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Optimization Localization in Wireless Sensor Network Based on Multi-Objective Firefly Algorithm

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Abstract. *Specifying the located nodes of a network plays an important role in the success of many wireless sensor network (WSN) applications including object tracking, detecting, monitoring, etc. In this paper, the multi-objective firefly algorithm for estimating the located nodes in a network is proposed to solve the localization issues in WSNs. Objective functions of estimating the locations of all the nodes of WSN are considered based on two criteria including the distance of nodes, and the geometric topology constraint. The simulation results are compared with other methods in the literature show that the proposed method produces the considerable improvement in terms of localization accuracy and convergence rate.*
Keywords: Multi-objective firefly algorithm; Swarm intelligent; Node localization; Wireless sensor networks.

1. **Introduction.** A wireless sensor network (WSN) could consist of hundreds or even thousands of low-cost nodes communicating among themselves[1,13,14]. It has become an important technology especially for several specialized applications including military applications, disaster management, wildlife and environmental monitoring[2]. In applications of WSN, such as environment monitoring, precision agriculture, vehicle tracking, and logistics, knowledge about the location of sensor nodes plays a key role[3]. The correlation of sensor measurements with physical locations is required in these applications, even if the accessible knowledge about positions of nodes is only approximate. Moreover, information about current locations is used in geographical-based routing, data aggregation, and various network services. Hence, self-organization and localization capabilities are one of the most important requirements in sensor networks.

Theoretically, location awareness can be enabled in principle by the use of a Global Positioning System (GPS). However, this solution is not always viable in practice, because a sensor network consists of thousands of nodes and GPS will be very costly. In addition, GPS is not well suited to indoor and underground deployments, and the presence of obstacles like dense foliage or high buildings may impair the outdoor communication with satellites. Several alternative techniques have been developed to deal with these limitations, as reviewed in[3], [4], among which fine-grained localization techniques may represent the most suitable ones. Instead of requiring all nodes installed GPS, in these schemes, only a few nodes of the network are called reference or anchor nodes which are endowed with their exact positions through GPS or manual placement. While other nodes in a network are able to derive their positions by estimating their distances to nearby nodes with using the measurement techniques included received signal strength (RSS) measurements, time of arrival (ToA), and time difference of arrival (TDoA).

Traditionally, most studies focused on using single-objective optimization problem to solve localization problems. The localization problem was modeled as a single-objective function for optimization with the space distance constraint. These studies have also achieved significant results in both accuracy and computational time. However, the single objective function did not count really all impacting or affecting from the other objective factors. But, if there is the combination of the objective functions into a multiobjective function that will obtain the meaningful result. For example, in some applications, the obtained results of estimated nodes localizations could meet the space distance constraint, but they could not meet the geometric topology constraint due to ranging errors. Recently, some works have proved the effectiveness of multiobjective optimization algorithms to solve conflict multiple objectives [5], [6] It is more reasonable to model the node localization as a multiobjective optimization problem, which can be described as solving a Pareto solution, rather than simply being described as a single-objective optimization problem. Based on this viewpoint, in this paper, a multiobjective model is adopted to solve the node localization problem with objective functions included the distances constraint and the topological constraint. Pareto optimal solutions for obtaining optimal solution is achieved by applying the multiobjective firefly algorithm (MFA).

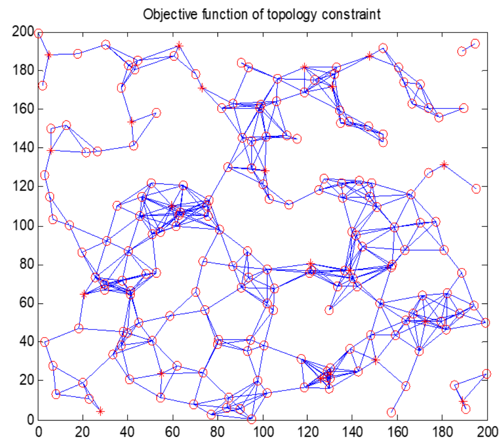
The rest of this paper is organized as follows: a brief review of multiobjective localization is given in Session 2. An analysis and designs for the localization algorithm based on MFA is presented in Session 3. Experimental results and the comparison with other methods are discussed in Session 4. Finally, the conclusion is summarized in Session 5.

2. **Localization model.** WSN assumes with n nodes that are deployed in two-dimensional space of Z^2 including m anchor nodes and $n-m$ unknown nodes in which $m<n$. The objective localization in a WSN is to estimate the coordinates of $n-m$ unknown nodes using the a priory information about the location of m anchor nodes. The coordinates of unknown nodes need to meet both the space distance constraint and the geometric topology constraint. An example of localization model has two objective functions that included the space distances and the geometric topology as shown in Figure 1.

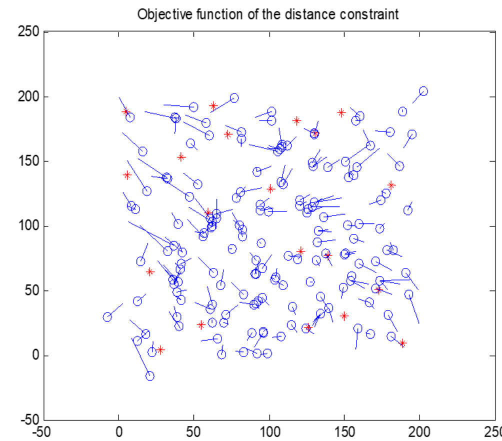
The reason for meeting the constraint of space distance is to make the estimated coordinates close to the real values, and the reason of meeting the geometric topology constraint is to make the network topology unique [3]. In the space distance constraint, the objective function for the WSN localization includes two-phase process. In the first phase, it was known as ranging process which nodes estimate their distances from anchor nodes using the signal propagation time or the received signal strength indicator (RSSI). In the second phase, position estimation of the nodes is carried out using the ranging information [7]. The localization error is minimized by using the optimization algorithm. Supposing the two nodes i and j being in the communication radius of each other and effect of measurement noise is simulated as a Gaussian additive white noise. In the first phase, each anchor nodes in the deployment estimates its distance from each of its neighboring target nodes. The ranging distance of the internode can be obtained by RSSI ranging technology and denoted as following.

$$d_{ij} = r_{ij} + n_{ij} \tag{1}$$

where r_{ij} is the actual distance between two nodes, and n_{ij} is a ranging error. r_{ij} is able to be calculated as given:



(a) The geometric topology



(b) Space distances

FIGURE 1. An example of localization model included two objective functions: the space distances and geometric topology

of localization model has two objective functions that included the space distances and the geometric topology as shown in Figure 1.

$$r_{ij} = \sqrt{((x_i - x_j)^2 + (y_i - y_j)^2)} \tag{2}$$

where (x_i, y_i) and (x_j, y_j) are coordination of node i and j location.

The neighbor effect factor N_i is set to $j \in 1, .., n, j \neq i$ if $r_{ij} \leq R$, and its complement $\bar{N}_i$ is set to $j \in 1, .., n, j \neq i$ if $r_{ij} > R$. Where R is the maximum distances for effective communication of node i.

The measurement noise n_{ij} is the ranging error of RSSI which follows a zero mean Gaussian distribution with variance ϑ^2, and it has a random value uniformly distributed in the range $[d_i - d_i P_n/100, d_i + d_i P_n/100]$. In second phase, the objective function for the space distance constraint can be framed as.

$$f_1 = \sum_{i=m+1}^{n} (\sum_{j \in N_i} (\widehat{d_{ij}} - d_{ij})^2) \tag{3}$$

where m is anchor nodes and $n - m$ is unknown nodes $(m < n)$, and $\widehat{d}_{ij}$ is the estimated distance between nodes i and j. It is defined as follows.

$$\widehat{d_{ij}} = \{ \begin{matrix} \sqrt{(\widehat{x}_i - x_j)^2 + (\widehat{y}_i - y_j)^2} \; if \; j \; is \; anchor \\ \sqrt{(\widehat{x}_i - \widehat{x}_j)^2 + (\widehat{y}_i - \widehat{y}_j)^2} \; otherwise \end{matrix} \tag{4}$$

where $(\widehat{x}_i, \widehat{x}_j)$ is the coordinate of the estimated $node_{(i,j)}$, and (x_j, y_j) is the coordinate of the $anchor_j$.

The second objective function of the geometric topology constraint is defined by

$$f_2 = \sum_{i=m+1}^{n} (\sum_{j \in N_i} \theta_{ij} + \sum_{j \in \overline{N_i}} (1 - \theta_{ij})) \tag{5}$$

The geometric topology constraint represents the connectivity constraint which dissatisfies the current estimated positions of non-anchor nodes [7]. And $\theta_i j$ is denoted by

$$\theta_{ij} = \begin{cases} 1 \; if \; \hat{d}_{ij} > R \\ 0 \; otherwise \end{cases} \tag{6}$$

The space distance constraint and the geometric topology constraint imply the accuracy of the coordinates of the nodes. The high accuracy of estimated coordinates of the unknown nodes consequently depends on the optimization approach for dealing with the objective functions.

Therefore, estimating coordinates of the unknown nodes can be modeled to search the optimum solution for the multiobjective optimization issues, which can be obtained by decreasing both values of the objective functions f_1 and f_2.

3. Multiobjective Firefly Algorithm for Localization.

The basic version of the firefly algorithm (FA) is only for single objective optimization. In order to solve multiobjective functions of the localization in WSN, FA is extended to multiobjective firefly algorithm (MFA). The basic version of FA and Pareto optimal front are first briefly reviewed, and the localization problem in WSN will be dealt with then it based on MFA.

3.1. The Basic Firefly Algorithm.

FA was developed by the inspiration of behavior of fireflies[8]. In essence, the three idealized rules were considered for simulation. First, the fireflies brightness is attractive to each other ones.

Second, the less bright one will move towards the brighter one.

Finally, attractiveness is proportional to the brightness and they both decrease as their distance increases.

The brightness of a firefly is affected or determined by the landscape of the objective function.

A firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies.

The variation of attractiveness β with the distance r is defined as given following.

$$\beta \ = \ \beta_0 \times e^{-\gamma r^2} \tag{7}$$

where β_0 is the attractiveness at $r = 0$.

The movement of a firefly i is attracted to another more attractive (brighter) firefly j determined by:

$$x_i^{t+1} = \ x_i^t + \beta_0 \times e^{-\gamma r^2} \times \left(x_j^t - x_i^t\right) + \alpha_t \epsilon_i^t \tag{8}$$

where x_i and x_j are locations of fireflies i and j.

The movement of firefly i is attracted to another more attractive (brighter) firefly j is determined by the second term dues to the attraction. The third term is randomization with α_t being the randomization parameter, and ϵ_i^t is a vector of random numbers drawn from a Gaussian distribution or uniform distribution at time t. If $\beta_0 = 0$, it becomes a simple random walk.

3.2. Pareto Optimal Front.

The domination of a solution vector $x = (x_1, x_2, .., x_n)^T$ on a vector $y = (y_1, y_2, .., y_n)^T$ for a minimization problem if and only if $x_i <= y_i$ for $\forall_i \in 1, ..., n$ and $\exists_i \in 1, ..., n$: $x_i < y_i$.

It means that is no component of x is larger than the corresponding component of y, and at least one component is smaller.

Similarly, the dominance relationship could be defined by:

$$x \preccurlyeq y \ \Leftrightarrow x \ \prec y \ \vee x = y. \tag{9}$$

For maximization problems, the dominance can be defined by replacing symbol of $\prec$ with the symbol of $\succ$.

Therefore, a point x_* is called a non-dominated solution if no solution can be found that dominates on it.

The Pareto front PF of a multi-objective can be defined as the set of non-dominated solutions as following.

$$PF \ = \ \{s \ \in \ S | \nexists \, s' \in \ S \ : s' \prec \ s\} \tag{10}$$

where S is the solution set.

A good approximation could be obtained from the Pareto front if a diverse range of solutions should be generated using efficient techniques[9].

3.3. Optimal Localization based on MFA.

The optimal solution of multiobjective optimization can be obtained from the Pareto optimal solution. Multiobjective optimization issue for a minimization problem with d-dimensional decision vectors and h objectives is given by

$$\begin{gathered} Minimize \; F(x) = (f_1(x), \; f_2(x), \; ..f_h(x)) \\ Subject \; to \; x \in [x_L, x_U], \end{gathered} \tag{11}$$

```
1. Define objective function PF(x) = ∑ f1(x), f2(x)  where x = (x1,...,xd)^T
2. Initialize a population of N fireflies xi, (i = 1,2,...,n)
3. while (t < MaxGeneration)
     for i, j = 1 to N
        Evaluate their approximations PFi and PFj to the Pareto front
        if i ≠ j and when all the constraints are satisfied
4.     if PFj dominates PFi,
        Move firefly i towards j using Eq. (8)
        Generate new ones if the moves do not satisfy all the constraints
       end if
5.     if no non-dominated solutions can be found
        Generate random weights wk, (k = 1,...,P)
        Find the best solution g*^t (among all fireflies) to minimize in Eq. (13)
        Random walk around g*^t using Eq. (14)
     end if
6.   Update and pass the non-dominated solutions to next iterations
     end for
7.  Sort and find the current best approximation to the Pareto front
8.  Update t = t + 1
end while
Post process results and visualization
```

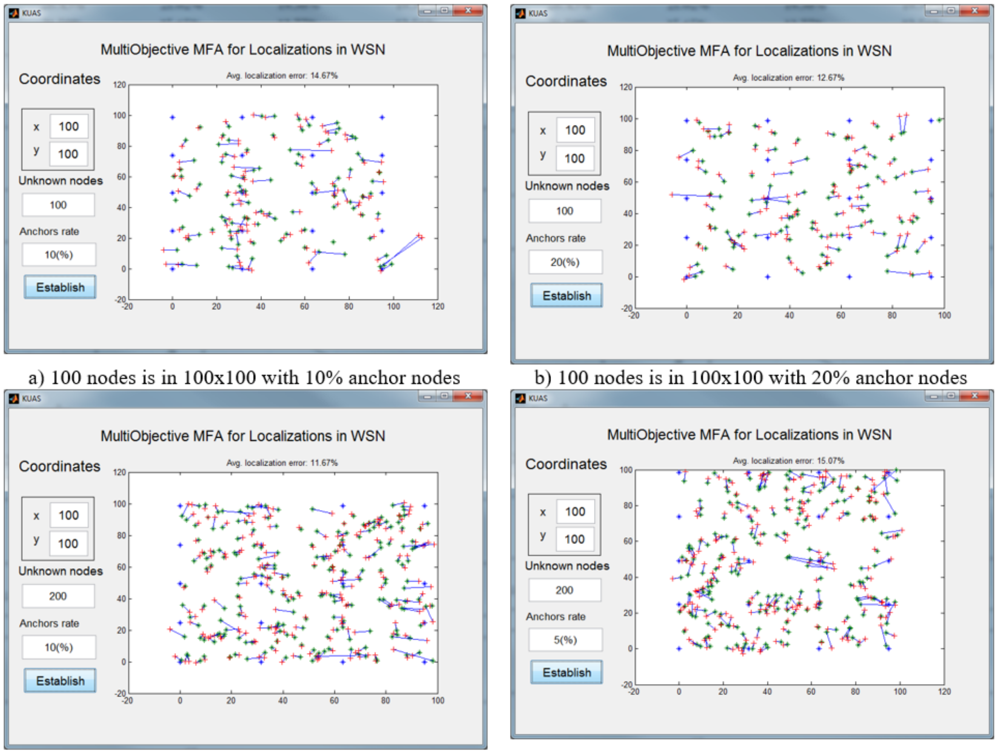
FIGURE 2. Pseudo Code of Multiobjective Firefly Algorithm (MFA) for Localization

where x is a decision vector as a set of $(x_1, x_2, .., x_u)X \in R^d$and $F(x)$ is the objective function with the objective vector as a set of $(f_1, f_2, .., f_u) \in Y \in R^h$. The decision vector x is belonging to the d-dimensional decision space X, which is corresponding to the space for d dimensional of fireflies in FA. The objective function $F(x)$ belongs to the h-dimensional objective space Y, in which it is mapping functions from the decision space to the objective space. x_L,and x_U are lower and upper bound constraints of the agent range, respectively. The set of all the fireflies meeting the constraints forms the decision space feasible set $\omega = x \in R^d | x \in [x_L, x_U]$.

The purpose of optimization is to find the Pareto-optimal solution. The decision space includes the dimension d and the objective space h. We begin with a generated population of N_p fireflies randomly so that these fireflies should distribute among the search space as uniformly as possible. This can be achieved by using sampling techniques via uniform distributions. The model the estimated coordinates of $n - m$ unknown nodes as the decision vectors, and the two objective functions defined by Eqs. (3) and (5) consist of the objective function *F(x)*. Therefore, from Eqs. (3)(5) and (11) are in MFA, it can be formulated in the optimum mathematical form as

$$\begin{gathered} Minimize\ F(x) = (f_1(\widehat{x}_i, \widehat{y}_i) f_2(\widehat{x}_i, \widehat{y}_i) \\ Subject\ to\ (\widehat{x}_i, \widehat{y}_i) \in (\widehat{x_L}, \widehat{y_L})(\widehat{x_U}, \widehat{y_U}) \\ i = m + 1, ..n, \end{gathered} \tag{12}$$

where decision vectors $x = (\widehat{x}_i, \widehat{y}_i)$are the estimated coordinates corresponding to solutions in FA. $(\widehat{x}_i, \widehat{y}_i) \in (\widehat{x_L}, \widehat{y_L})(\widehat{x_U}, \widehat{y_U})$ are the lower and upper bound constraint values, f_1 is the objective function of the space distance constraint, and f_2 is the objective function of the geometric topology constraint. Obtaining the multiobjective Pareto optimal solution is the ultimate goal of building a multiobjective optimal model for localization issues, which meets both the space distance constraint and the geometric topology constraint. Therefore the main essence of MFA can be described as determining the dominant relationship according to the decision space feasible set Ω and the Pareto front $F(x^*)$ saving Pareto optimal solution set$S$ in an archive by Eq. (10) and updating the best solution of multiobjective. An appropriate definition of objective functions with associated non-linear constraints. Once the tolerance or a fixed number of iterations is defined, the iterations



a) 100 nodes is in 100x100 with 10% anchor nodes
b) 100 nodes is in 100x100 with 20% anchor nodes
c) 200 nodes is in 100x100 with 10% anchor nodes
d) 200 nodes is in 100x100 with 5% anchor nodes

Figure 3. Setting up a network with different scenarios included: a) the number of nodes was 100 in an area of 100m×100m with 10% anchor node rate; b) the number of nodes was 100 in an area of 100m×100m with 10% anchor node rate; c) the number of nodes was 200 in an area of 100m×100m with 10% anchor node rate, and d) the number of nodes was 200 in an area of 100m×100m with 5%anchor node rate.

start with the evaluation of brightness or objective values of all the fireflies and compare each pair of fireflies. Then, a random weight vector is generated, so that a combined best solution g_* can be obtained. Noticed, the sum of generated weight is equal to 1. The non-dominated solutions are then passed onto the next iteration. At the end of a fixed number of iterations, the non-dominated solution points can be obtained to approximate the true Pareto front. The random numbers of the weight are generated based on the random walks that optimization of a combined objectives functions is summed up as:

$$F(x) = w_k \times f_1 + (1-w) \times f_2, \sum_{k=1}^{P} w_k = 1, \tag{13}$$

Here w_k is the weight which is generated by $\frac{p_k}{P}$, where p_k are random numbers, and P is a rescaling operation that is generated uniformly. Clearly, the weights w_k should be chosen randomly at each iteration, so that the non-dominated solution can sample diversely along the Pareto front. If a firefly is not dominated by others in the sense of Pareto front, the firefly moves according to Eq. (14).

$$x_i^{t+1} = g_*^t + \alpha_t \times \epsilon_i^t \tag{14}$$

where g_*^t is the best solution found so far for a given set of random weights. The main steps of the algorithm process are shown in Figure 2 as the pseudo code of multiobjective firefly algorithm (MFA) for localization in WSN.

4. **Simulations and Analysis.** In this section, the estimation of unknown nodes for the optimal localization in a sparse network based on the multiobjective firefly algorithm (MFA) method is investigated. The simulations have been done applying MFA with objective functions f_1 and f_2, and the localization issues had been done using methods of the parallel firefly algorithm [10] and Pareto archived evolution strategies [11] [12]. In these simulations, we focus on the average localization errors rate. To evaluate the proposed method MFA, the different situations have been implemented such as in varying nodes densities, anchor nodes, and diversity of the Pareto solutions for optimization localizations.

Simulation results show the effectiveness of the proposed two objective functions in tackling the fine-grained localization problem in WSNs. Sensor localization for the whole sensor network was conducted in the following manner. The network consists of n nodes are randomly deployed in 100m × 100m area with m anchor nodes being randomly generated from these nodes. Assuming that the RSSI ranging error e_{ij} follows a Gaussian distribution. The different scenarios of setting the network were the variety of percentage of anchor nodes and the density of nodes in the network, that shows in Figure3.

Table 1. The effect of the density for localization errors with different node number

Methods	Total number of nodes						
	80	100	120	140	160	180	200
FA	34.20%	26.30%	21.00%	20.00%	19.20%	18.50%	18.00%
pFA	31.20%	25.30%	20.00%	19.50%	19.20%	17.50%	17.00%
PAES	26.80%	24.80%	19.00%	19.00%	18.60%	16.90%	16.50%
MFA	25.20%	24.20%	18.70%	18.50%	18.30%	16.60%	16.50%

Table 1 reports the average localization errors, measured under the condition of changing the network nodes density and the total number of nodes while holding on the anchor node proportion as 20% and the communication radius of the radio range is fixed at 25 m. The increasing the number of anchors and the radio range of communication usually make the localization result more satisfactory, but this also implies incurring more cost.

Figure 4 shows the comparison of four method curves in the effective density to localization errors. All the average localization errors of three methods reduce as the nodes increase, and the number of nodes does little effect on the errors when it is over 100. Obviously, that the localization errors obtained by using PAES[11] and MFA were lower than the errors created by using FA, and pFA [10] due to the geometric topology constraint being considered by the first two methods.

Table 2 shows the relationship between the average localization errors and the anchor node proportion while keeping for setting the communication radius of the fixed radio range to 25 m. All the average localization errors decrease as the anchor node proportion increases due to the increase of anchor nodes around unknown nodes resulting in localization accuracy being improved. Figure 5 shows the comparison of the localization errors with the different anchor node proportion.

Clearly, the methods of the proposed MFA and PAES have better performance in localization accuracy than the pFA localization algorithm with the same anchor node proportion due to the two objective functions being considered in MFA and PAES compared to only one objective function being considered in FA, and pFA [10] without the topology constraint. For example, obverted in column 3 and column 5 of Table 2, the

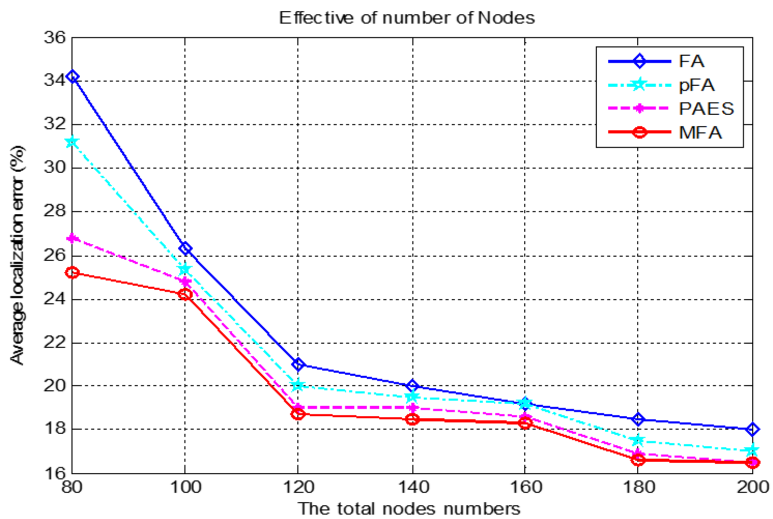


FIGURE 4. Comparison of the effective density to localization errors

TABLE 2. The effect of the proportion for localization errors with different anchor nodes rate

Methods	Anchor node proportion					
	5%	10%	15%	20%	25%	30%
FA	32.20%	26.30%	24.00%	21.00%	20.20%	19.50%
pFA	29.20%	23.30%	20.00%	19.50%	18.70%	17.50%
PAES	24.80%	22.10%	19.00%	19.00%	18.60%	16.60%
MFA	24.20%	21.20%	18.70%	18.40%	18.20%	16.55%

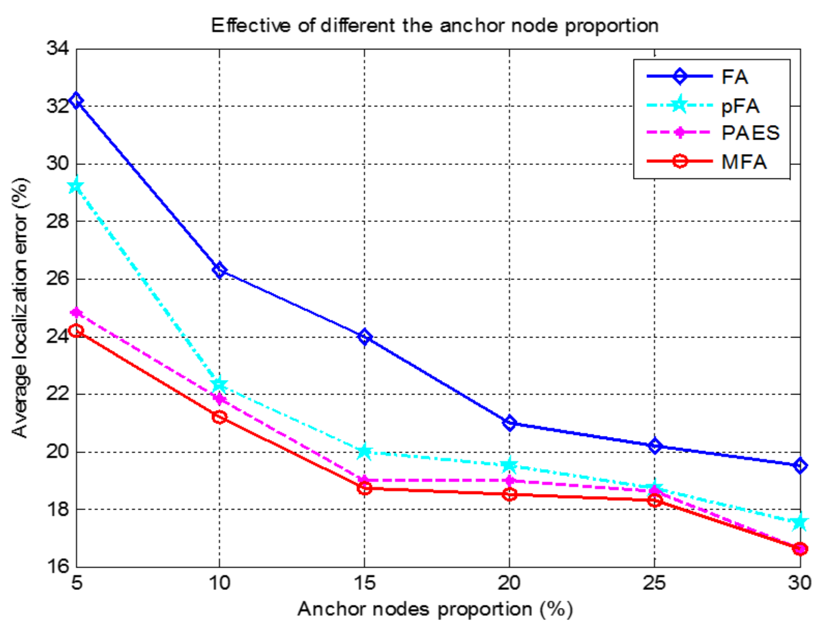


FIGURE 5. Comparison of the localization errors with the different anchor node proportion

the average localization error in MFA reduces 21.20% and 18.39% compared with the traditional pFA method: 23.30% and 19.50%, respectively, under the condition of 10% and 20% anchor node proportion. The proposed method MFA has slightly higher localization accuracy than PAES under the condition of the same anchor node proportions. Compared with PAES, the proposed method MFA reduces the average localization error 0.95% and 0.06%, respectively under the condition of 10% and 20% anchor node proportion.

5. **Conclusion.** In this paper, we proposed an optimization localization in wireless sensor network (WSN) based on multiobjective firefly algorithm (MFA). The localization model has made up two objective functions including the space distance constraint and the geometric topology constraint. The simulation results were compared with the obtained of PAES method, the localization accuracy of the proposed method MFA is slightly increase and the diversity rate of the proposed method is better than PAES method. Compared with traditional FA, and pFA localization algorithm, the proposed MFA method can improve the localization accuracy and convergence rate. In general, the performance of the proposed method is shown to be a useful scheme.

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