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Range-free 3D node localization in anisotropic wireless sensor networks

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ABSTRACT

In this paper, we propose two computationally efficient 'range-free' 3D node localization schemes using the application of hybrid-particle swarm optimization (HPSO) and biogeography based optimization (BBO). It is considered that nodes are deployed with constraints over three layer boundaries, in an anisotropic environment. The anchor nodes are randomly distributed over the top layer only and target nodes distributed over the middle and bottom layers. Radio irregularity factor, i.e., an anisotropic property of propagation media and heterogenous properties of the devices are considered. To overcome the non-linearity between received signal strength (RSS) and distance, edge weights between each target node and neighboring anchor nodes have been considered to compute the location of the target node. These edge weights are modeled using fuzzy logic system (FLS) to reduce the computational complexity. The edge weights are further optimized by HPSO and BBO separately to minimize the location error. Both the proposed applications of the two algorithms are compared with the earlier proposed range-free algorithms in literature, i.e., the simple centroid method and weighted centroid method. The results of our proposed applications of the two algorithms are better as compared to centroid and weighted centroid methods in terms of error and scalability.

1. Introduction

WSN is an emerging technology, which has captured the attention and vision of many researchers, encompassing a broad spectrum of ideas since last decade. Despite their variety, all WSN have certain fundamental feature in common. Perhaps most essential is that they are embedded in the real world.

Since the last decade, it has been observed that there is substantial furtherance in hardware and wireless networking technologies that have fueled the development of multi-hop wireless networks consisting of tiny, low-power, sensor devices termed as WSNs. Primal design objectives of the sensor networks focus on reliability, accuracy, flexibility, cost, effectiveness and ease of deployment. The fast and easy deployment, self-organization and fault-tolerance characteristics of WSNs make them be promising for a number of military and civilian applications [1–3]. In most of the applications, the basic principle of a WSN is to detect, compute, and report events which can be meaningfully ingested and responded to only if the precise location of the event is known. The locations of sensor nodes are often needed when identifying the location from where the accumulated information comes. Finding the coordinates of the sensors is one of ambitious problems and is referred to as the localization problem, in WSNs.

Localization techniques are employed to gauge the location of the sensor nodes whose coordinates are not known in a network (termed as target nodes). Using available a priori knowledge of positions of typically a few sensor nodes called anchors, based on inter-sensor parameters/measurements such as connectivity distance, time of arrival (TOA), time difference of arrival (TDOA), and angle of arrival (AOA) [4,5].

WSN localization is a two-phase process, i.e., ranging and position estimation process.

To overcome the limitations (i.e., hardware cost, energy consumption, scalability, limited range, etc.) of the range-based localization schemes, range-free solutions have been proposed. Range-free solutions calculate the coordinates of sensor nodes, either, based on the radio connectivity information among neighboring nodes, or based on the sensing capabilities that each sensor node possesses but less precise than range-based methods. Nowadays, range-free algorithms are currently/commonly used to find the coordinates of target nodes than the range-based algorithms [6–8].

In [9–11], we proposed the application of HPSO and BBO for range-based, distributed and non-collaborative 2D and 3D node localization. In this paper the application of HPSO and BBO algorithms for *range-free* is used for 3D node localization in anisotropic WSNs. Both algorithms performed better in terms of the more number of nodes localized, high localization accuracy and less computation time as compared to the earlier proposed algorithms.

Nodes are randomly deployed with constraints over three layer boundaries. The anchor nodes are randomly distributed over top layer only and target nodes distributed over at bottom layers. Radio irregularity factor, i.e., anisotropic

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properties of propagation media and heterogenous properties of devices are considered. Non-linearity between RSS and distance is modeled using FLS to reduce the computational complexity and further optimized by HPSO and BBO to minimize the error.

The rest of the paper is organized as follows: Literature appraisal on WSNs localization is presented in Section 2. Section 3 ushers the readership into a gentle overview of FLS, HPSO and BBO algorithms used for localization in this paper. This is followed with discussion on radio irregular model (RIM) in Section 4. Implementation of above said algorithms, simulation results and comparative study are presented in Section 5. Finally, conclusions and a projection on possible future research path are presented in Section 6.

2. Literature survey

In range-free localization algorithms, the information is usually collected by *radio coverage* and a *number of hops to an anchor node*. Anchors beacon their positions to neighbors that keep an account of all received beacons. Using this proximity information, a simple centroid formula is applied to estimate the listening nodes' locations. Ref. [7] proposed a range-free, proximity-based, coarse-grained localization algorithm, that uses anchors beacon, containing location information (x_i, y_i), to estimate node positions. After receiving these beacons, the node estimates its location using the centroid formula for 2D space [12]. Examples of classical range-free localization algorithms are centroid (CL) [7], DV-hop [13], Convex [4], approximate point-in-triangulation (APIT) [14], semi-definite position (SDP) [15], etc.

The range-free localization algorithms are cost effective, i.e., of lower cost as compared to range-based and easier calculation than the range-based ones, but the results of range-free algorithms are not more accurate than the range-based algorithms. Nowadays, the range-free algorithms are more popular than the range-based methods due to the cost factor.

In range-free schemes, only the path information, i.e., *number of hops to an anchor node* is used to calculate the Euclidean distance between two nodes. The Euclidean distance provides the real distance between the nodes. In isotropic networks, the hop count between two nodes can be used to estimate the distance between them. Thus, the distance is determined by computing the average per-hop distance multiplied by the hop count between the two nodes as in [6].

In [16], range-free weighted Voronoi diagram-based localization scheme (W-VBLS) is proposed to extend Voronoi diagram-based localization scheme (VBLS). In this scheme, RSSI technique is used to estimate distance from three similar distance neighbor. Further, node and two beacon form a triangle to calculate weighted bisector. Finally, estimate the position of the node with the biggest RSSI value as weight by three bisectors of the same group.

In [17], a multi-hop range-free localization algorithm is proposed for anisotropic networks with a small number of anchors. A detoured path detection is proposed to detect if the shortest path between nodes is detoured from their direct path by measuring the deviation in the hop count between the direct and shortest paths. A novel distance estimation method is introduced to approximate the shortest path based on the path deviation and to estimate their distance by taking into account the extent of the detour of the approximate shortest path.

In [18], two range-free localization schemes based on RSS information are presented. They employ soft computing techniques to overcome the limitations of previous range-free localization methods. In the first scheme, the localization is decomposed into a collection of individual problems in which the proximity of a sensor node to each anchor node is computed. The edge weights are modeled by FLS and optimized by GA. Contrary to the first scheme, the localization as a single problem is considered in the second scheme and approximate the whole mapping from the anchor node signals to the locations of sensor nodes by NN.

The methods proposed in this paper have following features:

1. Knowledge-based edge weight of the anchor node to determine the accurate coordinates of the target node.
2. A novel proximity-based performance index, to evaluate the proposed schemes.

3. Soft computing based algorithm (HPSO and BBO) for WSN localization

Soft computing algorithms have plenteous source of ideas for optimization, due to which these algorithms are popular because of their accuracy, and their meek computational burden [18–29]. An improve version of PSO, i.e., HPSO and a recent optimization algorithm, i.e., BBO are applied in [9–11] to achieve better and faster solution for range-based node localization. Ease of implementation and fast convergence are the qualities of *gbest* PSO, however, it is likely to get trapped in local optima that leads to pre-matured convergence. In this paper, we extend the application of HPSO and BBO for range-free 3D node localization. The following sections present a condensed overview of FLS, HPSO, and BBO.

3.1. Fuzzy logic system

Fuzzy logic is one of the most pragmatic ways to mimic human expertise in a naturalistic manner [30]. Computing with words allows us to develop mathematical models of the events articulated in language only. Fuzzy logic enhances the robustness of a system in that it arrives at an accommodation with the imprecision pervasive in any real world system. Its basic configuration consists of input and output scaling factors, fuzzifier, rule base, inference engine and a defuzzifier as shown in Fig. 1.

The structure of the rule base can be stated as in Eq. (1)

$$R_i: \text{ if } x_1 \text{ is } A_{i1} \text{ and } x_2 \text{ is } A_{i2} \text{ and } \ldots\ x_n \text{ is } A_{in} \text{ then } y_i \text{ is } W_i \tag{1}$$

where R_i is ith rule, x_j is jth input variable of FLS; n is the number of input variables, y_i is the ith output variable; A_{ij} are the fuzzy membership functions for inputs and W_i are the fuzzy membership functions for output in case of Mamdani type systems (functions of input variables in case of Sugeno type systems [33]). In this paper, we use Mamdani implication (though Sugeno type systems are more accurate but consistency of Mamdani systems cannot be ruled out. Mamdani System has solid defuzzification process and that keeps the result in consistent form), max aggregation (2) and center of sums defuzzification method [33] for an input $X = (x_1, x_2, \ldots, x_n)$, then y^* is the crisp (defuzzified) output of the fuzzy system and can be expressed as (3) while the overall output fuzzy set can be expressed as in (2):

$$\mu(y) = \max(\min(A_{in}, W_i)) \tag{2}$$

where max is aggregation operator and min is implication operator

$$y^* = \frac{\int_y y\{\sum_{k=1}^{m} W_k\}dy}{\int_y \{\sum_{k=1}^{m} W_k\}dy} \tag{3}$$

where y is a running point in a discrete universe of discourse, W_k are the individual output fuzzy sets and m is the number of individual output fuzzy membership functions.

3.2. H-best particle swarm optimization

Eberhart and Kennedy developed the PSO in 1995 [32] based on the analogy of bird flocks and fish schools where each individual