

Adaptive DV-HOP Location Algorithm Using Anchor-Density-based Clustering for Wireless Sensor Networks

Zhang Ming

College of Electronic Engineering, Huaihai Institute of Technology, Jiangsu, 222005, China

Tel.: 86+13003467058

E-mail: lyg690916@163.com

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Abstract: Localization is an important topic in the wireless sensor networks (WSN) because sensor nodes are randomly scattered over a region and can get connected into a network on their own. In this paper, we proposed an adaptive DV-HOP location algorithm using anchor-density-based clustering for wireless sensor networks. First, we select the maximum core density anchor node as head to reduce regional distance error; second, we divide cluster into different grade according to the number of anchor nodes and unknown nodes in each cluster; last, we use different method to locate unknown position for high-density cluster, low density cluster and sparse density cluster. The algorithm does not change the basic orientation of the traditional DV-Hop algorithm process, does not require additional hardware support and performs efficiently in regular as well as irregular network topologies. Simulation shows that the localization accuracy of the proposed algorithm is better and the communication overhead is lower than the traditional DV-HOP algorithm. *Copyright © 2013 IFSA.*

Keywords: Wireless sensor networks (WSN), DV-HOP, Anchor-density, Error correction, Localization.

1. Introduction

Recent advances in wireless communications and electronics have enabled the development to flow-cost, low-power, multifunctional sensor nodes that are small in size and communicate in short distances [1]. A sensor network is a wireless network composed of a large number of sensor nodes that are densely deployed in a field. A sensor node is a small device which has sensing, computing and communicating capabilities. It collects environmental data, processes the sensed data, and transmits them to other sensor nodes via wireless channels [2]. Sensor nodes tag their observations with their location information and such information is critical for illustrating a representative picture of the monitored environment.

Localization of sensor nodes has been an active research area in WSNs. Position information of nodes is a vital requirement in many WSN applications including monitoring, tracking and geographic routing [3]. But in WSNs, node positions may not be known prior to or at the time of deployment. The process of estimating the unknown node positions within the network is referred to as localization. The limited power supply, size and cost considerations in sensor networks may prohibit the use of a GPS [4] (Global Positioning System) module at each sensor node. Therefore, it is often the case with a general assumption that the positions of some nodes (called anchors), are known, so that it is possible to find the absolute positions of the remaining nodes (called free nodes) in the WSNs.

Many localization algorithms for wireless sensor networks have been proposed. These localization protocols are classified into range-based and range-free algorithms. The range-based algorithm uses absolute point-to-point distance or angle estimates for calculating the location, which are relatively precise but require additional hardware and their cost is relatively high [5]. On the contrary, the range-free algorithms do not need the distance or angle information to the sensor nodes from the anchor nodes for their localization, they provide more economic and simpler estimates than the range-based ones, but their results are not as precise as those of the range-based [6].

In this paper, we propose an adaptive DV-HOP localization algorithm using anchor-density-based clustering for wireless sensor networks. First, we compute the core density for all anchor nodes in each cluster and select the maximum core density anchor node as cluster head to ensure that head is in the density maximum and reduce distance error; second, we calculate the cluster density grade according to the number of anchor nodes and unknown nodes in cluster; last, we use different method to locate unknown location for high-density cluster, low density cluster and sparse density cluster. The algorithm does not change the basic orientation of the traditional DV-Hop algorithm process, does not require additional hardware support and performs efficiently in regular as well as irregular network topologies.

2. Related Work

In the past several years, a number of localization protocols have been proposed. Most localization solutions in sensor networks require a few nodes called anchors (which are also called beacons or reference points), which already know their absolute locations via GPS or manual configuration. The density of the anchors depends on the characteristics and probably the budget of the network since GPS is a costly solution. Anchors are typically equipped with high-power transmitters to broadcast their location anchors. The remainders of the nodes then compute their own locations from the knowledge of the known locations and the communication links [7]. Based on the type of knowledge used in localization, localization schemes are divided into two classes: range-based schemes and range-free schemes.

Range-based protocols use absolute point-to-point distance or angle information to calculate the location between neighboring sensors. Common techniques for distance/angle estimation include time of arrival (TOA), time difference of arrival (TDOA) [8], angle of arrival (AOA) [9]. TOA is based on the range estimations by the signal arrival time, while TDOA relies on the difference in time between two arrived signals. Angle of arrival (AOA) to estimate node position is proposed in [9], the principle of AOA is to

detect the originators of signals according to the angle of arrival, and then to calculate the positions of nodes by means of triangulation. Maximum likelihood estimation (MLE) is an alternative used in AHLOS system (Ad-Hoc Localization System) [10], whose aim is to minimize the differences between the measured distances and estimated distances to determine the position of nodes. While producing fine grained locations, range-based protocols remain cost-ineffective due to the cost of hardware for radio, sound, or video signals, as well as the strict requirements on time synchronization and energy consumption.

Due to the hardware limitations of sensor devices, range-free localization algorithms are a cost-effective alternative to the more expensive range-based approaches [11]. There are two main types of range-free localization algorithms that were proposed for sensor networks: (1) local techniques that rely on a high density of land marks so that every sensor node can hear several land marks, In [12], each node estimates its location by calculating the center of the locations of all anchors that it hears. If anchors are deployed regularly, the location error can be reduced, although this is almost impossible in WSN deployments. In [13], they proposed a distributed on line algorithm in which sensor nodes use geometric constraints induced by both radio connectivity and sensing to decrease the uncertainty of their position. The sensing constraints, which are caused by a commonly sensed moving target, are usually tighter than connectivity-based constraints and lead to a decrease in the average localization error overtime. Different sensing models, such as radial binary detection and distance-bound estimation, are considered. In [14], they proposed a localization scheme using a mobile anchor. Each anchor, equipped with the GPS, moves in the sensing field and broadcasts its current position periodically. The sensor nodes that obtain the information are able to compute for their locations. (2) hop-based techniques that rely on flooding a network. To provide localization in networks where land mark density is low, hop-based techniques propagate location announcements through out the network. The DV-Hop uses a technique based on distance vector routing. Each node maintains a counter denoting the minimum number of hops to each land mark, and updates that counter based on beacon packet received. Landmark location announcements propagate throughout the network. When a node receives a new land mark announcement, and its hop counter is lower than the stored hop count for the land mark, the recipient updates its hop count to the new value and retransmits the announcement with an incremented hop count value. The known positions of the land marks as well as the computed ranges are used to perform a triangulation to obtain the estimated node positions. The DV-Hop has the following properties: localized and distributed, does not require a special infrastructure or set up, provides global coordinates, and requires re-computation only

for the moving nodes. In [15], the method enhances the DV-Hop by proposing an additional refinement phase. Once a node has computed a coarse estimated position of its own location using the DV-Hop, the node obtains the estimated positions from all of its neighbors. Then it assumes that the neighboring nodes are reference nodes, the node re-computes the triangulation to refine its estimated position. In [16], they use the hop distances of sensor nodes from one or more designated sources in order to obtain estimations of inter-sensor Euclidean distances that are used to locate sensor position.

Many multi-hop WSN localization algorithms, both connectivity based (range-free) and distance based, have been formulated as non-linear optimization problems. Doherty et al. [17] formulated the localization as a convex optimization problem and solved using existing algorithms for solving linear programs and semi-definite programming (SDP). Biswas et al. [18] proposed a centralized SDP technique for sensor network localization under complete and accurate distance measurements, followed by a gradient-descent local search method to further refine the estimated positions. The idea of converting the distance information into the coordinate vector has become prevalent in WSN localization, ever since Shang et al. [19] proposed a centralized localization algorithm called MDS-MAP, using Classical Multi dimensional Scaling (CMDS). MDS is a data analysis technique first used in psychometrics, to find the configuration of points in space that satisfies a set of supplied dissimilarities. Shang et al. [20] improved the MDS-MAP and proposed MDS-MAP (P), a distributed method in which the individual nodes compute their local maps using local distance or connectivity information. Costa et al. [21] proposed a distributed localization algorithm based on a weighted version of multi dimensional scaling (dwMDS), which corresponds to non-linear Weighted Least Square (WLS) methodology and incorporates local communication constraints within the sensor network. A Non-Metric Multi dimensional Scaling (NMDS)-based WSN localization is proposed in [22] where the configuration of points maintain the rank of the dissimilarities instead of their pair-wise Euclidean distances. A two-objective evolutionary approach based on topological constraints for node localization in wireless sensor networks was proposed in [23], it takes concurrently into account during the evolutionary process both the localization accuracy and certain topological constraints induced by connectivity considerations. A direction-based localization scheme (DLS) was proposed in [24], whose main goal is for each sensor to determine its direction rather than its absolute position, DLS considers multiple messages received for a sensor to determine its direction and anchor deployment strategy to improve the estimated correctness in direction of the sensor within the communication range of the sink.

3. System Model

Localization in WSN can be regarded as the location discovery problem. Unlike much research, whose main objective is precise coordinate estimation, the localization problem we are concerned with is that given some anchors and each sensor is able to determine the hop distance.

There are a set of anchor nodes and a set of sensor nodes in a WSN. A fixed number of anchor nodes are placed with the regions of coverage overlapped and serve as reference points, broadcasting periodic anchor signals. The sensor nodes are distributed randomly in the sensing field and receive messages from anchor nodes. The main responsibility of the anchor nodes is to send out beacon signals to help the sensor nodes to locate themselves. Each sensor node listens for a fixed time period and collects the RSS information of all beacon signals from adjacent anchor nodes. In this environment, it is assumed that:

1) The network is a static densely deployed network. It means a large number of sensor nodes are densely deployed in a two-dimensional geographic space, forming a network and these nodes do not move any more after deployment.

2) There exists only one Sink node, which is deployed at a relative static place outside the WSNs. There are N anchor nodes, which their positions are known through GPS or by other means such as pre configuration, and M unknown nodes.

3) The anchor nodes know their positions through GPS or by other means such as pre-configuration.

4) The radio propagation is perfectly spherical and the transmission ranges for all radios are identical.

5) The whole area has been divided into many $k \times k$ fields, namely, cluster, which the cluster head only generates from anchor nodes in its cluster.

Fig. 1 shows the network model based on clustering, the entire network is divided into many $k \times k$ square, in each square, there are different anchor nodes and unknown nodes, the black square is the anchor node, the black circle is the unknown node, cluster head is generated from anchor nodes.

Let us consider a sensor network $SN = \{n_1, n_2, \dots, n_{M+N}\}$, among these nodes, nodes from 1 to M , with $M < N$, are anchor nodes whose coordinates are known, while from $M+1$ to N , are general nodes whose coordinates are unknown. All sensors are uniformly scattered in the network. The communication range of a sensor, denoted as r , is a circle centered at the sensor. Each sensor has the communication capability, so as to exchange messages. Currently, we consider an obstacle-free environment, in which each sensor is able to communicate with all of its neighbors. We also consider a connected network, within which each sensor has at least one neighbor.

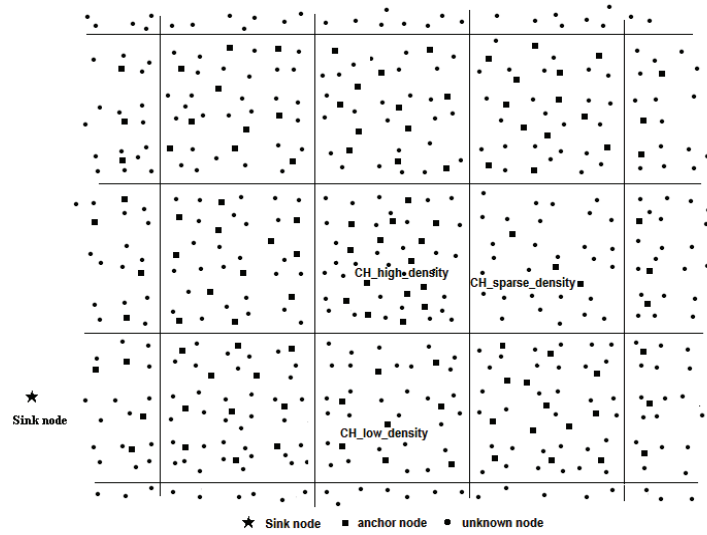


Fig. 1. Network model based on clustering.

Here, it is assumed that the anchor nodes are always aware of its physical position and helps in locating other nodes. Its position is obtained by manual placement or by external means such as a GPS receiver. This node forms the basis for most positioning systems in WSNs, we denote the position of anchor node i as

$$p_i = (x_i, y_i)^T \quad i = 1, \dots, M. \quad (1)$$

We define the real geographic distance between two anchor nodes i and j as

$$d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (2)$$

We adopt a simple disk model for network connectivity: nodes i and j can communicate with each other if and only if $d_{ij} < r$, where r is the connectivity range.

4. Adaptive DV-HOP Location Algorithm Using Anchor-Density-based Clustering

Adaptive location algorithm using anchor-density-based clustering has three phases, first is generates cluster head based on maximum core density; second is cluster grading; third is adaptive location algorithm.

4.1. Cluster Head based on Maximum Core Density

In initialization, in cluster CH $_t$, each anchor node i sends packet including ID, (x_i, y_i) , num_i et al, num_i is the neighbor of anchor node i , its initial value is 0, so

all anchor nodes in cluster can know other anchor nodes information.

We assume $Nr(i)$ is the ordered set of its direct neighbor, Cr is the threshold of core node number, which can be adjusted according to the network node density, $Nr(Cr)$ is the Cr th neighbor from anchor node i , $d(i, Nr(Cr))$ is the distance between anchor node i and Cr th node, we define the parameter α as formula (3)

$$\alpha = \begin{cases} d(i, Nr(Cr)), & Nr(i) > Cr \\ r, & Nr(i) \leq Cr \end{cases} \quad (3)$$

So we define the core density of anchor node is $\omega(i)$ as formula (4)

$$\omega(i) = \frac{Nr(i)}{\alpha} \quad (4)$$

Each anchor node respectively calculates its core density, then sends information to all neighbor anchor nodes including ID, $\omega(i)$ et al, so the anchor node which has the maximum core density will be the cluster head. Head broadcasts information to all nodes in cluster, when received information, each anchor node and unknown node send information to head, so head can calculates the numbers of anchor nodes Num_{anchor} and unknown nodes in cluster Num_{un_node} .

4.2. Cluster-Density Grading

The location accuracy is closely related to the number of anchor nodes, the more number of anchor nodes, the more accurate locating. In the case of uniform distribution, the ideal number of anchor nodes is the point number which meets triple coverage for the whole region [25].

Theorem 1: the number of meeting triple coverage is proportional to area.

We assume that S_{area} is the area of cluster, r is the radius of anchor node, a cluster requires at least the number of anchor nodes as formula (5)

$$N_{anchor} = \frac{S_{area}}{\frac{(\sqrt{3})}{2} \times r^2} \quad (5)$$

We assume that the number of unknown nodes in cluster CH_t is $Num_{un_node}(CH_t)$, $N_{anchor}(CH_t)$ is the number of triple coverage point which satisfy formula (5), so we define the average cluster density function as formula (6)

$$\rho_{3_cov} = \frac{Num_{un_node}(CH_t)}{\frac{N_{anchor}}{3}} \quad (6)$$

Then the cluster is divided into different grade, we assume τ is the threshold parameter, if $Num_{anchor}(CH_t) > N_{anchor}$ and $Num_{un_node}(CH_t) < \tau * \rho_{3_cov}$, we define this cluster is a high density cluster; if $Num_{anchor}(CH_t) < N_{anchor}$ and $\rho_{3_cov} \leq Num_{un_node}(CH_t) < \tau * \rho_{3_cov}$, we define this cluster is a low-density cluster; if $Num_{anchor}(CH_t) < N_{anchor}$ and $Num_{un_node}(CH_t) \geq \tau * \rho_{3_cov}$, we define this cluster is a sparse cluster.

4.3. Adaptive Location Algorithm for Different Grading

The entire network is divided in many clusters and each cluster has a grade, in order to reduce communication and improve accuracy, AL-ADC algorithm uses adaptive locating method for different grades.

1) High-density cluster location.

For high-density cluster CH_h , there are enough anchor nodes to satisfy triple coverage, so using these anchor nodes in cluster can locate those unknown nodes position, the specific method is as follows:

Step 1: each anchor node i calculates its average distance by formula (7)

$$Avg_i = \sum_{i \neq j} d_{i,j} / \sum_{i \neq j} h_{ij}, \quad (7)$$

where j is the neighbor anchor node of i , h_{ij} is the hops between the anchor node i and anchor node j .

Step 2: head uses formula (8) calculates the average distance of cluster CH_h .

$$Avg(CH_h) = \frac{Num_{anchor}(CH_h)}{\sum_{i=1} Avg_i / num_{anchor}(CH_h)} \quad (8)$$

Step 3: head calculates the whole cluster error through formula (9):

$$error_{CH_h} = \frac{Num_{anchor}(CH_h)}{\sum_{i=1} (Avg_{CH_h} - Avg_i) / Num_{anchor}(CH_h)} \quad (9)$$

Step 4: unknown node s calculates the distance from anchor nodes by $Avg(CH_h)$, h_{sj} and $error_{CH_h}$, namely, the estimate distance as formula (10), then calculates its location.

$$d_{estimate}(u) = \sum_{p=1}^{num_u} Avg(CH_h) \times h_{up} + \lambda \times error_{CH_h}, \quad (10)$$

where u is the unknown node, num_u is the anchor nodes which in u 's radius, λ is a variable parameter and can be dynamically adjusted according to network environment, $\lambda \in [-1, 1]$.

2) Low-density cluster location.

In the low-density cluster, we assume that is CH_{low} , the number of anchor nodes is less than the number of triple coverage nodes and there are many unknown nodes, so the anchor in cluster can not locate the unknown nodes accurate location, we use the anchor nodes of its neighbor cluster to help locate the unknown nodes, we assume the low-density cluster is CH_{low} the specific method is as follows:

Step 1: the low-density cluster head broadcasts information to its direct neighbor cluster, the neighbor head will send information including anchor location, anchor node number et al.

Step 2: head computes the distance d_{ij} between anchor nodes which belong to CH_{low} or neighbor cluster, then computes average distance by formula (11)

$$Avg(CH_{low}) = \frac{Num_{anchor}(CH_{low})}{\sum_{i=1} Avg_i / num_{anchor}(CH_{low})} \quad (11)$$

where $Num_{anchor}(CH_{low})$ is the number of anchor nodes including CH_{low} and its neighbor cluster.

Step 3: the head of CH_{low} computes the average distance error by formula (12)

$$error(CH_{low}) = \frac{N_{CH_{low}}}{\sum_{q=1}^{N_{CH_{low}}} (Avg(CH_p) \times Num_{anchor}(CH_p)) / Num_{anchor}(CH_q)} \quad (12)$$

where N_{CH} is the number of neighbor cluster add 1.

Step 4: using formula (10) to calculate the unknown node estimate distance.

3) Sparse-density cluster location.

For the sparse cluster, we use the anchor nodes of entire network to estimate the unknown distance. We assume CHs is the sparse-density cluster.

Step 1: each head broadcast its average distance and error, so all heads know other clusters information.

Step 2: head computes the average distance of the entire network through the formula (13).

$$Avg_entire_network = \frac{\sum_{i=1}^{Num(CH)} Avg(CH_i) / num(CH)}{Num(CH)} \quad (13)$$

where Num(CH) is the number of clusters in entire network.

Step 3: head computes the error of entire network by formula (14)

$$error_entire_network = \frac{\sum_{i=1}^{Num(CH)} error(CH_i) / Num(CH)}{Num(CH)} \quad (14)$$

Step4: the estimate distance of unknown node u can be computed through formula (15)

$$d_{estimate}(u) = \sum_{p=1}^{num_u} Avg_entire_network \times h_{up} + \lambda \times error_entire_network \quad (15)$$

where u is the unknown node, numu is the number of anchor nodes which in u's radius, λ is a variable parameter and can be dynamically adjusted according to network environment, $\lambda \in [-1, 1]$.

5. Simulation Results

This section provides a detailed quantitative analysis comparing the performance of our scheme with traditional DV-HOP.

In our experiments, the deployment area is a square plane of 1000 m by 1000 m. The plane is divided into 10×10 cluster. Each cluster is 100 m × 100 m, the number of nodes from 100 to 1000 randomly deploys in the area, and the anchor nodes accounted for 20 %, others are unknown nodes, the radius is from 10 m to 30 m. In order to effectively compare and analyze the performance of proposed algorithm and DV-HOP, all data is the average values from 10 tests. Summary of parameters and defined values are shown in Table 1.

Table 1. Parameters and defined values.

Simulation Parameters	Value
N (total nodes)	100-1000 nodes
A (network size)	1000×1000 m
Cluster size	100×100 m
Number of sink	1
Eelec	50 nJ/bit
$\mathcal{E}_{amp}$	0.0013 pJ/bit/m ²
Radius	50 m
Anchor rate	20 %
Simulation times	10 times

Fig. 2 is the location accuracy of the different communication radius, anchor nodes rate is 20%, the location accuracy of proposed algorithm is better than traditional DV-HOP, with the radius increased, the location accuracy of two algorithm is gradually increase, but our scheme has a better stability, proposed algorithm has a higher location accuracy under the changing radius conditions.

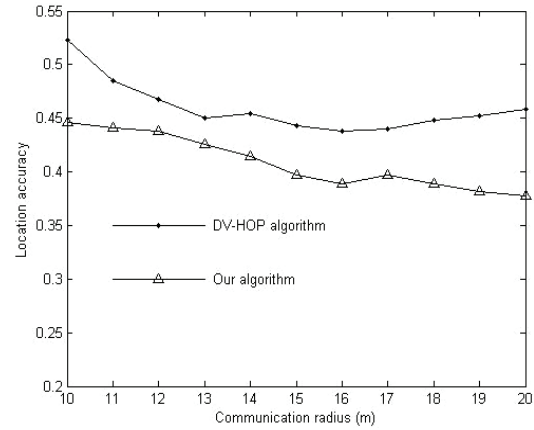


Fig. 2. The relationship between communication radius and location accuracy.

Fig. 3 is the relationship between the ratio of anchor nodes and location accuracy, we can see from Fig. 3, the location accuracy is increases with the ratio of anchor nodes increasing, there into, radius is 15 m, proposed algorithm has a better location performance under the same anchor ratio, for example, when the ratios is 20 %, the location accuracy of proposed algorithm is 0.36, while DV-HOP is 0.43. Especially when the ratio of anchor nodes is large than 12 %, the proposed algorithm has a better stability.

Fig. 4 shows the communication overhead is rapidly increases along the network size increasing, due to use cluster density grading strategy, the most unknown nodes location can be completed in the cluster or in combination with other neighbor clusters, only a small part of the unknown nodes locating needs in the entire network communication, so its communication overhead is approximately 1/4 of the conventional DV-HOP algorithm.

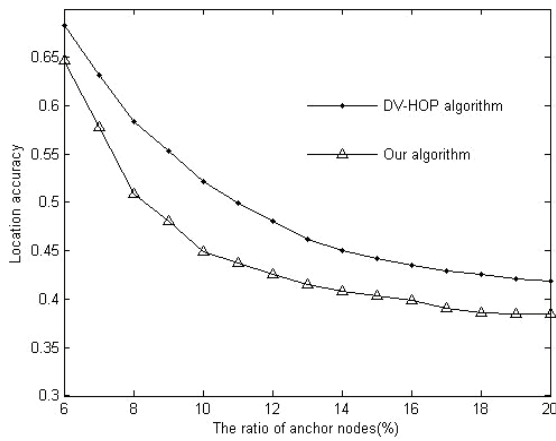


Fig. 3. The relationship between the ratio of anchor nodes and location accuracy.

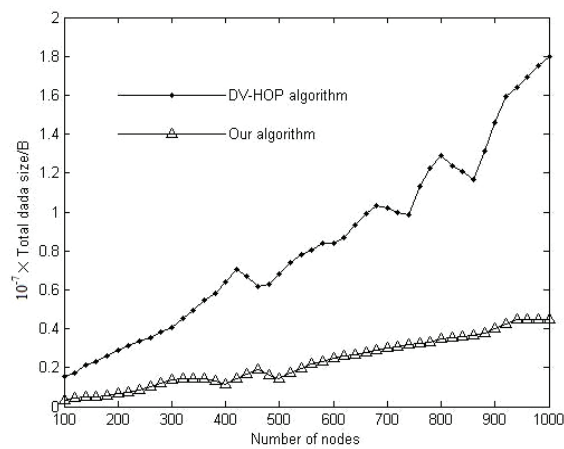


Fig. 4. The traffic of different network size.

6. Conclusions

The localization accuracy is the primary indicators to evaluate the positioning algorithm. In this paper, we have proposed an adaptive DV-HOP location algorithm using anchor-density-based clustering for wireless sensor networks, first, we compute the core density for all anchor nodes in each cluster and select the maximum core density anchor node as cluster head to ensure that head is in the density maximum and reduce distance error; second, we calculate the cluster density grade according to the number of anchor nodes and unknown nodes in cluster; last, we use different method to locate unknown location for high-density cluster, low density cluster and sparse density cluster. The algorithm does not change the basic orientation of the traditional DV-Hop algorithm process, does not require additional hardware support and performs efficiently in regular as well as irregular network topologies. From the results of the simulation, we can see that the localization accuracy of the proposed algorithm in irregular network is better than the DV-Hop algorithm, and the communication overhead is lower than the traditional DV-HOP algorithm.

Acknowledgements

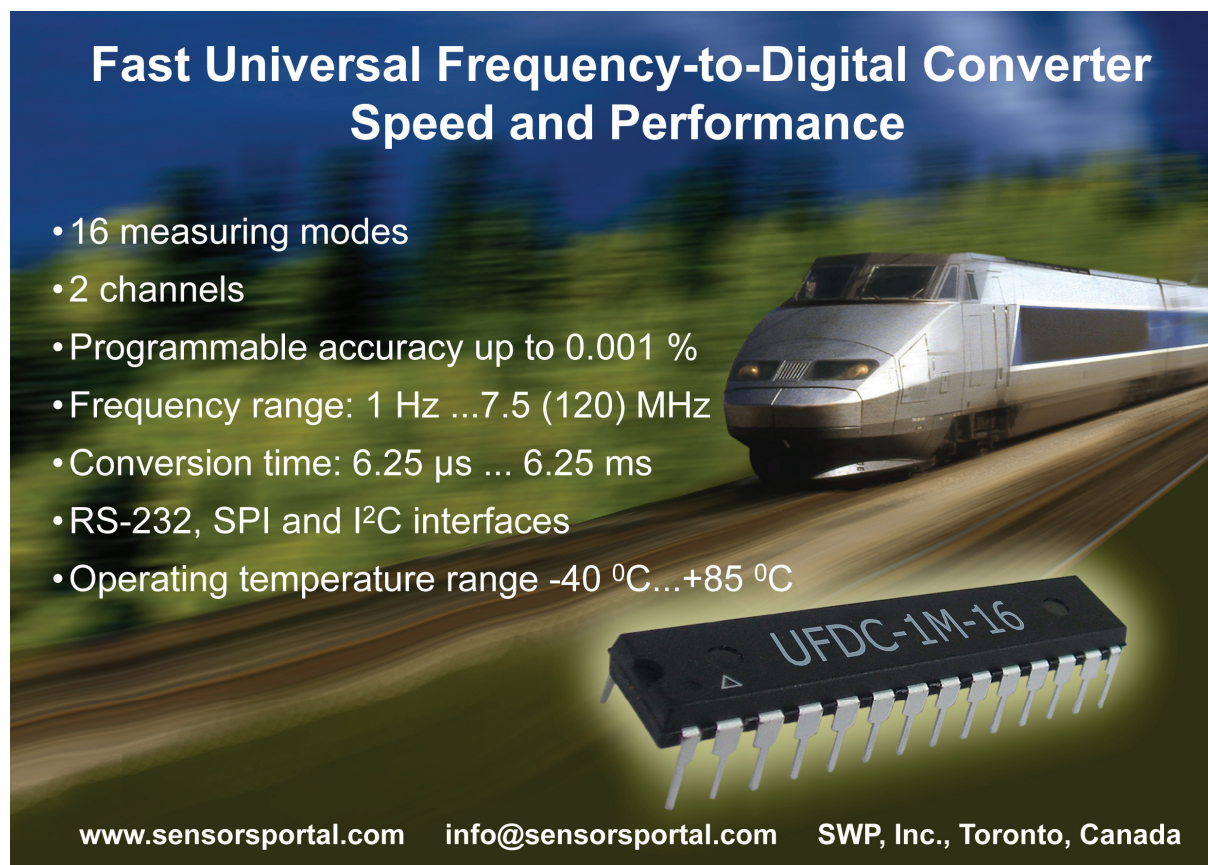
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