Supplemental Material of "Multi-Agent Swarm Optimization Method With Contribution-Based Cooperation for Distributed Multi-Target Localization and Data Association"

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A. *Parameter Investigation*

In this subsection, we investigate the parameter selection of the control parameter φ and the connection degree of the sensor network. First, the control parameter φ decides the relative influence of the contribution term in Eq. (17). The setting of the control parameter has a great impact on the algorithm performance. In this experiment, we set the value of φ to {0, 0.2, 0.4, 0.6, 0.8, 1}, and test the performance of MASTER respectively. In order to improve the generalization of experiment results, the localization effect of MASTER is tested on different numbers of targets in both 2D and 3D scenarios. To be specific, we set the number of targets to 4, 8, 16, and 30.

Fig. S1 shows the estimation error of MASTER with different control parameters. According to the results, when φ is set to 0.2, MASTER performs better than the others in six of eight cases. Sub-figure (a) and (e) are exceptions. In sub-figure (a), both estimation error of MASTER when φ is set to 0 or 0.2 is lower than $1E{-}20$, which means that the estimation is nearly optimal. Although the estimation error when $\varphi = 0.2$ is higher than that when $\varphi = 0$ in sub-figure(e), the p-value of Wilcoxon rank sum test is 0.249. It means that the advantage is not significant. In conclusion, 0.2 is the best parameter setting. It will be adopted in the subsequent experiments.

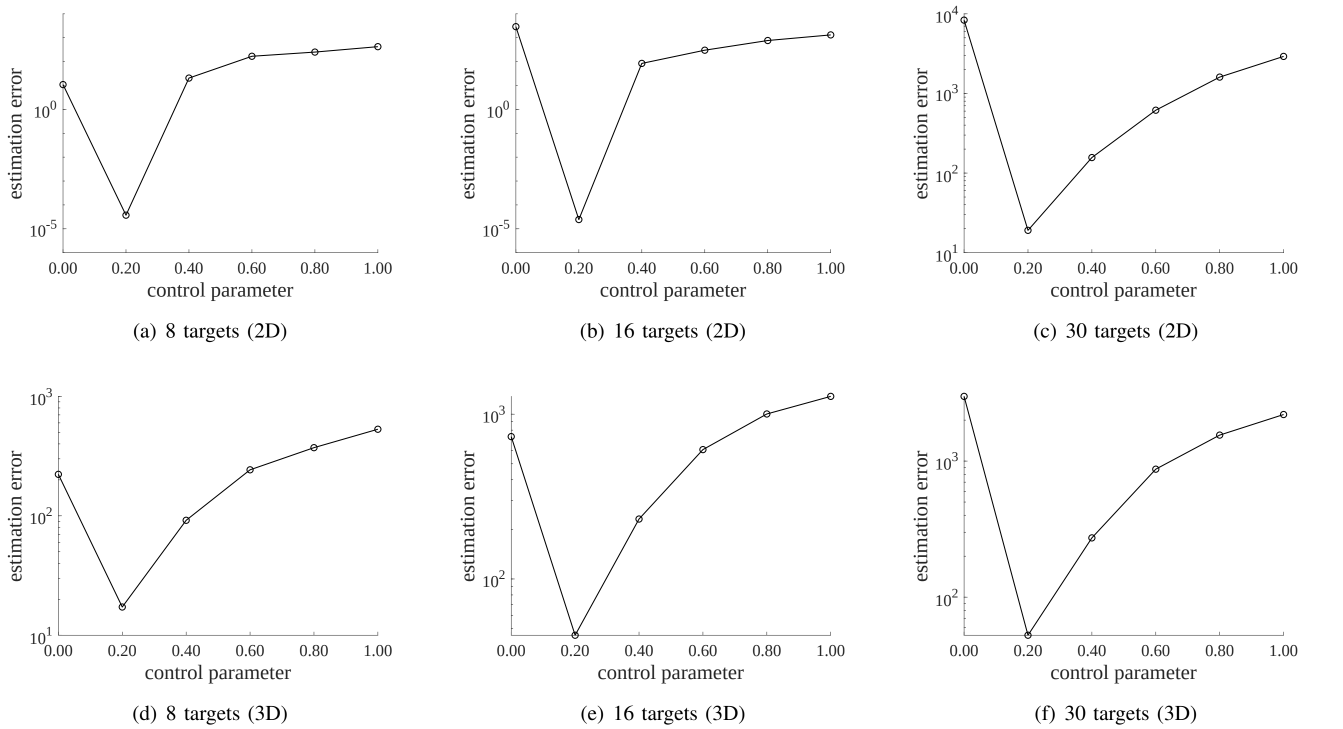
Most error curves in Fig. S1 are in V-shape, which indicates that the control parameter should be neither too large nor too small. As follows, we conduct experiments to analyze it.

1) We firstly consider conditions when the control parameter φ is larger than 0.2. Fig. S4 shows the estimation error curves of MASTER during optimization. According to the figures, the error curves when $\varphi > 0.2$ converge much faster than that when φ is 0.2 in most cases. In general, the larger φ, the faster the error curve converges. Therefore, the reason why the estimation error grows as φ grows is that MASTER converges too early and does not explore enough. This experimental result can also be explained from a physical point of view. When φ in Eq. (17) is large, more particles will be attracted to the average position of neighboring particles, which helps them converge to the same position. Thus, the wireless sensor network will reach a consensus more quickly.
2) Secondly, we consider the condition when the control parameter φ is smaller than 0.2. When φ is set to zero, Eq. (17) is reduced to only two terms, i.e., inertial term and contribution term. In this case, particles are not attracted to the average position of neighboring particles. In order to investigate the reason, we plot the distribution of the contribution-based weights in Eq. (16) during optimization in Fig. S3. The contribution-based weight has a high probability of being zero because particles may not progress during local optimization. Because particles are not attracted to the average position, they will be attracted to the minority of neighboring particles and ignore the others. As a result, the local objectives of the minority of sensors will dominate and then cause the algorithm to be trapped into a local optimum.

The comparison between cases when $\varphi = 1$ and $\varphi = 0.2$ is actually an ablation experiment about the contribution-based method. This is because the contribution-based term in Eq. (17) is canceled when $\varphi = 1$. Experiment results in the above show the effectiveness of the proposed contribution-based method.

Then, we conduct an experiment to investigate the impact of the network connection degree on the proposed algorithm. We construct seven 16-node sensor networks with average node degrees ranging from two to eight. Fig. S2 shows the estimation error of MASTER with different cases of connection degrees in eight tasks.

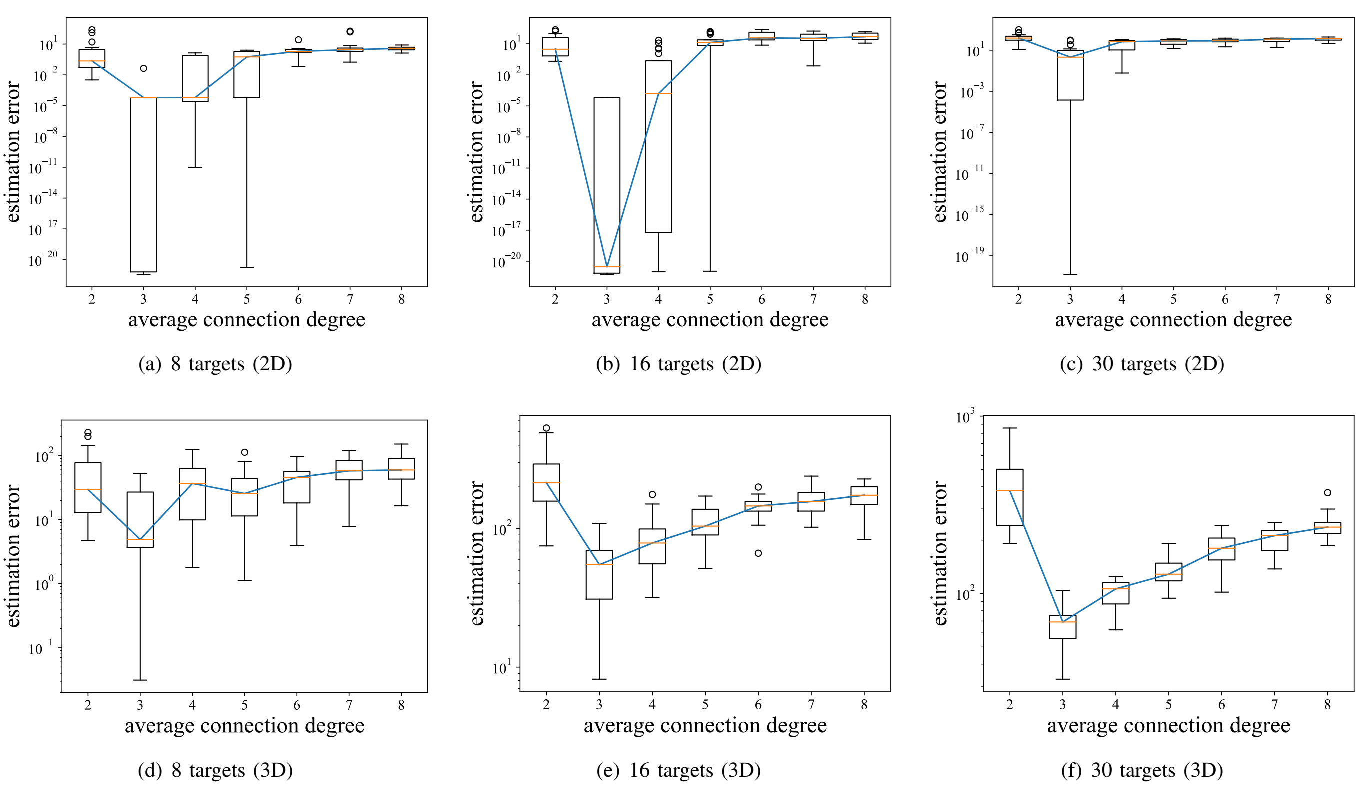
We have the following experiment findings: (1) When the connection degree is set to three, MASTER achieves a smaller estimation error than other degrees from the second to the eighth tasks (from Fig. S2(b) to Fig. S2(h)). For the left simple task in Fig. S2(a), the estimation error of MASTER is smaller than 1E-17 when the degree is larger than two, which has no significant difference. (2) Too large and too small connection degrees will increase the estimation error of MASTER. This is because the speed of information diffusion increases as the network degree increases. Therefore, when the degree is too large, the system will converge too fast. In this case, the sensors lack sufficient exploration for the optimization problem, which leads to a larger estimation error. On the contrary, when the degree is too small, the sparse communication relationship reduces the speed of information diffusion, which is not conducive to the cooperation and consensus of the system. Thus, the estimation error of MASTER on the network with node degree two is larger than the error on the network with node degree three.



(a) 8 targets (2D) (b) 16 targets (2D) (c) 30 targets (2D)

(d) 8 targets (3D) (e) 16 targets (3D) (f) 30 targets (3D)

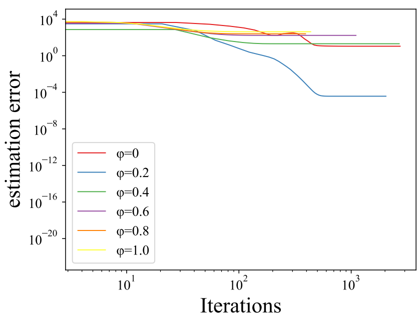
Fig. S1. Estimation error of MASTER with different control parameter φ



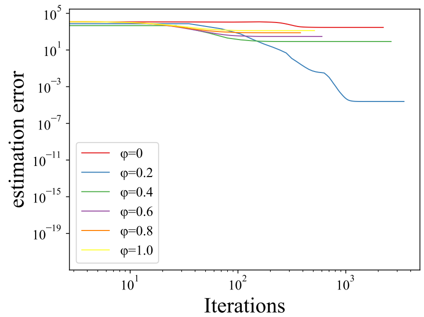
(a) 8 targets (2D) (b) 16 targets (2D) (c) 30 targets (2D)

(d) 8 targets (3D) (e) 16 targets (3D) (f) 30 targets (3D)

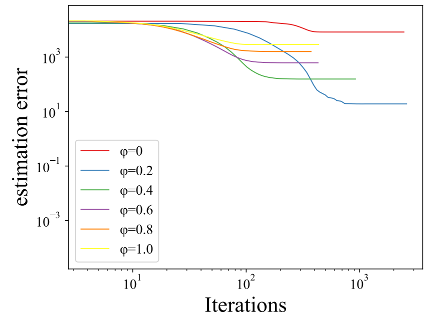
Fig. S2. Estimation error of MASTER with different cases of connection degree.



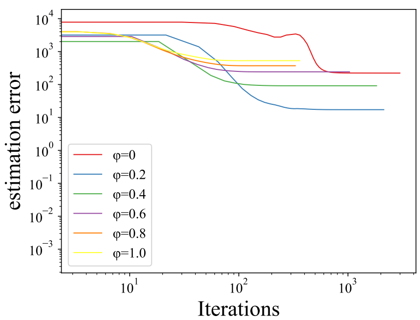
(a) 8 targets (2D)



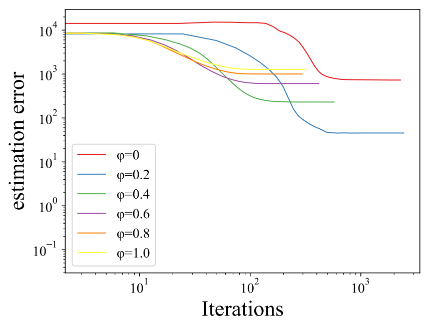
(b) 16 targets (2D)



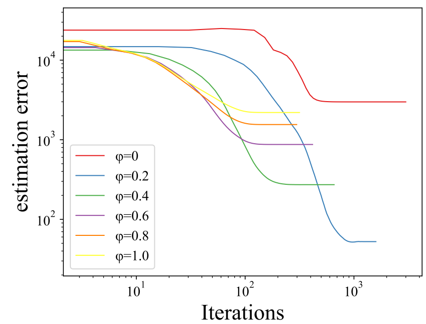
(c) 30 targets (2D)



(d) 8 targets (3D)



(e) 16 targets (3D)



(f) 30 targets (3D)

Fig. S3. Evolution curve of estimation error of MASTER with different control parameter φ. The algorithm terminates when the system reaches a consensus, so that the length of curves is different.

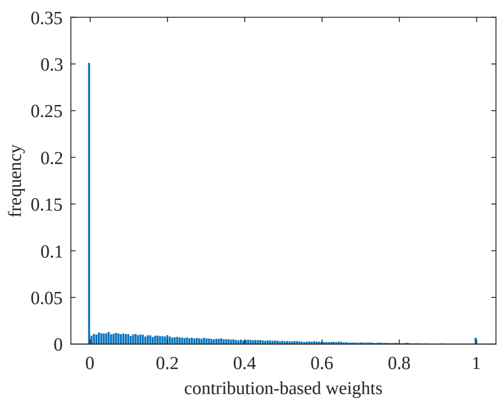


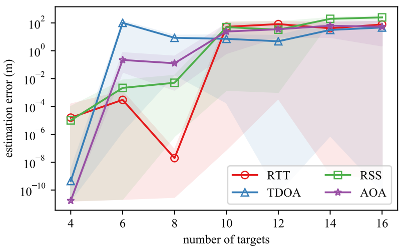
Fig. S4. The distribution of contribution weights. The frequencies of all weights sum to one.

B. Performance of MASTER with different measurement techniques

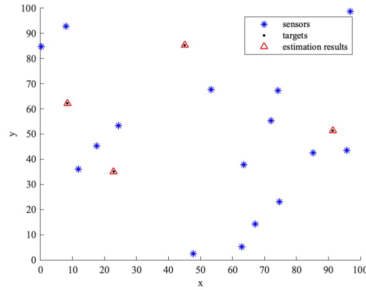
The proposed MASTER can address different types of measurement techniques because of its black-box characteristic. We conduct experiments to test its performance on four types of measurement techniques, i.e., roundtrip propagation time measurements (RTT), time-difference-of-arrival measurements (TDOA), received signal strength measurements (RSS), and angle-of-arrival measurements (AOA).

We first test the performance of MASTER with different numbers of targets based on the above four measurement techniques. Fig. S5 shows the estimation error and localization results of MASTER with different numbers of targets in the environment. According to sub-figures (a) and (d), we can conclude that: (1) The estimation error in the 3D scenario increases faster than that in the 2D scenario. In the 3D scenario, the average error is higher than 1 when there exist six targets. In the 2D scenario, the average error is higher than 1 when there exist six or ten targets. This phenomenon shows that 3D localization is more difficult. (2) The AOA measurement is more suitable for MASTER in 3D scenarios than other measurement techniques. The average estimation error of MASTER with AOA is much smaller than others, especially when the number of 3D targets is set to 6, 8, and 10.

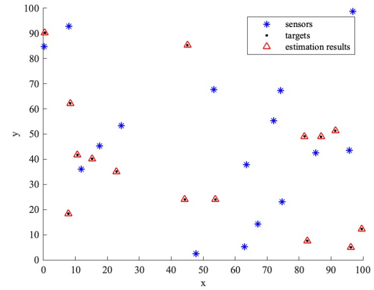
Then, we test the performance of MASTER with different numbers of sensors. To observe the effect of the number of sensors on their ability to counter noise, we set the noise level of measurements to 5%. Fig. S6 shows the estimation error and localization results of MASTER with different numbers of sensors in the environment. According to the results, we can find that MASTER is more stable with the AOA measurement in both 2D and 3D scenarios. Although the best case of the estimation error of RTT is close to that of AOA, the worst case of AOA is much smaller than that of RTT. Therefore, MASTER with AOA achieves a smaller average estimation error than others.



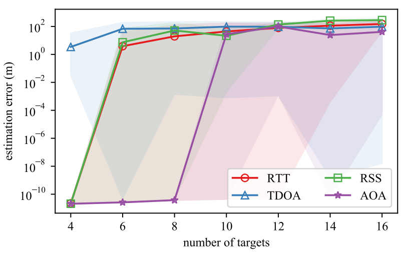
(a) 2D scenario: estimation error



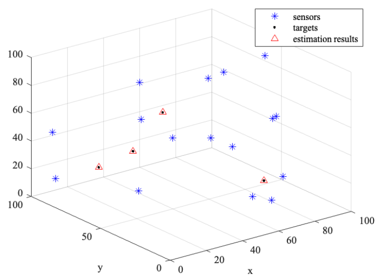
(b) 2D scenario: 4 targets in the environment



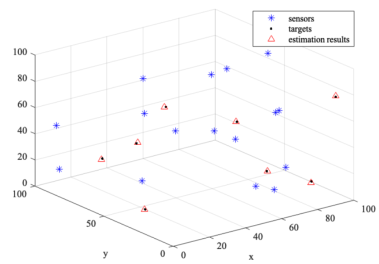
(c) 2D scenario: 16 targets in the environment



(d) 3D scenario: estimation error

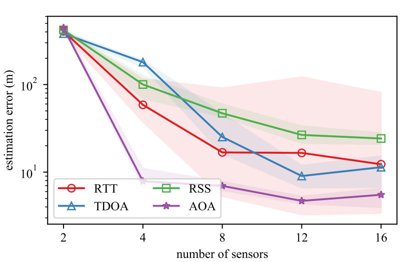


(e) 3D scenario: 4 targets in the environment

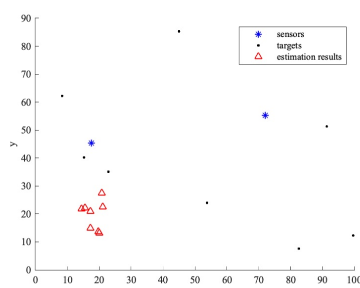


(f) 3D scenario: 16 targets in the environment

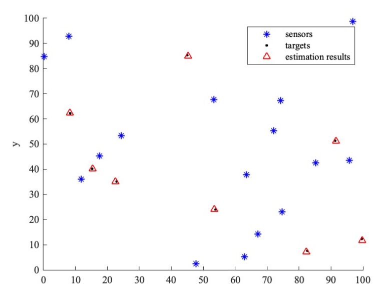
Fig. S5. Performance of MASTER with different numbers of targets. The number of sensors is set to 16. No ghost points appear in the positioning results.



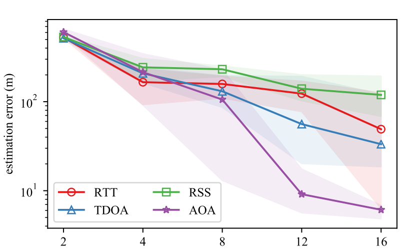
(a) 2D scenario: estimation error



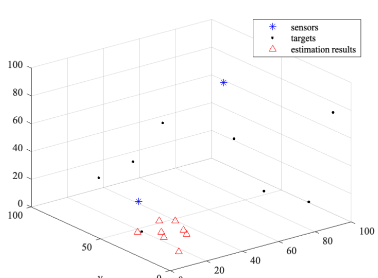
(b) 2D scenario: 2 sensors in the environment



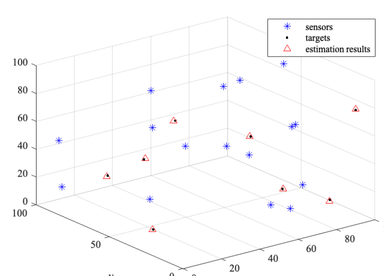
(c) 2D scenario: 16 sensors in the environment



(d) 3D scenario: estimation error



(e) 3D scenario: 2 sensors in the environment



(f) 3D scenario: 16 sensors in the environment

Fig. S6. Performance of MASTER with different numbers of sensors. The number of targets is set to 8. Sub-figures (a), (c), (e), and (f) show that more cooperative sensors help to improve the localization effect and the resistance to noise.

C. Numerical results of comparison with existing algorithms

TABLE S1
COMPARISON WITH EXISTING ALGORITHMS. THE NUMBER OF TARGETS AND SENSORS IS SET TO 16.

		MASTER (ours)	MASOIE	SDNO	GFPDO	RGF	DA-PSO
RTT (2D)	mean	7.779E+01	1.998E+02	1.480E+02	8.812E+02	6.981E+02	4.240E+02
	median	1.092E+02	2.016E+02	1.530E+02	8.721E+02	7.018E+02	4.349E+02
	std	5.256E+01	4.985E+01	3.129E+01	2.599E+01	1.592E+01	5.330E+01
	p-value	-	3.30e-04#	4.59e-03#	1.83e-04#	1.83e-04#	1.83e-04#
TDOA (2D)	mean	4.687E+01	4.268E+02	1.753E+02	8.635E+02	5.534E+02	3.959E+02
	median	7.808E+00	4.311E+02	1.605E+02	8.717E+02	5.536E+02	3.923E+02
	std	5.580E+01	2.562E+01	4.649E+01	2.950E+01	8.491E+00	3.782E+01
	p-value	-	1.83e-04#	5.83e-04#	1.83e-04#	1.83e-04#	1.83e-04#
RSS (2D)	mean	2.500E+02	2.631E+02	4.357E+02	9.135E+02	1.096E+03	4.101E+02
	median	2.408E+02	2.636E+02	4.407E+02	9.013E+02	1.099E+03	4.065E+02
	std	3.826E+01	2.113E+01	1.512E+01	3.037E+01	4.204E+01	4.080E+01
	p-value	-	3.070E-01	1.83e-04#	1.83e-04#	1.83e-04#	1.83e-04#
AOA (2D)	mean	5.324E+01	1.213E+02	2.749E+03	9.266E+02	1.107E+03	3.656E+02
	median	4.540E+01	1.369E+02	2.757E+03	9.652E+02	1.122E+03	3.628E+02
	std	4.041E+01	3.143E+01	5.295E+01	6.764E+01	6.705E+01	2.311E+01
	p-value	-	3.61e-03#	1.83e-04#	1.03e-04#	1.83e-04#	1.83e-04#
RTT (3D)	mean	1.503E+02	4.616E+02	3.462E+02	1.149E+03	9.243E+02	5.114E+02
	median	1.600E+02	4.666E+02	3.381E+02	1.150E+03	9.249E+02	5.145E+02
	std	5.307E+01	1.917E+01	2.642E+01	1.683E+01	1.997E+01	3.558E+01
	p-value	-	1.83e-04#	1.83e-04#	1.03e-04#	1.83e-04#	1.83e-04#
TDOA (3D)	mean	9.580E+01	7.110E+02	3.375E+02	1.139E+03	7.518E+02	5.887E+02
	median	1.004E+02	7.129E+02	3.341E+02	1.149E+03	7.489E+02	5.787E+02
	std	8.029E+01	1.322E+01	3.609E+01	4.332E+01	8.993E+00	5.617E+01
	p-value	-	1.83e-04#	1.83e-04#	2.80e-04#	1.83e-04#	1.83e-04#
RSS (3D)	mean	2.841E+02	4.842E+02	6.293E+02	1.160E+03	1.335E+03	5.119E+02
	median	2.821E+02	4.969E+02	6.336E+02	1.161E+03	1.333E+03	5.023E+02
	std	4.162E+01	3.063E+01	2.430E+01	2.251E+01	3.295E+01	5.550E+01
	p-value	-	1.83e-04#	1.83e-04#	2.80e-04#	1.83e-04#	1.83e-04#
AOA (3D)	mean	4.118E+01	2.387E+02	3.300E+03	1.208E+03	1.352E+03	5.638E+02
	median	1.719E-03	2.397E+02	3.289E+03	1.198E+03	1.350E+03	5.620E+02
	std	7.006E+01	2.676E+01	5.915E+01	3.713E+01	5.178E+01	3.818E+01
	p-value	-	3.30e-04#	1.83e-04#	1.83e-04#	1.83e-04#	1.83e-04#