Bio-inspired and Voronoi-based Algorithms for Self-positioning of Autonomous Vehicles in Noisy Environments *

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ABSTRACT
Many topology control methods for autonomous mobile vehicles assume exact knowledge of the locations of neighboring nodes to make meaningful movement decisions. We present our *node-spreading Voronoi algorithm* (NSVA) and *node-spreading Voronoi-based genetic algorithm* (NSVGA), for self-positioning autonomous nodes in noisy environments. The performance of NSVA and NSVGA were evaluated in simulation experiments by measuring the network area coverage, average distance traveled and number of disconnected nodes. Experimental results show that both NSVA and NSVGA can adequately cover the deployment area despite errors in neighbor location information. NSVGA can tolerate location errors and maintain network connectivity better than NSVA at the cost of increased movement.

Keywords
genetic algorithms, self-organizing networks, topology control, Voronoi tessellation, MANETs

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1. INTRODUCTION
Due to low cost and wide availability of ubiquitous mobile devices, mobile ad hoc networks (MANETs) have been adapted to support a vast array of commercial and military applications. MANETs that have the capability to position mobile nodes can be used in exploring difficult to access environments, search and rescue missions, and dynamic deployment terrains. However, when operating in MANETs, these applications usually encounter challenges such as high transmission error rates and limited bandwidth due to unpredictable transmission contention, dynamic and rapidly changing mobility and congestion. Autonomous topology control algorithms allow mobile nodes to adapt their movements only based on local information extracted from their surroundings without the use of a centralized infrastructure, thus reducing the reliance on unpredictable and under-provisioned wireless networks. However, many autonomous topology control algorithms depend heavily on precise neighborhood location information to calculate the next position to move. In real situations, mobile nodes may experience significant errors in detecting the locations of neighbors and thus may easily make inappropriate movement decisions.

This paper studies NSVA and NSVGA, introduced in our previous research [1], as two possible mechanisms to allow autonomous MANET nodes to spread themselves over unknown two-dimensional areas while experiencing significant location information errors. NSVA determines movement decisions for a node by traveling to the center of its Voronoi tessellation. NSVGA is based on genetic algorithms (GAs) and utilizes the expected ratio of a node's Voronoi cell size and its coverage as a fitness function to evaluate potential movement decisions.

In this paper, we introduce a parameter, called error rate (ER), to model the noisy environment experienced by mobile nodes operating in harsh and dynamic environments. We evaluate the performance of NSVA and NSVGA using various metrics such as the network area coverage (NAC), average

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distance traveled (ADT) and the total number of disconnected nodes (NOON). Simulation results demonstrate that ER does not significantly affect the NAC achieved by NSVA and NSVGA. In NSVGA, mobile nodes perform well with respect to connectivity in noisy environments, but at the expense of an increased movement directly correlated with increases in ER. Conversely, ADT is not significantly influenced by ER for mobile nodes guided by NSVA, and is much less than mobile nodes running NSVGA. However, the autonomous vehicles using NSVA are more prone to connectivity losses as ER increases. Our NSVGA can be used in applications that require reliable connectivity and rapid deployment in noisy environments. NSVA can be successfully used in applications where network lifespan is the highest priority.

The rest of this paper is organized as follows. Section 2 provides an overview of existing research. Our NSVA, NSVGA and ER model are briefly described in Sect. 3. In Sect. 4, we outline performance metrics for self-deployment mechanisms. The results of our simulation experiments are presented in Sect. 5.

2. RELATED WORK

In our previous research, we introduced two techniques, called *node-spreading Voronoi algorithm* (NSVA) and *node-spreading Voronoi-based genetic algorithm* (NSVGA) [1] for uniform distribution of mobile nodes. Novel quantitative metrics to evaluate the performance of MANET nodes with respect to uniform node distribution are introduced in [2]. Several decentralized topology control mechanisms are presented in [3, 4] based on GA and game theory. A Markov chain model used to demonstrate the convergence of our topology control mechanisms to a satisfactory topology is in [5, 6].

A significant research effort has been focused on developing control algorithms to manage large numbers of autonomous nodes with limited radio coverage [7]. For example, Wattenhofer et al. [8] propose a distributed algorithm that could increase network lifetime while guaranteeing global network connectivity. A comprehensive study of concepts and applications for Voronoi diagrams in wireless network has been presented in [9]. Nguyen et al. [10] outline Voronoi-based quality measures for point distribution. Amitabha et al. [11] propose topology control mechanisms for 3-dimensional networks based on the properties of spherical Voronoi diagrams.

For stochastic error models in MANETs, Kuo et al. [12] propose an error model based on probabilistic coverage for location estimation. An analytical model used to track moving objects in a densely covered sensor fields is presented in [13]. In [14], a simple broadcast algorithm, called double-covered broadcast (DCB), is proposed for proving a high delivery ratio under high transmission error rates.

3. SELF-POSITIONING TECHNIQUES

Guided by our Voronoi-based mobile node self-positioning techniques NSVA or NSVGA, each mobile node makes its own movement decision for the next position using solely the information that it gathers from its local neighbors. Nodes n_i and n_j are neighbors when the distance between them is less than the communication range R_C. Without loss of generality, we assume that all nodes have the same R_C. The local sensing area $A_{s,i}$ of a node n_i is circumscribed by its communication range R_C.

3.1 Voronoi Cell

Figure 1 shows an example of the Voronoi tessellation for node n_i's sensing area $A_{s,i}$. The Voronoi cell V_i (shown as the dark gray sector) represents the locations that are closer to node n_i than to any of n_i's neighbors. We formally define the Voronoi cell V_i as:

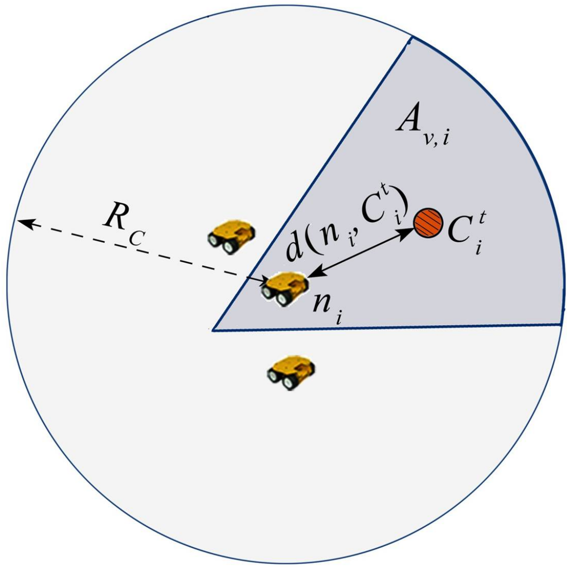


Figure 1: The Voronoi tessellation of sensing area $A_{s,i}$ at time t

$$V_i = \{\omega \in \Omega : d(n_i, \omega) < d(n_j, \omega), \forall_{n_j \in I \setminus \{n_i\}}\} \qquad (1)$$

where Ω represents the set of all positions in $A_{s,i}$, I is a set of all nodes, and $d(n_i, \omega)$ is the Euclidean distance between node n_i (i.e., (x_i, y_i)) and location $(x_\omega, y_\omega) \in \Omega$.

In Fig. 1, the physical size for the area of V_i is defined as $A_{v,i}$. At time t, the centroid of V_i is denoted as C_i^t marked by the small shaded circle. The distance between the current location of n_i and corresponding C_i^t is represented as $d(n_i, C_i^t)$.

3.2 Node-spreading Voronoi Algorithm

A node guided by our NSVA chooses its current Voronoi cell's center of mass as the next movement location in order to accomplish a uniform distribution of mobile nodes. At time t, centroid C_i^t of a corresponding Voronoi cell V_i is the preferred location for node n_i to control its surroundings and perform typical tasks such as reconnaissance, environment-sensing, etc. We define the movement decision for node n_i running NSVA as follows:

$$L_i^{t+1} = \begin{cases} C_i^t & \text{if } d(n_i, C_i^t) > \epsilon \\ L_i^t & \text{otherwise} \end{cases} \qquad (2)$$

where L_i^t is the location of node n_i at time t, C_i^t represents the center of mass of n_i's Voronoi cell V_i at step t and ϵ is a threshold to define locations acceptably close to the centroid of the Voronoi cell. Once node n_i is located sufficiently close to C_i^t (i.e., within ϵ distance), it remains in its current position. This eliminates jittering of mobile nodes in the network and reduces unnecessary energy consumption.

A mobile node n_i running NSVA utilizes only the information from $A_{s,i}$ to generate its V_i (Fig. 1) instead of considering the locations of all the nodes in the entire deployment space. V_i is limited to node n_i's communication range instead of extending to infinity as described in the classical Voronoi cell. In other words, our NSVA decision mechanism uses only local neighborhood information and does not require a central controller with global network knowledge.

3.3 Voronoi-based Genetic Algorithm

GAs are inspired by the process of natural selection observed in wildlife where children of fit parents are more likely to survive than their predecessors. GAs are useful when analytical or heuristic solutions are unavailable or can only provide insufficient results [15]. In our NSVGA, wireless mobile nodes use chromosomes to represent their movement directions and speeds. Chromosomes are updated by running NSVGA at each time step. NSVGA runs separately in each node, making it a suitable approach for MANETs. Unlike NSVA, NSVGA considers several candidate solutions (referred to as a population $\mathscr{P}$) for each time step. The quality of each candidate solution $L_j(k) \in \mathscr{P}$ is evaluated by our fitness function. Therefore, an appropriate fitness function is critical to the successful implementation of NSVGA.

In NSVGA, a node which intends to change its position first randomly selects a set of locations in its sensing area $\mathscr{P}_1$ (i.e., an initial population of movement decisions) as the candidate solutions. Each candidate location $L_i(k)$ is evaluated by our fitness function using the area size of a node's Voronoi cell A_v. One of the objectives for the self-organization of MANETs is the efficient coverage of the deployment space, therefore, increasing the area covered by all nodes and reducing overlapping communication coverage are important goals. For node n_i, the ratio of $A_{v,i}$ to $A_{s,i}$ can be an indicator of resource utilization. Therefore, the fitness of node n_i running NSVGA can be defined as:

$$f_i = \begin{cases} \frac{A_{v,i}}{A_{s,i}} & \text{if } |N_i| > 0 \\ 0 & \text{if } |N_i| = 0 \end{cases} \tag{3}$$

where $|N_i|$ is the number of near neighbors within n_i's communication range R_C. Candidate locations that would result in disconnecting n_i from all of its neighbors (i.e., $|N_i| = 0$) will be assigned a fitness of $f_i = 0$ in Eq. (3).

Candidate solutions are sorted according to their fitness values. Larger fitness values represent better locations to move. The best solutions from the pool of candidate solutions are then selected into the newly created population $\mathscr{P}_2$. To prevent NSVGA from getting stuck at a locally optimal point, individuals from population $\mathscr{P}_2$ have a small probability of being mutated. Node n_i will repeat this process until a maximum number of generations is reached.

Each node maintains records of the current neighborhood information, and runs its NSVGA software to find a better location to move at each time step if possible. Once there are no available locations to improve fitness, a node will stay in its current location until its environment changes such that *fitter* locations become available.

3.4 Noisy Environments

Mobile nodes may experience measurement errors in detecting the locations of neighbors in noisy environments. These types of errors cannot be eliminated or reduced without costly changes in hardware or increasing the sampling rate during operation. Therefore, it will be useful if the topology control algorithms can overcome these challenges. In order to mimic the impact of measurement inaccuracies on the performance of our topology control mechanisms, we introduce an error rate (ER) parameter in the detection of neighbor locations.

In our implementation, ER is the percentage of mobile nodes that will experience a measurement error at each time step. We define the total number of nodes as $|I|$. A randomly selected number of nodes (ER $\times\ |I|$) will encounter a measurement error. In such cases, the actual location of a neighbor is modified by adding Υ to it, where Υ is related to the distance between nodes n_i and n_j, and is defined as:

$$\Upsilon = \rho \times d_{ij} \tag{4}$$

where ρ is a random decimal in the range of $[-\frac{1}{4}, \frac{1}{4}]$. Let $L_{j\leftarrow i}$ represent the measurement of a neighbor n_j's position by node n_i:

$$L_{j\leftarrow i} = \begin{cases} L_j & \text{no error} \\ min\{L_j + \Upsilon, R_C\} & \text{measurement error} \end{cases} \tag{5}$$

The $L_{j\leftarrow i}$ will be equal to R_C once the measurement distance is greater than the node's communication range.

4. PERFORMANCE METRICS

In order to evaluate and compare the effectiveness of our topology control mechanisms, we present network area coverage, average distance traveled and total number of orphaned nodes as the performance metrics for MANETs [2].

4.1 Network Area Coverage

One of the main objectives of a MANET is to maximize its network coverage of mobile nodes. The network area coverage (NAC) is defined as the ratio of space covered by all the nodes and the complete deployment territory. Minimizing the overlap area among mobile nodes results in better resource usage. These overlapping regions are counted only once for NAC computation in our experiments. The total area covered by all nodes is given as:

$$\text{NAC} = \frac{\bigcup_{i=1}^{|I|} A_{v,i}}{A} \tag{6}$$

where $\cup$ represents the union operator and A is the area of the deployment terrain. NAC is a positive real number with an upper bound of 1, corresponding to a fully covered terrain. In Eq. (6), when a node's coverage space is entirely contained within the deployment area, the area of a node with a radius of R_C is counted toward NAC. If a node moves near a terrain boundary, only the part of its sensing area located inside the deployment terrain is included in the NAC calculation.

4.2 Average Distance Traveled

Another objective of a MANET is to extend the lifespan of a network. The metric that we used to evaluate this objective is the average distance traveled (ADT) by a mobile node before the desired network topology is achieved. Reducing the mobile node traveling distance is important in MANET applications since each node has limited power and movement is a very power-consuming operation. At a given time t, let $d(L^0_{n_i}, L^t_{n_i})$ denote the total distance traveled by n_i until time t. We define ADT(t) as the average distance traveled by all MANET nodes at time t:

$$\text{ADT}(t) = \frac{1}{\mid I \mid} \sum_{i=1}^{|I|} d(L^0_{n_i}, L^t_{n_i}) \tag{7}$$

ADT is a monotonically increasing function. When MANET nodes get closer to a uniform stable distribution, nodes stop moving and the derivative of ADT approaches zero.

4.3 Number of Orphaned Nodes

Sustaining network connectivity is an important goal of a MANET since multi-hop communication capability between any two nodes is essential for MANETs. A node is called an *orphan* when it does not connect to any other node (i.e., it has no neighbors). The total number of orphaned nodes (NOON) is used to evaluate the network connectivity in our experiments. For an ideal topology control mechanism, NOON should be 0.

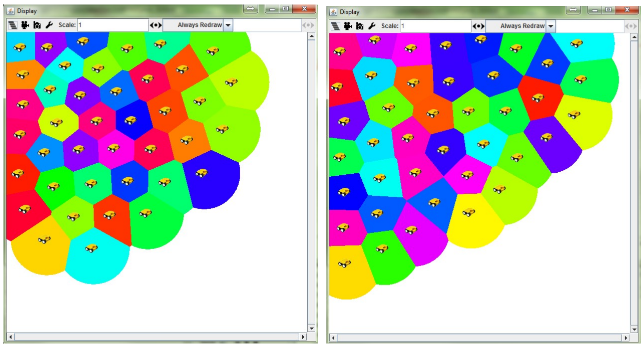
An orphaned node does not contribute to the network performance since it cannot share its collected information with any other node. Hence, reducing the NOON is vital and is a benchmark for the quality for topology control algorithms. Normally, the NOON will increase in the noisy environments since nodes' next movement calculation contains inaccurate location information. In our experiments, once a node becomes orphan, it will keep moving using its current direction and speed without running our NSVA or NSVGA. Once the orphaned node reaches the terrain boundary, it will change its velocity randomly and continue moving until it reconnects with another node.

5. SIMULATION EXPERIMENTS

We developed a software platform to analyze the performance of our NSVA and NSVGA. The MASON library [16] is included in our platform to observe the experimental results. Each experiment was repeated 20 times and the results were averaged. To mimic realistic deployment situations, 40 nodes are initially placed in the upper-left corner of the deployment space. The area was set to 100×100 square units and communication range for all mobile nodes was set to $R_C = 12$.

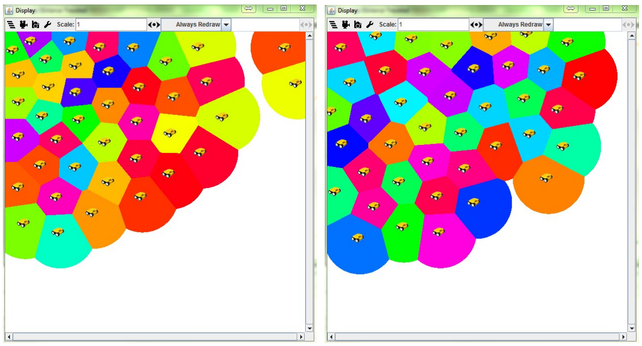
Figures 2 and 3 show the typical positions of mobile nodes after running NSVA and NSVGA for 100 steps in an error-free communication environment and typical final deployments of nodes for both algorithms in a noisy environment, respectively. Note that in Figs. 2 and 3, each region represents the Voronoi cell V_i for a particular node n_i within its R_C.

We can observe in Fig. 2(b) that nodes guided by NSVGA cover a slightly larger area in a noise-free environment than the



(a) (b)

Figure 2: A typical node distribution achieved by (a) NSVA and (b) NSVGA after running the simulation experiments for 100 steps in a noise-free enviroment



(a) (b)

Figure 3: A typical node distribution achieved by (a) NSVA and (b) NSVGA after running the simulation experiments for 100 steps in a noisy environment

mobile nodes moving in noisy conditions (Fig. 3(b)). However, in both noisy and noise-free environments, the network remains connected. On the other hand, the nodes guided by NSVA cover almost the same area in Fig. 2(a) (i.e., noise-free environment) and Fig. 3(a) (i.e., noisy environment). But some parts of the network becomes partitioned due to noise as observed in Fig. 3(a).

Figure 4 shows the improvement of NAC for the mobile nodes guided by NSVA and NSVGA with error rates of 0%, 5%, 10% and 20%. ER does not have a significant impact on the effectiveness of both algorithms with respect to NAC. Nodes running NSVA cover approximately 70% of the area compared to 67% covered with NSVGA, but NAC curves for NSVA are less stable (less smooth curves). After time step 60, the derivative of NAC becomes almost equal to zero for nodes running NSVGA. We also observe that the nodes can distribute themselves much faster with NSVGA than NSVA. For example, the mobile nodes only need to take 30 steps to reach 60% with NSVGA, however, the nodes running NSVA take approximately 90 steps to achieve the same level of coverage.

Figure 5 shows the results with respect to ADT for the nodes running NSVGA and NSVA. On the average, the nodes running NSVGA have to travel more than those using NSVA. For

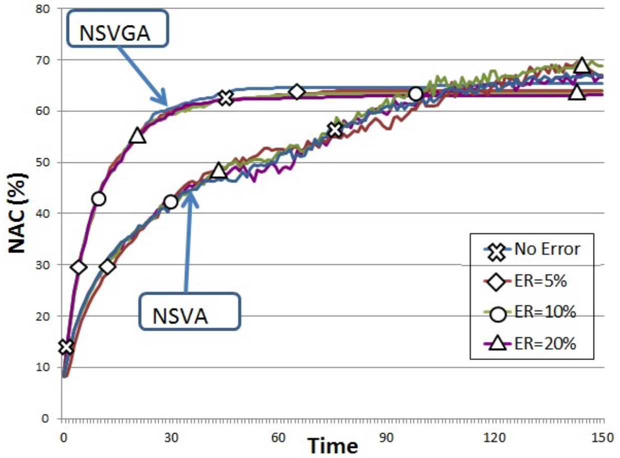


Figure 4: NACs obtained by 40 nodes with $R_C = 12$ with ER=0%, 5%, 10% and 20%

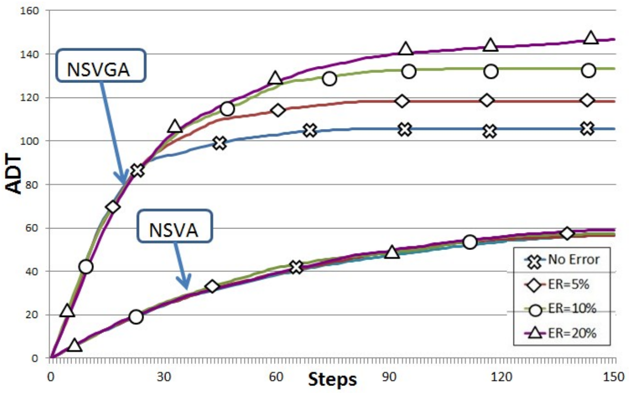


Figure 5: ADTs travel for a node with $R_C = 12$ with ER=0%, 5%, 10% and 20%.

the networks managed by NSVGA, the nodes with larger ER need to travel further distances to accomplish similar coverage as compared to the error-free case. Also, an increasing ER will cause the mobile nodes to take more time to become stable and stop moving. For example, in a noise-free run, the nodes need approximately 60 steps to stabilize with the average distance traveled by each node at the end of the experiment close to 110. When ER= 20%, more than 120 steps are needed to stabilize with ADT increasing to 140 by the end of the experiment.

For NSVA in Fig. 5, increasing ER values do not have a significant impact on ADT. With the higher ER values, the mobile nodes have difficulty in finding stable positions, thus the ADT continually increases over time (derivative of ADT is greater than zero). This result also explains the observation that the NAC curve for NSVA is not smooth even when the nodes do not continue to improve network coverage; the mobile nodes make inaccurate measurements for their neighbor locations and, hence, end up at incorrect positions.

Figures 6(a) - 6(d) show the NOON for NSVA and NSVGA with various error rates. The number of orphaned nodes is almost

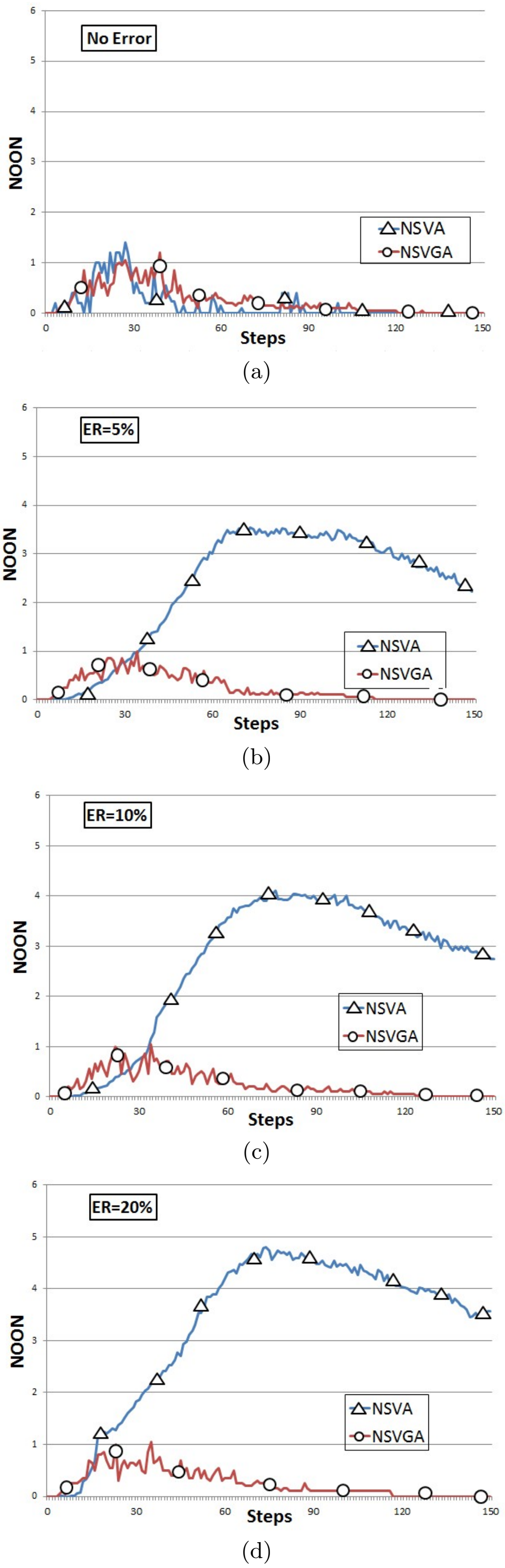


Figure 6: Number of orphan nodes for nsva and nsvga with ER= (a) 0%, (b) 5%, (c) 10% and (d) 20%.

the same for both NSVA and NSVGA when the error rate is zero (Fig. 6(a)). However, the nodes running NSVA could easy lose connection as ER increases. For example, at step 60, approximately 5 nodes have a degree of 0 when the error rate is 20% (Fig. 6(d)), whereas there are 3 orphaned nodes when the error rate is 5% (Fig. 6(b)). The NOON for NSVGA slightly changes when the environment becomes more prone to error. After 70 steps, on the average, there are almost no orphaned mobile nodes.

6. CONCLUDING REMARKS

One of the main goals for MANETs is to increase network area coverage while keeping the network connected and minimizing power consumption. In this paper, the performance of two self-spreading algorithms, called *node-spreading Voronoi algorithm* (NSVA) and *node-spreading Voronoi-based genetic algorithm* (NSVGA), operation in noisy environments have been compared, where the error rate ER represents the level of inaccurate measurements in harsh environments. We use network area coverage (NAC), average distance traveled (ADT) and a number of the orphaned nodes (NOON) to evaluate the performance of our topology control mechanisms. Our experimental results show that the nodes running NSVGA can keep the network connected and become stable in harsh environments, but the mobile nodes need to travel further and take longer to reach a stable positions compared to the noise-free case. In contrast, the nodes running NSVA travel less when the communication errors becomes worse, although they cannot stabilize and some of them will lose connectivity to their neighbors and partition the network.

Extensions of this work will include modeling of NSVA and NSVGA in more realistic situations, including the placement of obstacles and fluctuation of network population due to equipment malfunction and operations in hostile environments.

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