A Survey on Fusion-Based Indoor Positioning

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DISCIPLINE: MO611 - TELEPROCESSAMENTO E REDES - SC

Agenda

Motivation

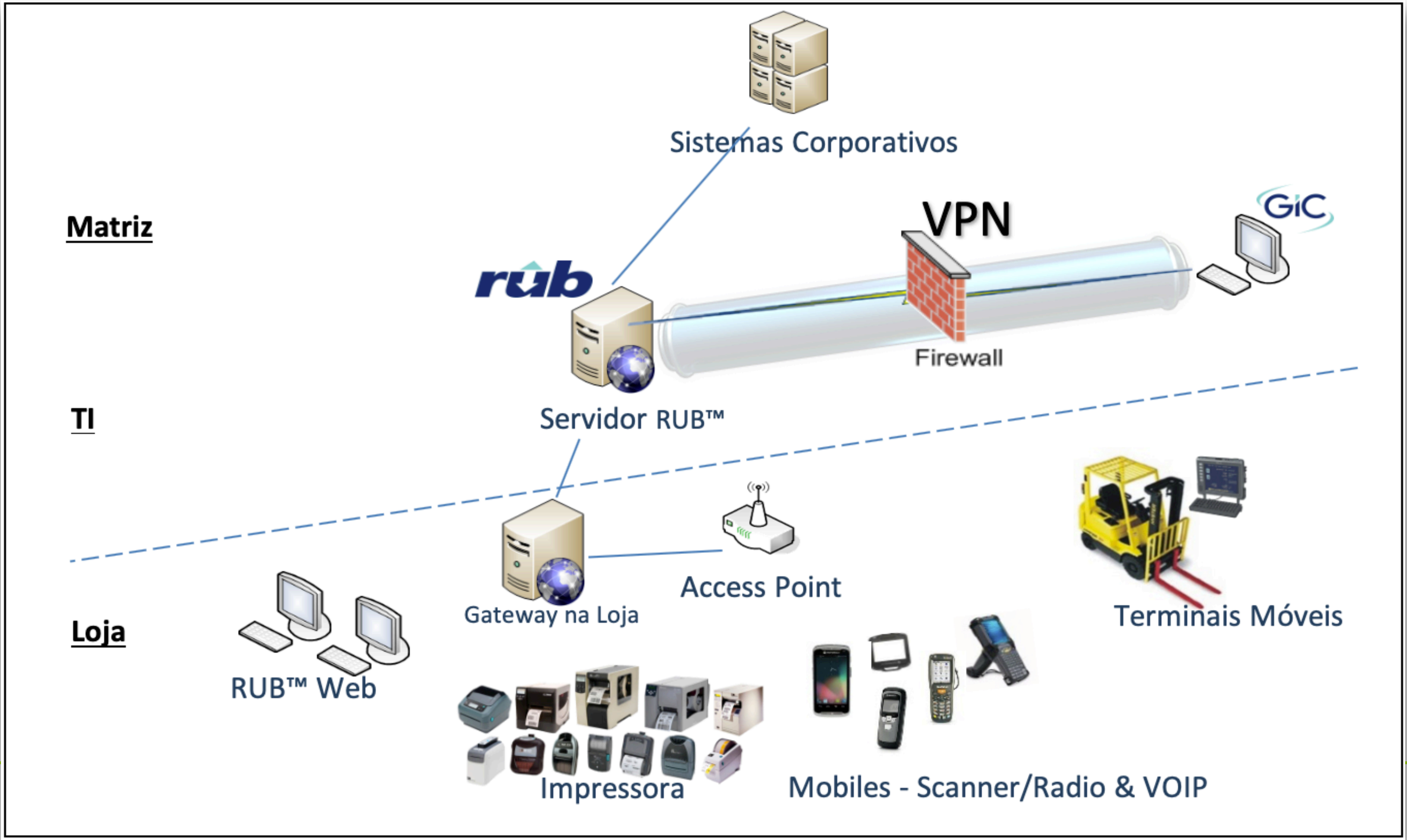
Motivation

Food Wholesale and Retail Industry

- Software manages:
  - Store floor automation
  - Allocation of employees
  - Flow of information
  - Reduction of levels of exposure rupture
  - Correct pricing of items
- Main goals:
  - Maximise sales
  - Improve shopping experience to the end customers

https://images.app.goo.gl/pRaPiZjoQNrkdsjd9

Motivation



https://www.gicbrasil.com/

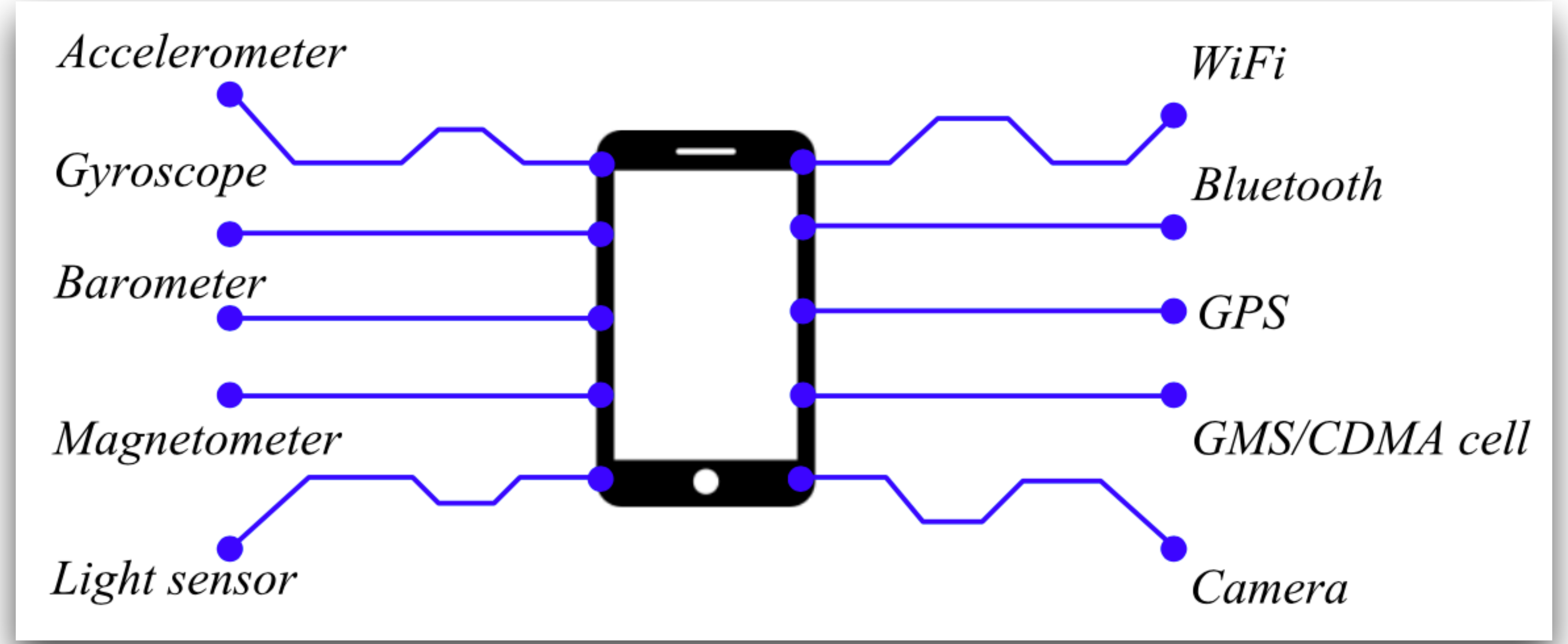
Introduction

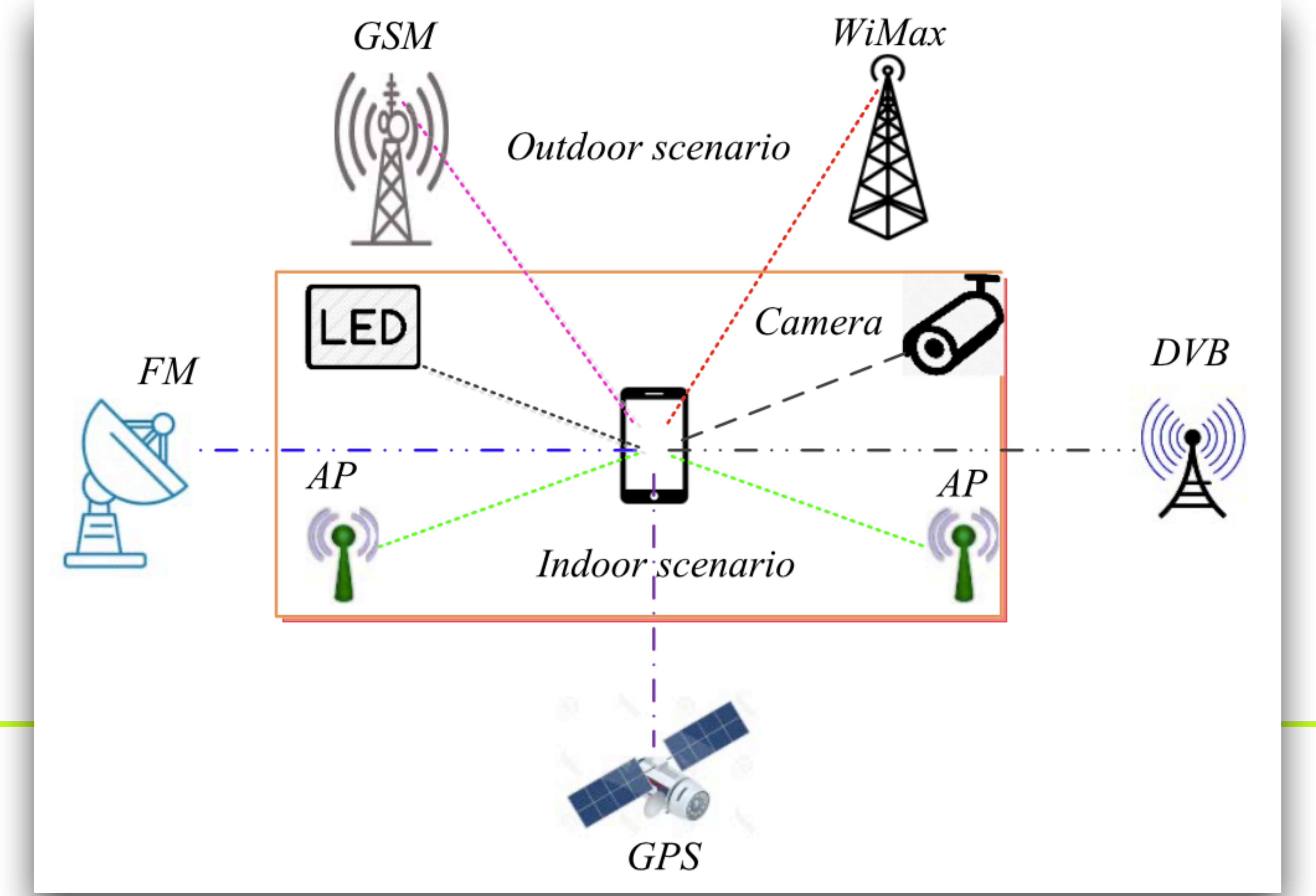
Indoor Positioning based Services (IPS)

- Commercial and military demands have spurred the development of indoor positioning techniques and systems:
  - Emergency personal navigation
  - Context awareness
  - Network management and security
  - Health monitoring
  - Personal information delivery
  - Smart City

User Equipments (UEs)

- Sensors can measure different information to yield a better location estimate
- Positioning or tracking based on a single measurement will aggravate the tracking/ positioning performance
- Fusion of multiple measurements from different sensors is becoming indispensable in order to improve the positioning performance
- Networks can offer different levels of location estimates from their own perspectives



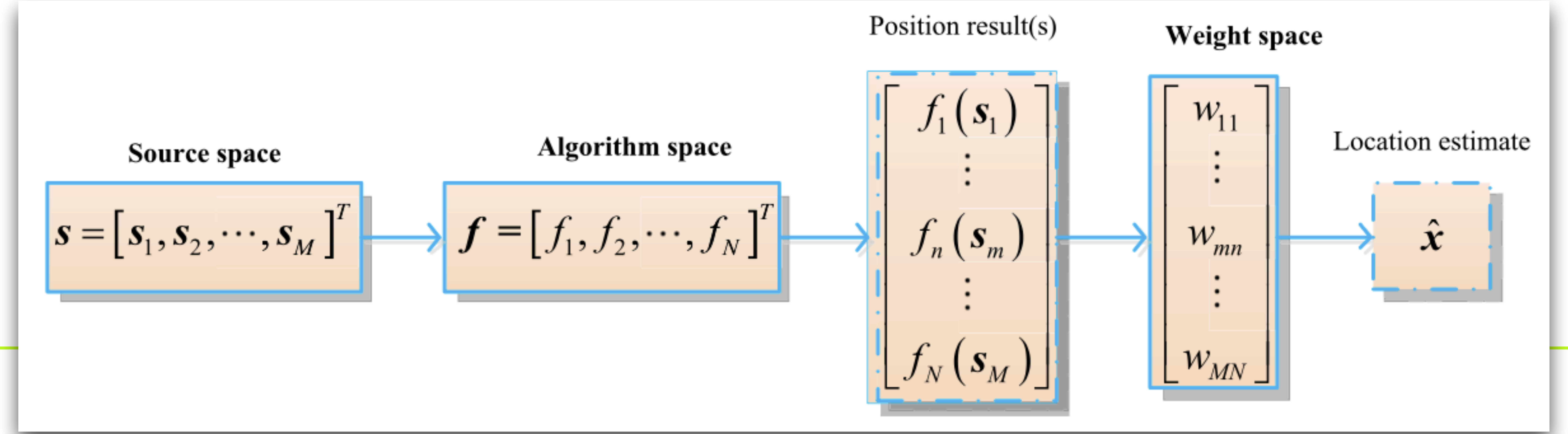


User Equipments (UEs) -
Inherent drawbacks in positioning accuracy

- Complex due to the metamorphic nature of indoor environments
- Different measurements
  - Time-Of-Arrival (TOA)
  - Time-Difference-Of-Arrival (TDOA)
  - Angle-of-Arrival (AOA)
  - Received Signal Strength (RSS)

Fusion-Based Indoor Positioning (FBIP)

- Existing FBIP system can be divided into:
  - Sources: information to be fused
  - Algorithms: obtain the positioning results
  - Weights: amalgamate all the positioning results to yield a better localisation estimate



FBIP: Source Measurements - Single vs. Multiple Networks

- Single Network
  - ✓ a.k.a. the fusion problem in the stand-alone network
  - ✓ Improves the robustness and stability of the positioning system
  - ✓ Cost of this kind of system such as a WiFi-based positioning system is low
  - ◉ Performance fluctuates due to the nature of WiFi signals
- Multiple Network
  - ✓ Enhanced accuracy and robustness
  - ◉ Relative higher cost

FBIP: Algorithms are the key

- Algorithm maps the measurement to the coordinate of the UE
- Conventional methods
  - Maximum Likelihood (ML)
  - Least Squares (LS)
  - Maximum A Posterior (MAP)
  - Minimum Mean Squares Estimate (MMSE)
- Popular machine learning methods
  - Neural networks
  - Support vector machine
  - Random forests

FBIP: Weights Assignment

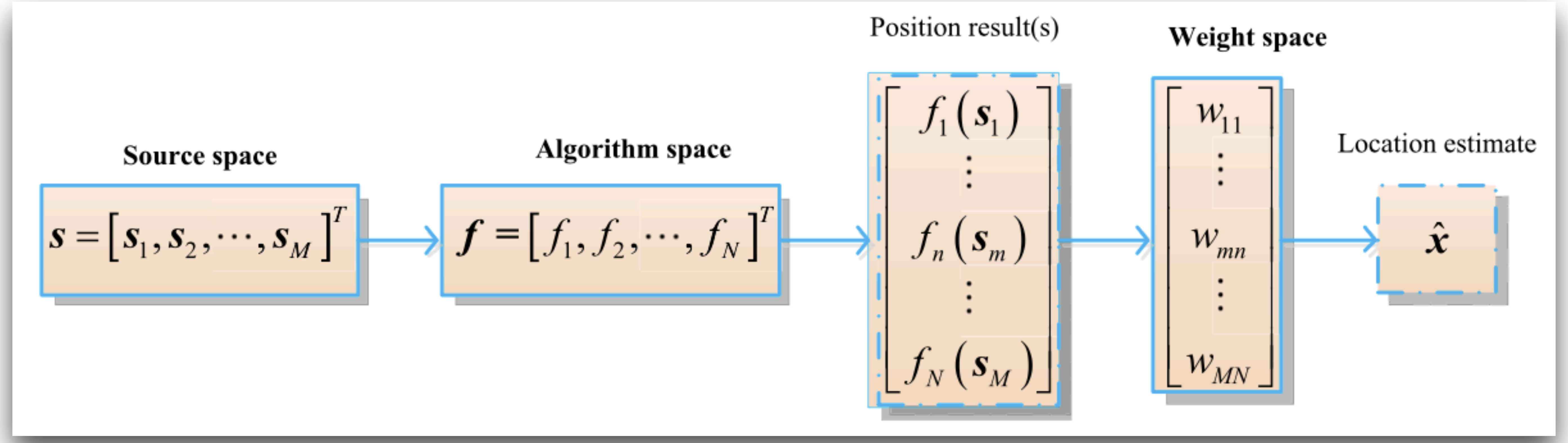
- Weights are assigned
  - Combine all the outputs of the algorithms to yield a more accurate positioning result
  - Obtained from the offline training with a supervised learning framework
  - Acquired by unsupervised learning in the online phase

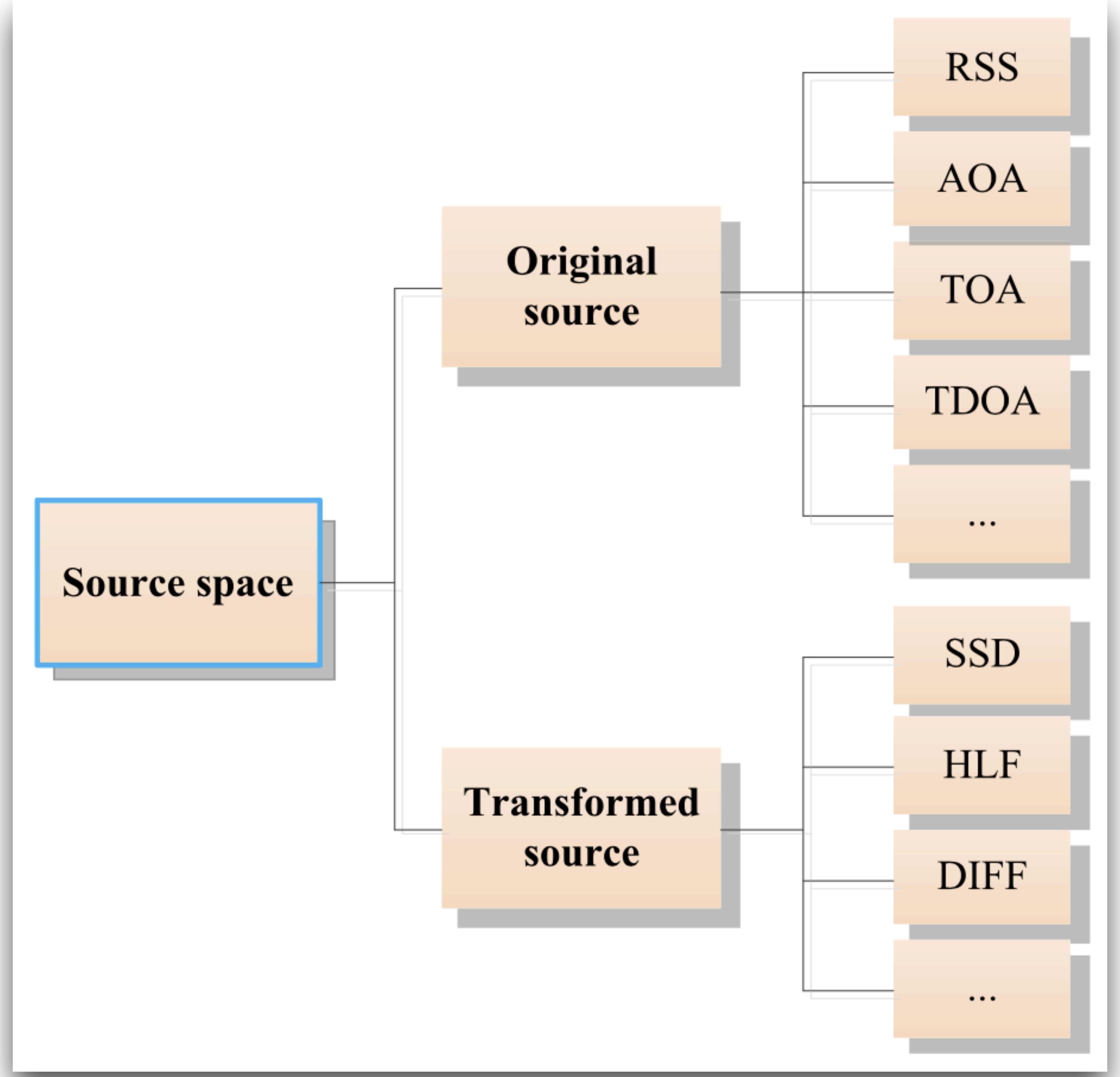
THE COMPARISON OF RELATED SURVEYS

References	Survey contents	Survey focus	Fusion techniques involved	Published year
[74]	Fundamental limits of localization, basic positioning system. Cooperative localization and hybrid data fusion. Learning algorithms for localization. Related applications.	Different techniques and methodologies in indoor localization.	Conventional techniques based on HDF. Fusion of maps and fingerprints. Fusion of inertial and camera information. Fusion of other information.	2016
[75]	Positioning metrics. Parametric and nonparametric to deal with spatial and temporal variation. Methods to address device heterogeneity. Fusion approaches.	Problems in wireless-based indoor positioning. State-of-the-art solution.	Fusing approaches that combine positioning data.	2016
[76]	Advances in localization algorithms. Deployment of WiFi fingerprint-based systems.	Advances in WiFi fingerprint-based indoor positioning.	Collaborative localization. Motion-assisted localization.	2016
[77]	Accuracy and error sources of localization approaches. Schemes for location estimation enhancement. Mathematical foundation of location estimation. Hybrid location estimation.	Improvement schemes for indoor location estimation.	Hybrid location estimation. Fusing multiple measurements.	2015
[78]	Problems of indoor wireless tracking of mobile nodes. Mapping problem. Statistical-based methods for resolving indoor tracking. Measurements and technologies are used for tracking of mobile nodes.	Indoor wireless tracking of mobile users from a signal processing perspective	The level of integration in fusion-based methods: Loose Integration. Tight Integration.	2015
[79]	Position estimation techniques. Data fusion techniques. Data fusion Architecture. Position performance. Future directions.	Data fusion architecture for TOA & TDOA.	First level data fusion: position estimator. Second level data fusion: state vector fusion. Final level data fusion: choice of best position estimate.	2001

A Unified Fusion Framework

A Unified Fusion Framework





Source Space

Source Space

THE DISTINCTION OF HOMOGENEOUS, HETEROGENEOUS, AND HYBRID POSITIONING SYSTEMS

	Network	**Measurement Technology**
Homogeneous positioning system	Stand-alone network	Single measurement technology
		Multiple measurement technologies
Heterogeneous positioning system	Multiple networks	Single measurement technology
Hybrid positioning system	Multiple networks	Multiple measurement technologies

Source Space: Measurement Technologies Used for Indoor Positioning

- **1) Received Signal Strength (RSS)**
  - Measurements extracted from different kinds of networks such as WLAN, GSM, GPS, and Bluetooth
  - Used for the model-based and fingerprint-based approaches
  - Model-based approaches calculate the distance d based on the log-normal path loss model, in which:

$$P(d) = P(d_0) + 10\gamma \lg\left(\frac{d}{d_0}\right) + n_\sigma$$

c is the path loss measured in dB at distance d

γ is the path loss factor

P(d₀) denotes the average path loss at d_0

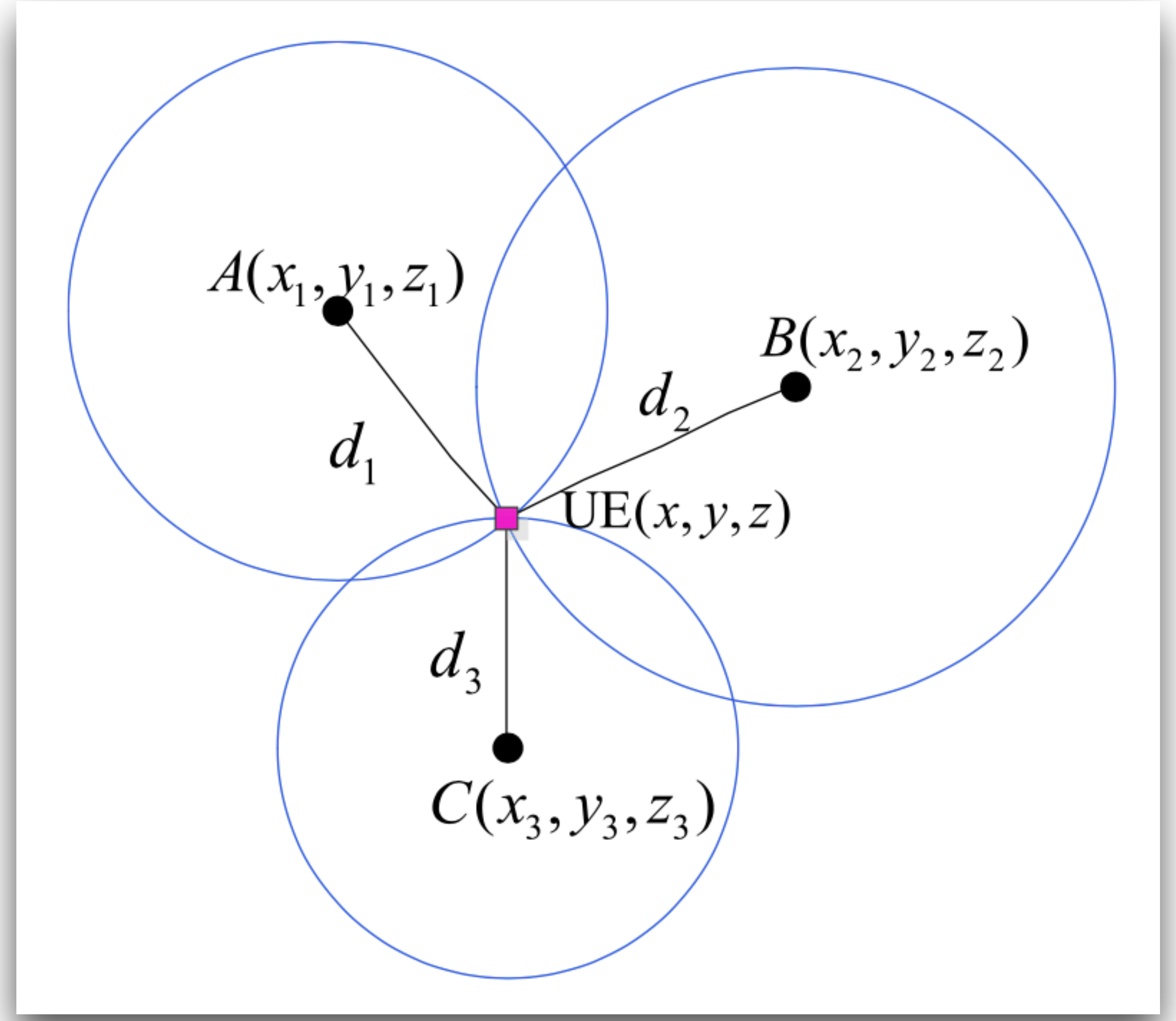
n_σ is a zero-mean normal random variable reflecting the attenuation in decibel caused by shadowing

Source Space: Measurement Technologies Used for Indoor Positioning

- **2) Channel State Information (CSI)**
  - Provides subcarrier-level channel measurements for indoor positioning
  - Obtained from some commodity WiFi NICs (Intel WiFi link (IWL) 5300 NIC)
  - Considerable impairments of signal when propagating in indoor environment due to shadowing, multipath propagation, and distortion
  - Uses two distinct methods: parametric and nonparametric methods
    - PhasePhi is a typical <u>nonparametric</u> method using the transformed phase information of CSI to construct the offline fingerprints for accurate WiFi positioning
    - The <u>parametric</u> methods calculate the distances or angles between the transmitters and receivers using the phase information extracted from CSI

Source Space: Measurement Technologies Used for Indoor Positioning

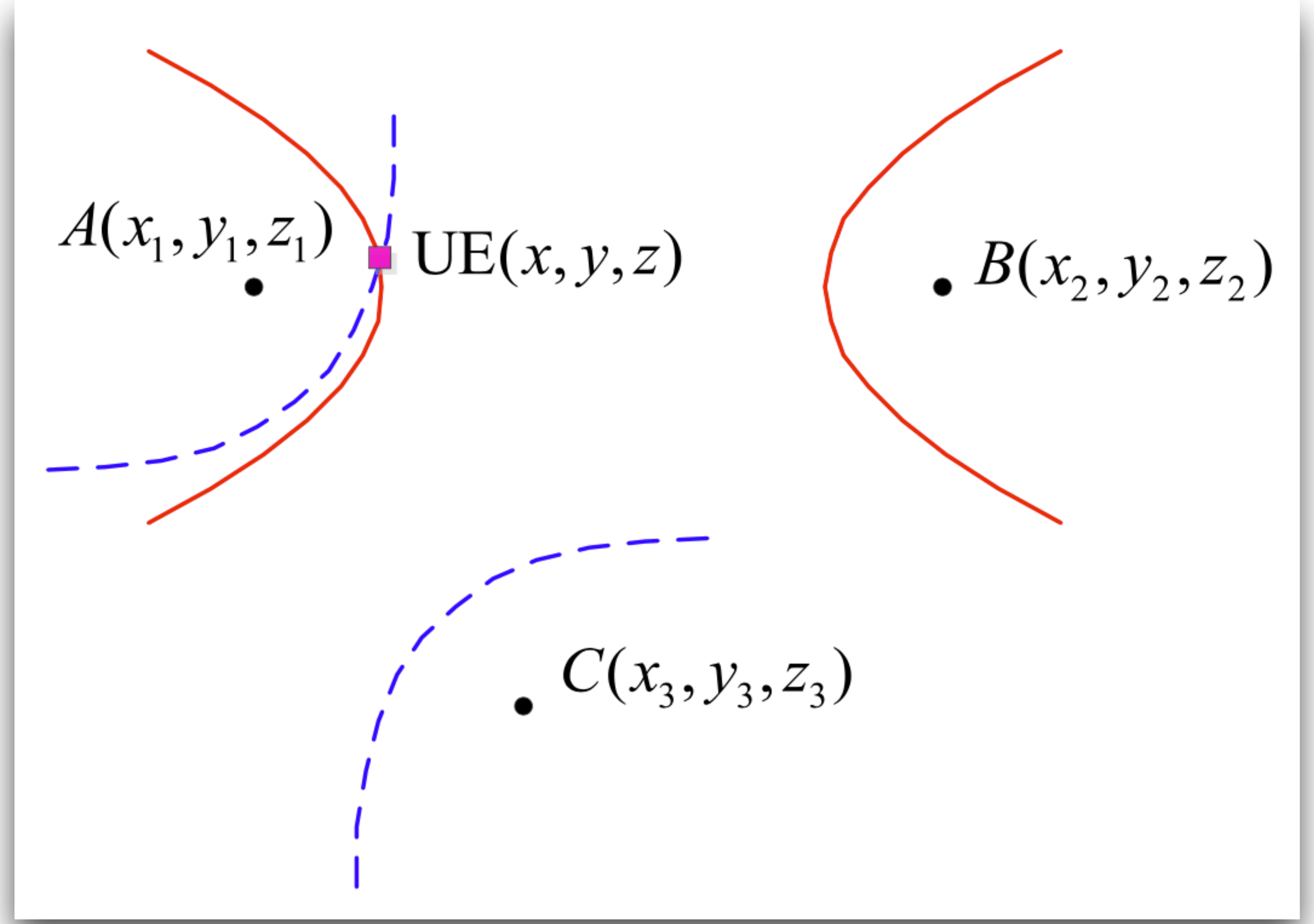
- **3) Time Of Arrival (TOA)**
  - Absolute travel time of a signal from a reference node to a UE
  - Requires stricter clock synchronisation
  - Lower energy cost
  - More suitable for real-time positioning



Source Space: Measurement Technologies Used for Indoor Positioning

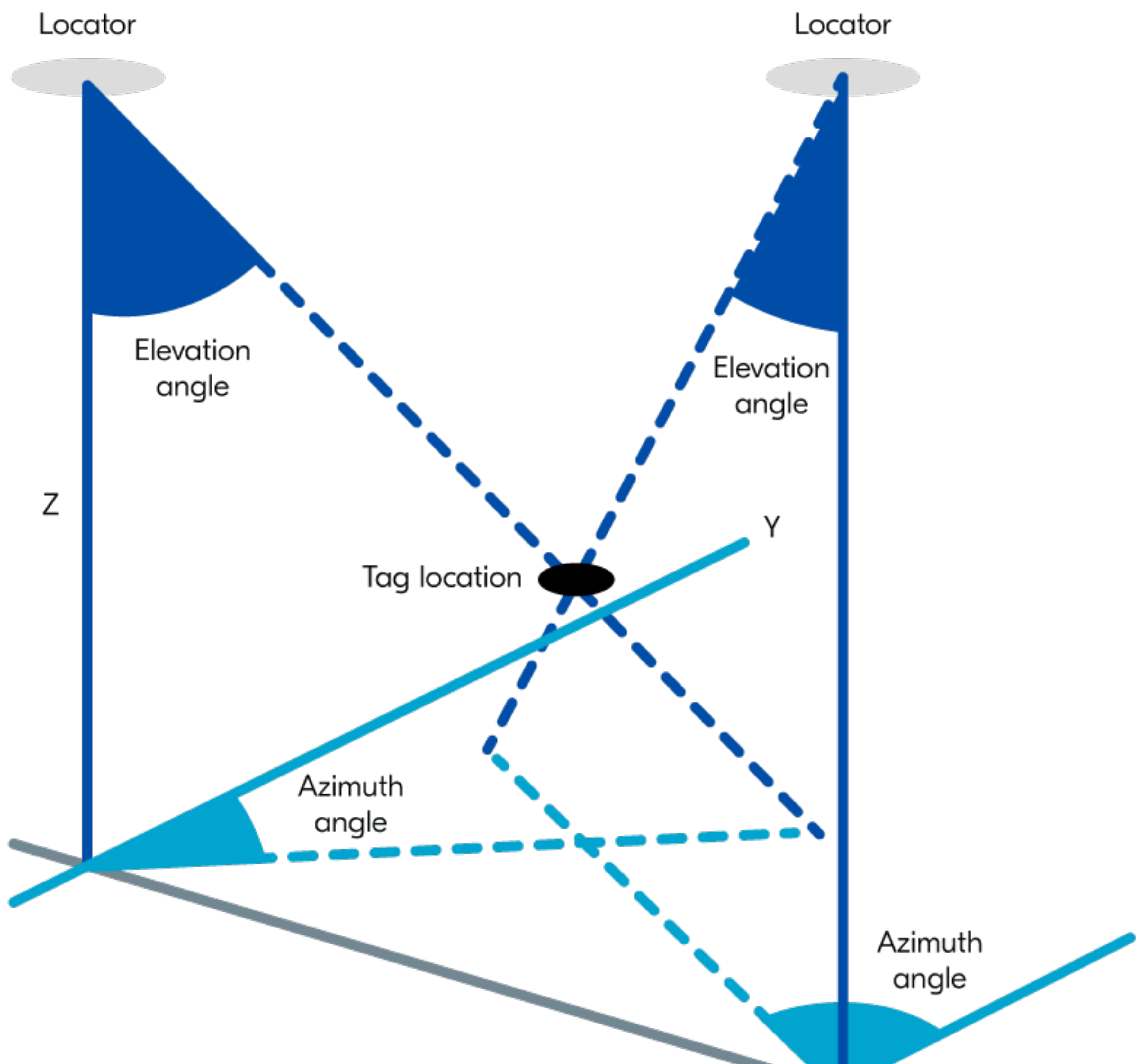
- **4) Time Difference Of Arrival (TDOA)**
  - Location of the UE can be obtained by the intersection of two hyperbolic curves
  - Distance difference for the reference nodes A and B is defined as

$$d_{1,2} = d_1 - d_2$$



Source Space: Measurement Technologies Used for Indoor Positioning

- **5) Angle-Of-Arrival (AOA)**
  - Needs the implementation of antenna arrays
  - Only two base nodes are sufficient to maintain full localization of a UE
  - Higher flexibility to AOA estimation techniques as compared to TOA or RSS estimation methods
  - Due to obstacle and multipath propagation of signals, the conventional outdoor AOA-based localization methods degenerate seriously in Complex Electromagnetic Environments (CEEs)

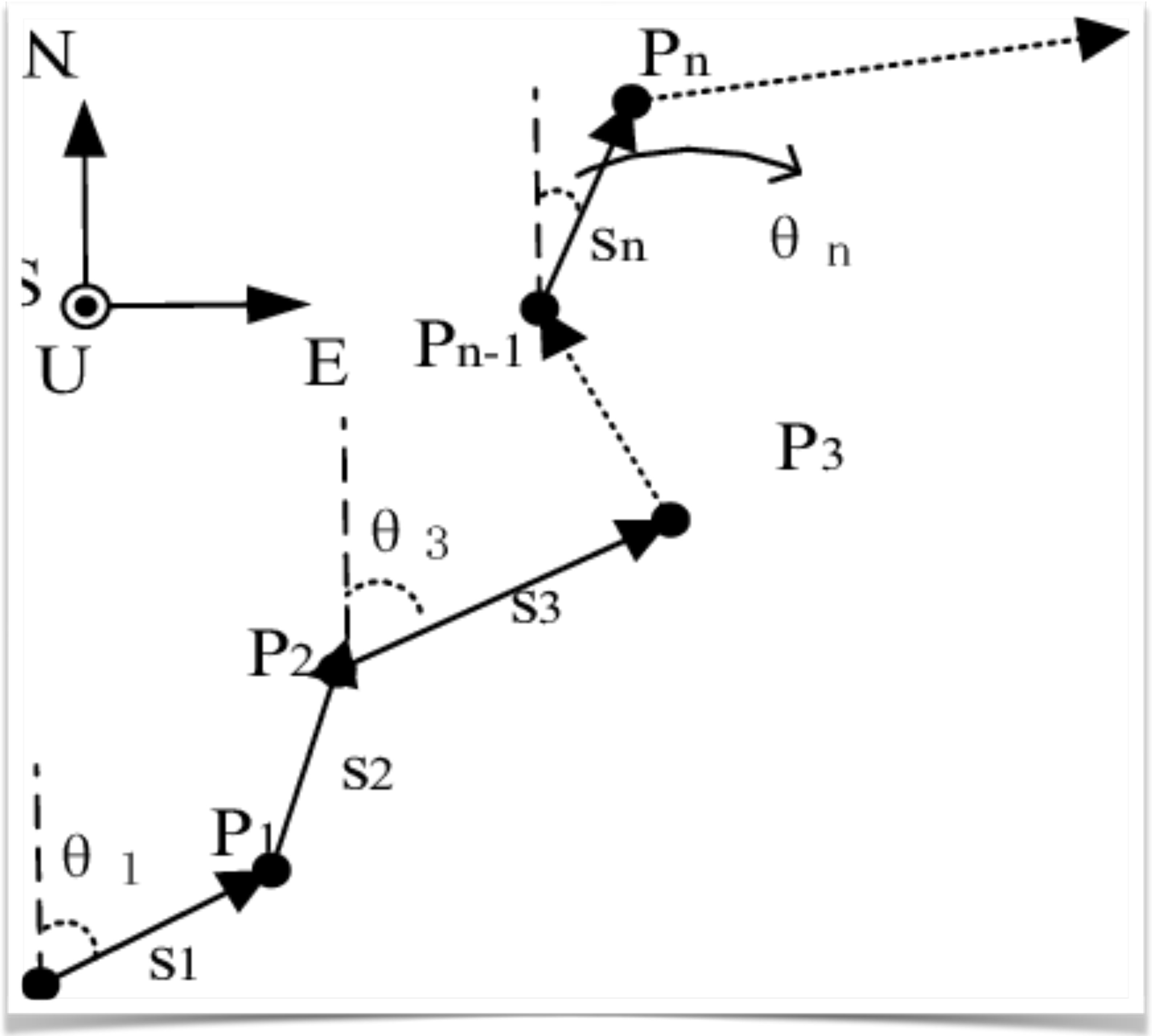


Tag location positioning in X,Y and Z planes using AoA direction finding.

https://www.nordicsemi.com/products/low%20power%20short-range%20wireless/direction%20finding

Source Space: Measurement Technologies Used for Indoor Positioning

- **6) Pedestrian Dead Reckoning (PDR)**
  - Provides the direction and distance obtained from inertial sensors of UEs
  - Current position estimate is calculated based on previously known position estimate
  - Initial point and map, can also affect the positioning accuracy



https://www.researchgate.net/publication/323619035_Simulation_of_Fusion_Localization_Based_on_a_Single_WiFi_AP_and_PDR

Source Space: Measurement Technologies Used for Indoor Positioning

- **7) Transformed Sources**

Transformed sources	Merits	References
Signal strength difference (SSD)	Alleviating device heterogeneity	[109], [110]
Hyperbolic location fingerprint (HLF)	Alleviating device heterogeneity	[95]
Difference fingerprint (DIFF)	Alleviating device heterogeneity	[96], [152]
Delta-fused principal strength (DFPS),	Alleviating RSS fluctuation	[43], [99]
Power delay doppler profile (PDDP)	Leveraging multipath information	[97]
Signal subspace (SS)	Reducing dimensionality and noise	[153], [154]
Fourth-order cumulant fingerprint (FoCF)	Robust to color noise	[32]
fractional low order moment fingerprint (FLOMF)	Robust to impulse noise	[32], [155]

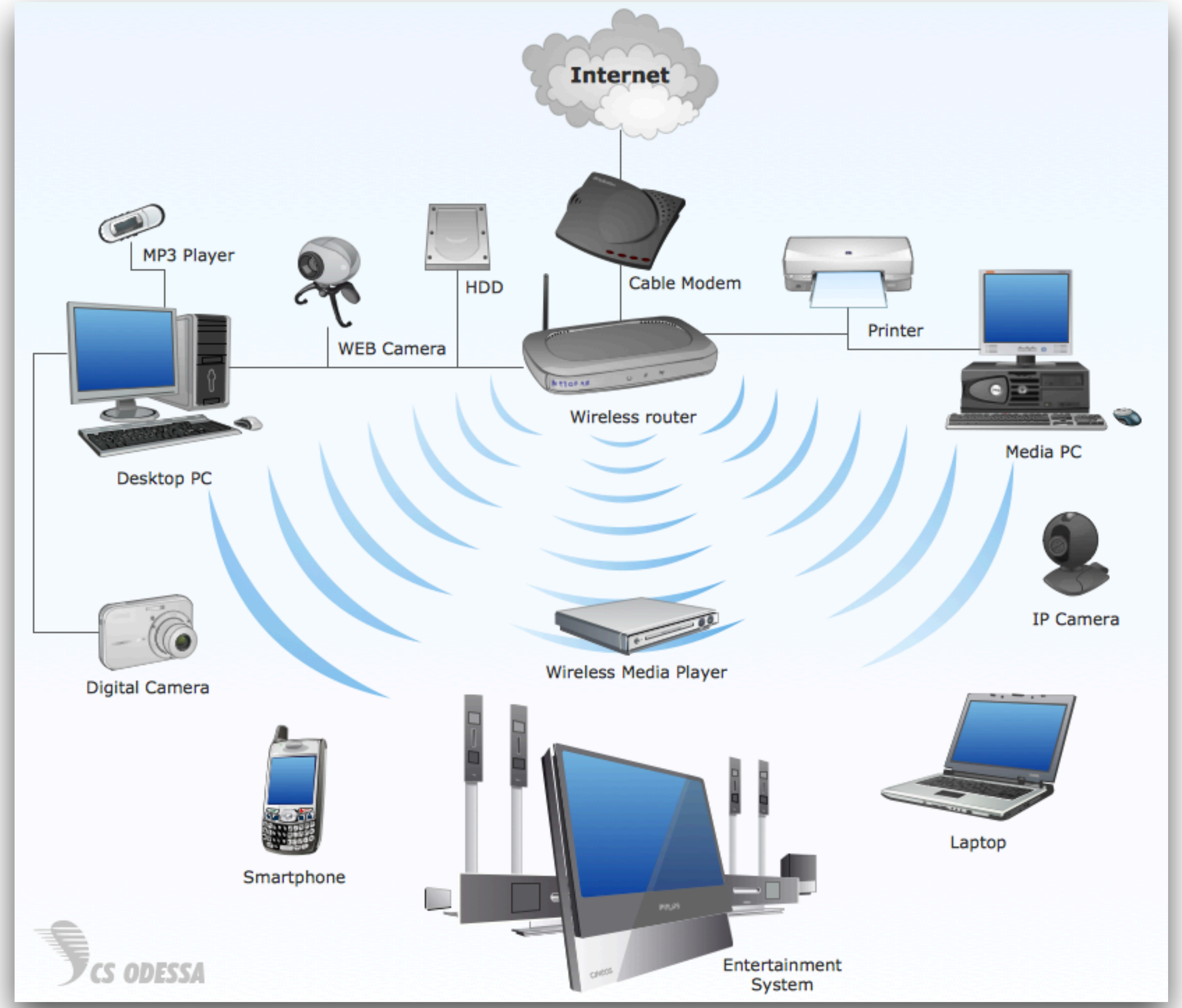
Source Space: Networks Used for Indoor Positioning

COMPARISON OF POSITIONING SYSTEMS

Networks	Base Stations	UEs	Positioning Accuracies	Positioning Methods	Advantages	Disadvantages
WLAN [50], [91], [92], [96], [113], [114], [162]	AP	Smartphone	cm-m	Fingerprint; trilateration.	Low-cost.	Affected by environment; need data collection.
Geomagnetism [163]–[168]	N/A	Smartphone	1m-5m	Fingerprinting.	Low-cost; no extra infrastructure; omnipresent and stable.	Need data collection.
UWB [169], [170], [201]	UWB anchor	UWB tag	cm-m	Multilateration.	NLOS; high-accuracy.	High-cost.
INS [7], [8], [87], [88], [173], [174]	N/A	Smartphone	1m	PDR.	Independent of environment.	Accumulative error.
RFID [147], [175], [175]–[179]	RFID reader	RFID tag	cm-m	Fingerprint; proximity detection.	High-accuracy; small-sized; low-cost.	Short-ranged.
Cellular network [79], [202], [203]	Cellular tower	Smartphone	m	TDOA; proximity detection.	Long-ranged; no extra infrastructure.	Performance depends on density of base stations.
ZigBee [42], [181], [183]–[185], [204]	Zigbee anchor	Zigbee tag	dm-m	Proximity detection; multilateration.	Low-cost; low-power.	Low-stability; affected by environment.
Bluetooth [186]–[190]	iBeacon	Smartphone	2m-10m	Proximity detection; multilateration; centroid determination.	Low-cost; small-sized; easy-deployment.	Low-stability; short-ranged.
Visible light [33], [134], [196], [197], [197]–[199], [205]	LED	Tag	cm	Trilateration; proximity detection; fingerprint.	Low-cost; energy-efficient.	Inevitable noise.

Source Space: Networks Used for Indoor Positioning

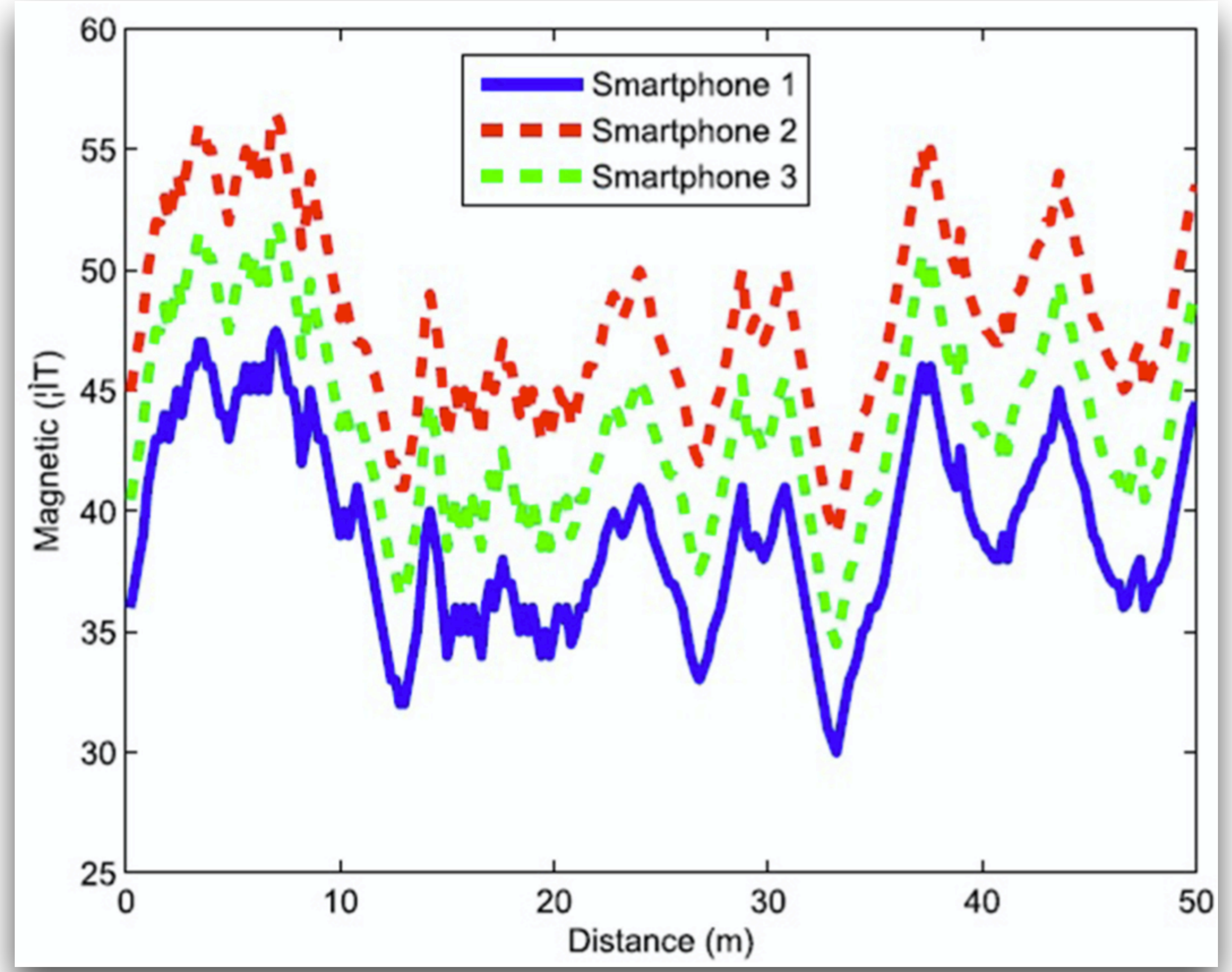
- **1) Wireless Local Area Network WLAN-Based Positioning System**
  - General methods of localisation
    - Fingerprinting
    - Trilateration: seldomly used due to shadowing, multipath and numerous obstacles in indoor environments
  - Conventional measurements are RSS and CSI
  - Fingerprint-based localization is a prominent technique
    - Mitigates the laborious process of fingerprint collection
    - Use of the fingerprints collected at different time periods and from different hardwares
    - Positioning algorithms with good performances, both in accuracy and robustness



https://www.pinterest.com/pin/572379433864670757/

Source Space: Networks Used for Indoor Positioning

- **2) Geomagnetic-Based Positioning System**
  - Geomagnetic field can easily differentiate the spatial variation in complex indoor environments
  - The signal is also ubiquitous and temporally stable
  - Different hardwares may yield different magnetic readings at the same location
  - Positioning accuracy is between 1-2m



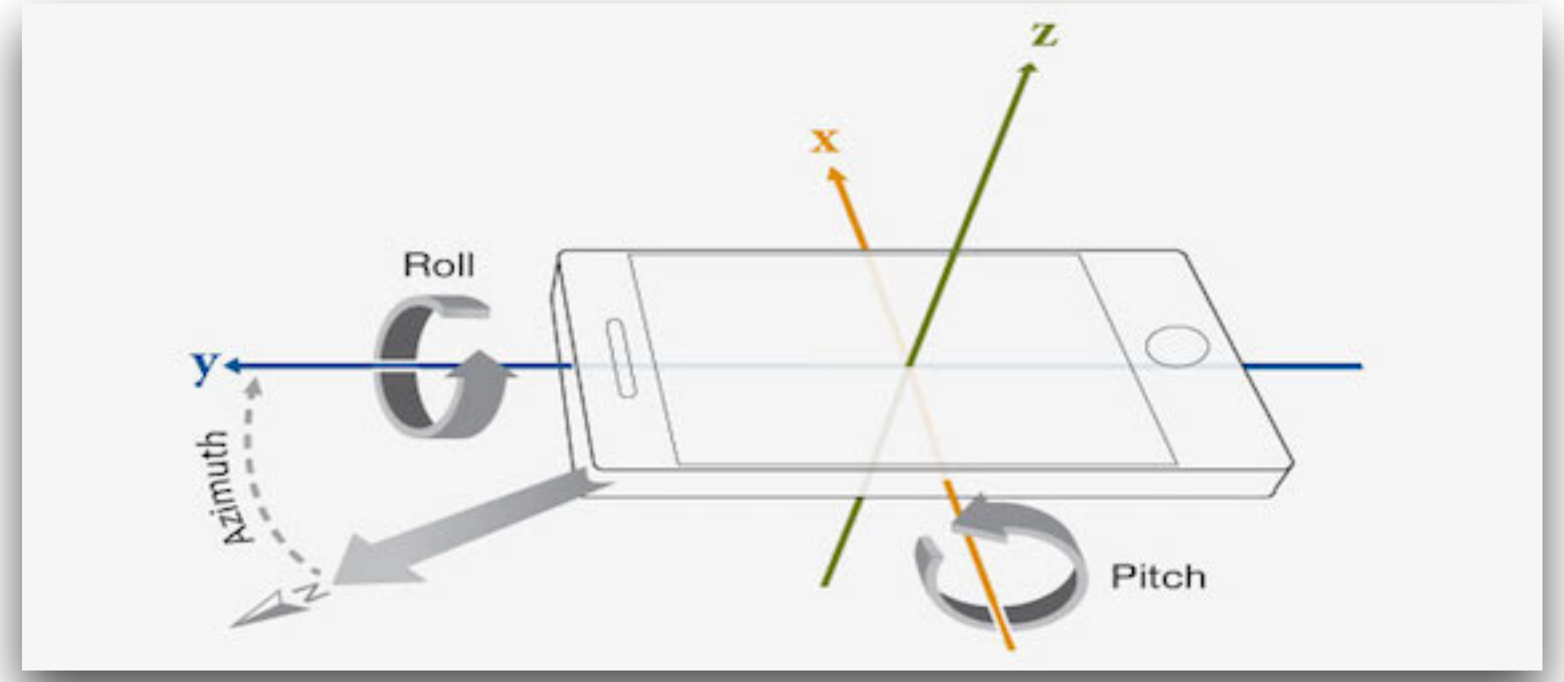
Source Space: Networks Used for Indoor Positioning

- **3) Ultra-Wideband (UWB)-Based Positioning System**
  - Transmits data by ultra-narrow pulses in the time scale of nanoseconds
  - Accuracy at centimeter-level
  - Incur high power and hardware requirements
  - Problems are incurred by fading, especially in dense or NLOS indoor scenarios

https://www.indoornavigation.com/wiki-en/indoor-positioning-with-ultra-wideband

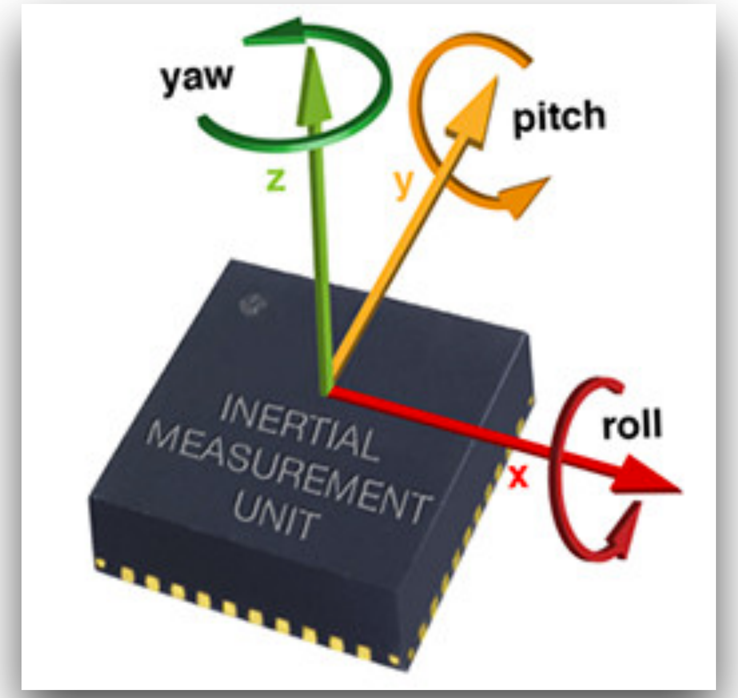
Source Space: Networks Used for Indoor Positioning

- **4) Inertial Navigation Systems (INS)**
  - Core components, Inertial Measurement Units (IMUs), consist of
    - Three orthogonal uniaxial accelerometers and three orthogonal gyros, in provisioning position, velocity, and pose measurements
  - Recent advances in electromechanical technology have enabled miniaturization of sensors and cost reduction
  - Most popular application is tracking a UE
  - Each detected step of a user is added to previously estimated position to determine the current position
  - Wrong estimation of the previously estimated position will result in the accumulation of errors.



https://beckernick.github.io/activity-prediction/

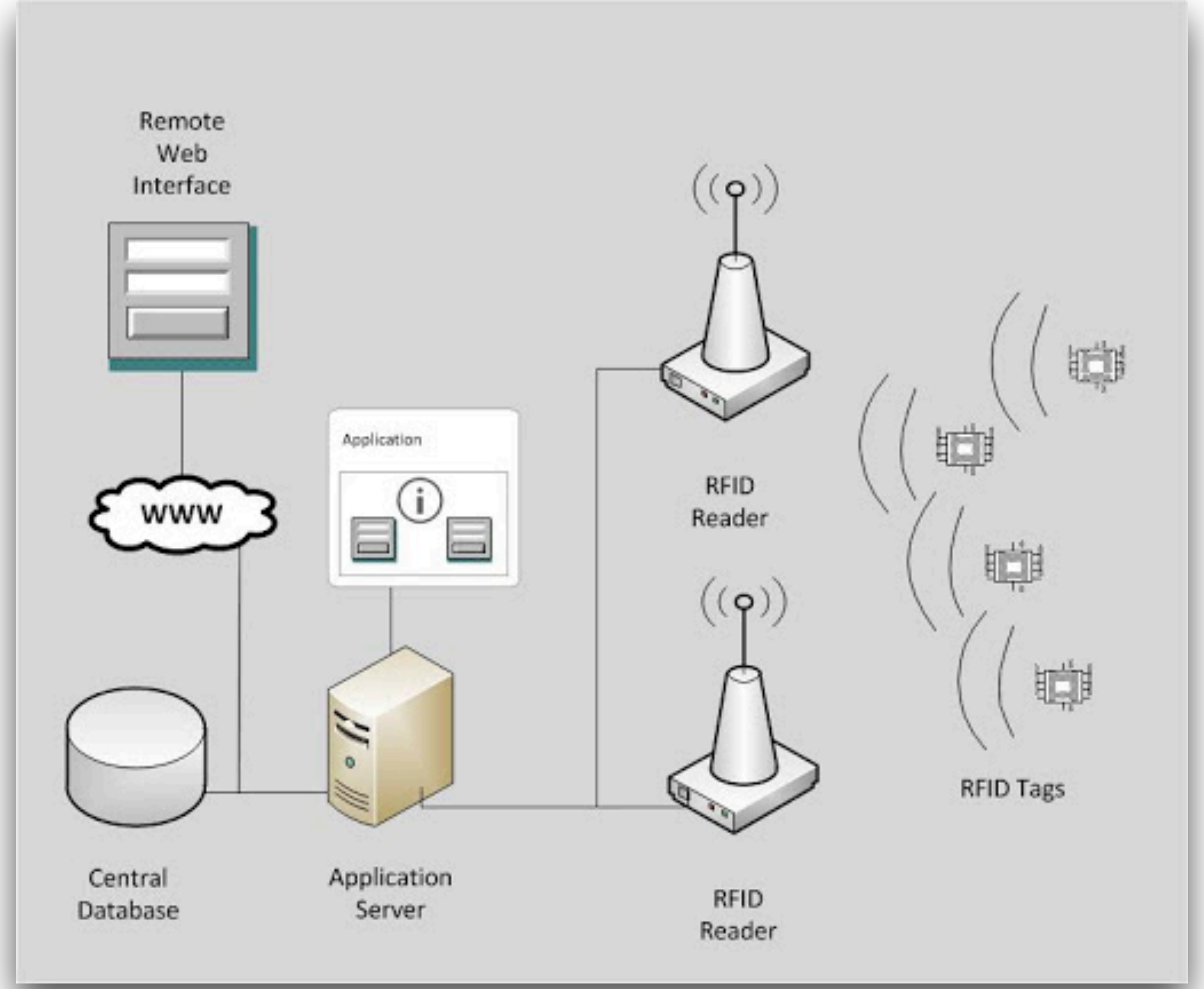
Angular accelerometers



https://www.linkedin.com/pulse/how-do-drones-work-part-9-imu-inertial-measurement-unit-fiorenzani/

Source Space: Networks Used for Indoor Positioning

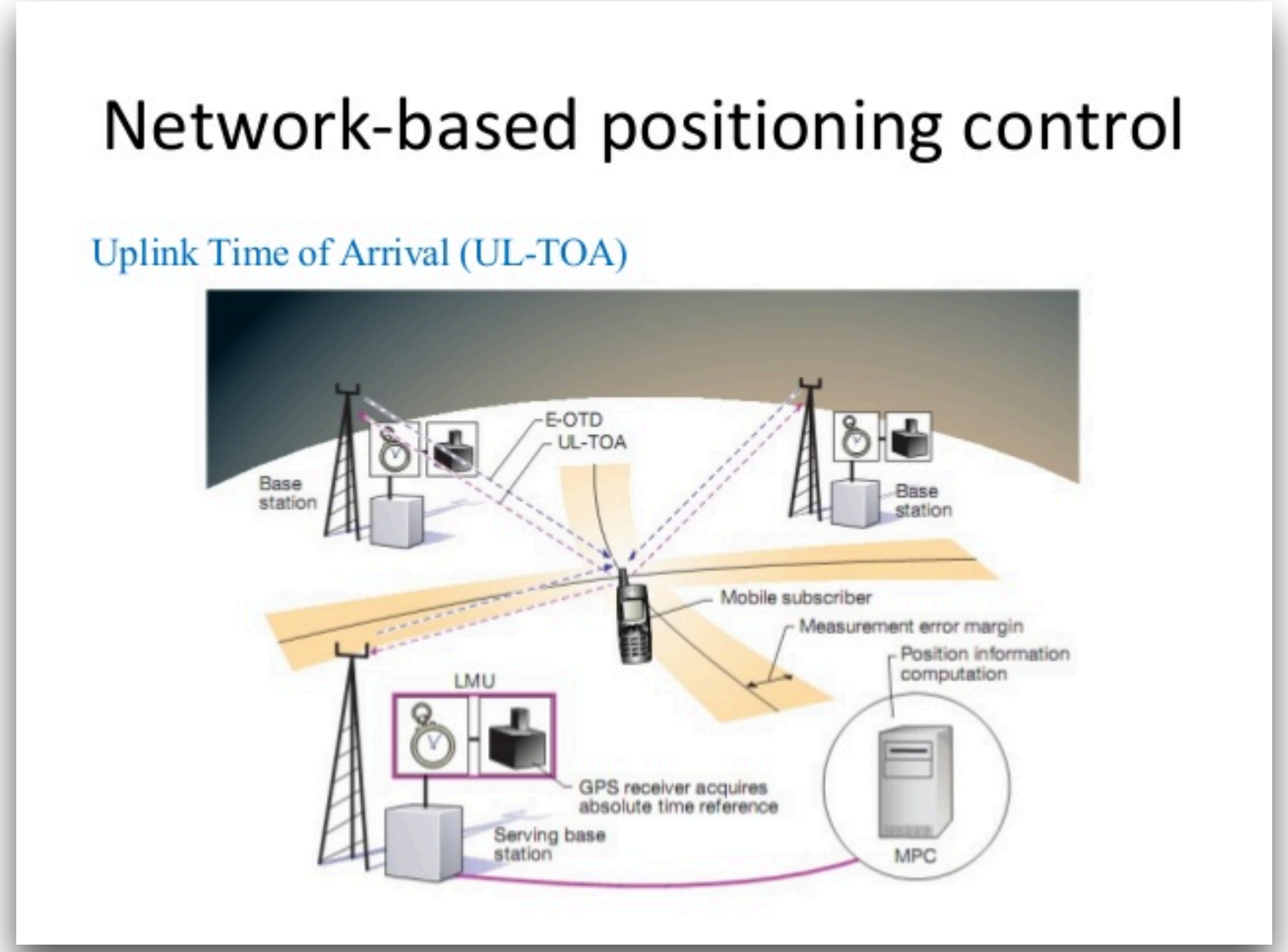
- **5) Radio Frequency Identification (RFID)-Based Positioning System**
  - Realize localization by writing, storing and reading information in electronic tag embedded in positioning targets
  - Classified into active and passive systems
  - Propagation of an active RFID signal can reach 30 m, longer than a passive one
  - Fingerprinting position method can be used for active RFID based on the RSSI measurement
  - Passive RFID positioning systems depending on inductive coupling usually use the proximity detection method to achieve positioning



http://www.csr.ro/?page_id=260&lang=en

Source Space: Networks Used for Indoor Positioning

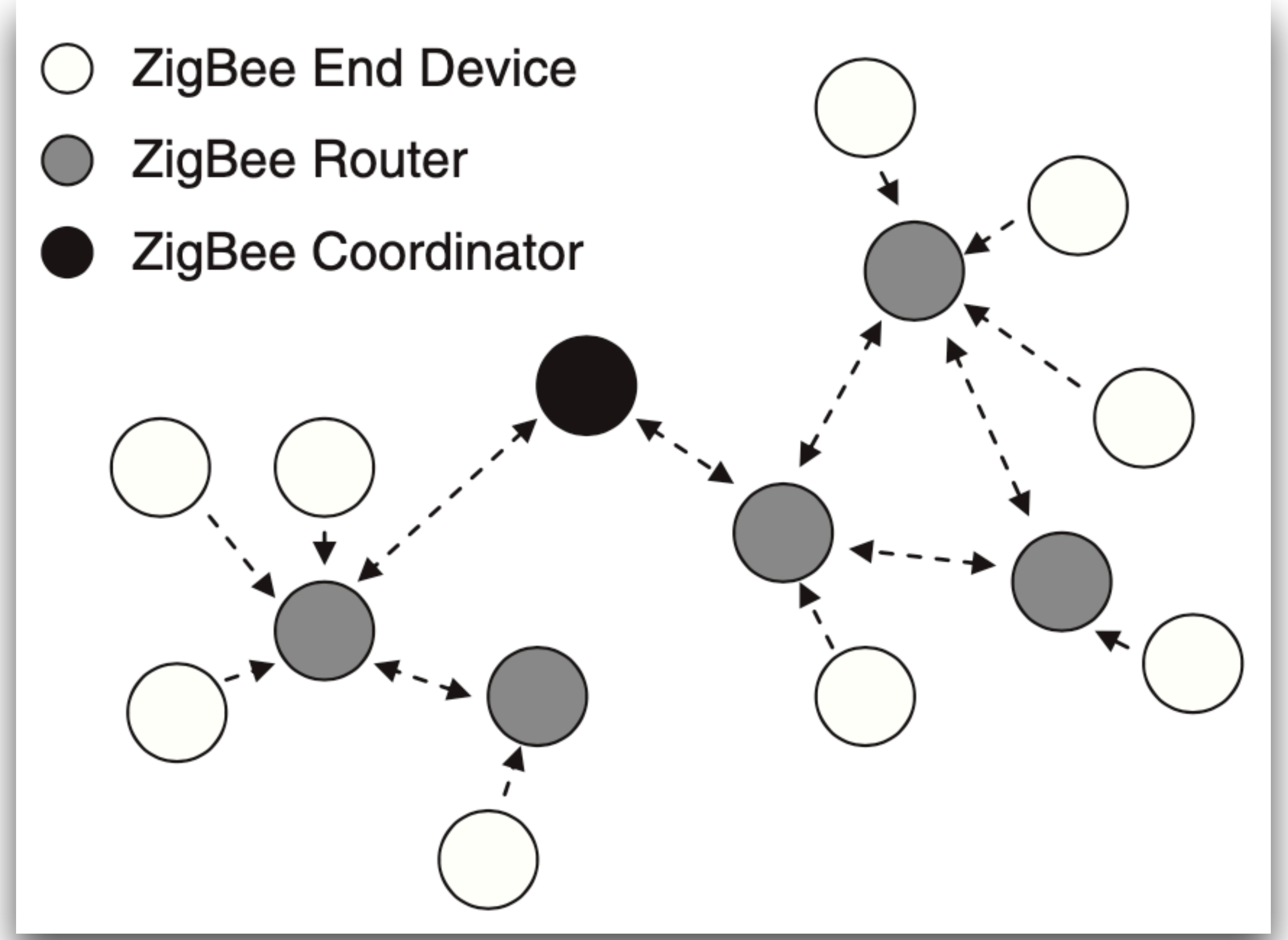
- **6) Cellular Network-Based Positioning System**
  - Cellular networks can be used to locate mobile phones
  - Researches have shown
    - Ye et al. [179]: Extract the channel parameters from long-term-evolution (LTE) down-link signals by using a feature extraction method
      - Radio channel fingerprints were collected for a feed forward neural network training
      - Based on the trained neural network, the location of UEs can be predicted when inputting the online testing signals
      - Experimental results showed a median error distance of 6 and 75 meters in indoor and outdoor environments respectively, by using only one LTE eNodeB.



https://www.slideshare.net/M_A_Abuibaid/mobile-positioning-system

Source Space: Networks Used for Indoor Positioning

- **7) ZigBee-Based Positioning System**
  - Low-power and short-range communication protocol based on the IEEE 802.15.4 standard
  - Accuracy reaching of 2.1 m.

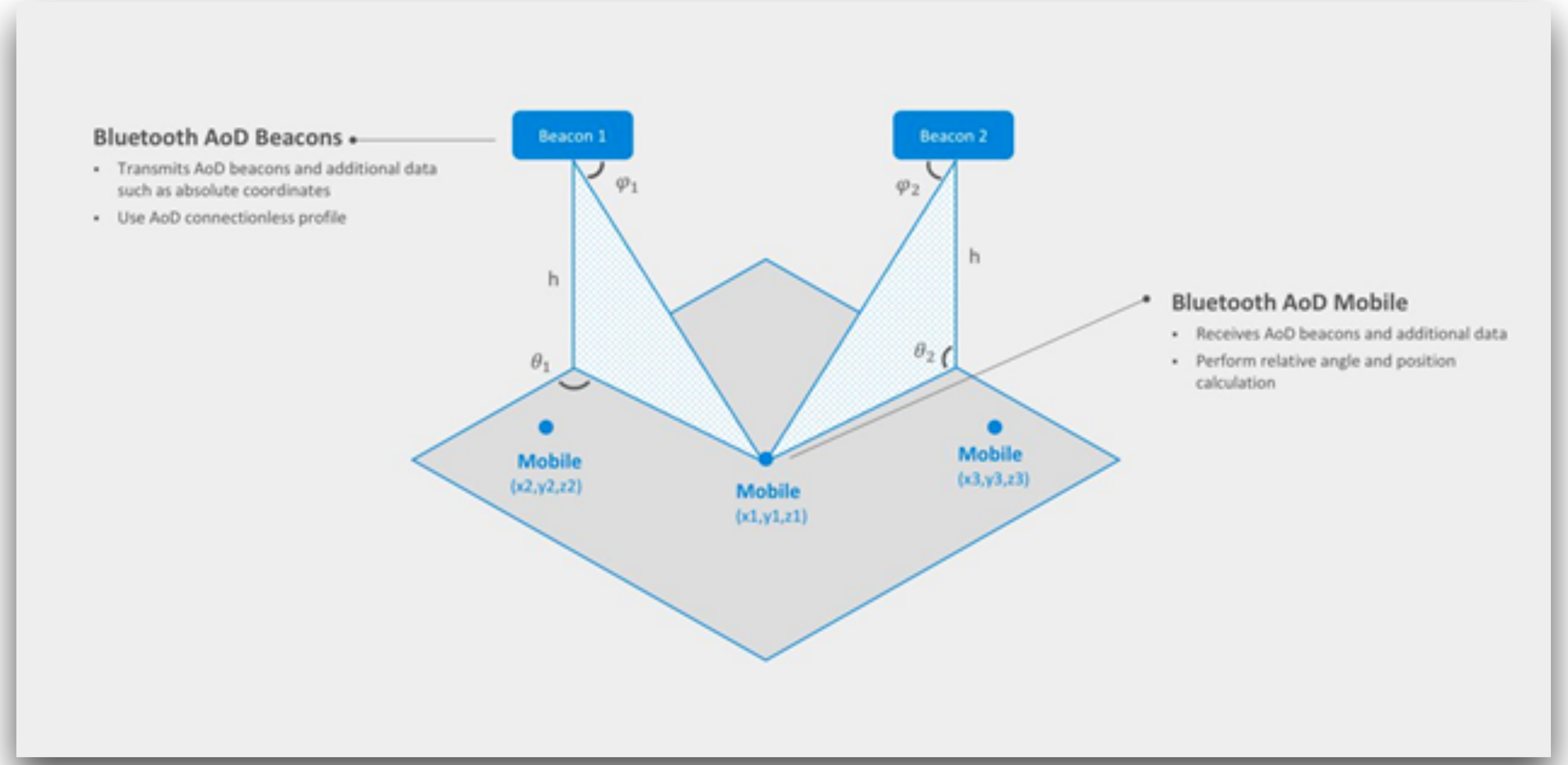


ZigBee: device types [2]

[2] Jean-Philippe Vasseur and Adam Dunkels. 2010. Interconnecting Smart Objects with IP: The Next Internet. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA. (Chapter 19)

Source Space: Networks Used for Indoor Positioning

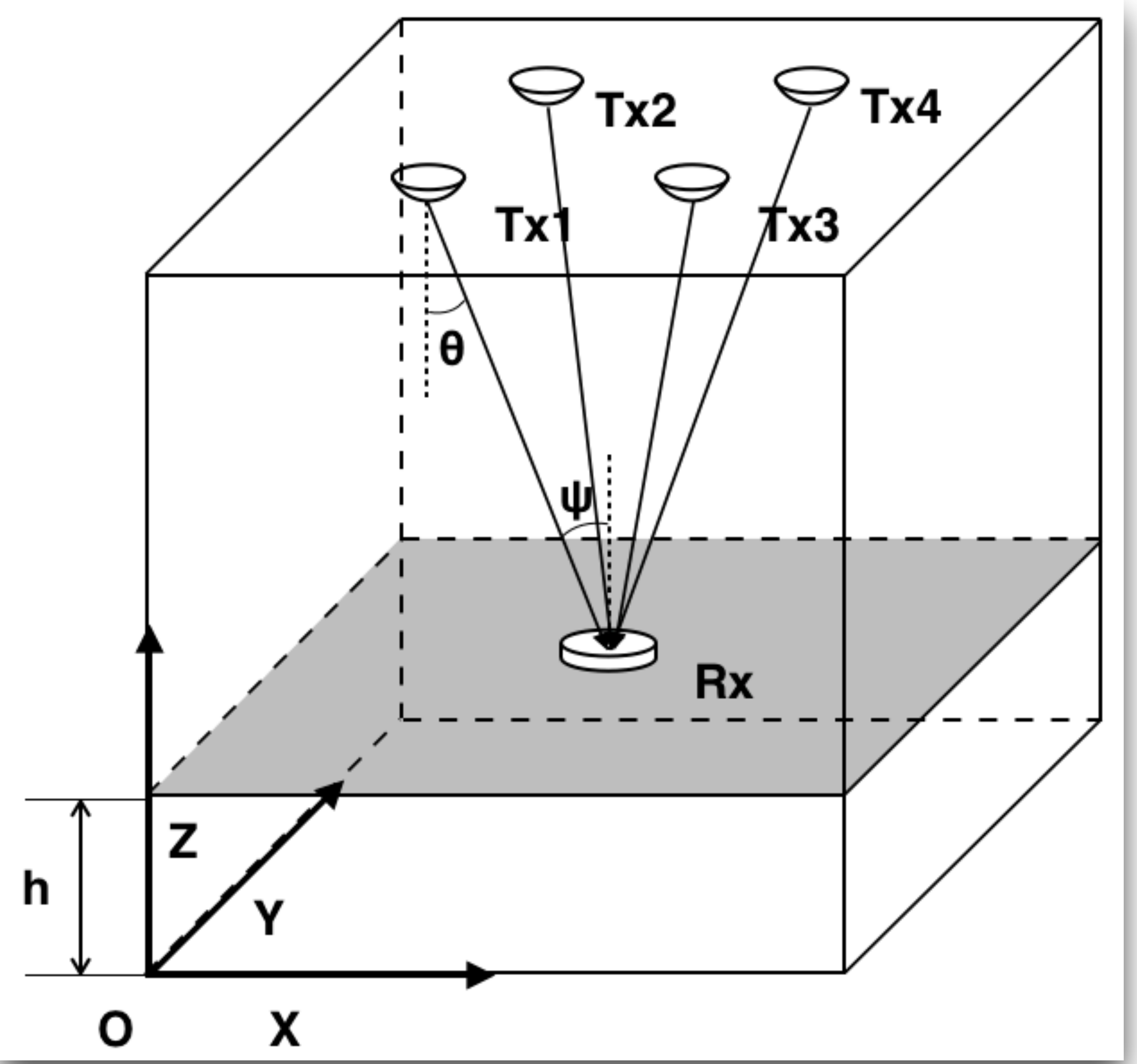
- **8) Bluetooth-Based Positioning System**
  - Close range, low power, and low cost
  - Accuracy within 1 m



https://medium.com/supplyframe-hardware/bluetooth-indoor-positioning-and-asset-tracking-solutions-8c78cae0a03

Source Space: Networks Used for Indoor Positioning

- **9) Visible Light Positioning (VLP) System**
  - Can be used in VLP systems:
    - RSS
    - AOA
    - TOA
    - TDOA



https://www.researchgate.net/publication/322753905_A_Survey_of_Positioning_Systems_Using_Visible_LED_Lights

Source Space of Homogeneous Positioning Systems

SOURCE SPACE OF FUSION-BASED INDOOR LOCALIZATION IN HOMOGENEOUS POSITIONING SYSTEMS

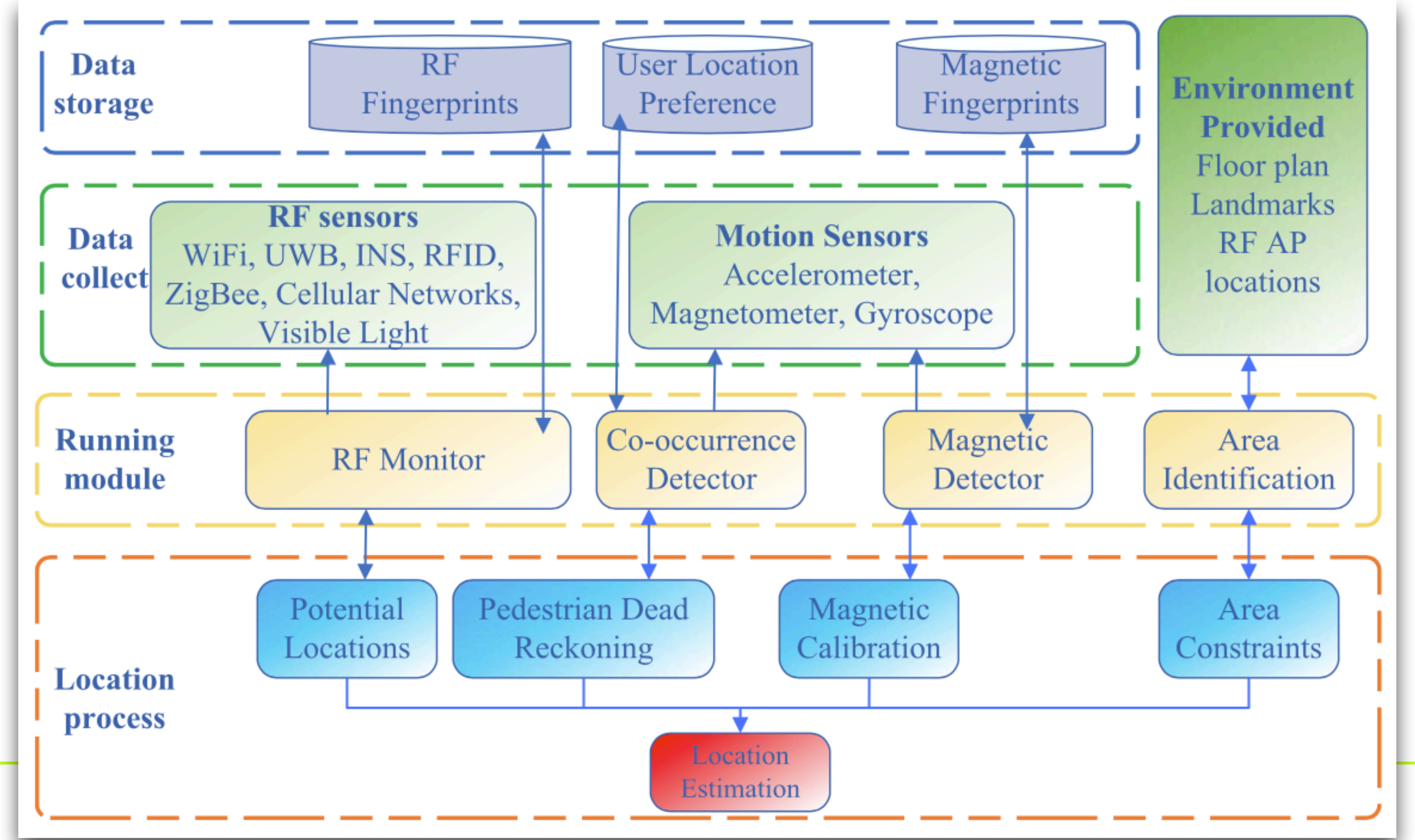
	RSS	TOA	TDOA	AOA	Single measurement technology	References	Contributions
WLAN	√				Yes	[27], [28], [32], [34], [99]	Make full use of potential information provided by RSS measurements in WLAN.
	√	√			No	[207], [208]	Find a balance between inaccurate but efficient RSS measurements; precise but more resources.
ZigBee	√				Yes	[42], [181], [204], [209], [210]	Take complementary advantages of various algorithms or fingerprints based on RSS provided by energy-efficient Zigbee.
GSM	√				Yes	[41], [202], [203], [211]–[213]	Fuse multiple classification algorithms or fingerprints to exploit the potential of information given by RSS measurements in GSM.
		√	√	√	No	[79]	Data fusion is used for merging disparate types of information from different measurements to enhance the accuracy of position estimates.
Visible light	√				Yes	[33], [205], [214]	Multiple classifiers based on RSSs are combined for better position estimation.
	√			√	No	[196], [215]	Use RSS and AOA-based positioning algorithm to overcome the limitation of installing multiple LED lamps.
UWB	√	√			No	[71]	Combine RSS-based ranging with TOA-based ranging to overcome the limitation of each standalone ranging techniques in a UWB localization system.
WSN	√	√			No	[58], [206], [208]	Utilize of the advantages of RSS positioning efficiency and TOF positioning accuracy comprehensively.

Source Space of Heterogeneous Positioning Systems

SOURCE SPACE OF FUSION-BASED INDOOR LOCALIZATION IN HETEROGENEOUS POSITIONING SYSTEMS

WLAN	Geomagnetism	Zigbee	RFID	Bluetooth	GSM	References	Contributions
√	√					[46], [219]	Combine the complementarity between RSSs provided by WLAN and Geomagnetism as WiFi signals are distinctive across distant locations whereas magnetic field is more locally discriminative.
√	√		√			[216]	Faced with the situation with disabled access points and the inaccuracy of radio map construction, WLAN can be combined with other different networks.
√				√		[35]	The accuracy of WLAN-based localization is improved by eliminating outliers via the cell identification performed by Bluetooth.
√		√		√		[80]	Combine information provided by different networks can acquire better positioning estimation. estimation.
				√	√	[218]	Using a multi-channel approach with up to eight redundant RSS readings derived from GSM and Bluetooth, the position estimation error can be reduced significantly..

Source Space of Hybrid Positioning Systems



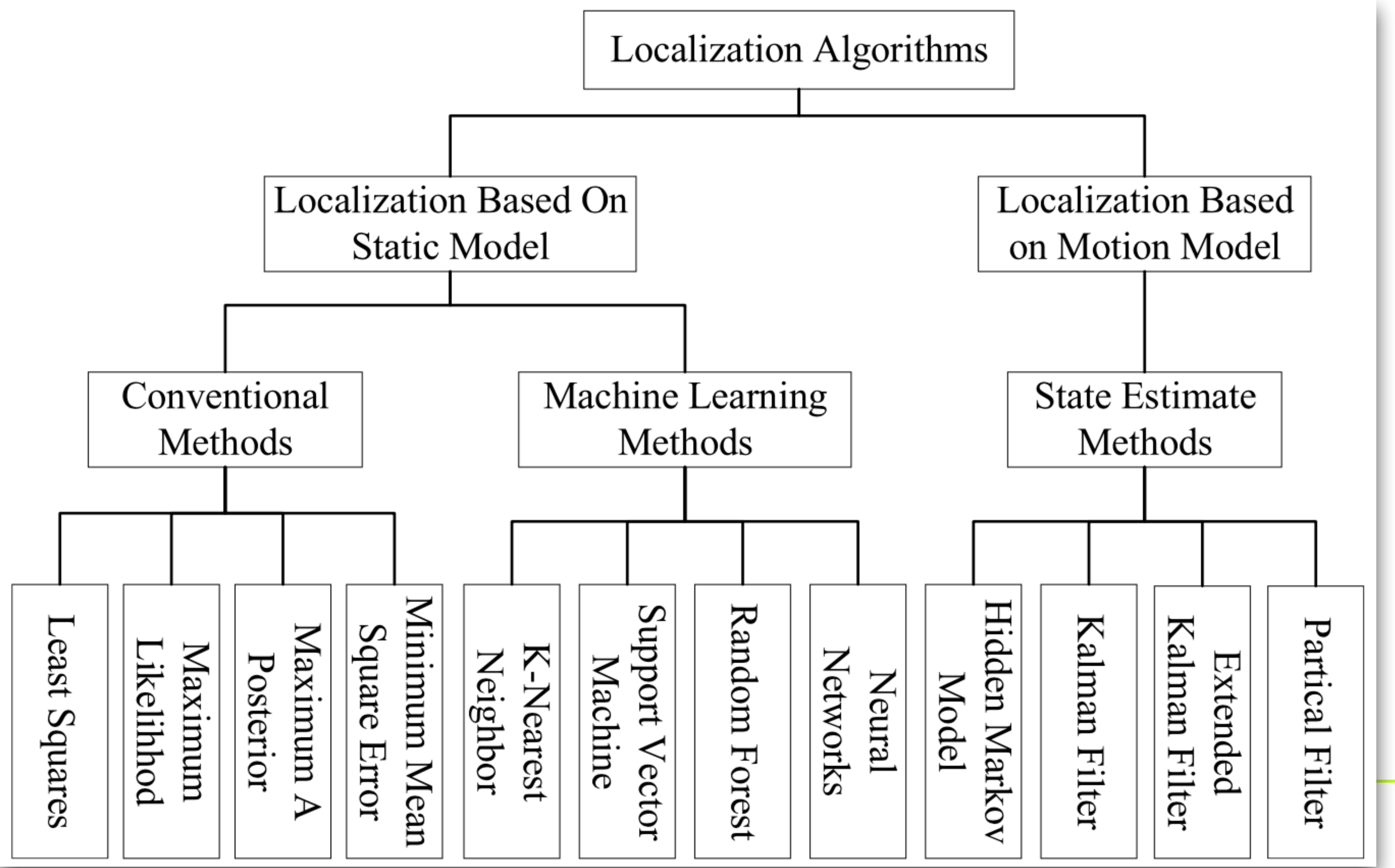
Source Space of Hybrid Positioning Systems

SOURCE SPACE OF FUSION-BASED INDOOR POSITIONING IN HYBRID POSITIONING SYSTEMS

	WLAN	INS	Geomagnetism	RFID	Vision	UWB	WSN	Ultrasonic	Bluetooth	References
RSS & Image capturing	√		√		√					[26]
	√	√								[89]
RSS & PDR	√	√	√							[38], [94], [224]
	√	√								[36], [39], [47]–[52], [220]–[222], [226], [228]–[233]
		√	√							[227]
		√		√						[234]
		√							√	[148], [186], [187], [223]
PDR & TOA		√				√				[7], [83], [235]
PDR & TDOA		√				√				[8]
PDR & Image capturing		√			√					[236]–[238]
PDR & DOA		√						√		[239]
TOA & Image capturing				√	√					[240]

Algorithm Space

Algorithm Space - Taxonomy of localization algorithms



Algorithm Space - Conventional Methods: Least Squares (LS)

- Solve an overdetermined system
- Minimize the sum of squares of the residuals of each equation to get an approximate solution
- When there is redundancy in observations, it is feasible to use LS estimation to obtain a unique answer
- Measurements such as AOA, TOA, TDOA, and RSS or their combinations can be solved by LS methods

Algorithm Space - Conventional Methods: Maximum Likelihood (ML)

- Probabilistic method of estimating the parameters of a statistical model
- The ML estimator requires the knowledge of the conditional probability density function of the source observation
- Combining the measurements from different sensors can improve the performance of the ML estimator

Algorithm Space - Conventional Methods: Maximum A Posterior (MAP)

- Based on empirical data to obtain point estimates of hard-to-observe quantities
- Probability of the model parameter itself is considered to be uniform in ML, i.e., the probability is a fixed value
- Maximum posterior estimate can be seen as a regularised maximum likelihood estimate.

Algorithm Space - Conventional Methods: Minimum Mean Square Error (MMSE)

- Minimizes the statistical average of positioning errors
- Makes use of range estimates derived from measurements between an UE and reference nodes

Algorithm Space - Conventional Methods

SUMMARY AND COMPARISON OF CONVENTIONAL METHODS

Algorithms	Strengths	Weaknesses	Localization Applications		
			References	Reported Mean Accuracies	Main Contributions
LS	Easy implementation.	Linear estimator.	[250]	Perform better in $20 \times 20m^2$	Combine distance and angle measurements.
			[256]	2.04m in a room	Weighted LS techniques based on standard hyperbolic and circular positioning algorithms.
			[185]	$< 2m$ in $36 \times 20m^2$	Convert the NLOS problem into an LOS problem with virtual stations.
			[254]	Perform better	Combine TDOA and AOA via a two-step LS estimator.
ML	No additional parameters needed.	Measurement probability assumption needed; cannot obtain closed-form solutions.	[40]	43% error reduction in floor	Propose a novel approach to extract the robust signal feature from RSSs.
			[54]	$1 \sim 2m$ in $9 \times 9m^2$	Derive CRBs and ML estimators under Gaussian and log-normal models for RSSs and TOA.
			[260]	Improve remarkably in room and corridor	Propose a probability-based ML for relative location estimation.
			[239]	0.267m in $7.8 \times 7.1m^2$	Use acoustic signals and inertial sensors to estimate the sensor positions simultaneously.
			[36]	2.76m in $156 \times 27m^2$	Combine WiFi and PDR by using ML algorithm.
			[52]	$< 1m$ in $40.8 \times 16m^2$	Leverage user motion against fingerprint ambiguity.
			[23]	$15\% \sim 20\%$ improvement	Derive a nonconvex estimator to tightly approximate ML.
MAP	No additional parameters needed.	Static or single point positioning; measurement probability assumption needed.	[55]	34.8% error reduction in $10 \times 10m^2$	Use the Baye's formula to deduce the probability density of each sensor node's.
			[56]	3cm in $8 \times 6m^2$	Use a tightly coupled sensor fusion approach.
MMSE	Easy implementation; Analytical tractability.	Posterior probability information needed.	[261]	Perform better and robust	Derive a weighted MMSE by using range estimates.
			[44]	3.7m in $37.83 \times 25.60m^2$	Fuse selected multiple location information in a theoretically optimal manner.

Algorithm Space - Machine Learning (ML) Methods

- Based on the measurement samples collected at known locations to model how the positioning information is distributed in different geographical areas
- Categorised into two groups: Classification & Regression
- Try to train the machine learning algorithm as a predictor to yield the location prediction
- ML methods outperform the conventional indoor positioning methods in mitigating the fluctuation of RSS in CEEs.

Algorithm Space - Machine Learning Methods

SUMMARY AND COMPARISON OF MACHINE LEARNING METHODS

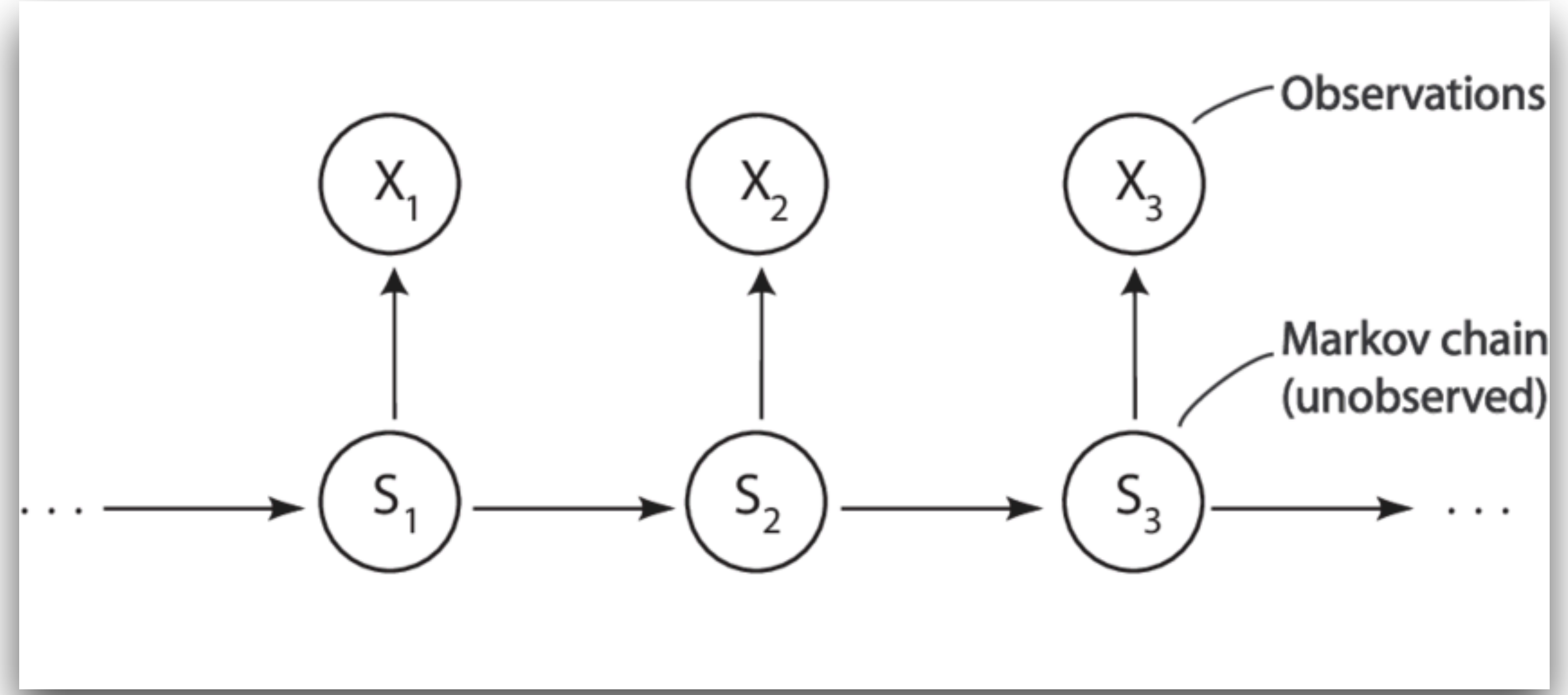
Algorithms	Strengths	Weaknesses	Localization Applications		
			References	Reported Mean Accuracies	Main Contributions
KNN	(1)Easy implementation; (2)Not sensitive to outliers.	(1)Heavy computation burden; (2)Intrinsic meaning of the data cannot be given.	[30]	3.4m in $73 \times 20\text{m}^2$	Fuse a group of fingerprints via global fusion profile.
			[156]	2.96m in $11 \times 23\text{m}^2$	Broadcast FM as a signal of opportunity.
			[264]	87% accuracy in 1600m^2	WiFi fingerprints via ZigBee interference signatures.
			[114]	4.6m in 1600m^2	WiFi fingerprints, crowdsourcing, and weighted KNN.
			[265]	85% accuracy in 1600m^2	Exploit the cross-technology interference.
			[24]	3.89m in $52.5 \times 52.5\text{m}^2$	Propose a new weighted method based on the physical distance of the RSSI.
			[266]	2.11m in $48 \times 22\text{m}^2$	Change the number of considered neighbors.
			[33]	93.17% accuracy < 5cm in $70 \times 70\text{cm}^2$	Fuse multiple classifiers based on RSS of visible light.
			[80]	1m in $32 \times 22\text{m}^2$	Use the combination of multiple wireless technologies.
SVM	(1)Non-linear mapping; (2)Low computational burden; (3)Excellent scalability.	(1)Complicated parameters optimization; (2)Sensitive to outliers.	[267]	1.37m in $40 \times 8.5\text{m}^2$	Design a grid search algorithm to optimize the parameters.
			[25]	95% accuracy is 1.81m	Design a kernel-based learning technique for RSS fingerprints based positioning.
			[62]	Improve remarkably in $43 * 13\text{m}^2$	Prior information of signals is considered.
			[63]	Reduce complexity in $100 * 100m^2$	A hierarchical SVM scheme is proposed.
			[64]	90% correct classification rate	Design the multi-class SVM approach designed for zoning localization.
RF	(1)Low cost; (2)Easy implementation; (3)Runs efficiently and stable.	(1)Complicated parameters set; (2)Time-consuming model.	[268]	3.6m in $17 \times 10\text{m}^2$	Exploit the RF in classification and regression techniques.
			[269]	83%$accuray$ in 98% of cases	RFID technology and a hierarchical structure of classifiers.
			[28]	Improve remarkably in $9.8 \times 6.3\text{m}^2$	Propose a sliding window aided mode-based fusion algorithm.
NN	(1)High accuracy; (2)Arbitrary complex nonlinear function can be approximated; (3)Fast and suitable testing.	(1)Large training set needed; (2)Complicated training; (3)Sensitive to dynamic environment.	[46]	0.75m in $13.4 \times 6.4\text{m}^2$	Combine RSSI of WiFi with magnetic field.
			[59]	1.13m in 144m^2	Employ a multi-layer NN for RSSs localization.
			[270]	1.893m in $45 \times 25\text{m}^2$	Study the affinity propagation clustering algorithm and the particle swarm optimization.
			[271]	1.337m in 70.84m^2	Combine RSSs with link quality indicator.
			[272]	1.49m in office	Use the generalized regression NN and weighted centroid localization.
			[60]	88.6% error under 4m in $24.6 \times 17.6\text{m}^2$	Design a novel discriminant-adaptive NN.

Algorithm Space - State Estimate Methods

- State estimate is used to estimate the state of targets
- a.k.a tracking technology
- Explores the measurements from different sensors or different networks to yield a position estimate
- Four popular state estimate methods
  - Hidden Markov Model (HMM)
  - Kalman Filter (KF)
  - Extended Kalman Filter (EKF)
  - Particle Filter (PF)

Algorithm Space - State Estimate Methods: Hidden Markov Model (HMM)

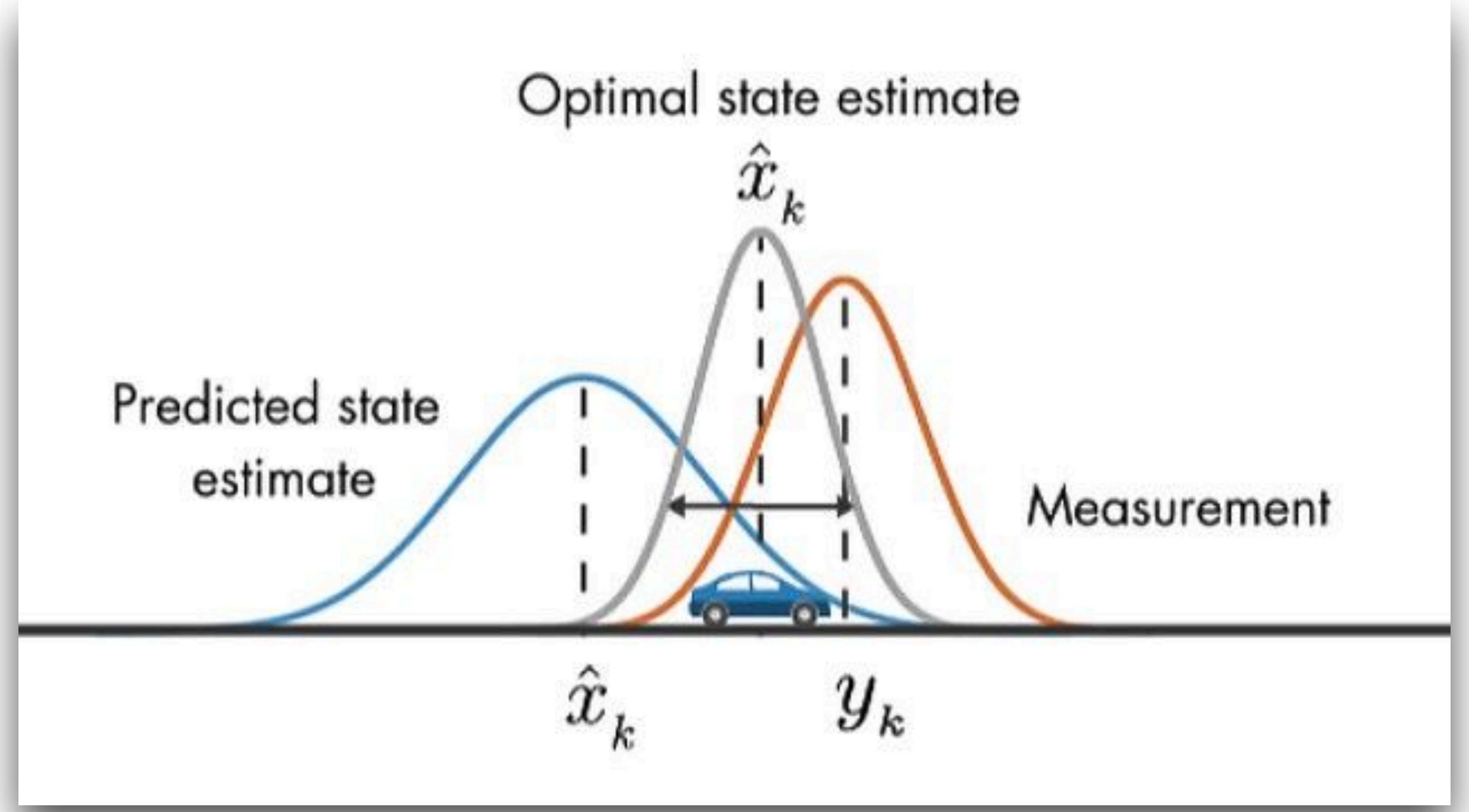
- Used to represent processes that are not fully observable because the physical states may be unobservable (e.g., target position)
- Applied in indoor positioning environments
- Applied to compute the probability based on given observed sequence in indoor positioning
- A combination of WiFi measurements and motion information is also widely adopted in the design of HMM



https://www.researchgate.net/publication/24115579_Application_of_Hidden_Markov_Models_and_Hidden_Semi-Markov_Models_to_Financial_Time_Series

Algorithm Space - State Estimate Methods: Extended Kalman Filter (EKF)

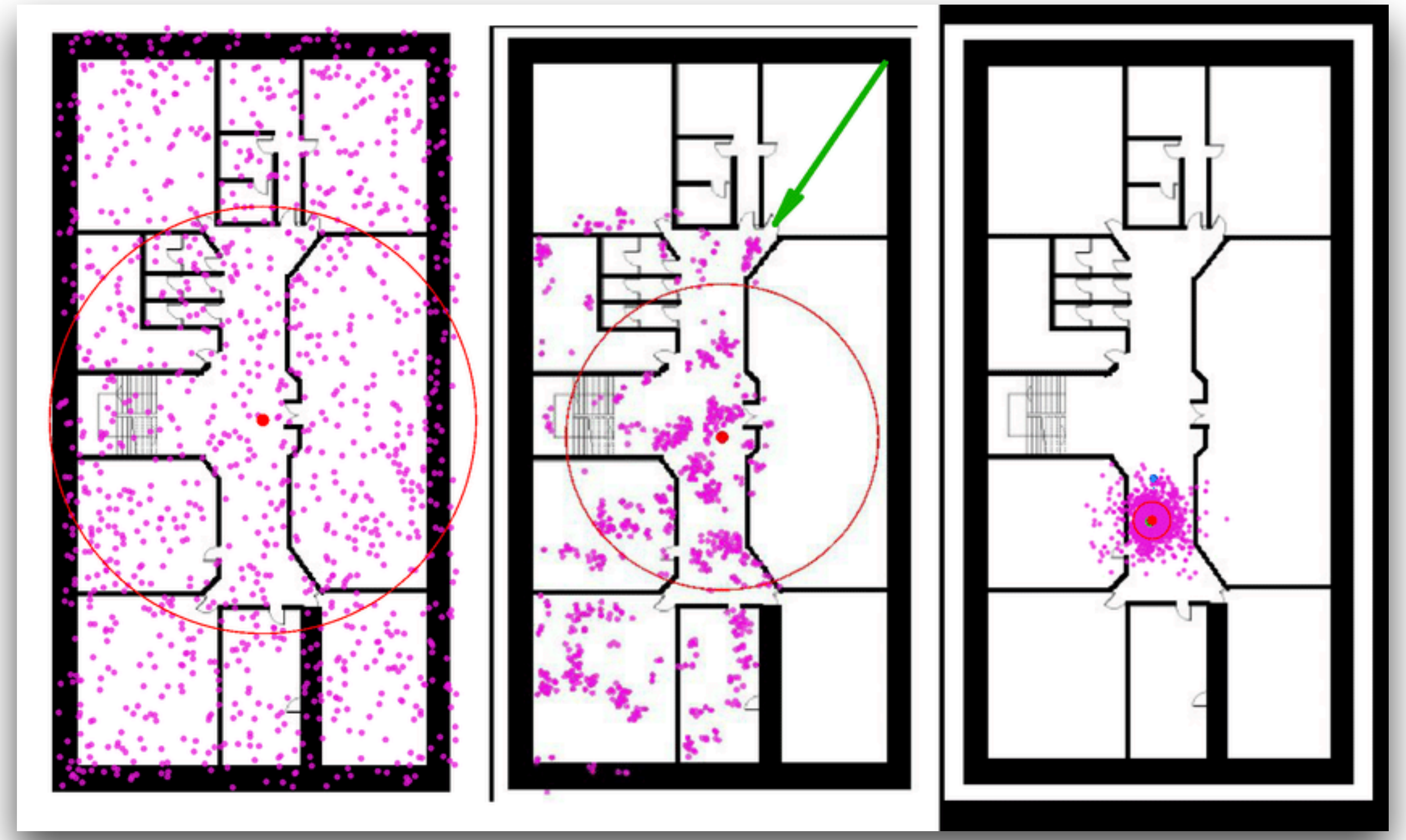
- Cope with nonlinear and non-Gaussian problems
- EKF usually approximates the observed signal distribution with a Gaussian distribution and does not consider potential variables in the state linearization process
- Computations of Jacobians are extremely expensive in EKF.
- Successfully applied for indoor positioning especially for the fusion of hybrid positioning measurements
- Most common positioning application is to combine PDR and other positioning systems, such as UWB and PDR, WiFi and PDR or the combination of multiple system



https://www.freelancer.co.za/contest/Extended-Kalman-Filter-in-C-1312625-byentry-20756836?w=f&ngsw-bypass=

Algorithm Space - State Estimate Methods: Particle Filter (PF)

- Recursive implementation of the sequential Monte Carlo method
- Replace the integral operation with a set of samples that are close to the posterior probability to obtain a final state estimate
- Can describe any probability distribution
- PF can adapt to non-Gaussian, nonlinear problems, and can converge to true posterior probability
- Walking distance and map information can be integrated in PF



https://www.researchgate.net/figure/Particle-filter-for-localization-Left-the-initial-state-of-particles-Middle-particles_fig2_328992992

Algorithm Space - State Estimate Methods

SUMMARY AND COMPARISON OF STATE ESTIMATE METHODS

Algorithms	Strengths	Weaknesses	Localization Applications		
			References	Reported Mean Accuracies	Main Contributions
HMM	(1)Easy implementation; (2)Without extra cost requirement; (3)Continuous position estimation.	(1)Large training set needed; (2)Expensive training process; (3)Environment dependency; (4)Independence assumption needed.	[67]	1.3m in $52.5 \times 52.5\text{m}^2$	An activity sequence-based localization using HMM.
			[68]	80% accuracy is 1.09m in office	Propose a backward sequences matching algorithm to optimize HMM.
			[273]	2.07m in office	Fuse measurements of smartphone sensor with wireless signals.
			[51]	75% error reduction in office	Combine WiFi positioning with dead reckoning.
			[70]	One third or one half error reduction	Exploit the Weibull function, the accelerometer sensor, and the HMM based on PF.
KF	(1)Minimum error property; (2)Easy implementation; (3)Low cost and low complexity.	(1)Gaussian distribution assumption needed; (2)Linear requirement.	[48]	$< 1.5\text{m}$ in $20 \times 20\text{m}^2$	Combine WiFi and PDR, RSS recovery, and cluster selection.
			[226]	1m in a lab	Combine WiFi, PDR, and landmarks.
			[277]	$< 1\text{m}$ in a corridor	Fuse PDR, BLE modules.
			[82]	23% ~ 25% improvement	Fuse WiFi, BLE, and PDR.
			[179]	1.35m in $60 \times 20\text{m}^2$	A tight KF-based INS/RFID integration.
			[8]	Perform better in a room	Fuse inertial measurement unit and impulse-based UWB localization.
EKF	(1)Non-linear; (2)Non-Gaussian.	(1)System is almost linearly required; (2)Heavy computational burden.	[84]	3.2m in a office	Adopt the strengths of model-based methods to a heterogeneous distributed and networked systems.
			[49]	0.57m in a corridor	Propose an adaptive step detection based on time window and dynamic threshold.
			[85]	1.70m in 1100m^2	Propose a crowdsourcing and multisources fusion-based fingerprints sensing.
			[86]	1.28m in $25.0 \times 17.0\text{m}^2$	Apply iBeacon to calibrate the drift of the PDR approach.
			[14]	Perform robust in $10 \times 12\text{m}^2$	Utilize a self-built ultrasonic transmitter and a receiver.
			[186]	0.5904m	Propose a constrained EKF based on sensor fusion.
PF	(1)Non-linear; (2)Non-Gaussian; (3)High accuracy; (4)Arbitrary probability can be described.	(1)High computational complexity; (2)Particles cannot converge in a highly free situation; (3)Difficult to implement.	[87]	50% error reduction	Implement WiFi integration based on a fast version of mixture PF.
			[276]	0.35m in $21 \times 18\text{m}^2$	Present a dynamic interval PF algorithm based on PDR information and RSSI.
			[88]	$30 \times 35\text{m}^2$	A single-hidden layer feed-forward networks to model the probabilistic estimations.
			[39]	4.30m in office	Combine WlAN positioning, MEMS accelerometer, and map information.
			[144]	1.53m in $40 \times 40\text{m}^2$	Propose a self localization structure based on KF and PF.
			[38]	1.6m in 380m^2	Optimally select the fusion strategy according to the identified smartphone status.
			[89]	80% accuracy is 2m in $87.4 \times 50\text{m}^2$	Adopt the localization information from signals, camera, and IMU.
			[90]	91% accuracy is 1.34m	Design a context-aware PF framework using geomagnetic and visual sensing.
			[26]	87.3% accuracy in $90 \times 50\text{m}^2$	Fuse WiFi, magnetic fingerprints, image, and people co-occurrence.
			[174]	1.4m in floor	A real-time PF was presented for 2D and 3D hybrid indoor positioning.
			[219]	90% accuracy is 3.5m	Design a two-pass bidirectional PF process.

Weights Space

Weights Space

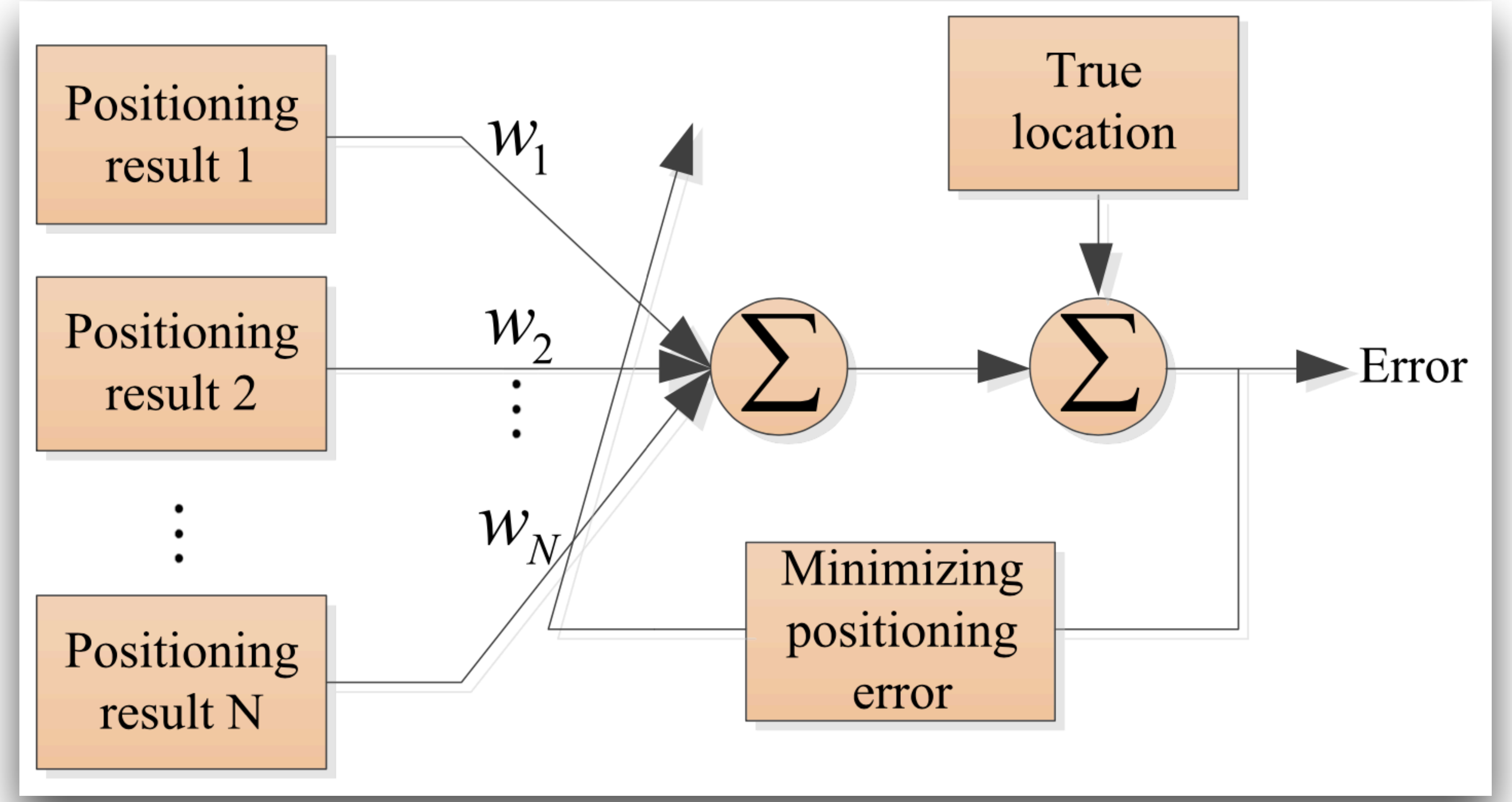
- Given a set of location estimates $\{z_{11}, z_{12}, \ldots, z_{MN}\}$ obtained from multiple sources or multiple algorithms and $z_{mn} = f_n(s_m)$ denotes the location estimate obtained from the m-th measurement by using the n-th algorithm
- These results are then combined/weighed (w)

$$\hat{\boldsymbol{x}} = \sum_{m=1}^{M} \sum_{n=1}^{N} w_{mn} \boldsymbol{z}_{mn}$$

- Key problem: achieve good fusion performances by selecting optimal weights
- Mining the weights is a critical issue in fusion-based positioning
- Strategies to acquire weights
  - supervised learning: attempts to learn the weights by using the labeled data in the offline phase
  - unsupervised learning: learns the weights by using online data directly

WEIGHTS SPACE - Supervised Weights Learning

- How to estimate the performance of different algorithms to obtain reasonable weights when training data are available
- Two key components in supervised weights learning
  - Weights Learning Methods
    - Minimization of the positioning errors
    - Maximization of the source efficiency
  - Weights Selection Methods
    - Select the weights based on the average of the outputs of multiple algorithms
    - Select the weights of the grid predicted by the best algorithm



WEIGHTS SPACE - Unsupervised Weights Learning

- Exploits the online measurements to calculate the weights
- More robust to changing environments as compared with supervised weights learning
- There are two typical methods:
  - *Conventional Unsupervised Weights Learning*:
    - It learns the weights by some rules, such as Best Linear Unbiased Estimate (BLUE) and Majority Voting
  - *Truth Discovery Methods*:
    - It is a data mining method used in text classification and other big data applications
    - Find the most credible positioning result among the multiple candidate positioning results

WEIGHTS SPACE - Unsupervised Weights Learning

SUMMARY AND COMPARISON OF WEIGHTS SPACE

Learning Mechanisms	References	Training Rules	Matching Rules	Fused		Weights Characteristics		Environment		Reported Mean Errors	Limitations
				Sources	Algorithms	Adaptability	Weights Dependency	Range	Complexity		
Supervised	[41]	Minimize positioning errors	Signal difference	RSS	Bayesian, NN	Fixed	Region-dependent	Campus	LOS	19.28% ~ 27.78% errors reduction	Optimizes the weights sequentially, sensitive to signals fluctuations.
	[159]		Optimal classifier and fingerprint selection	RSS, SSD, HLF	Any kind of machine learning method			$1460m^2$	NLOS	2.49m	Robust to signals fluctuations, higher accuracy.
	[31]		Optimal classifier selection	RSS, SSD, HLF	KNN, Random forests, Adaboost, naive Bayesian			$1460m^2$	NLOS	3.4m	Sensitive to signals fluctuations, higher computation complexity required.
	[210]			Any kind of position-based measurement	fingerprints-based method gradient-based search, linear least squares, multidimensional scaling			Lab	NLOS	98.67% error is $< 1.25m$	Sensitive to signal fluctuations, easy to trap in a local optimal.
	[27]		Multiple functions average, optimal function selection	RSS	NN, KNN, Random forests, extreme learning machine			$140m^2$	NLOS	2.55m ~ 2.66m	Sensitive to signals fluctuations, higher computation complexity required.
	[33]		minimize Euclidean distance	power spectral density	KNN,Random forests, extreme learning machine		Both region-independent and dependent	$70 \times 70cm^2$	LOS	88.78% error is $< 5cm$	Sensitive to signals fluctuations.
	[278]	Maximize APs usefulness	N/A	Selected Aps	ensemble learning		Region-independent	$29.8 \times 16.3m^2$	NLOS	2.14m	Affected by the performance of weak APs.
	[44]	Minimize mean square error		RSS	KNN triangulation, smallest M-vertex polygon			$38.83 \times 25.60m^2$	NLOS	1.6m	Consider the performance of each network independently.

SUMMARY AND COMPARISON OF WEIGHTS SPACE

Learning Mechanisms	References	Training Rules	Matching Rules	Fused		Weights Characteristics		Environment		Reported Mean Errors	Limitations
				Sources	Algorithms	Adaptability	Weights Dependency	Range	Complexity		
Unsupervised	[280]	Minimize signal difference		fingerprints, mutual distances	Convex optimization	Dynamic		Campus	LOS	40% accuracy improvement	Higher computation complexity required.
	[34]	Maximize algorithms contributions		RSS	ML, KNN, NN, distance model			$4 \times 6m^2$	N/A	0.96m	Higher computation complexity and memory required.
	[32]	Minimize exponential loss		RSS, covariance matrix, signal subspace, fractional low-order moment and fourth-order cumulant	MUltiple Classifiers mUltiple Samples (MUCUS) fusion			$9.8 \times 6.3m^2$	NLOS	0.3153m	Limited by the small fusion space.
	[28]	Minimize entropy		RSS, covariance matrix, signal subspace, power spectral density, fractional low-order moment and fourth-order cumulant	A sliding window aided mode-based (SWIM) fusion			$9.8 \times 6.3m^2$	NLOS	Performs robust	Require the classifiers as accurate as possible.
	[50], [281]	Minimize signal difference		fingerprints, mutual distances	convex optimization			Airport, atrium	NLOS	30% accuracy improvement	Only consider the step length, computationally expensive.
	[30]	Minimize localization error		RSS	KNN, SVM, logistic regression			$73 \times 20m^2$	NLOS	2.60m	Ignore the confidence level of each classifier.

Challenges

Challenges

- Issues that limit the adoption of fusion-based positioning
  - Positioning Accuracy of Single Network
  - Positioning Cost
  - Fusion Efficiency
  - Fusing Data From Diverse Networks

Reference

Reference

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