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Direction finding in sensors model based automatic modulation classification

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ABSTRACT

In this paper, the RSSI testing as well the Angle of Arrival (AoA) have been examined for position prediction also produce the front specified composition of the possibility distribution of the location of a sensor node. "Multiple Signal Classification" (MUSIC) defined as a popular "Eigen" construction approach with large declaration, which broadly utilized for predicting the total of waveforms, as well their corners of arrival. In this research an examination of the ability to development of part of key specifications of the "MUSIC" technique has been presented, which might improve the response of the prediction operation. The outcomes of the simulation of this approach point out that the position of the sensor node may be evaluated in a little time period values as well that the condition of the explanation is competitive beside last techniques.

Keywords: Sensors, Angle of Arrival, Multiple Signal Classification, Eigen, Direction Finding

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1. Introduction

The primary aim of a localization algorithm is to decide the location of a node. However, such conditions must be fulfilled by the algorithm in order for it to be useful. The parameters are normally defined by the form of the application for which the "localization algorithm" is intended. The following are the general architecture goals or optimal features of an ideal localization algorithm [1]: RF-based localization algorithms are particularly desirable. A short-range RF transmitter is installed into the sensor nodes. In addition to its primary function of data transmission, an effective localization algorithm allows use of this radio capability for localization. The essence of a "wireless sensor network is ad hoc". The ad hoc design of the network should be considered by the localization algorithm. The nodes must be capable to decide their location in as little time as possible, enabling the "localization algorithm" to react rapidly. This will allow for the rapid deployment of sensor nodes. The location of the sensor node calculated via such technique must be precise sufficient for the implementation for which it is being utilized. The technique should be stable in order to work under unfavorable constraints. The technique must be flexible, so that even if sensor nodes are inserted or withdrawn, it can always determine the location of the nodes. Additionally, the technique can yield satisfactory outcomes for sensor structure with a limited to large number of nodes. Since sensor nodes are self-ruling also typically do not have an exterior origin of electricity, the localization algorithm should be energy effective and, ideally, energy conscious. Beacon nodes that are accessible In general, a localization algorithm can calculate more reliable estimates of node locations with a larger number of beacon nodes. The technique must be effective enough to calculate node positions with the fewest number of beacon nodes available. The technique must be uniform such that it can calculate node positions in a number of evolving ecosystems and weather conditions. It can, in fact, function in both confined also unconstrained settings, such as indoors and outdoors. Just an optimal "localization algorithm" would be capable to achieve any of the previous objectives. In reality, localization algorithms can only satisfy a subset of these requirements, based on the application for which they are built.

1.1. Distance estimation

Range-based algorithms perform an essential role called distance estimation between two nodes. A distance-dependent technique calculates the location of a sensor node using range knowledge among the nodes, that has been determined utilizing part of physically systematic variety. The distances among dumb nodes also beacon nodes are typically computed through attaching an extra hardware to the nodes, or by utilizing the sensor nodes' current radio contact facility. The disparity between dumb and beacon nodes influences many aspects of wireless contact among them. When such features are multitude also calculated at the receipting sensor node, the range among the nodes may be determined. The following features are widely used for this purpose:

1. "Received Signal Intensity Indicator ("RSSI")
2. "Angle of Arrival" ("AoA")
3. "Time of Arrival" ("ToA")
4. "Time Difference of Arrival" ("TDoA")

Modulation classification is a method where modulation type is determined without prior knowledge. This would support the convergence of various communications devices. This will involve getting the signal in real time instead of doing demodulation and de-multiplexing after the signal was collected. Software-defined radio would benefit from this kind of capability because the transmitter and receiver would no longer need to agree on a specific modulation scheme beforehand. Blind Modulation Classification had important publications in the field due to the advantages it offers. There is no widespread consensus which ways of producing music to be regarded. Within the same family, there are innumerable variances and nuances [1].

By and large, the "WSN" area methods might be characterized into two classifications, that is, without range and reach based localization. Solidly talking, sans range localization can gauge the general distance by thinking about the internode availability and the organization geography relationship. Contrasted and reach free localization, the reach-based localization claims higher exactness. There are some regular reach-based methodologies, like season of appearance ("TOA") [7], time distinction of appearance ("TDOA") [8], point of appearance ("AOA") [9, 10], and got signal strength sign ("RSSI") [12]. Among them, "TOA", "TDOA", and "AOA" strategies have high precision, yet they require complex equipment and extra energy utilization. The "RSSI"-based technique uses the data given by radio recurrence ("RF") contraption, and needn't bother with extra expense [14]. Subsequently, "WSN" frameworks are adept to embrace the "RSSI"-based techniques to gauge the area of sensor hubs

The remainder of the paper is organized accordingly. The latest related work is seen in section 2. The detailed process of the proposed "QIGA" algorithm is given in Section 3. Section 4 presents the findings of the experiments and their discussion. We end this paper in Section 5.
There are a few researches zeroed in on considering the "RSSI"-based area issues from alternate points of view. For instance, Kumar et al. received "RSSI"-based area method to appraise the internode distances which further utilized for assessing the hubs' area [20]. They reasoned that the distance-assessed blunder for RSSI based area conspire in WSN is generally indistinguishable under ideal sending conditions. Awad et al. proposed a distance-based area strategy in WSN dependent on RSSI estimations [21] and tracked down that the principal impact on the distance estimations is the force transmission. Alippi and Vanini proposed a RSSI-based incorporated area procedure for open air conditions and tracked down that this methodology is the least demanding executed path in "RSSI"-based multihop area frameworks [22]. Subaashini et al. examined the connection between ZigBee sensor hub's "RSSI" esteems and the general climate particulars for variation kinds of deterrents put among transmitter and beneficiary [23]. They tracked down that some "RSSI" esteem in online stage has not been fingerprinted in the preparation stage, and consequently, the area can't be resolved. Adewumi et al. processed the internode distance of a "WSN" depending on "RSSI"-based model and found that the distance-assessed mistake in indoor climate is more noteworthy than that in outside climate [24].

2. Proposed algorithm

"Automatic modulation classification" ("AMC") is an important subject in the digital communication field. However, conventional methods of classification of modulation are not precise enough. In addition, existing GA-based prediction methods suffer from high computing costs, non-convergence to optimal global convergence and premature convergence. In order to eliminate possible errors in the GA-based modulation classification, the systematic QIGA model is sufficient for the modulation classification. This paradigm, which is capable of addressing grouping, without which the diversity of the population continues to steadily vanish and will cause the algorithm to stagnate at the local level.

This section details the proposed quantum-inspired prediction method in automated modulation classification. The input signal includes 10 modulations which are 'BPSK,' 'QPSK,' '8PSK,' '16QAM,' '64QAM,' '256QAM,' '2PAM,' '4PAM,' '8PAM' and '16PAM.' The system adapts GA in order to achieve the optimum modulation classification functions. Figure Figure 2 illustrates the key elements of the current classification scheme and how such elements are related well-adjusted, also the succeeding subsections explain the measures in detail.
Given the randomly signals data set that consists of 10 classes; each sensor will receive the signals and transmit it again to the fusion center. Fusion center will select the best signal according to its signal noise ratio. The features which are extracted from the dataset are "Enhanced Cumulates". These captions are saved in a midmost database together with the headlines classification of each modulation.

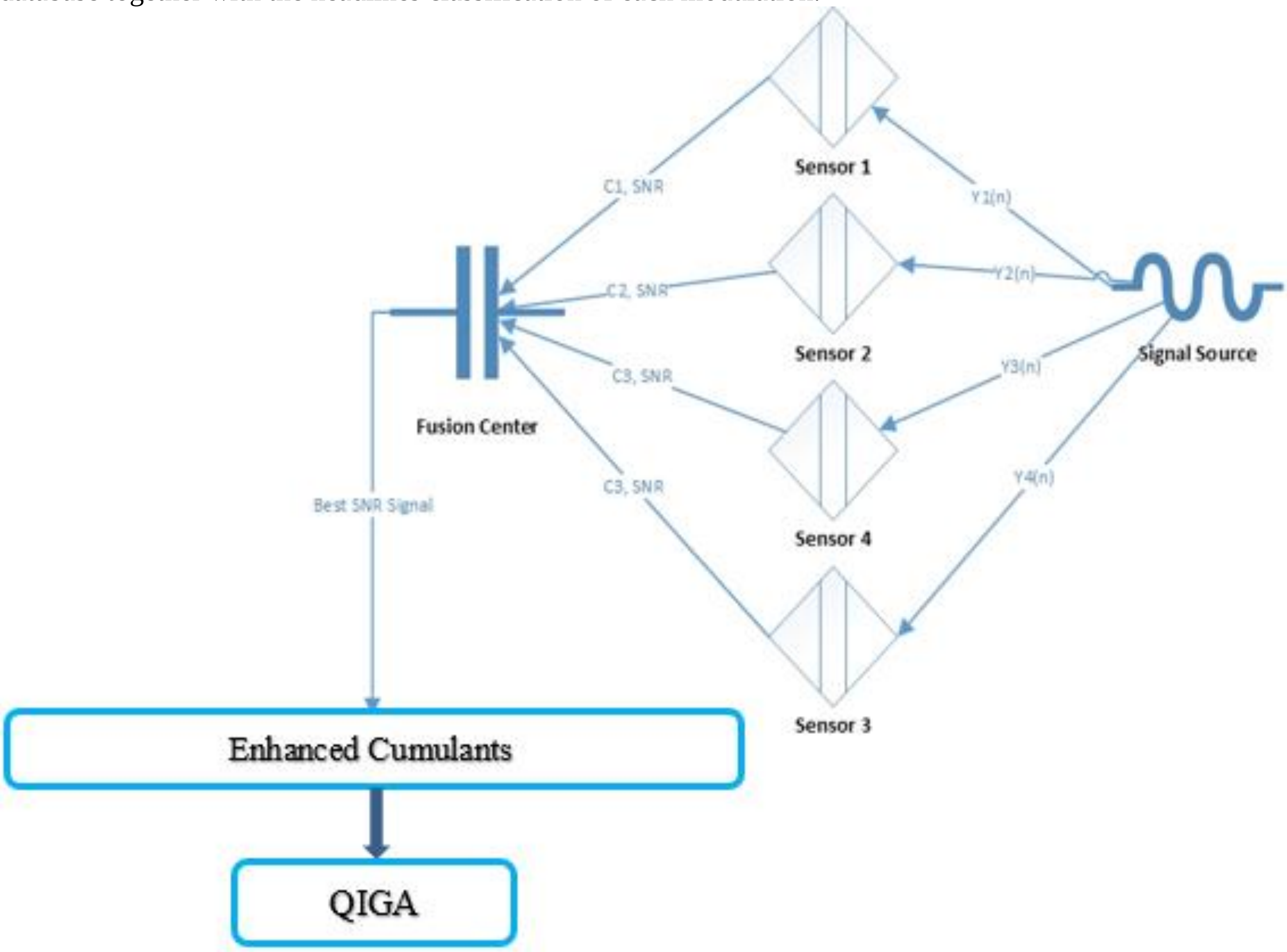


Figure 1. Location and position estimation model

2.1. Position prediction in wireless sensor networks (Time of Arrival and Angle of Arrival)

This distance estimating methodology employs the following relationship, which compares the distance traveled by a signal to the time taken if the speed of propagation is established.

$$d = v \times t$$

where, d is distance, v is speed of the signal and t is time taken by the signal to travel the distance d. Therefore, if the time taken by a signal to propagate from the beacon node to the dumb node, which is called *time of arrival* or *time of flight* is measured and speed of propagation of the signal is known, the distance and hence position of the dumb node can be calculated. "Signal-to-Noise" ratio "SNR" is that value used in communications as well analysis which looks at the peak of an optimal waveform to the clamor value. "SNR" is represented as the ratio of the force of a sign (significant contribution) to the force of foundation commotion (futile or undesirable info):

$$\mathrm{SNR}=P_{signal}/P_{noise}$$

where P is normal force. Both sign and commotion power should be estimated at something very similar or identical focuses in a framework, and inside a similar framework data transmission
For estimating its location, the orientation of incoming of the waveform at the stupid node might further be utilized. The location of a detected wave may be measured by the angle of reference or inclination it produces. The angle between the stupid node and the phone node may be calculated instead. The angles of arrival of at least three light nodes are calculated for the position of a stupid node with this technique. The positioning of a dumb node may be estimated using position knowledge from three or more beacon nodes coupled with the three arrival angles.

The arrival angle may be determined by means of directional antennas, a special antenna array arrangement or a mixture of them. These may be installed on the beacon nodes by means of directional antennas. A directional antenna on a beacon node rotates around its axis and hence transmissions light signals in both directions to support several stubborn nodes. A stupid node will use the antenna setup in a similar path to transmit beacon signals. Otherwise, stupid nodes can often be used to obtain and calculate the arrival angle of a lightning signal with unique antenna array setups. As an antenna array is used, an established separation is imposed in the array. To predict the position of the signal arrived, the time delay for the arrival of the wave front at various antennas [12].

Due to the difficulty of deploying special antennas, realistic application of this strategy is restricted. For e.g., it is difficult to install rotating directional antennas on small nodes, also the revolving part is much susceptible to failure. In the same way, antennas in the array should be positioned apart by a particular range if an antenna array arrangement is used, that is also a hard suggestion given the small sizes of sensor nodes. In comparison, a higher precision is obtained only where the distance between the antennas is limited in the series. But more complicated and precision hardware is required for the calculation of period variance with less separation size [12].

An estimate of the "angle of arrival" ("AOA") is the mechanism by which the path of the input signal from the dispatchers to sensors is calculated. The procedure for estimating the pseudo spectrum PMU (θ) historically is used. The role may also be identified by many possible approaches: "beam forming, array correlation matrix, Eigen analysis, linear prediction, minimum variance, maximum likelihood, MUSIC, root-MUSIC", as well several alter techniques.

2.2. MUSIC algorithm

MUSIC manages the disintegration of "correlation matrix" into double symmetrical grids, signal-subspace and commotion subspace. Assessment of course is implemented using either of such subspaces", accepting that clamor in each channel is exceptionally uncorrelated. This causes the "correlation matrix" diagonal. In this context, "MUSIC" discusses the breakdown of the "correlation matrix" to two orthogonal matrices, signal subspace and noise "subspace". Path prediction is carried out from each of these ""subspaces", provided that noise is strongly uncorrelated in each channel medium. Then, as seen in the flow chart in Figure 3, we will summarize previous measures to approximate "AOA" with "MUSIC". See [30] [16] for more information. Table 3 illustrates the used "MUSIC" parameters.

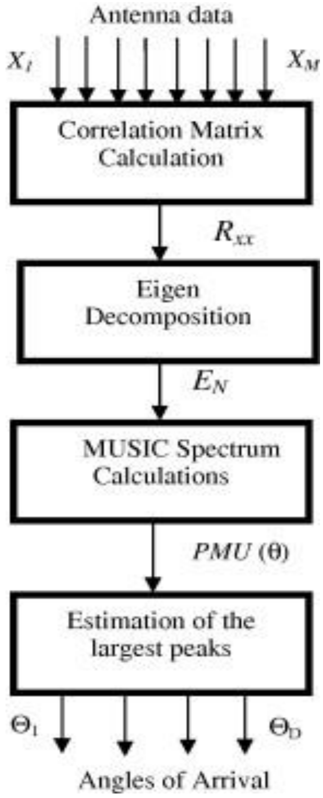


Figure 2. "MUSIC" implementation flow chart [42]

Table 2. MUSIC parameters

Parameter	Default Value
Number of Elements M	10 Antennas/ Sensor
Phase of the antenna 1 ϕ_1	Random Number n^o (0^o-90^o)
Phase of the antenna n ϕ_2	68^o
Element Spacing “Space between 2 antennas” d	1 Meter
Wavelength λ	2* Element Spacing =2M
Frequency	Light Speed / Wavelength λ=*150 MHz*
Distance Between Sender and Receiver	Random from100m to 10 km

2.3. Quantum genetic algorithm figure

As of late, in "Quantum Inspired Genetic Algorithm" ("QIGA"), the Q-bit portrayal was received for lowest issues dependent on the idea and guideline of quantum processing. The attribute of the portrayal is that any straight superposition can be addressed. The littlest unit of data put away in a two-state quantum PC is known as a Q-bit, which might be in the "1" state, or in the "0" state, or in any superposition of the two. The condition of a Q-spot can be addressed as follows:

$$|\psi_s\rangle = \gamma|0\rangle + \beta|1\rangle \quad (1)$$

So that α with β defined as "complex" values which decide the possibility capacities of the analogous phases. $|\gamma|^2$ with $|\beta|^2$ represent the possibility which makes the Q-bit to be evaluated in the “1” phase as well “0” phase, respectively. Normalization of the phase to the unity assures:

$$|\gamma_1|^2 + |\beta_2|^2 = 1 \tag{2}$$

2.4. Received signal strength

"Received signal strength" ("RSS") is prescribed as the potential tested via a "received signal strength indicator" ("RSSI") circuitry. Frequently, "RSS" is equally detailed as estimated power, i.e., the squared extent of the sign strength. The "RSS" of acoustic, "RF", or different signs can be thought of. Remote sensors speak with adjoining sensors, and "RSS" of "RF" signs can be estimated by every beneficiary during ordinary information correspondence, without introducing extra transmission capacity or energy necessities. Since RSS estimations are moderately economical and easy to execute in equipment, they are a significant and well known subject of localization research. However, "RSS" estimations are famously eccentric. On the off chance that they are to be helpful and part of a powerful localization framework, their wellsprings of blunder should be surely known [21].

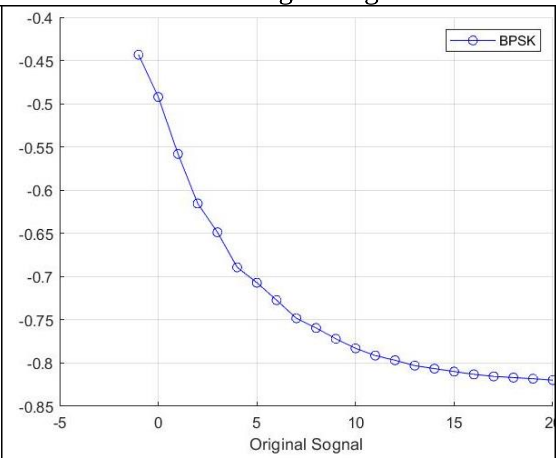
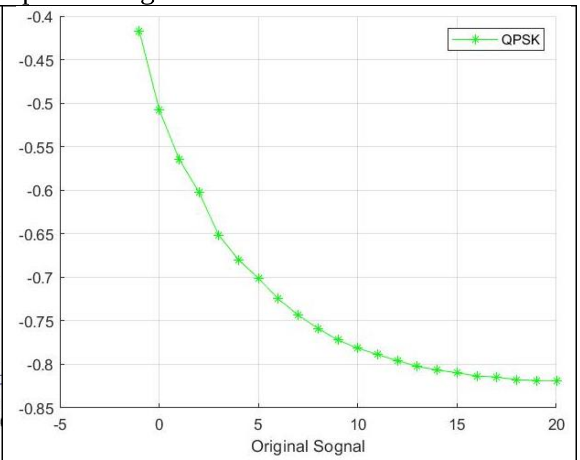
2.5. Angle-of-Arrival

Pragmatic utilization of this procedure is restricted because of the intricacies of arrangement of extraordinary radio wires. For instance, mounting pivoting directional receiving wires on small hubs is tricky and the turning parts are more inclined to disappointment. Also, if a radio wire exhibit arrangement is utilized, receiving wires in the cluster should be put explicit distance separated which is again a troublesome recommendation thinking about the small sizes of sensor hubs. Additionally, a more noteworthy exactness of point estimation is accomplished just when detachment distance between receiving wires in the exhibit is little. In any case, with more modest partition distance, more refined and exact equipment is required for time contrast estimations. Besides, shadowing, multipath blurring and non-view conditions present a lot of blunder in the assessed position which is more than same sort of mistakes in other comparable strategies for example "RSSI", "ToA" and "TDoA". Because of these reasons, point of appearance is thought about to a lesser degree a decision for localization in sensor networks [22] [16].

3. Simulation result and analysis

This portion validates the performance of the proposed method by conducting a series of experiments. Furthermore, the output is contrasted with the standard genetic algorithm in order to determine the precision of the classification of the proposed solution. Many separate modulation databases may be used to assess the feasibility of the proposed model. Genetic Function Approximation (GFA) algorithm provides a new solution to the AMC problem. Unlike most other research algorithms, GFA offers multiple models where model populations are generated by the evolution of random initial models using a genetic algorithm.
The framework is introduced in the form of a MATLAB library built to be simple for utilized in traditional implementations. Tests was carried out on a computer with Intel(R) Zeon(R) CPU E5430@ 2.66GHz (2 processor), 16GB RAM PC operating Microsoft Windows 10-64 bit. The findings of the simulation approve the potential of the proposed technique to obtain a detailed classification of modulation.

Table 7. Original signals vs different paths using 4 sensors

Original Signal		

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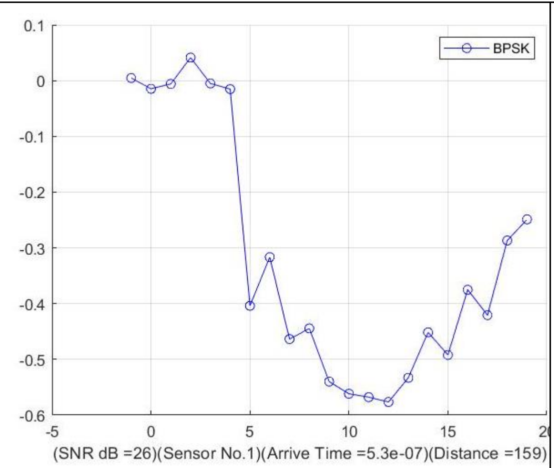

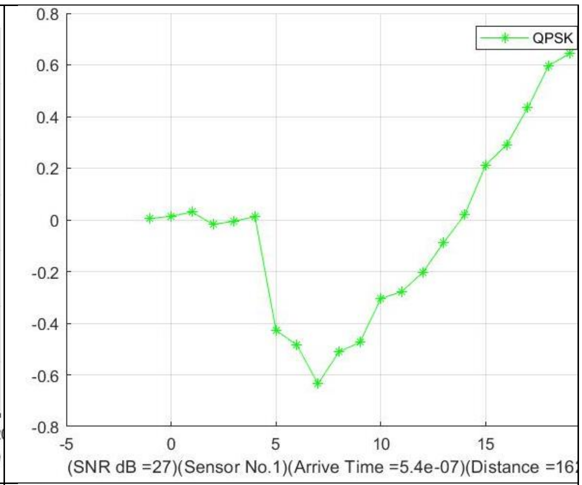

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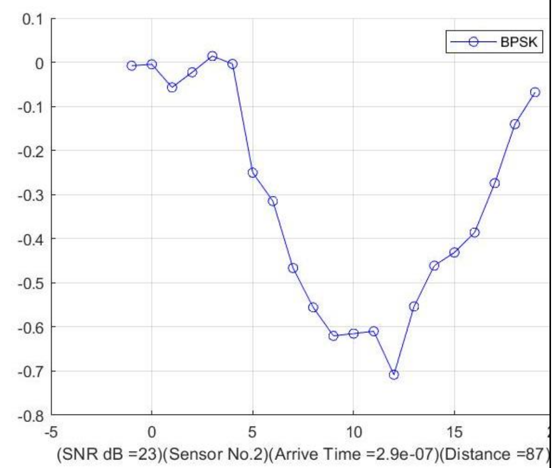

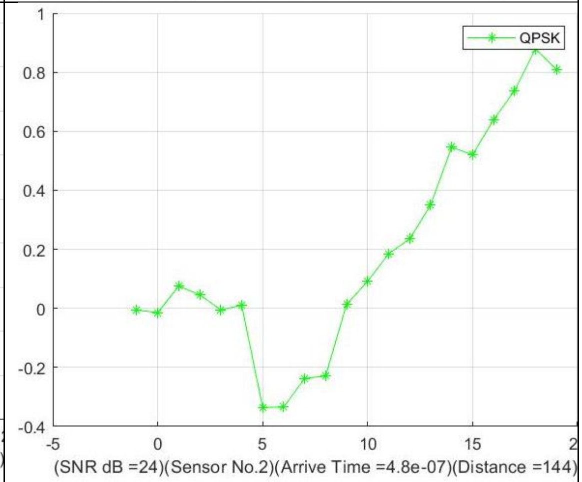

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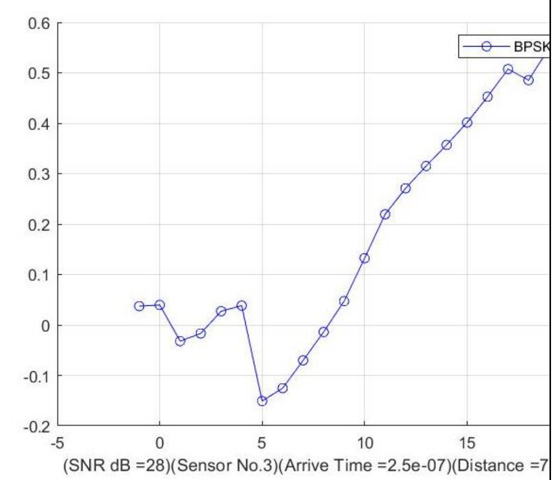

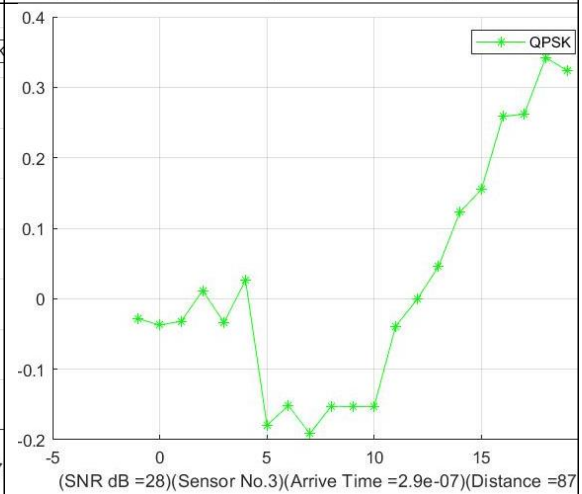

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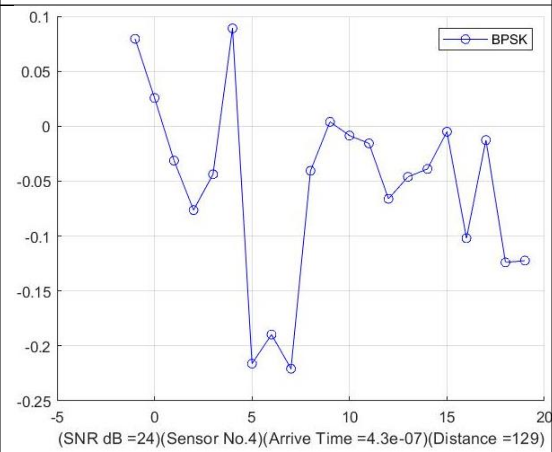

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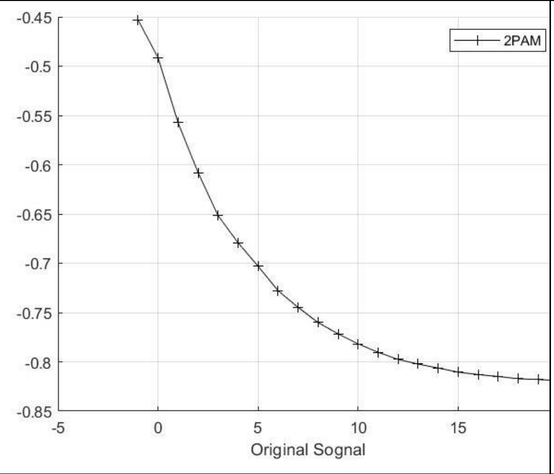
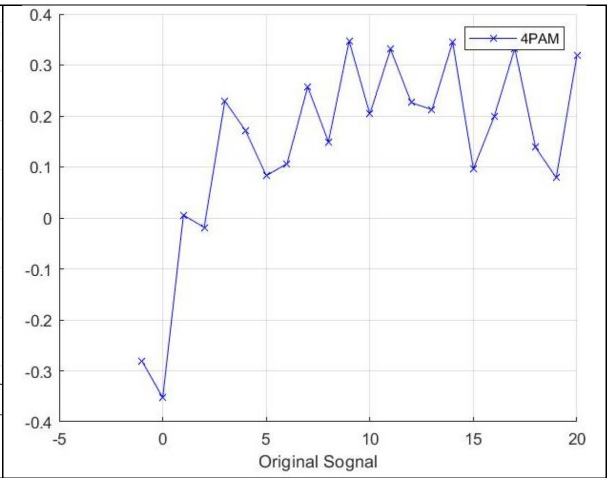
<tr><td>Original Signal</td><td>
</td><td>
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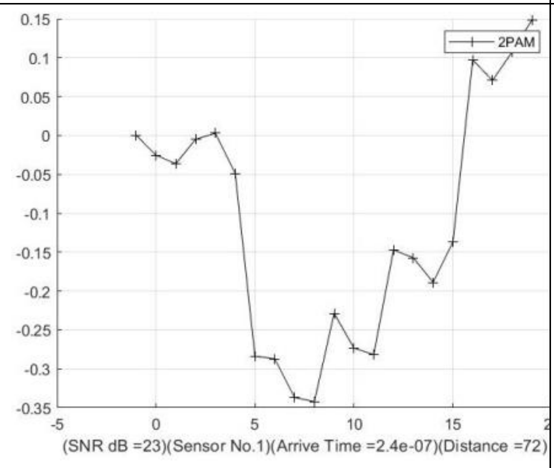
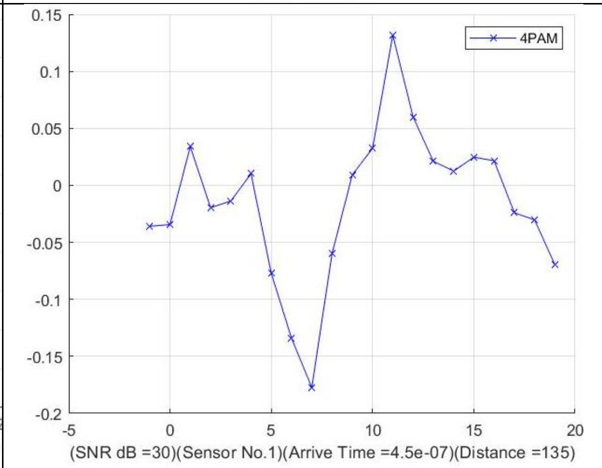
<tr><td>Sensor 1</td><td>
</td><td>
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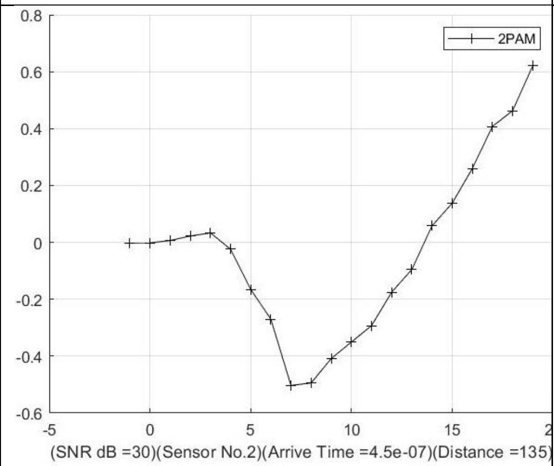
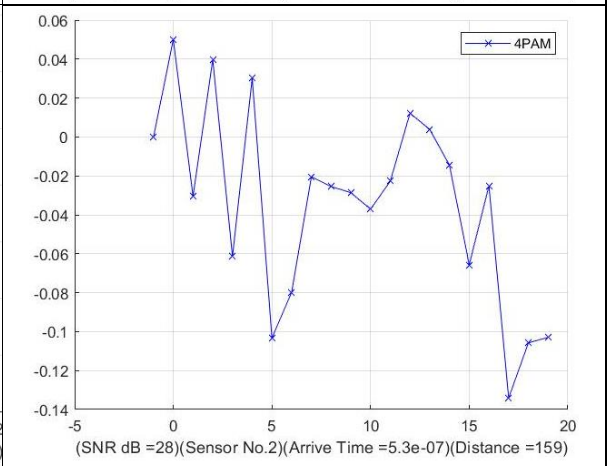
<tr><td>Sensor 2</td><td>
</td><td>
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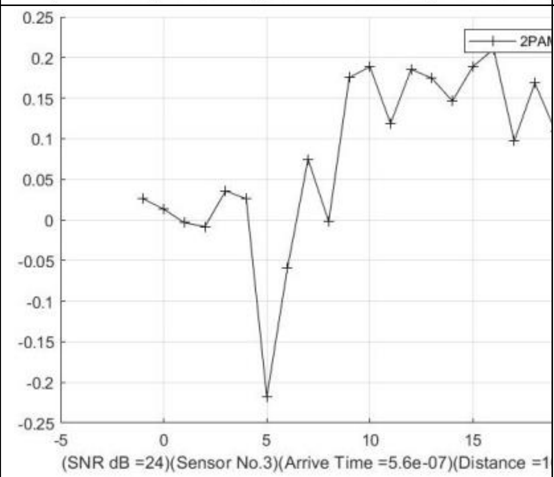
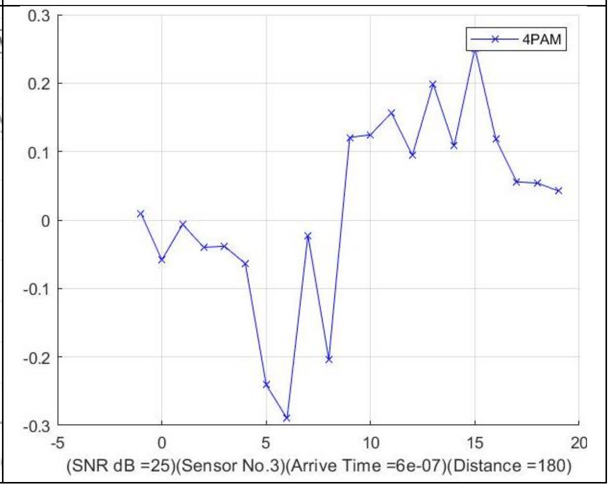
<tr><td>Sensor 3</td><td>
</td><td>
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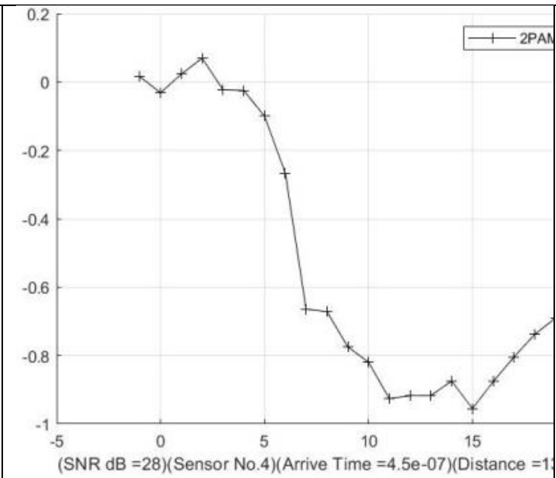
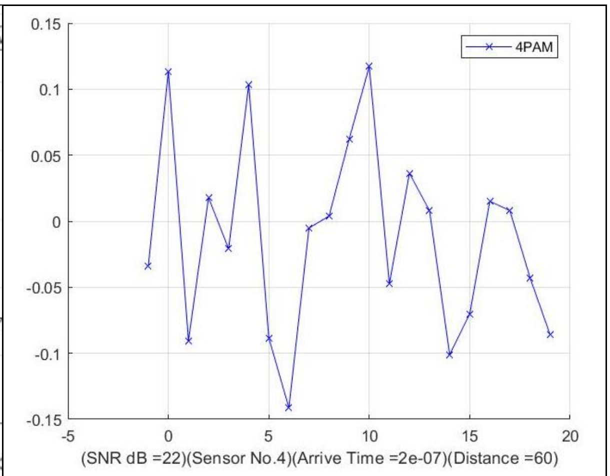
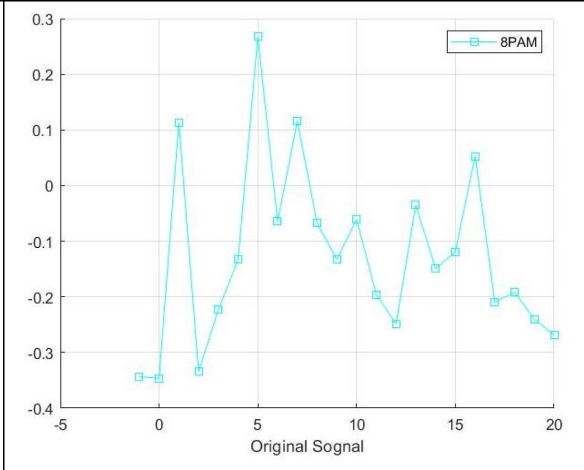
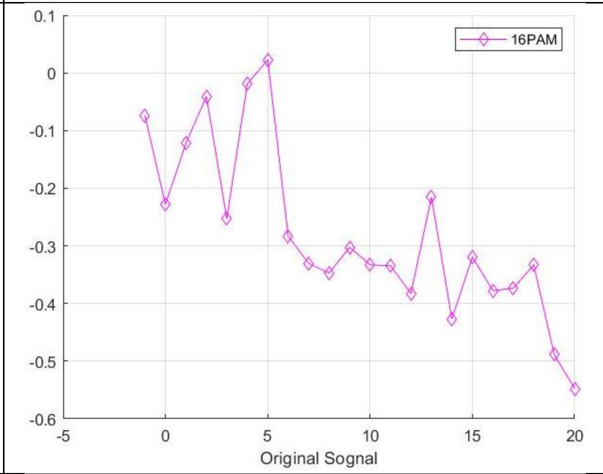
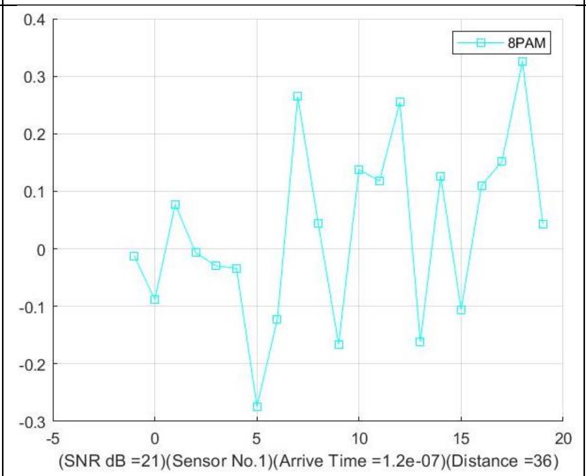
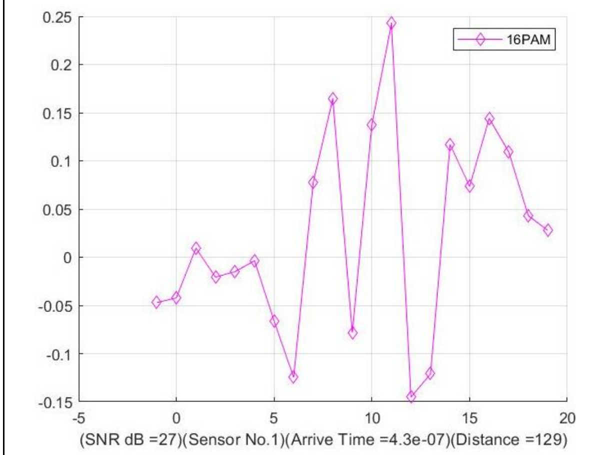
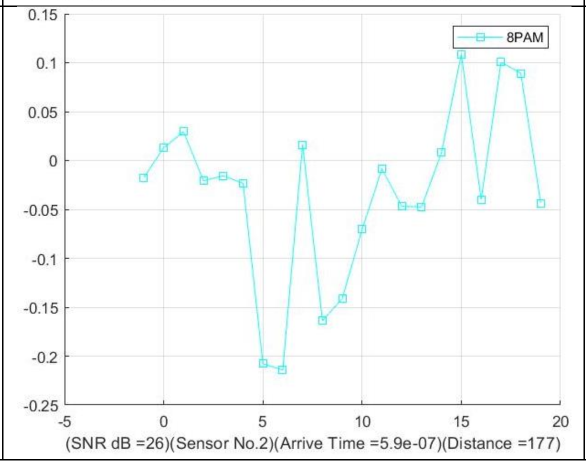
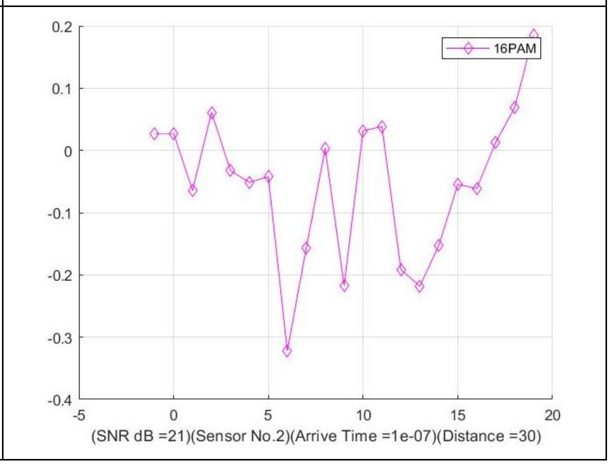
Sensor 4		
Original Signal		
Sensor 1		
Sensor 2		

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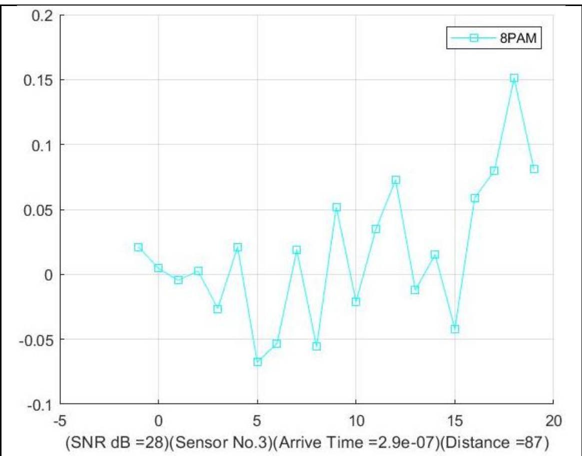

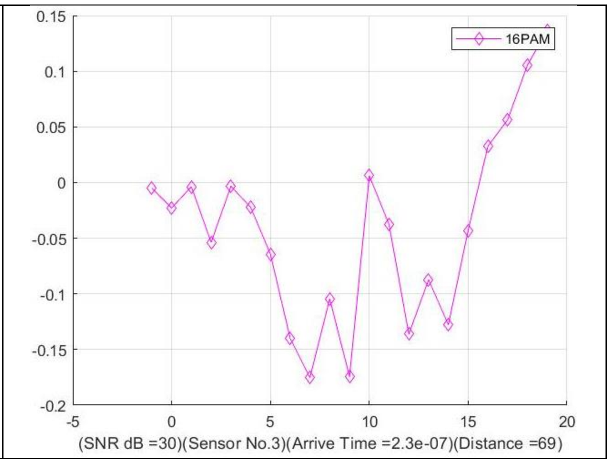

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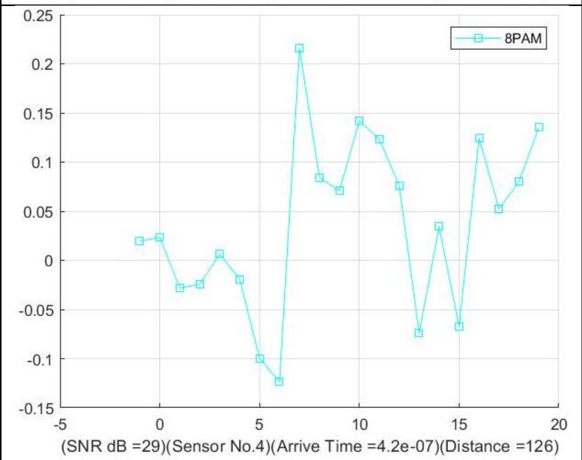

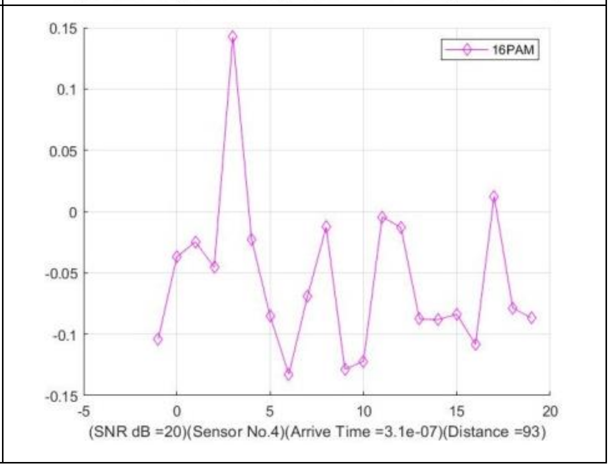

Table 8. SNR values by increasing sensors

Signal	Sensors									
	1	2	3	4	5	6	7	8	9	10
BPSK	14.053	14.053	17.557	18.649	18.649	21.396	21.396	21.396	21.396	21.396
QPSK	13.890	13.890	17.237	18.268	18.268	20.837	20.837	20.837	20.837	20.837
8PSK	14.409	14.409	17.980	19.099	19.099	21.937	21.937	21.937	21.9372	21.937
16QAM	8.9822	8.9822	10.877	11.406	11.406	12.666	12.666	12.666	12.665	12.666
64QAM	17.811	17.811	21.47	21.735	21.735	31.959	31.959	31.959	31.952	31.959
256QAM	16.658	16.658	17.771	18.037	18.037	27.132	27.132	27.132	27.133	27.132
2PAM	13.450	13.450	17.500	18.586	18.586	21.325	21.325	21.325	21.327	21.325
4PAM	4.8682	5.0855	5.0855	5.0855	5.0855	5.0855	5.1021	5.1021	5.1021	5.1021
8PAM	1.2137	1.2137	1.389	1.4338	1.4338	1.5277	1.5277	1.5277	1.5276	1.5277
16PAM	2.4435	2.4435	3.0419	3.0419	3.0419	3.0419	3.0419	3.0419	3.0418	3.1236

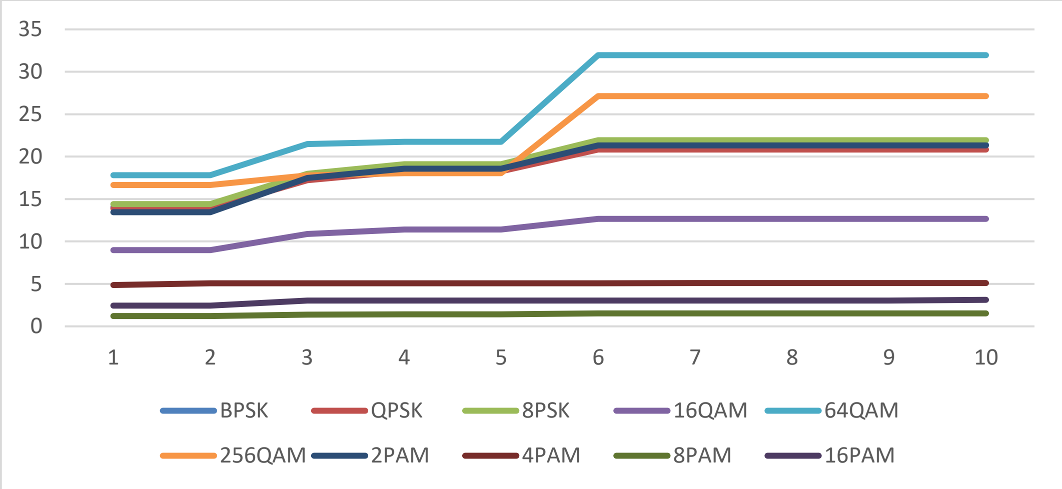

Figure 9. Representing of Table 7 data

Table 9. SNR, time and distance in case of 1 sensor

	SNR (dB)	Node	Time Second	Distance KM	AoA°	RSSI (dB)
BPSK	14.05342	1	2.03E-08	6.1	41	0.502432
QPSK	13.89059	1	2.03E-08	6.1	41	0.546856
8PSK	14.40987	1	2.03E-08	6.1	41	0.406377
16QAM	8.982277	1	2.03E-08	6.1	41	0.349403
64QAM	17.81198	1	2.03E-08	6.1	41	0.439594
256QAM	16.65886	1	2.03E-08	6.1	41	0.536495
2PAM	13.45064	1	2.03E-08	6.1	41	0.575998
4PAM	4.868291	1	2.03E-08	6.1	41	0.610568
8PAM	1.213729	1	2.03E-08	6.1	41	0.543049
16PAM	2.443565	1	2.03E-08	6.1	41	0.507777

Table 10. SNR, Node Number Time and Distance in case of 2 Sensors.

	SNR (dB)	Node	Time Second	Distance KM	AoA°	RSSI (dB)
BPSK	14.05342	1	2.03E-08	6.1	41	0.502432
QPSK	13.89059	1	2.03E-08	6.1	41	0.546856
8PSK	14.40987	1	2.03E-08	6.1	41	0.406377
16QAM	8.982277	1	2.03E-08	6.1	41	0.349403
64QAM	17.81198	1	2.03E-08	6.1	41	0.439594
256QAM	16.65886	1	2.03E-08	6.1	41	0.536495
2PAM	13.45064	1	2.03E-08	6.1	41	0.575998
4PAM	5.085589	2	3.23E-08	9.7	50	0.624219
8PAM	1.213729	1	2.03E-08	6.1	41	0.543049
16PAM	2.443565	1	2.03E-08	6.1	41	0.507777

Table 11. SNR, node number time and distance in case of 3 sensors

	SNR (dB)	Node	Time Second	Distance KM	AoA°	RSSI (dB)
BPSK	17.5574403	3	9.33E-09	2.8	47	0.505835
QPSK	17.2370514	3	9.33E-09	2.8	47	0.465741

	SNR (dB)	Node	Time Second	Distance KM	AoA°	RSSI (dB)
8PSK	17.9807796	3	9.33E-09	2.8	47	0.502915
16QAM	10.8775082	3	9.33E-09	2.8	47	0.467547
64QAM	21.472103	3	9.33E-09	2.8	47	0.490139
256QAM	17.7711866	3	9.33E-09	2.8	47	0.391207
2PAM	17.5005506	3	9.33E-09	2.8	47	0.407934
4PAM	5.08558889	2	3.23E-08	9.7	50	0.624219
8PAM	1.38945011	3	9.33E-09	2.8	47	0.460131
16PAM	3.04194803	3	9.33E-09	2.8	47	0.480514

Table 12. SNR, node number time and distance in case of 4 sensors

	SNR dB	Node	Time Second	Distance KM	AoA°	RSSI dB
BPSK	18.64908	4	7.33E-09	2.2	45	0.483618
QPSK	18.26875	4	7.33E-09	2.2	45	0.580517
8PSK	19.09976	4	7.33E-09	2.2	45	0.629898
16QAM	11.40679	4	7.33E-09	2.2	46	0.570713
64QAM	21.73553	4	7.33E-09	2.2	45	0.567371
256QAM	18.03784	4	7.33E-09	2.2	45	0.340983
2PAM	18.58646	4	7.33E-09	2.2	45	0.44687
4PAM	5.085589	2	3.23E-08	9.7	50	0.624219
8PAM	1.433891	4	7.33E-09	2.2	45	0.599498
16PAM	3.041948	3	9.33E-09	2.8	47	0.480514

Table 13. SNR, node number time and distance in case of 5 sensors

	SNR (dB)	Node	Time (Second)	Distance (KM)	AoA°	RSSI (dB)
BPSK	18.64908	4	7.33E-09	2.2	45	0.483618
QPSK	18.26875	4	7.33E-09	2.2	46	0.580517
8PSK	19.09976	4	7.33E-09	2.2	45	0.629898
16QAM	11.40679	4	7.33E-09	2.2	45	0.570713
64QAM	21.73553	4	7.33E-09	2.2	45	0.567371
256QAM	18.03784	4	7.33E-09	2.2	45	0.340983
2PAM	18.58646	4	7.33E-09	2.2	45	0.44687
4PAM	5.085589	2	3.23E-08	9.7	50	0.624219
8PAM	1.433891	4	7.33E-09	2.2	45	0.599498
16PAM	3.041948	3	9.33E-09	2.8	47	0.480514

Table 14. SNR, node number time and distance in case of 6 sensors

	SNR dB	Node	Time Second	Distance KM	AoA°	RSSI dB
BPSK	21.396591	6	4.00E-09	1.2	56	0.481151
QPSK	20.8379165	6	4.00E-09	1.2	56	0.541572
8PSK	21.9377248	6	4.00E-09	1.2	56	0.542078
16QAM	12.6668532	6	4.00E-09	1.2	56	0.387887

	SNR dB	Node	Time Second	Distance KM	AoA˚	RSSI dB
64QAM	31.9598151	6	4.00E-09	1.2	56	0.592337
256QAM	27.1325259	6	4.00E-09	1.2	56	0.630504
2PAM	21.3251674	6	4.00E-09	1.2	56	0.437409
4PAM	5.08558889	2	3.23E-08	9.7	50	0.624219
8PAM	1.52770562	6	4.00E-09	1.2	56	0.510891
16PAM	3.04194803	3	9.33E-09	2.8	47	0.480514

Table 15. SNR, node number time and distance in case of 7 sensors

	SNR dB	Node	Time Second	Distance KM	AoA˚	RSSI dB
BPSK	21.39659	6	4.00E-09	1.2	56	0.481151
QPSK	20.83792	6	4.00E-09	1.2	56	0.541572
8PSK	21.93772	6	4.00E-09	1.2	56	0.542078
16QAM	12.66685	6	4.00E-09	1.2	56	0.387887
64QAM	31.95982	6	4.00E-09	1.2	56	0.592337
256QAM	27.13253	6	4.00E-09	1.2	56	0.630504
2PAM	21.32517	6	4.00E-09	1.2	56	0.437409
4PAM	5.102111	7	3.33E-08	10	36	0.449601
8PAM	1.527706	6	4.00E-09	1.2	56	0.510891
16PAM	3.041948	3	9.33E-09	2.8	47	0.480514

Table 16. SNR, node number time and distance in case of 8 sensors

	SNR dB	Node	Time Second	Distance KM	AoA˚	RSSI dB
BPSK	21.39659	6	4.00E-09	1.2	56	0.481151
QPSK	20.83792	6	4.00E-09	1.2	56	0.541572
8PSK	21.93772	6	4.00E-09	1.2	56	0.542078
16QAM	12.66685	6	4.00E-09	1.2	56	0.387887
64QAM	31.95982	6	4.00E-09	1.2	56	0.592337
256QAM	27.13253	6	4.00E-09	1.2	56	0.630504
2PAM	21.32517	6	4.00E-09	1.2	56	0.437409
4PAM	5.102111	7	3.33E-08	10	36	0.449601
8PAM	1.527706	6	4.00E-09	1.2	56	0.510891
16PAM	3.041948	3	9.33E-09	2.8	47	0.480514

Table 17. SNR, node number time and distance in case of 9 sensors

	SNR dB	Node	Time Second	Distance KM	AoA˚	RSSI dB
BPSK	21.396591	6	4.00E-09	1.2	56	0.481151
QPSK	20.8379165	6	4.00E-09	1.2	56	0.541572
8PSK	21.9377248	6	4.00E-09	1.2	56	0.542078
16QAM	12.6668532	6	4.00E-09	1.2	56	0.387887
64QAM	31.9598151	6	4.00E-09	1.2	56	0.592337
256QAM	27.1325259	6	4.00E-09	1.2	56	0.630504

	SNR dB	Node	Time Second	Distance KM	AoA°	RSSI dB
2PAM	21.3251674	6	4.00E-09	1.2	56	0.437409
4PAM	5.10211117	7	3.33E-08	10	36	0.449601
8PAM	1.52770562	6	4.00E-09	1.2	56	0.510891
16PAM	3.04194803	3	9.33E-09	2.8	47	0.480514

Table 18. SNR, node number time and distance in case of 10 sensors

	SNR dB	Node	Time Second	Distance KM	AoA°	RSSI dB
BPSK	21.39659	6	4.00E-09	1.2	56 Figure 10	0.481151
QPSK	20.83792	6	4.00E-09	1.2	56 Figure 10	0.541572
8PSK	21.93772	6	4.00E-09	1.2	56 Figure 10	0.542078
16QAM	12.66685	6	4.00E-09	1.2	56 Figure 10	0.387887
64QAM	31.95982	6	4.00E-09	1.2	56 Figure 10	0.592337
256QAM	27.13253	6	4.00E-09	1.2	56 Figure 10	0.630504
2PAM	21.32517	6	4.00E-09	1.2	56 Figure 10	0.437409
4PAM	5.102111	7	3.33E-08	10	36 Figure 11	0.449601
8PAM	1.527706	6	4.00E-09	1.2	56 Figure 10	0.510891
16PAM	3.123691	10	5.67E-09	1.7	49 Figure 12	0.512696

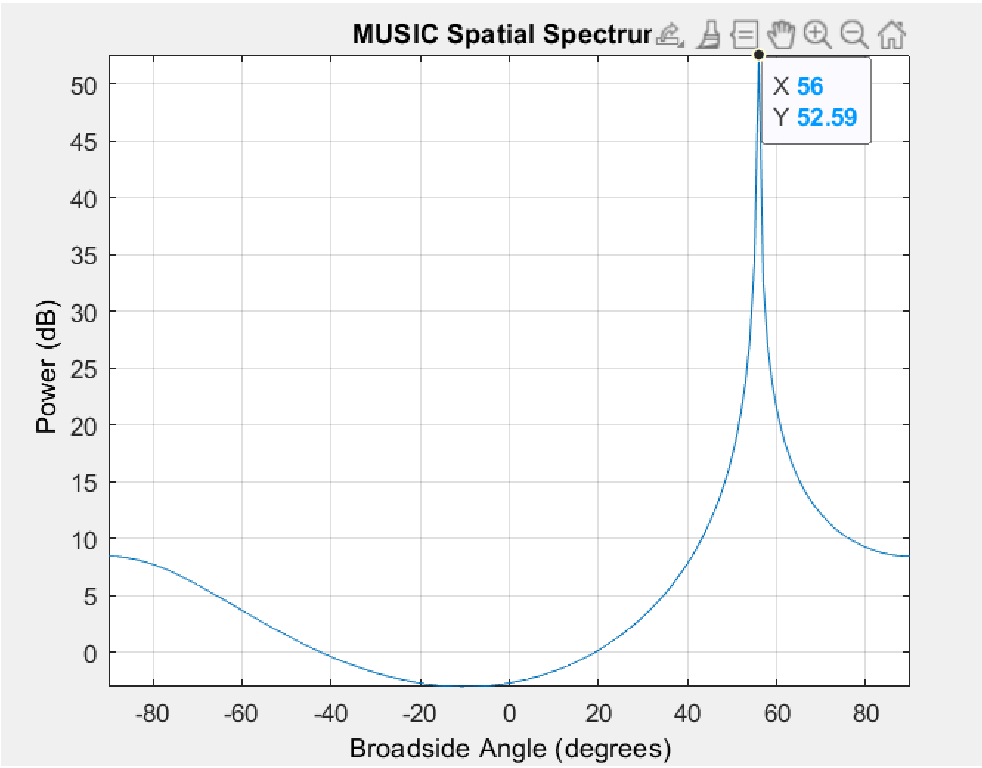

Figure 10. Arrival Angel Measurements of BPSK signals

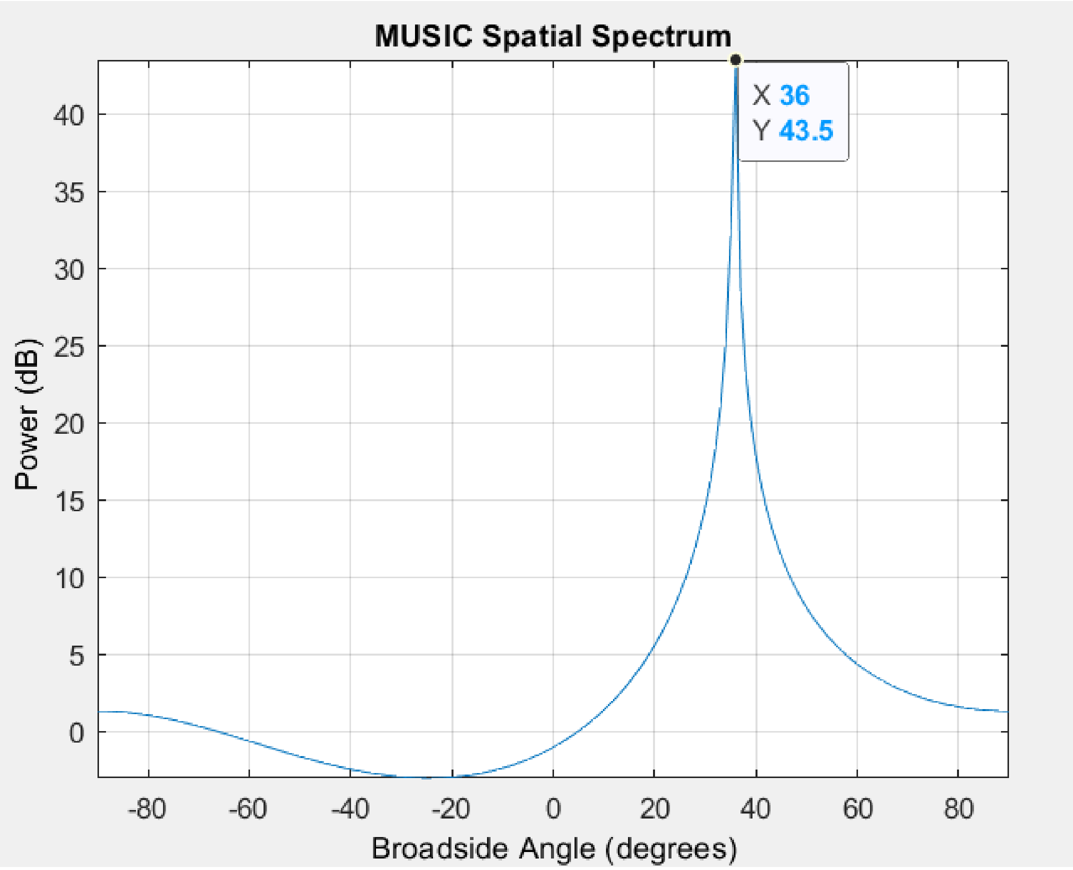

Figure 11. Arrival Angel Measurements of QPSK signals

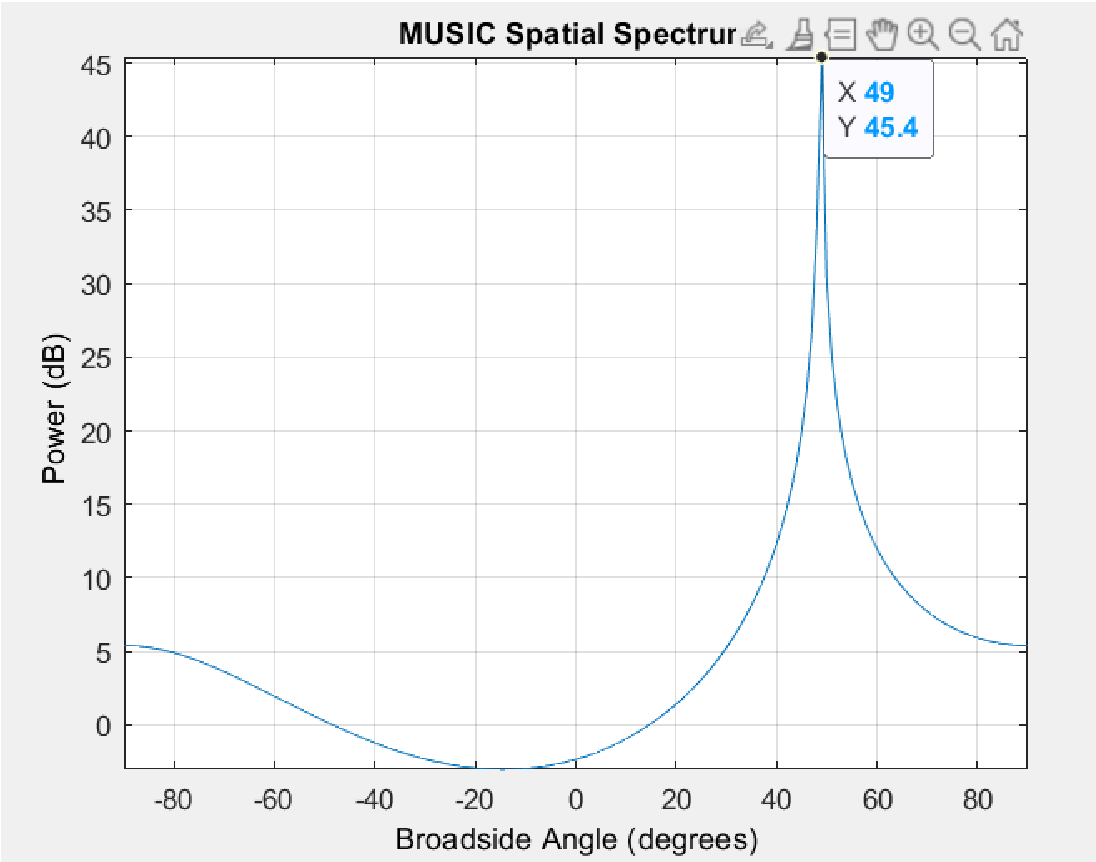

Figure 12. Arrival Angel Measurements of 8PSK signals

Table 19. SNR values by increasing distance

Signal	SNR (Db)	Distance (Km)
16PAM	2.443565	6.1
	3.041948	2.8
	3.123691	1.7
16QAM	8.982277	6.1
	10.87751	2.8
	11.40679	2.2
	12.66685	1.2
256QAM	16.65886	6.1
	17.77119	2.8
	18.03784	2.2
	27.13253	1.2
2PAM	13.45064	6.1
	17.50055	2.8
	18.58646	2.2
	21.32517	1.2
4PAM	4.868291	6.1
	5.085589	9.7
	5.102111	10
64QAM	17.81198	6.1
	21.4721	2.8
	21.73553	2.2
	31.95982	1.2
8PAM	1.213729	6.1
	1.38945	2.8
	1.433891	2.2
	1.527706	1.2
8PSK	14.40987	6.1
	17.98078	2.8
	19.09976	2.2
	21.93772	1.2
BPSK	14.05342	6.1
	17.55744	2.8
	18.64908	2.2
	21.39659	1.2
QPSK	13.89059	6.1
	17.23705	2.8
	18.26875	2.2
	20.83792	1.2

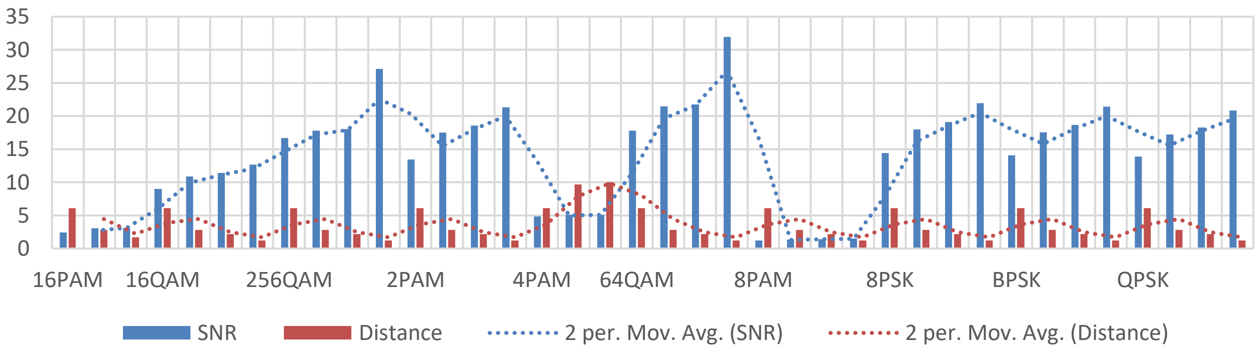

Figure 13. Representing data of Table 19

4. Conclusion

In this work, one must understand that the mentioned techniques illustrate just the essential concepts with algorithms that could be utilized for sensor nodes localization. A full localization implementation as well structure of a workable "wireless sensor network" might be constructed utilizing a composition of such approaches. The essential incitation of here research is the ability of augmentation of weights which may influence the response of "AOA" estimation utilizing "MUSIC" technique. Hence the outcomes might be summated by the following points:

- The response of "MUSIC" enhanced using much components beginning with M = 10.
- As "SNR" ascends, improved precision will be achieved that points to noise free medium.
- The event of such dominant amount of ‘‘d’’ could be blamed to the reduction of the annoying portions of the antenna array at such particular amount of ‘‘d’’, as well thus an ascended precision in the evaluation of the "AOA" is the straight reactions of that dominant amount.
- When increase number of sensors, the accuracy well be best to find location of the transmitter based on sensors .

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