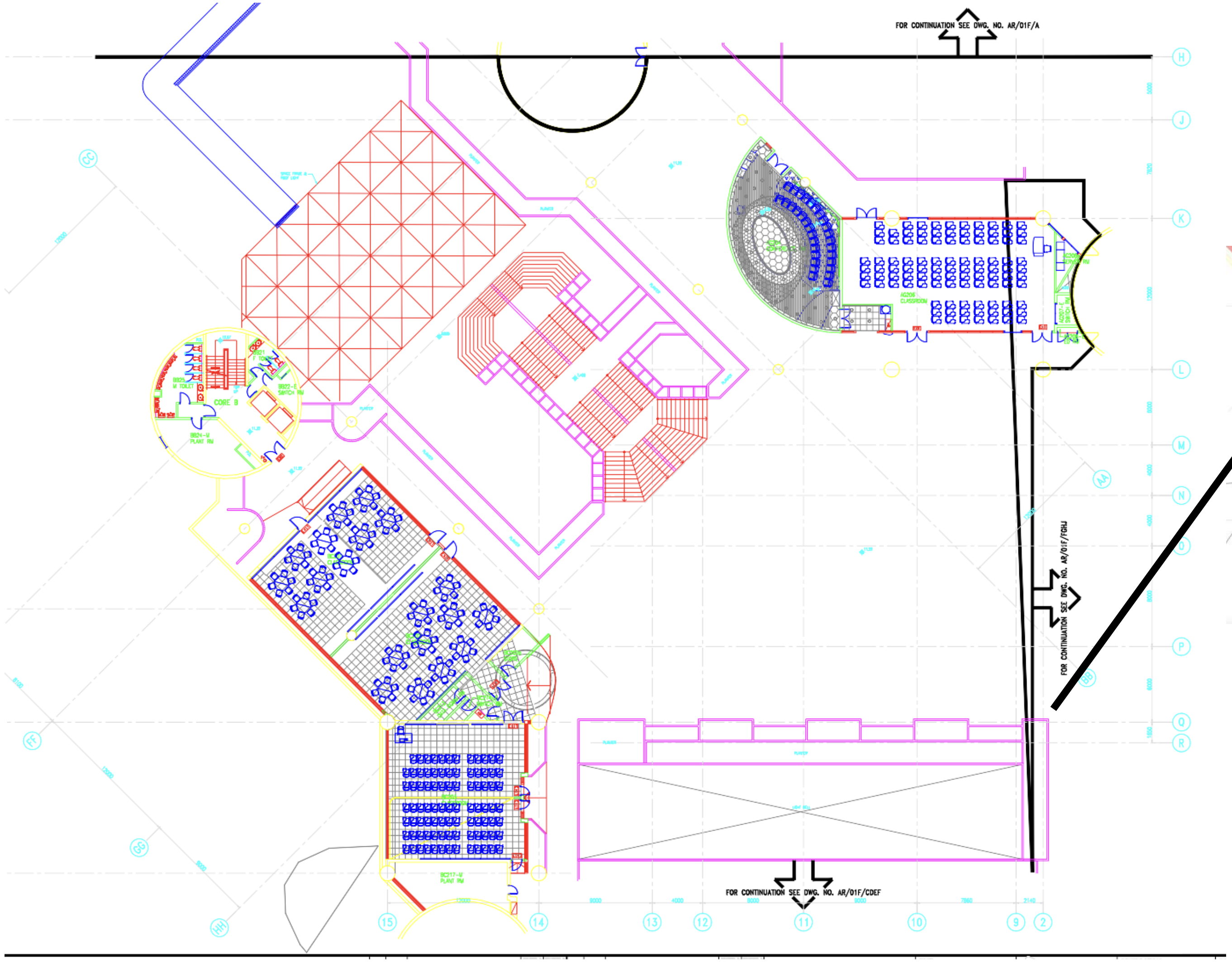
$$\mathbf{F}_k = \begin{bmatrix} \mathbf{I}_{3\times3} & \Delta t\mathbf{I}_{3\times3} \\ \mathbf{0}_{3\times3} & \mathbf{I}_{3\times3} \end{bmatrix} \qquad \mathbf{x} = \begin{bmatrix} x \\ y \\ z \\ v_x \\ v_y \\ v_z \end{bmatrix}$$

Sensor Type	**Measurement Vector**	**Measurement Covariance Matrix**
GNSS Receiver	$\mathbf{z}_{\mathrm{GNSS}} = \begin{bmatrix} \phi_{\mathrm{GNSS}} \\ \lambda_{\mathrm{GNSS}} \\ h_{\mathrm{GNSS}} \end{bmatrix}$	$\mathbf{R}_{\mathrm{GNSS}} = \begin{bmatrix} 655.00 & 0 & 0 \\ 0 & 655.00 & 0 \\ 0 & 0 & 655.00 \end{bmatrix}$
UWB Sensor	$\mathbf{z}_{\mathrm{UWB}} = \begin{bmatrix} x_{\mathrm{UWB}} \\ y_{\mathrm{UWB}} \\ z_{\mathrm{UWB}} \end{bmatrix}$	$\mathbf{R}_{\mathrm{UWB}} = \begin{bmatrix} 1.00 & 0 & 0 \\ 0 & 1.00 & 0 \\ 0 & 0 & 1.00 \end{bmatrix}$
Camera	$\mathbf{z}_{\mathrm{cam}} = img_{\mathrm{cam}}$	$\mathbf{R}_{\mathrm{cam}} = \begin{bmatrix} 0.15 & 0 & 0 \\ 0 & 0.15 & 0 \\ 0 & 0 & 0.15 \end{bmatrix}$

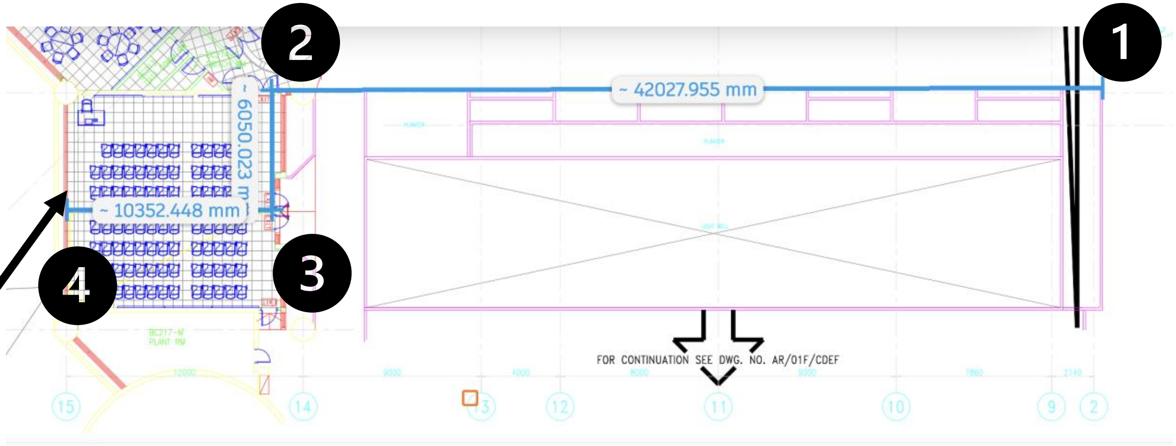
Sensor Type	**Control Input Vector**	**Control Input Matrix**	**Process Noise Covariance**
IMU	$\mathbf{u}_{\mathrm{IMU}} = \begin{bmatrix} a_x \\ a_y \\ a_z \\ \omega_x \\ \omega_y \\ \omega_z \\ m_x \\ m_y \\ m_z \end{bmatrix}$	$\mathbf{B}_{\mathrm{IMU}} = \begin{bmatrix} \frac{\Delta t^2}{2}\mathbf{I}_{3\times3} \\ \Delta t\mathbf{I}_{3\times3} \end{bmatrix}$	$\mathbf{Q} = \begin{bmatrix} \frac{\sigma_a^2\Delta t^4}{4}\mathbf{I}_{3\times3} & \frac{\sigma_a^2\Delta t^3}{2}\mathbf{I}_{3\times3} \\ \frac{\sigma_a^2\Delta t^3}{2}\mathbf{I}_{3\times3} & \sigma_a^2\Delta t^2\mathbf{I}_{3\times3} \end{bmatrix}$

Experiment

Experiment Setup



The experiment took place in a seamless 60-meter environment



10,000+ data entries are collected

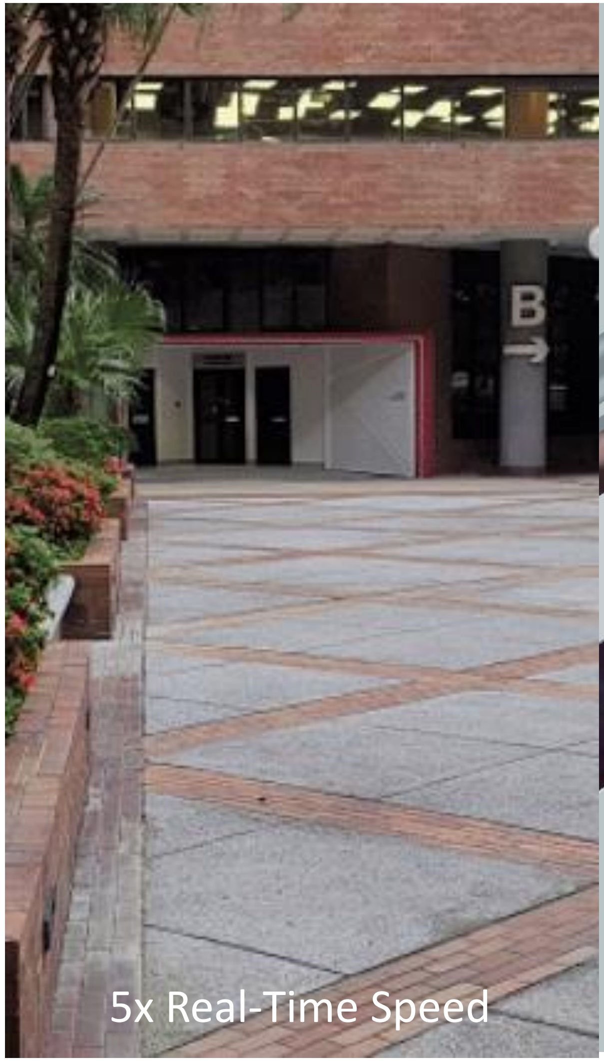
Experiment Setup

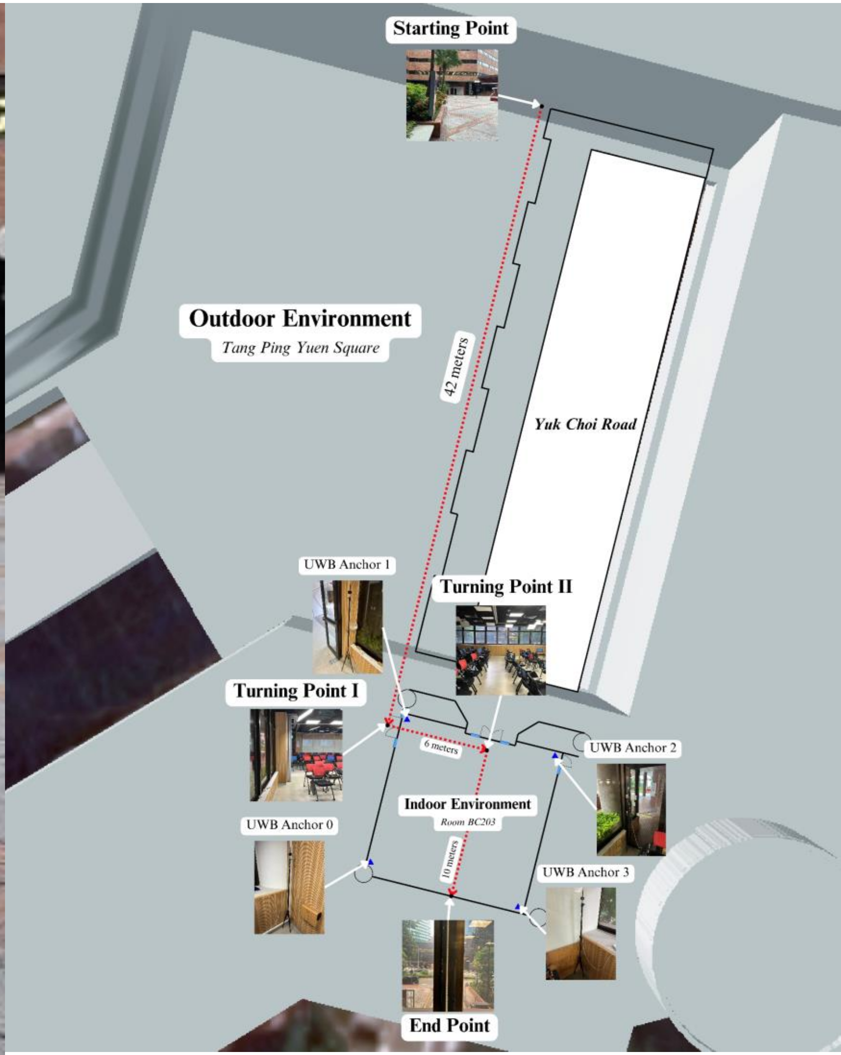
> **Streaming Sensors:**

- GNSS [11]
  - U-blox F9P
  - iPhone 14 Pro
- UWB [12]
  - Nooploop LinkTrack P-A Series
- VPS [13 – 14]
  - Samsung Galaxy Note 20 Ultra
- IMU [15]
  - iPhone 14 Pro

> **Location**

- Tang Ping Yuen Square + BC203

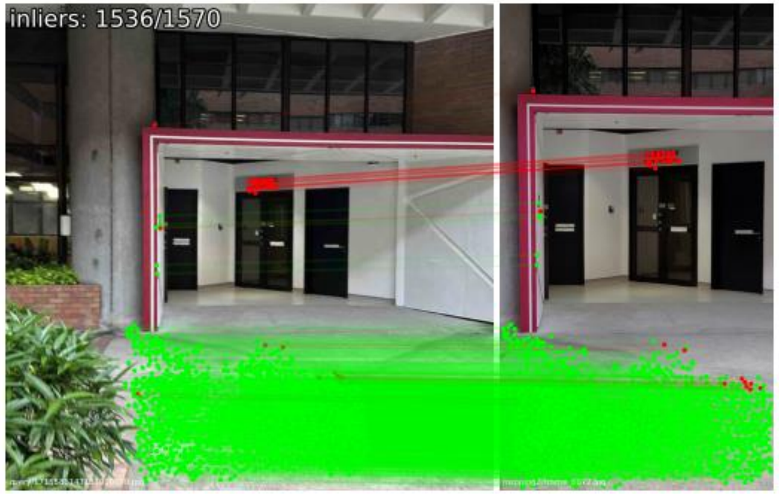


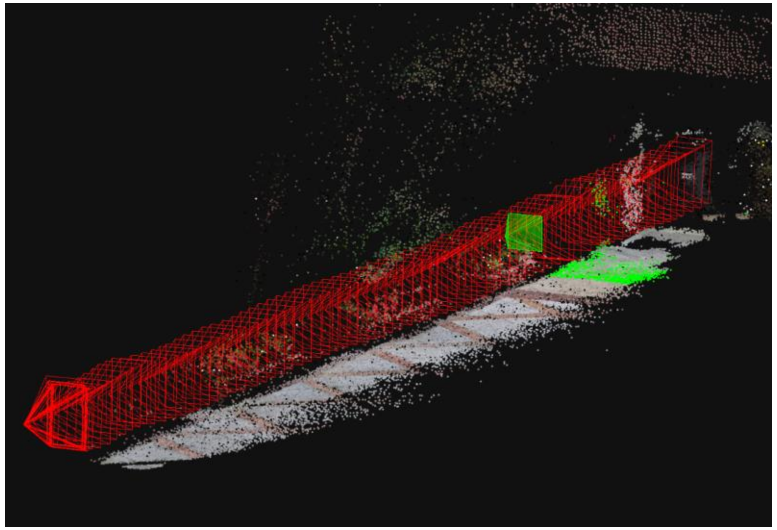


[11] “ZED-F9P module,” U-blox. https://www.u-blox.com/en/product/zed-f9p-module (accessed May 21, 2024).
[12] “UWB High-Precision Positioning: LinkTrack P-A Series,” Nooploop.https://www.nooploop.com/en/linktrack/ (accessed May 21, 2024).
[13] P. -E. Sarlin, C. Cadena, R. Siegwart and M. Dymczyk, ”FromCoarse to Fine: Robust Hierarchical Localization at Large Scale,”2019 IEEE/CVF Conference on Computer Vision and Pattern Recog-nition (CVPR), Long Beach, CA, USA, 2019, pp. 12708-12717, doi:10.1109/CVPR.2019.01300.
[14] P. -E. Sarlin, D. DeTone, T. Malisiewicz and A. Rabinovich,”SuperGlue: Learning Feature Matching With Graph Neural Net-works,” 2020 IEEE/CVF Conference on Computer Vision and PatternRecognition (CVPR), Seattle, WA, USA, 2020, pp. 4937-4946, doi:10.1109/CVPR42600.2020.00499.
[15] K. T. H. Choi, “tszheichoi / awesome-sensor-logger,” GitHub.https://github.com/tszheichoi/awesome-sensor-logger/.

Experiment Setup

Visual Positioning System*





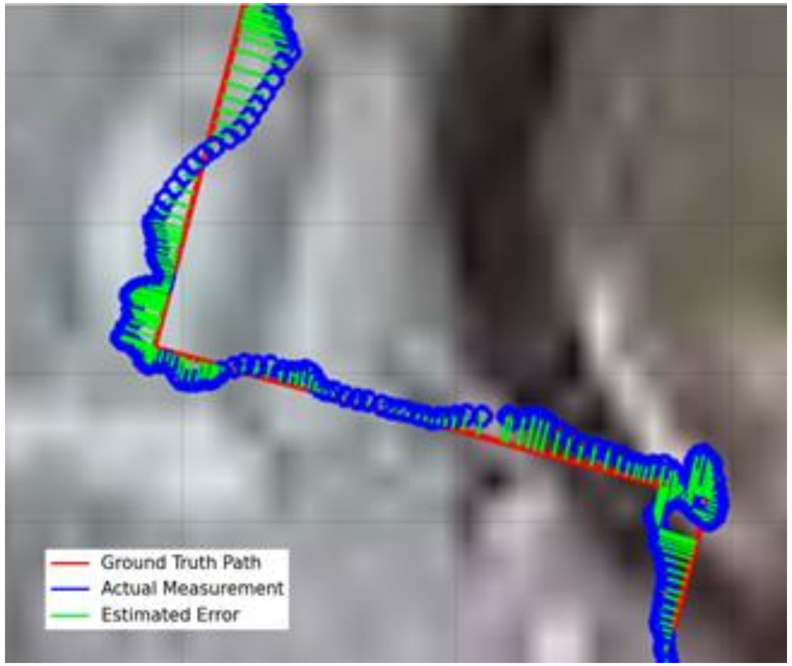
*Compromised performance in indoor environments.

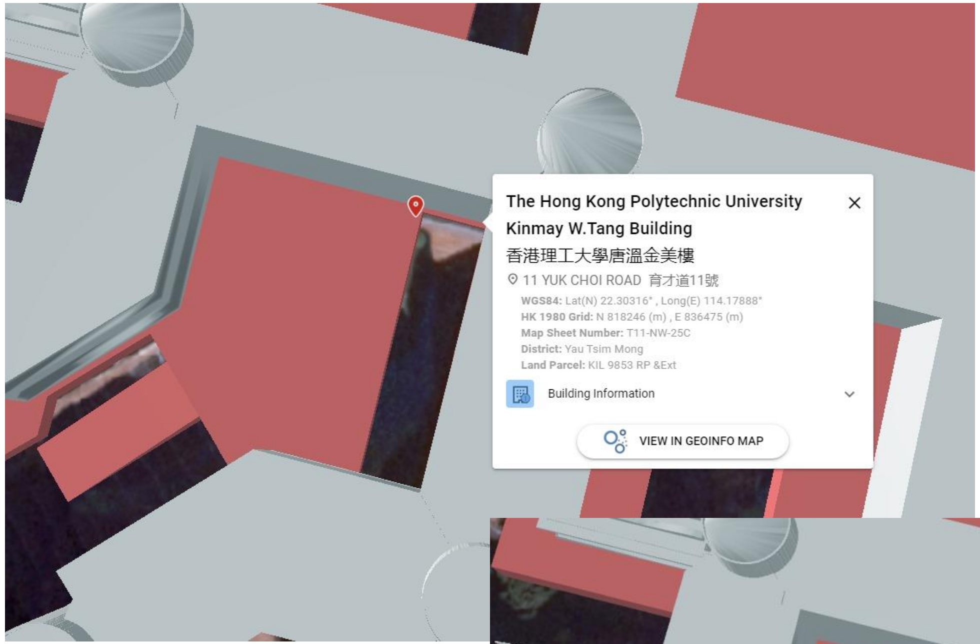
Ultra-wideband

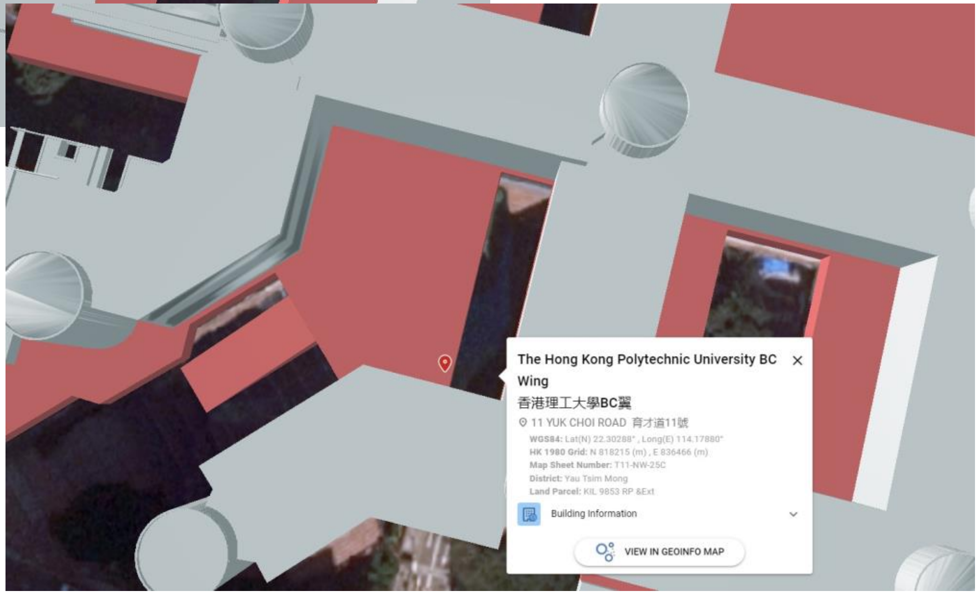
Experiment Setup

> **Ground Truth**
  - HKSAR Gov's GeoInfo Map
  - Detailed Floor Plan

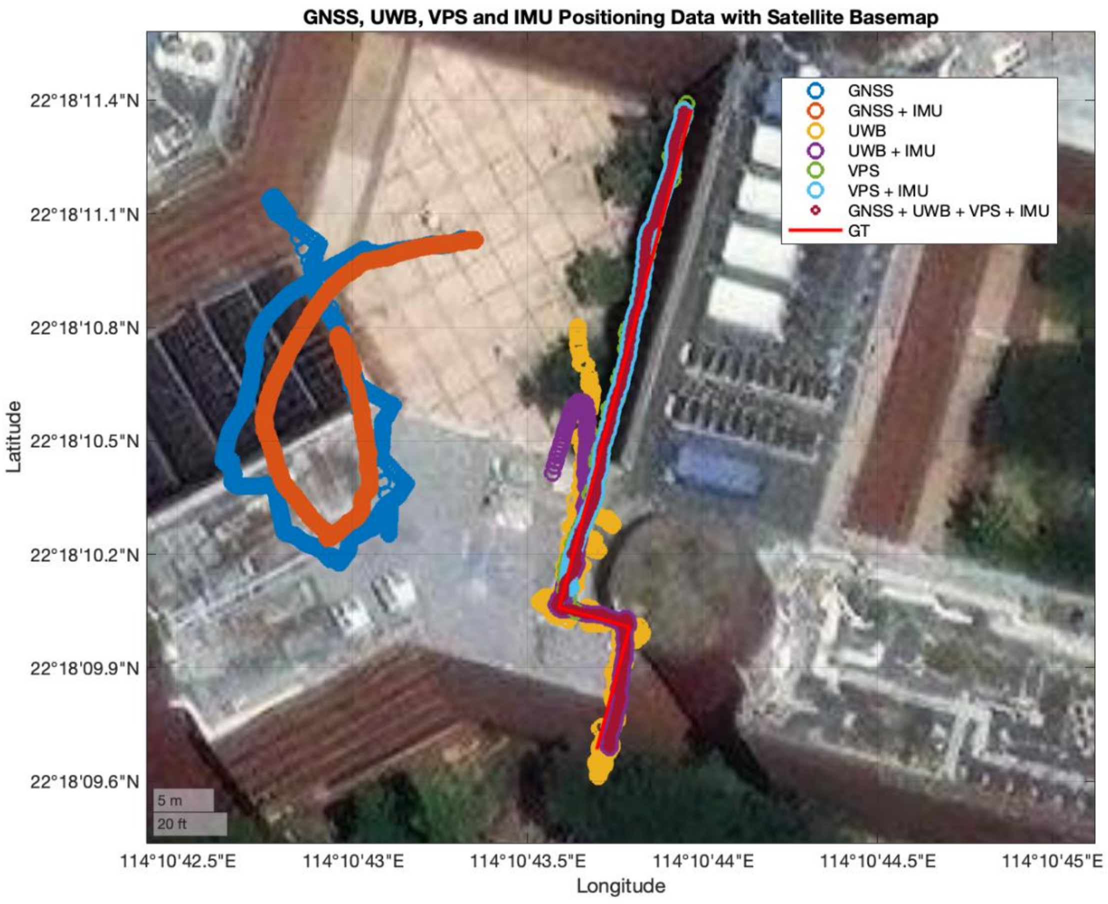
> **Absolute Trajectory Error (ATE)**
  - $E = \sqrt{(x_m - x_t)^2 + (y_m - y_t)^2}$



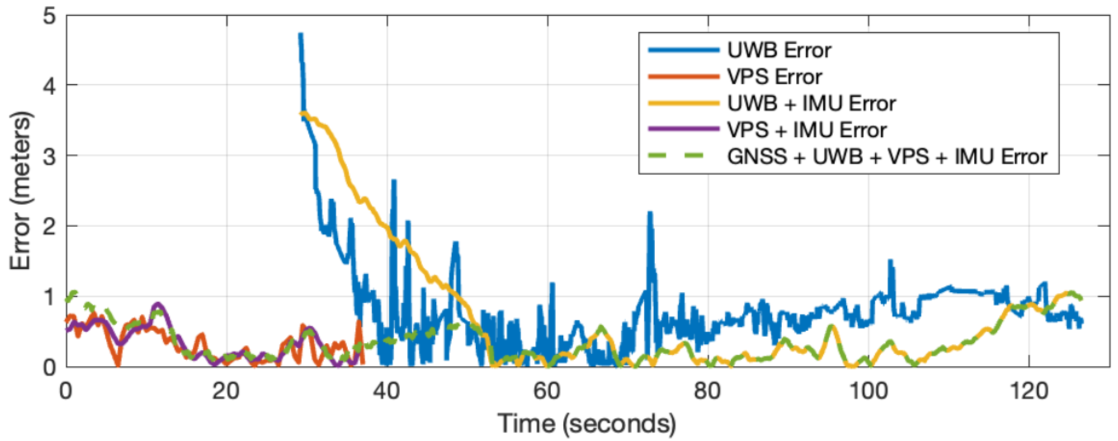




Experiment Results



Method	Mean Error (m)	Std. Dev. (m)	RMSE (m)	Median Error (m)	Max Error (m)
GNSS	25.02	5.47	25.61	25.21	33.75
GNSS + IMU	23.24	4.22	23.62	23.38	29.40
UWB	0.79	0.62	1.00	0.71	4.75
UWB + IMU	0.69	0.89	1.13	0.31	3.92
VPS	0.32	0.23	0.39	0.30	0.76
VPS + IMU	0.33	0.23	0.41	0.31	0.91
GNSS + VPS + UWB + IMU	**0.33**	**0.24**	**0.41**	**0.27**	**0.95**



Sensor data from multiple devices can be seamlessly fused under our proposed framework to achieve optimized positioning results.

Evaluation of Common Data Input Issues & Success Rate

> **Non-uniform Units**

- The framework achieved an 89.47% success rate in converting specified units to standard units
- Examples of correct and incorrect conversion:

Attribute	Input	Output	Correct Conversion?
Name	"UWB"	"UWB"	Yes
Time	1683302400000	1683302400000000000	Yes
X	180cm	1.8	Yes
Y	230cm	2.3	Yes
Z	420cm	4.2	Yes

Attributes	Input	Output	Correct Conversion?
Name	"UWB"	"UWB"	Yes
Time	1683302400000	1683302400000000000	Yes
X	180	180	**No**
Y	230	230	**No**
Z	420	420	**No**

- Cause: The current system has some limitations in unit recognition.

Evaluation of Common Data Input Issues & Success Rate

> **Missing Entries**

- The framework demonstrated an 82.35% accuracy in identifying and labeling missing entries as Null
- Example of incorrect conversion:

Attributes	Input	Output	Correct Conver-sion?
Name	"Location"	"Location"	Yes
Time	1683302400000	1683302400000000000	Yes
Latitude	0	0	Yes
Longitude	-122.4194	-122.4194	Yes
Altitude	10.0	10	Yes
Speed	(missing)	0	**No**
Speed Accuracy	0.5	0.5	Yes
Bearing Accuracy	(missing)	0	**No**
Horizontal Accuracy	1.5	1.5	Yes
Vertical Accuracy	(missing)	0	**No**
Bearing	(missing)	0	**No**

- Cause: The model often fail to recognize the absence of data correctly, mistakenly inserting default numeric values like 0 instead of Null with datasets that contain large or inconsistent missing entries.

Evaluation of Common Data Input Issues & Success Rate

> **Unstructured Data & Data Type Mismatches**

- The framework effectively addressed all issues related to these two issue types
- Example of correct conversion of data type mismatches:

Attributes	Input	Output	Correct Conver-sion?
Name	”UWB”	”UWB”	Yes
Time	1683302400000	1683302400000000000	Yes
X	”1.8”	1.8	Yes
Y	”2.3”	2.3	Yes
Z	”4.2”	4.2	Yes

Conclusion

> **Innovation**

- Successfully integrated LLMs with EKF for real-time sensor data standardization.

> **Performance**

- Reduced positioning errors to **0.33 meters** by fusing data from diverse sensors.
- Achieved **89.47% accuracy** for correcting non-uniform units.
- Achieved **82.35% accuracy** for addressing missing data.
- Converted **all Unstructured Data & Data Type Mismatches** issue types.

> **Limitations**

- High computational demands in real-time and resource-constrained environments.
- Dependency on high-quality training data.
- Privacy concerns in dynamic environments.

Future Directions

> Develop **adaptive algorithms** for real-time schema updates and environmental feedback.

> Optimize **LLM training** to reduce computational overhead and handle edge cases.

> Enhance **data security** and improve integration with both legacy and modern IoT infrastructures.

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Thank you for your attention!

Questions, Comments and Collaboration are welcome.

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