Application of Virtual Force Method for Deploying Mobile Sensor Networks

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Abstract. The virtual force method is applied for deploying a mobile sensor network in an uncertain environment. A mobile sensor network is a distributed collection of nodes, each of which has sensing, computation, communication and locomotion capabilities. Previous studies of mobile sensor deployment adopted a round by round process, that is, sensors move iteratively until the maximum coverage is reached. However, the mobile sensors probably move in a zig-zag way that waste a lot of energy in comparison with that of moving directly to a final location. We proposed a cluster-based virtual force algorithm (CVFA), which is an energy efficiency deployment strategy. CVFA can enhance the coverage after an initial random placement of sensors. By constructing virtual force, each node is attracted or repelled by other nodes, thereby forcing the network to spread itself throughout the environment. In CVFA, global information of k-hop neighbours can be acquired by the inter-cluster communications, and sensors can grasp their target locations logically. Experimental result, using ns-2 simulator, suggests that CVFA can significantly reduce the energy consumption compared to previous work, especially on maintaining similar coverage.

1. Introduction

Wireless Sensor Networks (WSNs) is a paradigm of pervasive computing. Advances in sensor hardware and wireless network technologies are the last mile of bridging the gap between the physical world and the virtual information world [1-4]. These networks have a large number of tiny sensors that have sensing, computation and communication capabilities but with limited battery. Users can deploy these sensors near or inside the region of observation to gather, process, analyze and disseminate collaboratively sensing data through these sensors. In order to collect precise sensing data based on a well coverage level, the proper sensor deployment is critical for the efficiency of sensor systems [5-10]. In general, sensor nodes are considered to be fixed in such an environment that is dynamic and unknown or hostile regions like disaster areas, battlefields, and deserts. Most of the previous works considered these tiny sensors being deployed to result in a random placement [11-14] through air drop [15] for...
decreasing the cost and latency. Clearly, these sensors may be distributed unevenly, creating holes and disconnected islands. Such uncovered areas can be shrunk by increasing the number of sensors dropped. However, no matter how many sensors dropped, the coverage rate is limited since of the influence of wind force and or the quiescence of obstacles.

In a mobile sensor network [11], mobile sensors can move around to self-deploy. That is, these sensors have the ability of node spreading from an initial random topology to a desired uniform topology to achieve maximum coverage. A uniform topology has the advantage that it can prolong the system lifetime since each node has even energy consumption per communication. It is worth nothing that the average moving distance should be minimized, since movement may be much more expensive than communication and computation in terms of energy [5]. This paper utilizes the virtual force approach [5] is like the equilibrium of molecules, which is inter-nuclear repulsion and attractions between molecules to achieve the maximum coverage of mobile sensors. In this paper, we assume that we deploy a wireless sensor network by mobile nodes. Clearly, if sensors are located too close to each other, the gain in coverage is not high since of additional sensors. Therefore, we can adapt the concept of repulsive force that can repulse each other sensor to gain more coverage. On the contrary, if sensors are located too far away from each other, the coverage regions may not be connected and cause a partitioning of the network. Therefore, we can adapt the concept of an attractive force that can attract each other to connect the coverage of network partitions. With the combination of attractive and repulsive forces, each sensor can move to an ideal target location that is computed by local environment information such as neighbor sensor’s locations and obstacles.

Zou and Chakrabarty [16] proposed the Virtual Force Algorithm (VFA) for the clustered sensor network. The cluster-head of a cluster in that network is assumed to have more computational capabilities. The head has the capability to compute the target location of each node within the cluster range by executing VFA. Clearly, this algorithm is a centralized approach (by cluster-head) that may suffer from the problem of fault of the head. The fault tolerance is important for such easily ruined sensor networks. To overcome the problem of the edge effect and the energy efficiency, Heo and Varshney proposed an intelligent energy-efficient deployment algorithm [5], called an Intelligent Deployment and Clustering Algorithm (IDCA), for clustered WSN. IDCA is also based on the virtual force approach, but the movement of each node is computed by itself, allow by each node moves by itself to a sparse region during sensor deployment process. Energy efficiency and edge effect for self-deployment of mobile nodes to form uniformly distributed node topologies was considered. Each node can decide its own mode either as a clustering mode [17, 18] or as a peer-to-peer mode, according to the local density (D) that is the number of nodes within its one-hop communication range (cR). The local density is higher when the local environment is denser. In general, wireless sensor networks desire dense deployment [19]. The dense deployment allows the use of redundancy for fault tolerance [20], allows multi-hop narrow communications for reducing energy consumption [3], and provides sufficient number of nodes to cooperate work for improving sensing accuracy and operation efficiency. However, if the communication of the sensors is not properly managed, a denser network accompanies the problem of channel contention that is a larger number of collisions and congestions in the network. So that the latency of the network will be increased and its energy efficiency will be reduced. To solve this problem, the clustering methodology [21] can also effectively manage communications in a dense network for energy efficiency. But all the above works [5, 16] didn’t consider the problem of channel contention in dense sensor networks.

This paper deals with energy efficiency for self-deployment of mobile sensors with better coverage. The deployment tries to form a uniform topology in an unknown environment. The Cluster-based Virtual Force Algorithm (CVFA) is proposed as an energy efficiency deployment strategy in a mobile sensor network. CVFA is based on a round by round process, where mobile sensors move iteratively until the maximum coverage is reached in a distributed way. The major concept of CVFA is to decrease unnecessary excessive movements through efficient communications. Because of the movement is much more expensive than communication and computation in terms of energy [5]. In CVFA, more global information of k-hop neighbors can be acquired by the inter-cluster communications. Hence, mobile
sensors can calculate their target locations, move logically, and update new logical locations through inter-cluster communications. Actual movement only occurs when sensors determine their final locations. Simulation results show that CVFA can significantly reduce the energy consumption compared to previous work, while maintaining similar coverage.

2. Preliminary: the concept of virtual force
The original virtual force concept was first proposed by Khatib [22], which is used for robot’s navigation and obstacle avoidance. Further, the virtual force concept was introduced to mobile sensor networks by Howard et al. [11], and they call it as potential field method. Potential field method is able to achieve good coverage without global maps, communication, and explicit reasoning. This method has an assumption that each sensor allows to determine the range with nearby sensors or obstacles. This method has the advantage that it does not require centralized control, localization or communication so as that the method has a scalability to very large networks. But this approach has the problem that its coverage is contained within line-of-sight connectivity, because each sensor does not have capability of communication to control moving distance.

Zou et al. [16] further utilized the concept of VFA to clustered-based WSN. For a given number of sensors, VFA attempts to maximize the coverage by attractive and repulsive forces. During the sensor deployment, sensors can determine a sequence of virtual motion paths for the randomly placed sensors. When the effective target positions are computed, a one-time movement is carried out to redeploy the sensors at these positions. But VFA algorithm didn’t consider the edge effect and less energy efficiency. These have been described in section 1.

Afterward, Heo et al. [5] proposed an IDCA algorithm that is also based on virtual force approach. This algorithm is first energy-efficiency deployment algorithm in clustered-based WSN. During sensor deployment, each sensor considers its remaining energy to decide its moving distance for reducing the difference of battery of each sensor. Therefore, IDCA algorithm can prolong the lifetime of whole network. However, this algorithm considered only one-hop neighbors’ information but did not consider the channel contention in dense field.

In this paper, we modify the IDCA algorithm [5] such that it is more suitable for dense mobile sensors. As detailed in [5], the local density (D) of a node indicates the number of nodes within its one-hop communication range (cR). Each node can decide its own mode to be either in a clustering mode [17, 18] or in a peer-to-peer mode according to the local density (D). If D is not equal to the expected density, the node selects the peer-to-peer mode. In a peer-to-peer mode, each node moves itself to a sparse region by the partial force $f_{\partial/\mu}^{i,j}$, so that the coverage of the network may increase and/or an energy-efficient node topology may be achieved.

3. Deploying mobile sensor networks
A distributed Cluster-based Virtual Force Algorithm (CVFA) is used to identify the target locations of mobile sensors, and, with the force, the mobile sensor networks directly move to latest target locations. To achieve this goal, we propose the idea of one-time movement, where all mobile sensors logically move from dense fields to sparse fields by intra-cluster and inter-cluster communications, and rotating cluster-heads. All mobile sensors move directly to their final locations only after they find those locations. The process of CVFA is illustrated in Fig. 2.

In the initialization phase, a specified number of nodes are deployed randomly in a given rectangle region. We can calculate the sensor number N according to $\mu_{cR} = \left(\frac{N \cdot \pi \cdot cR^2}{A}\right)^{\frac{1}{2}}$ [5], where A is the sensing area, $\mu$ is the expected density. The sensing range sR and communication range cR are assumed to be given. Each node can sense or detect an event within its sR and any pair of nodes within their cR can communicate with each other. This communication is needed for finding neighbors, obtaining neighboring locations, and transmitting and forwarding sensed data. The neighbors of a node are defined here as nodes within its cR.
In the clustering phase, CVFA adopts a one-hop cluster structure [23] to partition whole network into several local areas from a whole deployment region. In a one-hop cluster structure, each node is at most one-hop away from its cluster-head within one-hop intra-cluster cR. And each cluster-head can reach any other cluster-head within one-hop inter-cluster cR. So, a cluster-head can directly communicate the others without additional routing information. These features of one-hop cluster facilitate mobile sensors to deploy adaptively in an unknown and dynamic pre-deployment environment. Besides, a cluster-head has several (e.g., six) cluster power level for radio communications [21]. The length of communication range depends on the cluster power level. In this paper, each cluster-head operates in “dual” power mode, intra-cluster power level and inter-cluster power level respectively. Intra-cluster power level is a lower power level for members to communicate directly within a cluster, and inter-cluster power level is a higher power level for cluster-heads to communicate directly among different clusters. Each sensor can tune its intra-cluster cR by enlarging or narrowing intra-cluster power level k time, and the largest intra-cluster cR is as large as sR. The inter-cluster cR of a cluster-head is two times the intra-cluster cR. Moreover, to reduce this type of interference, the intra-cluster and inter-cluster communication use different CDMA codes.

After the clustering phase, CVFA adopts the virtual force concept to deploy clustered mobile sensors in the intra-cluster deployment and inter-cluster deployment phase. In the intra-cluster deployment phase, the intra-cluster communications emphasize less communication power and avoidance of channel contentions. Further, the inter-cluster communications emphasize the precise deployment location of whole cluster in the inter-cluster deployment phase. Finally, all mobile sensors move to their target locations only in the last phase.

The assumptions made in this paper are described as follow:

1. Each sensor has identical capabilities for sensing, communication, computation, and mobility;
2. Each sensor has the same initial energy level, and the energy level (ranging from 0 to 1) varies along with movement and other activities;
3. Sensing coverage [13] and communication coverage (cR) of each node is assumed to be ideal, which means that both coverage areas have a circular shape without any irregularity;
4. Each sensor has the ability to know its own location by some method, such as the global positioning system or iterative multilateration [24];
5. The channel contentions are possible to happen when sensors located in high density fields; In other words, there are errors during transmission of data and in the calculation of locations;
6. Each sensor has ability to vary cluster power level to change its intra-cluster cR;
7. The inter-cluster cR is k times range than the intra-cluster cR;
8. Each sensor has only local information from the neighboring nodes within its direct one-hop intra-cluster cR;
9. Each cluster-head has only local information from the neighboring cluster-heads within its direct one-hop inter-cluster cR;
10. Each sensor is capable of detecting obstacles;
11. Each sensor has bound information of the region.

3.1. Clustering by density
Clustering, is a hierarchical networking concept, is employed in many WSN scenarios to take advantage of local information and to reduce energy consumption. In deployment issue, we want to utilize a cluster structure to control mobile sensors to move effectively. Because of choosing cluster-heads optimally is
an NP-hard problem [25]. Moreover, deploying mobile sensors to a uniform topology fast is preferred. So we adapt a LEACH-like clustering method.

LEACH[26] is a self-organizing, adaptive clustering protocol that uses randomization to distribute the energy load evenly among the sensors in the network and incorporates data fusion to reduce the amount of information that must be transmitted to the base station. The differences between LEACH and our clustering method are that LEACH must decide the number of cluster-heads at first, and LEACH doesn’t adapt the local density of deployment environment. Hence, LEACH would result in different degree clusters. If the number of degree is too high, the high computation and communication overhead of a cluster-head is resulted; on the contrary, the number of cluster-head is too many to reduce wide range inter-cluster communications that would waste more energy. Hence, we propose a density-based clustering method, that is based on distributed divide-and-conquer approach and none attempts to find the optimum of the network topology.

A CLUSTER message is only three bytes. So each cluster-head can count the number of member accurately through small CLUSTER message that member send back. In order to maintain appropriate member number of a cluster, our clustering method would narrow radio range in greedy manner, when the number of degree is larger than the expected density. Finally, the degree of all clusters restricts to lower than the expected density after clustering. Therefore, there are two advantages of finding the minimum communication power level with connectivity and decreasing the probability of channel contentions in the clustering by density phase. A sensor can spend less communication power though minimum communication range is analyzed in [26]. By narrowing communication range, a sensor can decrease the number of neighbors to decrease channel contentions is proved in [28]. We provide a simple case to illustrate the process of density-based clustering method. In Fig. 2, there are several sensor nodes that are randomly distributed in a rectangle region. Here, we assume the expected density is set to 4. At first, each node waits for a random time to become a cluster-head. Node B is the first to run this method, it becomes a cluster-head due to its state is ordinary node initially. Then node B broadcasts CLUSTER message to its neighboring node A and C. So node A and C would become cluster-head B’s member after they got cluster-head B’s CLUSTER message, and then send back to cluster-head B to compute the number of member. Then cluster-head B checks this number of member that is smaller than expected density, so cluster-head B arrives to steady-state. Notice that any node doesn’t become cluster-head in cluster B due to it has to check its current state at running time. After cluster B was formed, node F starts to check its state. In the same way, node E becomes a cluster-head. Node D, F and G becomes cluster-head E’s member. Therefore, the clustering by density method only need low overhead to fast partition the whole network into clusters.

![Figure 2. A simple case of clustering by density method.](image)
Our clustering method can adopt the varied density of network topology by narrowing radio range. There is a dense case in Fig. 3. The node C is chosen to a cluster-head, but its number of member is larger than the expected density. Hence cluster C narrow its intra-cluster cR to decrease the number of degree of all nodes in cluster C. And each node waits a random interval time to decide the cluster-head in this local field. Finally, cluster A and F is formed in the same way.

(a) The number of member of cluster-head C is larger than the expected density. (b) The number of member of cluster-head A and F is smaller than the expected density.

**Figure 3.** A dense case of clustering by density method.

### 3.2. Clustered Deployment

In general, each mobile node can compute the optimal deployment location if it has global information of the environment. However, it is virtually impossible to have complete global information regarding the dynamic and unknown environment, where a WSN is likely to be deployed. Moreover, a node utilizes too much wide range communications to obtain global information to compute more precise target location requires a huge amount of energy, and also increases the probability of channel contentions that would result in more energy consumptions. This is an unaffordable overhead on a WSN with limited power supply.

CVFA provides a solution of above problem. It utilizes cluster structure to aggregate multiple-hop information, to compute more precise target location of clusters, and to control one-time movement of whole clusters. After clustering, each cluster can be regarded as a sub-region of the deployment, and all mobile sensors maintain minimal radio range to communicate with their cluster-head. So, the overhead of each mobile sensor is low compared to utilize equivalent cR. Moreover, each cluster can decrease probability of channel contentions. Hence CVFA can adapt any varied environment of deployment.

In the intra-cluster deployment phase, the task of each mobile node is to achieve the distance equilibrium of intra-cluster with its one-hop neighboring node within its intra-cluster cR. A mobile node i only receives current location $p_j^n$ of other neighboring node j to compute the partial intra-cluster force $f_{intra,n}^{i,j}$ at time step n. Clearly, if mobile nodes are located too close to each other, they expert partial repulsive intra-cluster forces that can repulse each other node to gain more coverage. On the contrary, if mobile nodes are located too far away from each other, they expert partial attractive intra-cluster forces that can attract each other to connect the coverage of network partitions. With the combination of partial attractive and repulsive intra-cluster forces, each mobile node can get the intra-cluster force to move to an equilibrated target location that is computed by locations of one-hop neighboring nodes within intra-cluster cR. The partial intra-cluster force $f_{intra,n}^{i,j}$ can be computed through formulation (1).
where $i^n_p$ represents the location of node $i$ at the time step $n$; $j^n_p$ represents the location of neighboring node $j$ of node $i$ at the time step $n$; $n$ represents the current time step.

The local density LD of a node indicates the number of nodes contains itself within its one-hop intra-cluster cR. So the density factor $\frac{1}{LD}$ is considered for achieving intra-cluster equilibrium. The intra-cluster equilibrium range $ER_{\text{intra}}$ indicates the balance distance between nodes. Therefore, node $j$ exerts node $i$ a partial attractive force $f_{\text{intra},n}^{i,j}$, if the distance between node $i$ and node $j$ is larger than $ER_{\text{intra}}$ at time step $n$. On the contrary, node $j$ exerts node $i$ a partial repulsive force $f_{\text{intra},n}^{i,j}$, if the distance between node $i$ and node $j$ is smaller than $ER_{\text{intra}}$ at time step $n$. Finally, a node $i$ has an intra-cluster force $f_{\text{intra},n}^i$ in (2) that summarizes all partial forces form its neighbors as

$$f_{\text{intra},n}^i = \sum_{j, j \neq i} f_{\text{intra},n}^{i,j}$$  \hspace{1cm} (2)$$

where $k$ represents the number of partial intra-cluster forces; $n$ represents the current time step.

In Fig. 4, each sensor exerts its neighborhood a partial intra-cluster force within one-hop intra-cluster cR. Simultaneously, each sensor can also include influences of some neighborhoods that belongs other clusters through clustering mechanism. Finally, each sensor can update its intra-cluster equilibrium location in the intra-cluster deployment phase that is illustrated in Fig. 5.

In order to allow each cluster to maintain an appropriate distance with the border of the deployed area, each cluster-head that has current locations of all its members after computing the intra-cluster force, also compute the partial border forces $f_{\text{border},n}^{i,j}$ of all cluster nodes. This partial border force $f_{\text{border},n}^{i,j}$ is presented in (3). Notice that we assume the border equilibrium range $ER_{\text{border}}$ is 1/2 times of the intra-cluster equilibrium range $ER_{\text{intra}}$ in (4). And then each cluster-head combines all partial border force into border force $f_{\text{border},n}$, this combined force will lead whole cluster to repulse the border.
of deployed area. The border force $f_{\text{border}_n}$ is presented in (5). Finally, each cluster-head stores this border force for one-time movement. Notice that all mobile nodes always move with one-time in the one-time movement phase.

$$f_{\text{border}_n}^{i,j} = \left( ER_{\text{border}} - \left| p_n^i - p_n^j \right| \right) \times \frac{p_n^i - p_n^j}{\left| p_n^i - p_n^j \right|} \quad (3)$$

$$ER_{\text{border}} = \frac{ER_{\text{intra}}}{2} \quad (4)$$

$$f_{\text{border}_n} = \sum_{j, j \neq i}^{k} \frac{f_{\text{border}_n}^{i,j}}{k} \quad (5)$$

where $p_n^i$ represents the location of node $i$ at the time step $n$; $p_n^j$ represents the location of border of deployed region; $k$ represents the number of partial border forces; $n$ represents the current time step.

Hence, the border force can increase its sensing coverage and sensing density, and further influence target locations of other neighboring mobile nodes in next deployment round.

In order to save energy consumption and avoiding channel contentions, each mobile node limits its intra-cluster communication power level to minimal in the clustering by density phase. However, for computing more precise target location of each node, a mobile sensor needs long range communication to obtain global information. Hence, through wide inter-cluster communication of cluster-heads in this phase, multi-hop neighbors were included while computing next nodal target location. After intra-cluster deployment phase, each cluster-head $i$ has intra-cluster equilibrium locations of all members, and it can compute the cluster centric point $cp_n^i$ through k-mean like method [29]. The cluster centric point $cp$ is figured out by formula (8). It can be represented as a whole cluster.

$$cp_n^i = \sum_{j}^{k} \frac{tp_n^j}{k} \quad (6)$$

where $tp_n^j$ represents the target location of node $j$ in cluster $i$ at the time step $n$; $k$ represents the number of partial border forces; $n$ represents the current time step.

The cluster density CD of a cluster-head indicates the number of clusters contains itself within its one-hop inter-cluster cR. So the cluster density factor $1/\text{CD}$ is considered of the equilibration and the connectivity among clusters within its inter-cluster cR. The inter-cluster equilibrium range $ER_{\text{inter}}$ indicates the balance distance between the centric points of each cluster. If clusters are located too close to each other, the repulsive force is exerted. On the contrary, if clusters are located too far away from each other, the attractive force is exerted. After computing inter-cluster force, each cluster-head would check the borders of all member nodes, due to its cluster would be exerted to the borders by inter-cluster force. Each cluster-head can compute the border force again through formula (3-5), and combine original border force computed in the intra-cluster phase. Finally, each cluster-head combines the inter-cluster force $f_{\text{inter}_n}^i$ and the combined border force $f_{\text{border}_n}^i$ into the combined cluster force $f_{\text{combine}_n}^i$ in (7) as

$$f_{\text{combine}_n}^i = f_{\text{inter}_n}^i + f_{\text{border}_n}^i \quad (7)$$
In order to lead whole cluster to move together, each cluster-head send this combined cluster force to its all members after computing the inter-cluster force. And all nodes update its target location computed in intra-cluster phase when they receive this combined force. Consequently, the updated target locations of all nodes would achieve the intra-cluster equilibrium and the inter-cluster equilibrium simultaneously.

At last phase, because of the one-time moving distance is shorter than the greedy moving distance, so each node combines all virtual forces include intra-cluster, inter-cluster, and border forces to obtain the final target location to achieve one-time movement. Therefore, CVFA can decrease necessary moving distances and promote the energy efficiency.

After moving, each cluster-head has to check its stability as its cluster density (CD). If CD is not close to the expected cluster density, the status of a cluster considers unstable, and all nodes of this cluster have to participate deployment in next round. On the contrary, if CD is close to the expected cluster density, the status of a cluster considers stable. Each node has two criteria to be terminated. One is the number of stability and the other is the number of oscillations. A node is regarded to be in the stability status, if this node moves less than the threshold of movement distance. And a node is regarded to be in the oscillation status, when this node moves back and forth between almost the same locations many times. When the number of stability or the number of oscillations is higher or equal than a specific number, this node would stop to move.

4. Performance evaluations

The performance of the heuristic algorithms in the paper is evaluated by simulation. In the experiment, 30, 60, 90, and 120 randomly placed nodes in a region of size 6 m × 6 m, 8 m × 8 m, 10 m × 10 m, and 12 m × 12 m are used to run the DSSA, IDCA and CVFA, respectively. These algorithms are implemented in the ns-2 (version 2.29) simulator. Based on the information from [5], the sR used in the experiment is 2 m, and the intra-cluster cR and inter-cluster cR used in the experiment are 2 and 4 m at first, respectively. The maximum permitted velocity in this experiment is 0.4 m/s. Unlike the experiment in [5], our experiment environment is a high density region of deployment, thus it would cause the situations of channel contentions. Note that the target location of a sensor would be computed inaccurately when data collisions happened. Four metrics are of particular interest: sensing coverage (i.e., what is the area covered by the network), uniformity (i.e., what is the standard deviation of length between nodes), average energy consumption, and average moving distance. Coverage, average energy consumption and uniformity are related to the performance of sensor networks after the deployment of sensors is complete. Average moving distance prior to convergence is directly related to the performance of the deployment scheme itself.

4.1. Coverage

Generally, coverage can be considered as the measure of quality of service of a sensor network. The concept of coverage as a paradigm for the system-level functionality of multi-robot systems was introduced by Gage [30]. In this paper, coverage [12] is defined as the ratio of the union of areas (in square meters) covered by each node and the area (in square meters) of the entire ROI. Here, the covered area of each node is defined as the circular area within its sensing radius R. Perfect detection of all interesting events in the covered area is assumed

\[ c = \bigcup_{i=1, 2, 3, \ldots, N} A_i \]

where \( A_i \) is the area covered by the ith node; \( N \) is the total number of nodes; \( A \) stands for the area of the deployment region.

The overall coverage of a sensor network is composed of the covered regions of each sensor node. Though the coverage of a sensor is expressed by a sensor model which is binary or stochastic, the overall coverage of a sensor network depends on the locations of the sensor nodes in the sensor field. The
topology including the locations and spacing of sensor nodes determines the overall coverage of the network as well as the expected lifetime of the network. In Fig. 6, the 30 randomly placed node locations and coverage of the initial random deployment before running the algorithms are shown. Tiny circles represent the positions of nodes and small (shaded) circles are used to show the sR of the nodes, respectively. We also assume the default cR is two times of sR. Sensor information may be collected within the sR and communications between nodes are possible within the cR. It’s easy to see that there is a high density in the deployment region in Fig. 14. Hence, the initial coverage in this case is higher than the low density case.

Fig. 6. Initial distribution of 30 sensor nodes.

Fig. 7. Final node distribution after running DSSA.

Fig. 8. Final node distribution after running IDCA.

Fig. 9. Final node distribution after running CVFA.

Fig. 7 shows the 30 node locations and coverage after running the DSSA. The deployment region is fully covered after running the algorithm. The parameter values used in this simulation run are: sR = 2m, cR = 4m, expected density = 4, stable status limit = 3, oscillation limit = 3, and threshold for oscillation and stable status is 0.15. Now, the network is fully connected and also covers the entire deployment region. Note that the spatial node distribution is more uniform than the initial random distribution shown in Fig. 6. Fig. 8 shows the 30 node locations and coverage after running the IDCA. The deployment region is also fully covered after running the algorithm. The same as DSSA, the parameter values used in this simulation run are the same, and the spatial node distribution is also more uniform than the initial random distribution shown in Fig. 6. Fig. 9 shows the 30 node locations and coverage after running the CVFA. The deployment region is also fully covered after running the algorithm. The cR in CVFA is different from others due to cluster structure. Hence, the different parameters compared with the other algorithms are intra-cR = 2m and inter-cR = 4m.
4.2. Moving distance

| DSSA | IDCA | CVFA |
|------|------|------|
| ![30 sensor-node movements after running DSSA.](image) | ![30 sensor-node movements after running IDCA.](image) | ![30 sensor-node movements after running CVFA.](image) |
| ![60 sensor-node movements after running DSSA.](image) | ![60 sensor-node movements after running IDCA.](image) | ![60 sensor-node movements after running CVFA.](image) |
| ![90 sensor-node movements after running DSSA.](image) | ![90 sensor-node movements after running IDCA.](image) | ![90 sensor-node movements after running CVFA.](image) |
| ![120 sensor-node movements after running DSSA.](image) | ![120 sensor-node movements after running IDCA.](image) | ![120 sensor-node movements after running CVFA.](image) |

**Figure 10.** The sensor-node movements.
The movement may be much more expensive than communication and computation in terms of energy [5]. Therefore, the core problem of energy saving is that how to decrease the unnecessary movements of mobile sensors, since movement is the dominant factor in energy consumption. In addition, the average moving distance by each node is related to the energy required for its movement. So, the expected moving distance is important for the estimation of energy required when each node has a limited energy supply. Fig. 10 shows the moving path of all sensors after running these three algorithms in cases of 30, 60, 90 and 120 nodes.

**Figure 10.** The moving path of sensors after running three algorithms.

In Fig. 11, we can see that CVFA has the least movement among these algorithms. The reason is as follow. CVFA adds inter-cluster communication that can decrease channel contentions, to acquire global information to compute more precise target location than DSSA or IDCA, and actual movement only occurs when sensors determine their final locations. On the other side, the mobile sensors may move in a zig-zag way, if DSSA or IDCA utilizes narrow range to acquire local information. However, the mobile sensors may also move in a zig-zag way, if DSSA or IDCA utilizes wide range to acquire global information. The channel contention problem is the major reason. When there are a large number of mobile sensors within a wide communication range, channel contention occurs more often and these sensors have to move more than once, because channel contention results in data lost so as to their target locations would be computed incorrect. Comparison between DSSA and IDCA, IDCA has less movement since sensors that located high density move less for energy efficiency. This is the same result illustrated in [5].

**4.3. Energy Consumption**

Energy consumption in the deployment procedure comes from two major sources, mechanical movement and radio communication. We use the moving distance as the metric for the energy consumption in mechanical movement and the amount of message as the metric for the energy consumption in communication. We assume the energy consumption of movement is 30J to move one meter, it is calculated from the data of the mobile sensor platform [2]. In addition, we also assume that the energy consumption of intra-cluster communication and inter-cluster communication in CVFA is 100.4nJ and 101.6nJ to send one message, respectively. These consumptions are calculated from the first order radio model in [26]. Note that the default cR in DSSA and IDCA is the same with inter-cluster cR, so the energy consumption of communication is also 101.6nJ to send one message.

Fig. 12 shows that CVFA has the least energy consumption of movement, and that is the same result in Fig. 11. However, CVFA has the most energy consumption of communication in Fig. 13, because adding the inter-cluster communication and cluster management. To consider both factors in Fig. 14, we conclude that CVFA is much more energy efficient because the mechanical movement consumes much more energy than radio communication.
Figure 12. The comparison of average energy consumption of movement.

Figure 13. The comparison of average energy consumption of communication.

Figure 14. The comparison of average energy consumption.

5. Conclusion
This paper raised the issue of deploying mobile sensor network in an uncertain environment. A deployment region needs to be covered by clusters grouped form a specific number of nodes with limited sensing and communication range. We designed a distributed virtual force algorithm to increase energy-
efficiency of sensors in the deployment of clustered WSN. In addition, we proposed a synergistic combination of intra-cluster and inter-cluster deployment scheme. Through aggregation of global information, localized coordination and control ability of clusters, our method can decrease unnecessary node movement and the probability of channel contentions. The performance of our method is determined by the percentage of region covered, the average moving distance required for deployment, and uniformity of the networks. By experiment, under high density region of deployment, our method achieves less average moving distance and more energy efficiency in comparison with previous studies. In future work, we would consider to study how to improve the performance and management of clustering, and how to deploy hierarchical clustered WSN in heterogeneous networks [31, 32]. On the other hand, the relation between cluster-size and neighborhood-size probably influences the degree of saving energy. It is well worth studying the optimal deployment.

References
[1] A.H. Anisi, G. Abdul-Salaam, M.Y.I. Idris, A.W.D. Wahab, Ahmedy I. Energy harvesting and battery power based routing in wireless sensor networks, Wireless Networks, 23(1), 249-266, 2017.
[2] K. Sohrabi, J. Gao, V. Ailawadhi, and G.J. Pottie, Protocols for self-organization of a wireless sensor network, IEEE Personal Communication, Vol. 7, pp. 16-27, 2000.
[3] G.J. Pottie, and W.J. Kaiser, Wireless integrated network sensors, Communications of the ACM, 43(5), pp. 51-58, 2000.
[4] S. Guo, L. He, Y. Gu, B. Jiang, B. He, Opportunistic Flooding in Low-Duty-Cycle Wireless Sensor, Networks with Unreliable, Transactions on Computers, 63(11), 2787-2802, 2014.
[5] N. Heo and P.K. Varshney, Energy-efficient deployment of Intelligent Mobile sensor networks, IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans, Vol. 35, No. 1, pp. 78-92, 2005.
[6] S. Tilak, N. Abu-Ghazaleh, and W. Heinzelman, Infrastructure tradeoffs for sensor networks, In Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications, pp. 49-58, 2002.
[7] T. Clouqueur, V. Phipatnasuphorn, P. Ramanathan, and K. Saluja, Sensor deployment strategy for target detection, In Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications, pp. 42-48, 2002.
[8] E.H. Callaway Jr, Wireless Sensor Networks: Architectures and Protocols, CRC press, 2003.
[9] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, A survey on sensor networks, IEEE Communications Magazine, Vol. 40, pp. 102-114, 2002.
[10] D., Suh, K. Jeon, S. Chang, J. Kim, Auto-localized multimedia platform based on a modular Cyber Physical System aligned in a two-dimensional grid, Cluster Computing, 18(4), 1449-1464, 2015.
[11] A. Howard, M.J. Matarić, and G.S. Sukhatme, Mobile sensor network deployment using potential fields: A distributed, scalable solution to the area coverage problem, In Distributed Autonomous Robotic Systems, Vol. 5, pp. 299-308, 2002.
[12] A. Howard, M.J. Matarić, and G.S. Sukhatme, An incremental self-deployment algorithm for mobile sensor networks, Autonomous Robots, Vol. 13, No. 2, pp. 113-126, 2002.
[13] X.Y. Li, P.J. Wan, and O. Frieder, Coverage in wireless ad hoc sensor networks, IEEE Transactions on Computers, Vol. 52, No. 6, pp. 753-763, 2003.
[14] A.F. Winfield, Distributed sensing and data collection via broken ad hoc wireless connected networks of mobile robots, In Distributed Autonomous Robotic Systems, Vol. 4, 2000, pp. 273-282.
[15] S.S. Dhillon and K. Chakrabarty, Sensor placement for effective coverage and surveillance in distributed sensor networks, IEEE, Vol. 3, 2003, pp. 1609-1614.
[16] Y. Zou and K. Chakrabarty, Sensor deployment and target localization in distributed sensor networks, ACM Transactions on Embedded Computing Systems, Vol. 3, No. 1, pp. 61-91.
2004.

[17] V. Kawadia and P.R. Kumar, Power control and clustering in ad hoc networks, In INFOCOM, Vol. 1, 2003, pp. 459-469.

[18] A. Abuarqoub, and H. Al-Bashar, Dynamic clustering and management of mobile wireless sensor networks, Computer Networks, vol. 117, pp. 62-75, 2017.

[19] M. Tubaishat and S. Madria, Sensor networks: an overview, Potentials, Vol. 22, No. 2, pp. 20-23, 2003.

[20] K. Lalitha, R. Thangarajan, S.K. Udgata, C. Poongodi, A.P. Sahu, GCCR: An Efficient Grid Based Clustering and Combinational Routing in Wireless Sensor Networks, Wireless Personal Communication, 97(1), 1075-1095, 2017.

[21] O. Younis and S. Fahmy, HEED: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks, IEEE Transactions on Mobile Computing, Vol. 3, No. 4, pp. 366-379, 2004.

[22] M. Guerra, D. Efimov, G. Zheng, W. Perruquet, Finite-time obstacle avoidance for unicycle-like robot subject to additive input disturbances, Autonomous Robots, 41(1), 19-30, 2017.

[23] L. Tang, Q. Zhao, and S. Adireddy, Sensor networks with mobile agents, In IEEE Military Communications Conference, Vol. 1, 2003, pp. 688-693.

[24] H.G. Wen, Y.H. Qi, Z.B. Weng, A Multiband Dual-Polarized Omnidirectional Antenna for 2G/3G/LTE Applications, 17(2), 331-335, 2017.

[25] J.H. Qin, W.M. Fu, H.J. Gao, W.X. Zheng, Distributed $k$-Means Algorithm and Fuzzy $c$ – Means Algorithm for Sensor Networks Based on Multiagent Consensus Theory, IEEE Transactions on Cybernetics, 47(3), 772-783, 2016.

[26] S.P. Singh, S.C. Sharma, A Survey on Cluster Based Routing Protocols in Wireless Sensor Networks, Procedia computer science, 45, 687-695, 2015.

[27] P. Rodriguez, S.M. Tan, and C. Gkantsidis, On the feasibility of commercial, legal P2P content distribution, ACM SIGCOMM Computer Communication Review, Vol. 36, No. 1, pp. 75-78, 2006.

[28] L.H. Yen and C. Yu, Link probability, network coverage, and related properties of wireless ad hoc networks, In IEEE International Conference on Mobile Ad-hoc and Sensor Systems, 2004, pp. 525-527.

[29] M.C. Su and C.H. Chou, A modified version of the K-means algorithm with a distance based on cluster symmetry, IEEE Transactions on Pattern Analysis & Machine Intelligence, Vol. 6, pp. 674-680, 2001.

[30] A. Kupcsik, and G. Neumann, Model-based contextual policy search for data-efficient generalization of robot skills, Artificial Intelligence, 247, 415-439, 2017.

[31] K. Zheng, H. Meng, L. Hou, K. Lin, and L. Hu, Dynamic offloading schemes for mobile cloud computing services in heterogeneous networks, Journal of Internet Technology, Vol 16, No. 2, pp. 335-342, 2015.

[32] W.T. Cho, Y.W. Ma, and Y.M. Huang, A smart socket-based multiple home appliance recognition approach over IoT architecture, Journal of Internet Technology, Vol. 16, No. 7, pp. 1227-1238, 2015.