Passive Radio Frequency-based 3D Indoor Positioning System via Ensemble Learning

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Outline

Passive Radio Frequency Sensor Research

- Research leading up to this proposed system
- Utility of calculating RSSI from I/Q data

Long-term DDDAS

- Comparison with Instantaneous DDDAS
- Related Approaches

PRF-based Indoor Positioning System (PIPS) in DDDAS

- Objectives and Approach
- Evaluation of PIPS

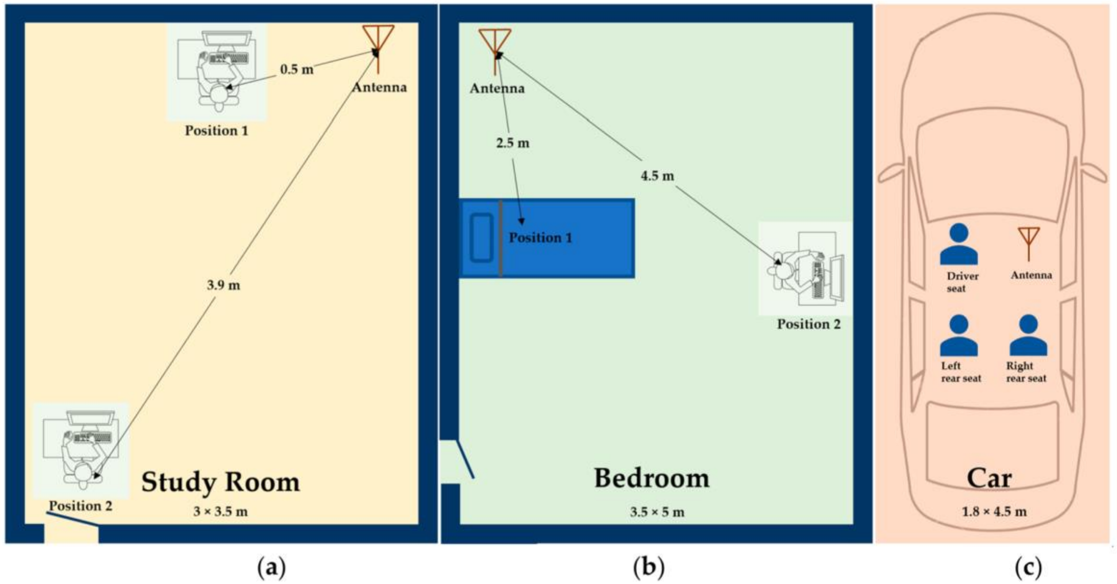
Experiment Setup and Results

- Performance of tested systems
- Comparison with related works

Future Work

- Overview of progress with the conclusion
- Any Questions from the audience

Passive Radio Frequency



Liu et al., 2020

Passive Radio Frequency Research

- Human Heterogeneous Passive RF Fusion (Vakil et al., 2022)
- Identification and Activity Recognition (Yuan et al., 2022)
- Visualization of PRF Data (Vakil et al., 2021)
- Human Indoor Positioning (Mu et al., 2021)
- Synthesis Human Signatures (Liu et al., 2021)
- Human Occupancy Detection (Liu et al., 2020)
- Sensor Fusion for Passive RF (Vakil et al., 2020)

Software Defined Radio

- Utilizing passive in-phase quadrature (I/Q) data
- No transmitters, ID tags, only the received RSSI data is necessary.
- Identification and tracking of human and vehicle targets

Yuan et al., 2022

DDDAS

	Theory	Simulation	Data	Application
Measurement aware: Assimilation, uncertainty quantification				
Tractable non-Gaussian representations in dynamic data driven coherent fluid mapping	Reduced order modeling with ensemble filtering	Atmospheric plumes	UAV tracking plume detection	Unmanned aerial systems
Dynamic data-driven adaptive observations in data assimilation for multi-scale systems	Information-theoretic particle filtering	Lorenz 1963 weather data	Weather augmented nonlinear flight	Sensor selection in dynamic flight
Dynamic data-driven uncertainty quantification via generalized polynomial Chaos	Polynomial Chaos and GMM uncertainty quantification	Satellite tracking	Ionosphere-thermosphere models	Orbital awareness
Signals aware: Processes monitoring				
Towards learning Spatio-temporal data stream relationships for failure detection in avionics	Declarative data estimation and learning	Airplane sensor data	Aircraft weight, airflow measurements	Avionics sensor failure
Markov modeling of time series data via spectral analysis	Reduced-order Markov modeling w maximum entropy partitioning	Time-series combustion modeling	Gas, pressure, temperature	Combustion engine diagnostics
Dynamic space-time model for syndromic surveillance w PF and and Dirichlet Proces	Particle filters with Dirichlet processes	Biohealth outbreak	Indiana public health emergency surveillance sys	Health protection
Structures aware: Health modeling				
A computational Steeriig framework for large-scale composite structures	Variational multiscale fluid structure interaction (FSI)	Isogeometirc Analysis (IGA) approach lie finite-element modeling	Structures composite element relation network with ultrasonic sensor	Compsitie wing control for aerodynamic flight
Intelligent self-healing composite structure using predictive self-healing	Modified beam theory	Structures crack and delanation healing	Double-cantilever beam fracture and healing test	Structural self-healing

Blasch et al., 2018

DDDAS

- Exploitation of efficient data collection, full scale modeling, management and data mining from available sources.
- Weather forecasting (strongly dynamic data)
- Wildfire monitoring
- Biosensing

Instantaneous DDDAS vs Long-Term DDDAS

Instantaneous

- Weather forecasting
- Volcanic ash, atmospheric contaminants
- Wildfires detection
- Autonomous driving
- Fly-by-feel aerospace vehicle
- Biohealth outbreak

Long-Term DDDAS

- CO_2 concentration
- Sea level
- Earth moon distance
- Identification of biomarkers in DNA methylation
- Multimedia content analysis
- Image processing
- ***Our proposed positioning system***

Long-Term DDAS Example

DDDAS Framework Model

- Objective: Go to McDonald's to get some sweets or treats like ice cream, preferably Oreo McFlurry, but others are acceptable.
- How does the framework suggest we move forward to achieve the objective?

DDDAS Framework Model

- Initial Conditions: Capable of traveling to the nearest McDonald's; Objective: Oreo McFlurry or an acceptable substitute.
- Boundary Conditions: At least some sweets; normal/acceptable prices, efficient time expenditure.
- Inputs: Drive to the nearest McDonald's and order an Oreo McFlurry.
- Parameters: Driving time; price; flavor.
- States: Unknown

Long-Term DDDAS Example

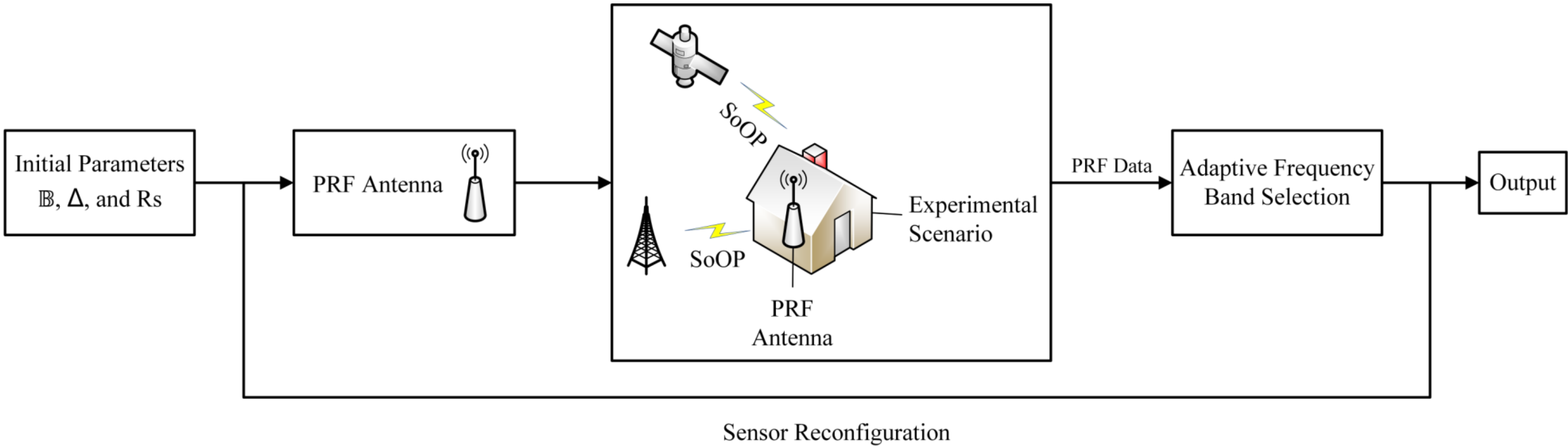
DDDAS Framework Model

- The DDDAS framework aims to make **optimal decision** in the task of buying Oreo McFlurry.
- Ensuring that the purchasing process is within acceptable parameters to meet the objective.

DDDAS Framework Model

- Are other products acceptable without Oreo McFlurry? Or should I go to another McDonald's? Maybe, it depends on how far the other McDonald's is (dynamic input). If accepted, then we drive to another McDonald's (reconfiguration).
- Is it acceptable to wait for it? Considering the time to wait (dynamic input). To accept or not to accept (reconfiguration).
- What if I buy all McDonald's sweets or treats? Do not accept, it is expensive and unnecessary waste (boundary).

PRF-based three-dimensional (3D) Indoor Positioning System (PIPS) in DDDAS



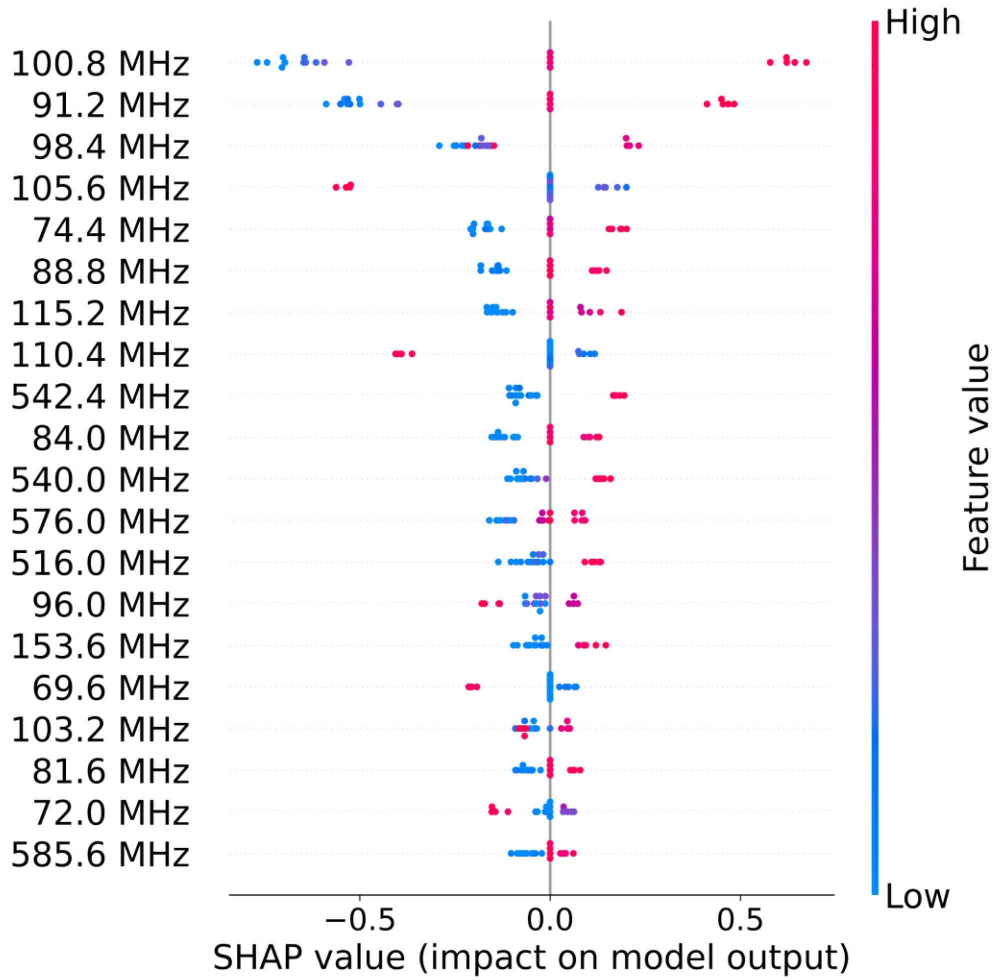
PIPS

- Indoor positioning under the framework of DDDAS.
- Dynamically conduct sensor reconfiguration based on the data collected in the scenario.

Frequency Band DDDAS

- Primarily handled with frequency band where sampling is performed, a major factor that affects accuracy, sampling speed, and cost.
- Sensitive frequency bands selected are dynamic because the most sensitive frequency bands change according to scenario, including factors such as house structure, time, house location, etc

Frequency Ranking Via SHAP



Yuan et al., 2022

Impact of Frequency Bands

- Frequency band ∈ {91.2, 93.6, 96.0, 98.4, 100.8}
- MHz; Step size = 2.4 MHz
- Sampling rate = 2.4 MHz
- Having already processed this information allows for the continuity of the frequency to be maintained, without loss of generality with the selected frequency bands.
- Collection time for each data sample is reduced to 1 second.

PIPS in DDAS Framework

TEN MOST IMPACT FREQUENCIES ARE FOUND FROM SHAP, PCA, AND STATISTICAL VARIANCE.

Frequency Ranking	$\mathbb{B}_{\mathrm{SHAP}}$ (MHz)	$\mathbb{B}_{\mathrm{PCA}}$ (MHz)	$\mathbb{B}_{\mathbb{V}}$ (MHz)	PCA Explained Variance (%)
1st	100.8	100.8	100.8	67.46
2nd	91.2	105.6	98.4	12.64
3rd	98.4	180.0	91.2	1.94
4th	105.6	103.2	103.2	1.94
5th	74.4	31.2	96.0	1.35
6th	88.8	636.0	576.0	1.13
7th	115.2	756.0	88.8	0.97
8th	110.4	31.2	105.6	0.74
9th	542.4	24.0	74.4	0.62
10th	84.0	756.0	84.0	0.51

Yuan et al., 2022

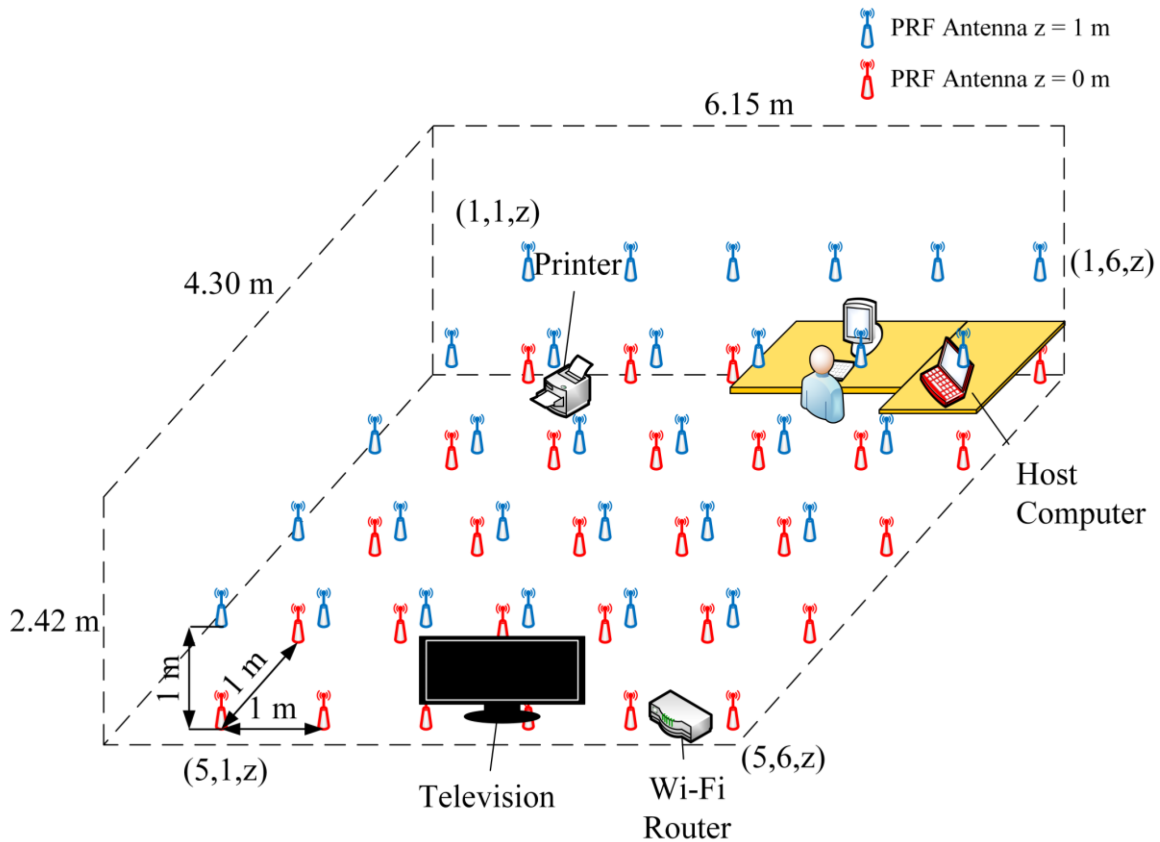
Selection of Frequency Bands

- Frequency band ∈ {91.2, 93.6, 96.0, 98.4, 100.8} MHz; Step size = 2.4 MHz; Sampling rate = 2.4 MHz
- Optimal solution that relies on SHAP by implementing pre-sampling in the target scenario then analyzing the collected samples to find the optimal Frequency Band, Step Size, and Sampling Rate.

Results

- **98% sampling time reduced!** 5 frequencies (under DDDAS) vs 400 frequencies (full band). Without DDDAS Framework to find optimal frequency, data collection over the full frequency band will require much longer period of data collection.
- **Sensor redeployment time is 300 s/m^3.** This reduction allows for greater scaling with new environments for the system, 100 sensors could reduce redeployment in a warehouse the size of a football field down to 6 hours.
- **High accuracy and reliability.**

Experiment Setup



Living Room Conditions

- Red (0 M) and Blue (1 M) represented with respect to distance from the ground at 60 locations in the selected frequency bands in 3D Indoors Scenario.
- 60x gridded positions total as coordinates setup in 3D space for data collection.
- Scenario room has a length of 6.15m, width of 4.3m, and a height of 2.42m for the preliminary verification of the PRF positioning.

Processing

- Usage of impactful frequency bands to obtain signals of opportunity (SoOP).
- Generalized using Scikit-Learn and SHAP toolkit with TensorFlow Framework.
- PCA (10 components with highest significant variance).
- Prebuilt linear SVM classifier to classify at different positions.

Experiment Setup

Table 1. Single regressors to implement positioning tasks and serve as baselines for PIPS.

Regression	RMSE (m)	R^2	95% CE (m)	Time (s)
SVR	1.229	0.777	2.214	1.026
KNR	0.268	0.986	0.412	0.002
GPR	0.612	0.967	1.248	1.508
DTR	0.603	0.930	1.111	0.016
MLP	1.506	0.562	2.534	2.104

Evaluation Criteria

- Root Mean Square Error (RMSE)
- Coefficient of Determination R^2
- 95 % Confidence Error (CE)
- Fitting Time

Comparison with Baseline

- RMSE
- 95 % CE

Experiment Results

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Table 4. Performance of ensemble learning models under the stacking strategy.

Ensemble Strategy	Final Estimator	RMSE (m)	R^2	95% CE (m)	Time (s)
Stacking	SVR	0.271	0.988	0.463	97.281
	KNR	0.259	0.990	0.446	92.678
	GPR	2.115	0.273	3.924	97.241
	DTR	0.327	0.984	0.086	93.218
	MLP	0.263	0.990	0.459	95.106
	ABR	0.334	0.984	0.258	97.657
	GBR	0.258	0.990	0.317	94.338
	HGBR	0.254	0.990	0.371	95.478
	RFR	0.255	0.990	0.431	93.835
	ETR	0.259	0.990	0.334	93.808

Comparison with Baseline (GBR)

- RMSE
- 95 % CE

Discussion

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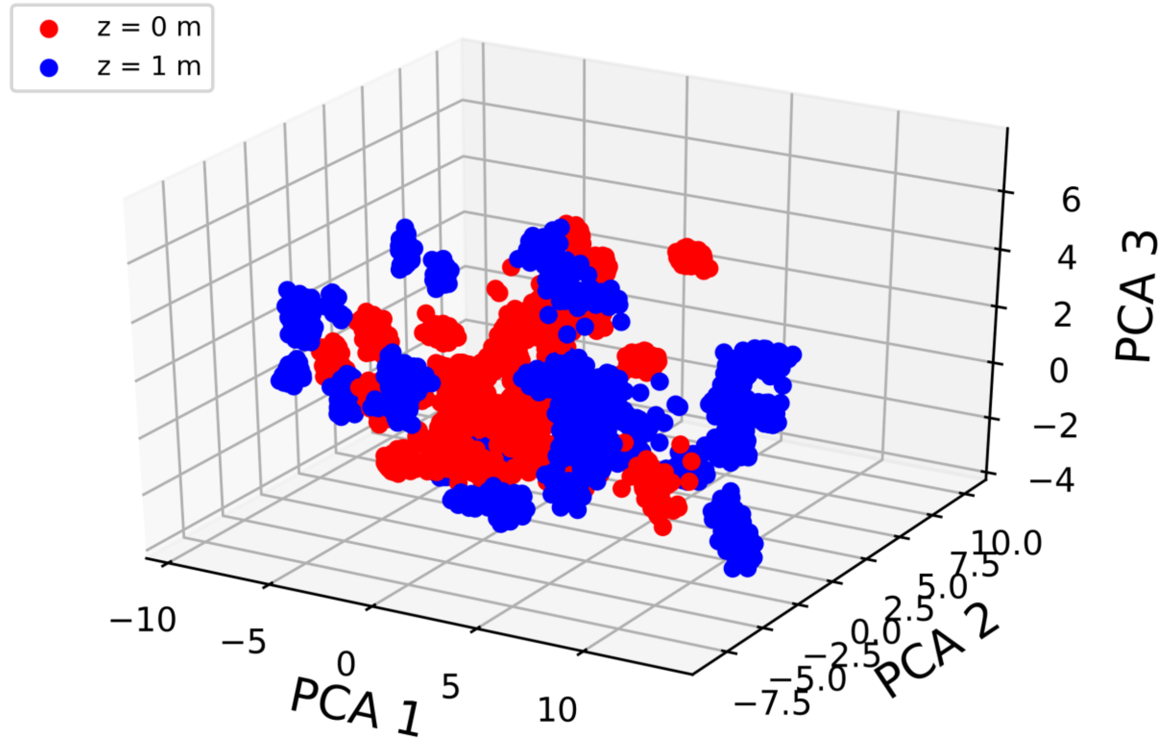
Comparison with Baseline

- RMSE
- 95 % CE

Future Work and Questions



Conclusion

- Proposed PIPS 3D system does not require any transmitters, using PRF data (RSS calculated from I/q Data) to determine positioning.
- Traditional positioning that uses RF is active and requires number of transmitters and has reduced accuracy at greater sampling distances.
- Detroit Metropolitan area is located from ranges 88.1 to 107.9FM which coincides with frequency bands impact.
- Current research is limited with frequency selection technology, choosing the 5 most sensitive frequency bands from 400 available frequencies with the full frequency band under the DDDAS framework.

Future Research Direction Towards Dimensionality Reduction

- With dimensionality reductions, although similar in terms of results, have effects, such as with the PCA reducing the complexity of the data it can't reduce the sampling time needed.
- Benefits of dimensionality reduction lie in privacy considerations for users and visualization applications. In IoT applications, performing PCA locally can reduce dimensionality of data so that user privacy can be protected after uploading to the cloud, into two- or three-dimensional format as seen above.