Dynamic Multiple Swarming for Mobile Sensing Cluster based on Swarm Intelligence

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***Abstract*—In recent years, the Internet of Things(IoT) is expected to achieve an advanced information society based on real world things. For such an achievement, the Wireless Sensor Networks(WSNs) are an essential technology. They are configured as precondition under which the location of the sensing event and the number of the sensing events are known. On the other hand, there are many situations that the locations and the number of events are unknown in real world. In the situation, the mobile sensing with multiple autonomous mobile devices, such as robot, is required to search for and actuate many events in a limited time. Accordingly, we previously proposed the Mobile Sensing Cluster(MSC), which applies swarm intelligence to autonomous mobile devices to dynamically forms multiple swarms that can be applied to any situation and quickly search for and actuate many events. In this paper, we consider and describe optimizing mechanism of dynamic multiple swarming in MSC for the purpose that searching and actuating a lot of events in a limited time.**

***Index Terms*—Wireless Sensor Networks, Particle Swarm Intelligence, Autonomous mobile device.**

I. Introduction

In recent years, the Internet of Things(IoT) [1] is expected to achieve advanced information society. Since IoT aims to actuate real world based on sensing a lot of events in real world, the Wireless Sensor Networks(WSNs) [2] is an essential network technology in IoT. The utilization for WSNs are generally classified into stationary or mobile sensing. The stationary sensing [3] uses a WSNs that deploys sensor nodes around specified location of events, and the mobile sensing uses a WSNs that make mobile sensor nodes patrol specified locations of events. The both sensing premises that the locations of sensing events are known.

On the other hand, in many situations, the locations of events and number of events are unknown in real world. A typical example of the situation is a searching for damages to structures and infrastructure and a rescuing survivors during a disaster.

The method [4] is proposed to apply to the above situation. In [4], a autonomous mobile device searched for the locations of events by sensing, and then the device actuates the discovering events. That is, the autonomous mobile device is required to take the following actions:

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- searching for the locations of events by sensing physical information from events;
- actuating the events, remaining around the discovering events;
- repeating a search and actuating for multiple events;
- attempting to search and actuate more events within limited time.

To address the above issues, most attempts form a single swarm with multiple autonomous mobile devices to improve the search and actuation performances. However, since forming a single swarm requires sequential searches and the actuation of multiple events, the turnaround time for multiple events becomes too large. On the other hand, the Mobile Sensing Cluster(MSC) [5] forms dynamic multiple swarms with multiple autonomous mobile devices for the issues, and balances cooperativeness and parallelism for searching and actuating. In searching for and actuating unknown events, MSC is superior to the parallel method in which all devices behave selfish, and the cooperative method which forms a only one swarm with all devices [5].

MSC consists of multiple autonomous mobile devices and assumes that a single device has the following functions:

- self-location estimation;
- sharing information by wireless communication among multiple-mobile devices;
- sensing strength of the physics information emitted from events;
- actuation to the events.

MSC applies Particle Swarm Optimization(PSO) [6] to multiple autonomous mobile devices and extends it to form dynamic multiple swarming. In MSC, the formation of dynamic multiple swarming is an essential mechanism to the above issues. In this paper, we consider and describe an optimization mechanism for dynamic multiple swarm formation in MSC, based on a scheme that selects leaders in each swarm.

The rest of this paper is organized as follows. We describe related works in Section Ⅱ, and MSC in Section Ⅲ. In Section Ⅳ, we show our simulation results and draw a conclusion is drawn in Section Ⅴ.

II. Related work

A. Robotic technologies in search and rescue operations

Robotic technologies have been used to search for and rescue victims in a disaster scenes [4]. A robot is equipped with a camera, sensors, and a mobility function to search for and rescue objects. Most of investigations with robotics technologies focus on the integration of above functions in a single robot. However, investigation on robots cooperation remains undeveloped.

B. Consensus problem in multiple agents systems

Multiple agents systems, which cooperatively controls cooperatively arbitrary systems by multiple agents, are expected to be used in the field of sensor networks or to control autonomous robots. In such systems, the velocity of robots and the values of sensing data coverage to an arbitrary value called a consensus problem [7]. The systems aims to only obtain a consensus among multiple agents, therefore, they consider the formation of a single swarm.

C. Reynolds Flocking Model

The Reynolds Flocking Model [8], which simply simulates by computer the swarming behavior of flock of birds, was introduced by Reynolds in 1987. Each agents moves based on the following three rules [9]:

- alignment: agents adjust their velocity to the velocity of their neighbor agents;
- cohesion: agents are attracted to the average position of their neighboring agents;
- collision avoidance: agents are repulsed from their neighboring agents.

The Reynolds Flocking Model has no function to search for an event because its algorithm maintains a swarm's form, which is organized by multiple agents. Therefore, it also considers the formation for a single swarm.

D. Particle Swarm Optimization

The Particle Swarm Optimization(PSO) [10], which is inspired by the swarm behavior of flocks of birds and schools of fish, is a mathematical search model based on multiple particles. Each particle has a location and a velocity, and its own location is evaluated using a fitness function. The velocity of each particles is derived by its personal best and global bests. The former is the best previous location of the particle itself, and the latter is the best previous location of all the particles.

Since PSO is a mathematical search model, it does not consider the physical restrictions, which are collisions between particles and the range of communication among them. Additionally, PSO does not show the optimizing mechanism for search with swarm since it's just a model.

III. Mobile Sensing Cluster

Since the MSC aims to search for and actuate unknown events of which location and numbers are unknown in the real world, it consists of the two following mechanisms:

- search and actuation mechanism based on PSO to unknown events using wireless communication for interaction between mobile devices;
- a dynamic multiple-swarming mechanism that extends PSO to emergence of behavior that aggregates and divides in multiple swarms.

MSC assumes the following:

- Mobile devices can autonomously move.
- They can estimate their own locations.
- They can sense such physical information strength as radio waves, temperature, and smells.
- They can actuate an event.
- An event itself emits itself physical information.

In this section, based on the above assumption, we explain MSCs.

A. Search and actuation mechanism

1) Location updating rule: To search for and actuate unknown events in the real world, the mechanism operates in each mobile device to derive a location to move toward based on the updating rule as following:

$$\begin{aligned} v_i(t+1) = wv_i(t) + pb_i(t)(x_i^{Pbest}(t) - x_i(t)) \\ + lb_i(t)(x^{Lbest}(t) - x_i(t)) + \vec{S_i} \end{aligned} \tag{1}$$

$$x_i(t+1) = x_i(t) + v_i(t+1), \tag{2}$$

where t is the time, $v_i(t)$ is the velocity of device i at iteration t, $pb_i(t)$ is the weight of the personal best, $lb_i(t)$ is the weight of the local best, x_i^{Pbest} is the personal best location, $x_i^{Lbest}(t)$ is the best location of the neighbors, and $\vec{S_i}$ is the collision avoidance vector of device i.

2) Personal best location and local best location: The personal best location is a location that each mobile device derives by itself sensing physical information strength from events, and is derived in according with the personal best evaluation value as follows:

- If the personal best evaluation value improves, randomly update the velocity vector around current moving direction.
- Otherwise, randomly update the velocity vector around the opposite direction to a current moving direction.

$$x_i^{Pbest}(t) = \begin{cases} |v_i(t-1)|(\cos(\alpha+\beta), \sin(\alpha+\beta)) + x_i(t) \\ \quad if \;\; E_i^{Pbest}(t-1) > E_i^{Pbest}(t) \\ -|v_i(t-1)|(\cos(\alpha+\beta), \sin(\alpha+\beta)) + x_i(t) \\ \quad otherwise. \end{cases} \tag{3}$$

Here $E_i^{Pbest}(t)$ is a personal best evaluation value of the device i at time t, α is an angle of $v_i(t-1)$ with x axis, and β is a random angle in $[-\theta, \theta]$.

The local best location is a location whose a neighbor device is most nearest the events in the neighbor devices in the wireless communication range. The indirect distance to the nearest event in the neighbor devices is used as the local best evaluation value.

3) Evaluation value: The above updating rule uses the following three evaluation values:

- The personal best evaluation value shows the distance from the nearest event in the discovery and sensing neighbor events. The evaluation value is derived as follows:

$$E_i^{Pbest}(t) = \min_{k \in discovery_i(t)} \{E_i^k(t)\}, \tag{4}$$

  where $discovery_i(t)$ is a set of discovered events by device i at time t, and $E_i^k(t)$ is an evaluation value showing the distance from event K based on sensing the physical information strength of event K in device i at time t.
- The local best evaluation value shows the minimum distance to an event in the neighbor devices, and it is derived based on the self-evaluation value, which shows the distance to an event in each device:

$$E_i^{Lbest}(t) = \min_{j \in neighbor_i(t)} \{E_j(t)\}, \tag{5}$$

  where $E_i^{Lbest}(t)$ is the local best evaluation value of device i at time t, $neighbor_i(t)$ is a set of devices which are neighbor devices on device i is found at time t, and $E_j(t)$ is a self-evaluation value of device j at time t.
- A self-evaluation value shows the distance to an event. If the personal best evaluation value is less than the personal best evaluation values of the neighbors in the wireless communication range, the self-evaluation value is the personal best evaluation value, and otherwise it is the sum of the local best evaluation value and the distance to the local best location, derived as follows:

$$E_i(t) = \begin{cases} E_i^{Pbest}(t) \\ \quad if \;\; E_i^{Pbest}(t) < \min_{j \in neighbor_i(t)} \{E_j^{Pbest}(t)\} \\ E_i^{Lbest} + C_i^{Lbest}(t) \\ \quad \text{otherwise.} \end{cases} \tag{6}$$

  Here $E_i(t)$ is the self-evaluation value of device i at time t, and $C_i^{Lbest}(t)$ is the distance to the local best location of device i at time t.

4) Electing leader: As a leader in a swarm, MSC chooses a device, which has a minimum personal best value for an event. The leader only moves based on the personal best, and any devices other than a leader (called "followers") just moves based on the local best; that is, the leader selfishly moves to the events and the followers obey the leader to search forming a swarm. To emerge the above behavior in the swarm, the weights of the personal best and that of local best are derived as follows.

$$pb_i(t) = \begin{cases} 1 & if \;\; E_i^{Pbest}(t) < \min_{j \in neighbor_i(t)} \{E_j^{Pbest}(t)\} \\ 0 & otherwise. \end{cases} \tag{7}$$

$$lb_i(t) = \begin{cases} 0 & if \;\; E_i^{Pbest}(t) < \min_{j \in neighbor_i(t)} \{E_j^{Pbest}(t)\} \\ 1 & otherwise. \end{cases} \tag{8}$$

5) Collision avoidance control: MSC extends the collision avoidance in the Reynolds Flocking Model. All devices have collision avoidance vectors that repulse from other devices. A collision avoidance vector is derived from the distance between itself and other devices. The vector, which becomes a strong repulsion vector as the device moves closer to the neighbor, derived as follow:

$$\vec{S_i} = c_3^i \sum_{j \in n} \frac{\overrightarrow{V_{ji}(t)}}{|V_{ji}(t)|(d_{ij}(t))^k} \tag{9}$$

where c_3^i is the avoidance weight of device i, $\overrightarrow{V_{ji}(t)}$ is the velocity vector to device i from device j, n is the neighbor devices of device i, d_{ij} is the distance between device i and device j, and k is the avoidance degree.

6) Search and actuation phases: MSC repeatedly turns between the search and actuation phases. In the former, as described above, the devices search for the events by communicating with other neighbor devices based on Eqs.(1) and (2). If the device senses the strength of the physical information over the threshold, it decides that it has reached an event, and turns to the actuation phase.

To stay within a range where the physical information is strong over a threshold, the device decelerates, and to evenly diffuse in the range, it adjusts the distance among the neighbors. Next, the velocity vector in Eq.(1) and the collision avoidance weight in Eq.(9) are derived as follows:

$$c_3^i = \begin{cases} c_3^{Search} & if \;\; E_i > T \\ c_3^{Search}/n & otherwise. \end{cases} \tag{10}$$

$$v_i(t) = \begin{cases} \frac{v_i(t)}{|v_i(t)|} M^{upper} & if \;\; |v_i(t)| > M^{upper} \\ v_i(t) & otherwise \end{cases} \tag{11}$$

where c_3^{Search} is the separation weight in the search phase, n is an integer value n, T is a threshold entering the actuation phase, and M^{upper} is the upper limit of the velocity per seconds.

In the actuation phase, if a device becomes unable to sense the physical information from an event in a period, it realizes that the actuation for a event is completed. Then, to search for other events, it discards the current evaluation values and return to the search phase.

7) Wireless communication among multi-mobile devices: MSC utilizes wireless communication for sharing information among the devices, which advertise information as follows and share it among neighboring devices:

- self-location;
- personal best evaluation value;
- self-evaluation value.

The devices, which received the above information, utilize it to update the self-location and each best evaluation values, and the election of leader.

B. Dynamic multiple swarming mechanism

MSC dynamically forms multiple swarms in order to search for and actuate in parallel to multiple events. To emerge the above behavior, it introduces an event crowd degree for deriving the personal best, and a neighbor crowd degree for deriving the local best, and then divides a swarm into mulit-swarms, and controls the number of devices that form a swarm in each swarm.

1) Multiple leader for division to multiple swarms: As described above, only one device is elected as a leader in a swarm. The dynamic multiple swarming mechanism elects the multiple leaders for multiple events in order to search for and actuate by multiple leaders and multiple swarms. To divide into multiple swarms based on multiple events, the weights of the personal and local bests respectively are revised:

$$pb_i(t) = \begin{cases} 1 & if \quad E_i^{Pbest(K)}(t) < \min\limits_{j \in neighbor_i(t)} \{E_j^{Pbest(K)}(t)\} \\ 0 & otherwise. \end{cases} \tag{12}$$

$$lb_i(t) = \begin{cases} 0 & if \quad E_i^{Pbest(K)}(t) < \min\limits_{j \in neighbor_i(t)} \{E_j^{Pbest(K)}(t)\} \\ 1 & otherwise. \end{cases} \tag{13}$$

Here $E_i^{Pbest(K)}(t)$ is a personal best evaluation value of device i for event K at time t.

In addition, the event crowd degree is introduced to derive a personal best to control the number of devices in a swarm. The event crowd degree for an event K is a value that accords with the number of neighbor devices in a swarm that approaches an event K. By applying the event crowd degree to the personal best value, since another leader can be elected to search for other events in a swarm, a swarm is divided into multi-swarms. The event crowd degree and the personal best evaluation value that apply that degree are shown as follows:

$$D_i^k(t) = \{x | x \in neighbor_i(t), P^k(x,t)\} \tag{14}$$

$$E_i^{Pbest(K)}(t) = \min_{k \in discovery_i(t)} \{E_i^{Pbest(k)}(t) + c_4 |D_i^K(t)|\} \tag{15}$$

where $P^K(x,t)$ is a set of the devices approaching an event K at time t, $D_i^K(t)$ is a set of the event crowd degree for event K of device i, and c_4 is a coefficient of the event crowd degree.

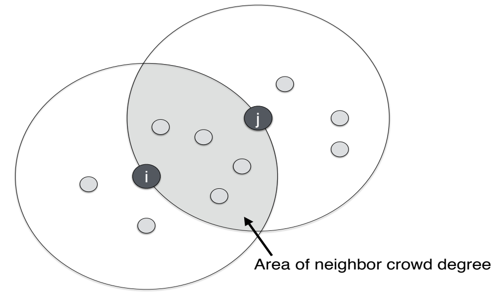

Fig. 1. Area of neighbor crowd degree.

2) Impartial swarm size among multi-swarms: To optimize the search and actuation mechanisms based on multi-swarms, the swarm size which is the number of devices forming a swarm should be impartial among multi-swarms. Therefore, to make the number of followers uniform among multi-swarms, the neighbor crowd degree is applied to derivation in the local best evaluation value. The neighbor crowd degree is a value that accords with the number of devices between a device and its neighbor devices in Fig.1. If the neighbor device degree for a neighbor has a large value, that is, the swarm among the neighbors is croweded, it follows another device with a lower neighbor device degree. To emerge the above behavior, the local best evaluation value is derived with the neighbor device degree:

$$N_i^j(t) = \{x | x \in neighbor_i(t), x \in neighbor_j(t)\} \tag{16}$$

$$E_i^{Lbest}(t) = \min_{j \in neighbor_i(t)} \{E_j(t) + c_4 |N_i^j(t)|\} \tag{17}$$

where $N_i^j(t)$ is a neighbor crowd degree of device i for neighbor device j at time t.

IV. Analysis of Dynamic Multiple Swarming Based on Simulation

The number of leaders in a swarm is a critical issue for dynamic multiple swarming in MSC. In this section, we analyzed the issue in the case, where the physical information from events includes random error, based on simulation for MSC, and show the optimal number of the leaders in each swarm.

A. Simulation specification

The simulation parameters are shown in Table I. The devices and events are defined as follows:

- A device is equipped with an IEEE802.11b interface, and periodically advertises its self-information, shown at III-A7.
- An event is equipped with an IEEE802.11b interface, and periodically advertises a beacon including such event identities as a MAC address.

Each device receives the self-information from neighbor devices, and beacons from some events, and it can identify events

TABLE I
SIMULATION PARAMETERS

Parameters	Values
Simulator	ns-3.26
Simulation time(sec)	5000
Number of trials for each simulation scenario	10
Number of devices	10∼40
Number of events	1,10∼40
Update cycle of velocity vector(sec)	0.1
Inertia weight w	0.5
Avoidance weight c_3 in search phase	15
Avoidance weight c_3 in actuate phase	5
Avoidance degree k	2
Coefficient of the crowd degree	-10
Random number space for β in Eq.(3)	$[-30, 30]$
M^{upper} in search phase(m/sec)	1
M^{upper} in actuate phase(m/sec)	0.3
Actuate capacity of an event	300
Wireless communication	IEEE802.11b
Transmission power(dBm)	17.0206
Fading model	Rician fading
Initial location of devices(m×m)	(30,30)
Initial location of events(m×m)	(100,100)
Distance to collision(m)	1

based on the received beacons. Each device also derives the three evaluation values and they are defined them as follows:

- Personal best evaluation value(E_i^{Pbest})
  Based on Eqs.(14)(15), a personal best evaluation value is defined:
  $$E_i^{Pbest(K)}(t) = \min_{k \in discovery_i(t)} \{|RSSI_i^k(t)| + c_4|D_i^K(t)|\} \tag{18}$$
  where $RSSI_i^k(t)$ is the RSSI of a beacon that the device i receives from the event k at time t, and $discovery_i(t)$ is a set of events from which device i receives any beacons at time t. If a device cannot receive a beacon from any events, let the personal best evaluation value be a positive infinity.
- Local best evaluation value (E_i^{Lbest})
  Based on Eqs.(16) and (17), a local best evaluation value is defined:
  $$E_i^{Lbest}(t) = \min_{j \in neighbor} \{E_j(t) + c_4|N_i^j(t)|\}, \tag{19}$$
- Self-evaluation value (E_i)
  Based on Eq. (6), a self-evaluation value is defined:
  $$E_i(t) = \begin{cases} E_i^{Pbest(K)}(t) \\ \quad if \;\; E_i^{Pbest(K)}(t) < \min\limits_{j \in neighbor_i(t)} \{E_j^{Pbest(K)}(t)\} \\ E_i^{Lbest} + |RSSI_i^{Lbest}(t)| \\ \quad otherwise. \end{cases} \tag{20}$$
  where $RSSI_i^{Lbest}(t)$ is the RSSI of the self-information that the device i received from a device that is treated as a local best device at time t.

The rice fading model is applied to the radio propagation model, and the RSSI fluctuates instantaneously, and RSSI includes random error. An event has an actuate capacity, which is the amount necessary to complete the event's caputure. The device in the actuating mode decreases 1 actuation capacity per 1 sec. When the actuated capacity of an event becomes 0, it disappears from the simulation field.

In this simulation, we compared the five cases where the number of leaders in a swarm ranges from 1 to 5.

B. Simulation result

The turnaround times for searching and actuating based on the number of leaders in each swarm at K-factors 0dB, 3dB and 6dB are respectively is shown in Figs.2, 3 and 4. The K-factor indicates the ratio of the direct and indirect waves, and if the value is large, the direct wave is a major element.

In the Figures, that is, in any K-factors and in any number of events, the turnaround time decreases as the number of devices increases, and it increase as the number of leaders in each swarm increases. Therefore, these results show that the optimal number of leaders in each swarm is a just one.

C. Discussion

In searching for and the actuating of unknown events, MSC outperformed the independent method in which all the devices behave selfishly, and outperformed the single swarm which is also configured by one selfish leader and other unselfish followers [5]. Additionally, the superiority of MSC to the others increases as the number of devices increases, and also the superiority increases as the number of events increases.

In the above MSC, we realized that the searching and actuating performances for unknown events with a swarm improves by dynamically adjusting the number of swarms to searching and actuating states. We assumed that the result is derived from the moderate diversity of searching and actuating by multiple swarms, and supposed that the moderate diversity by the multiple leaders in each swarm also derives a effectiveness in searching and actuating, especially since the diversity is effective in searching with the instantaneous fluctuation of RSSI. However, the elected multiple leaders lets multiple devices be based on their personal best evaluation values for an event, and the elected leaders are not necessarily those that are the closest to an event. Therefore, while searching, the leaders, which are not closest to an event, entire followers to choose a detour way, and the multiple leaders weaken the united behavior in a swarm.

The reason why a swarm with a single leader is superior to one with multiple leaders is that the tolerance to the instantaneous fluctuation in RSSI is not achieved by the searching with multiple leaders; it is achieved by a sensing beacon in diverse points where multiple devices are located. Therefore, the multiple devices in the swarm sense a beacon from an event at the diverse points where they are located, and, in diverse sensing with the multiple devices, the electing the closest device to an event can absorb the instantaneous fluctuation in RSSI and let the swarm approach an event through in a way has minimum distance.

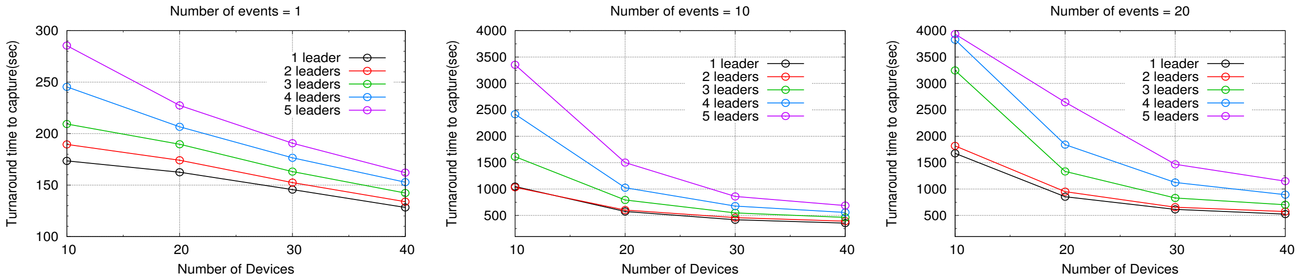

Fig. 2. Comparison of turnaround time based on the number of leaders in a swarm at K-factor 0dB

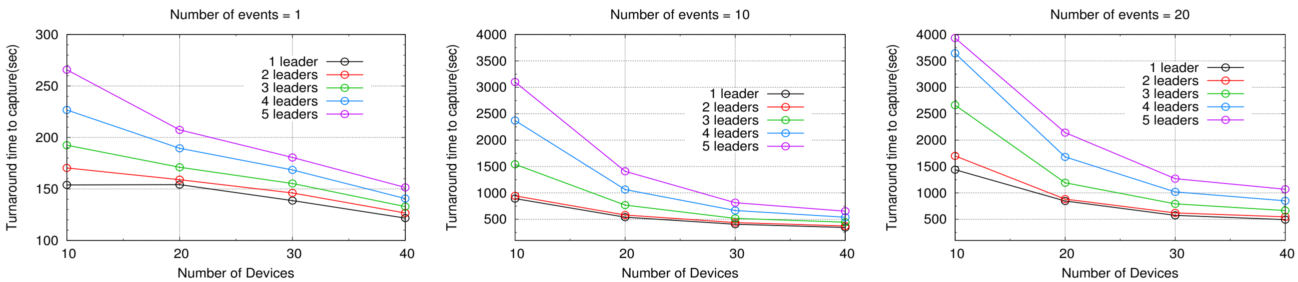

Fig. 3. Comparison of turnaround time based on the number of leaders in a swarm at K-factor 3dB

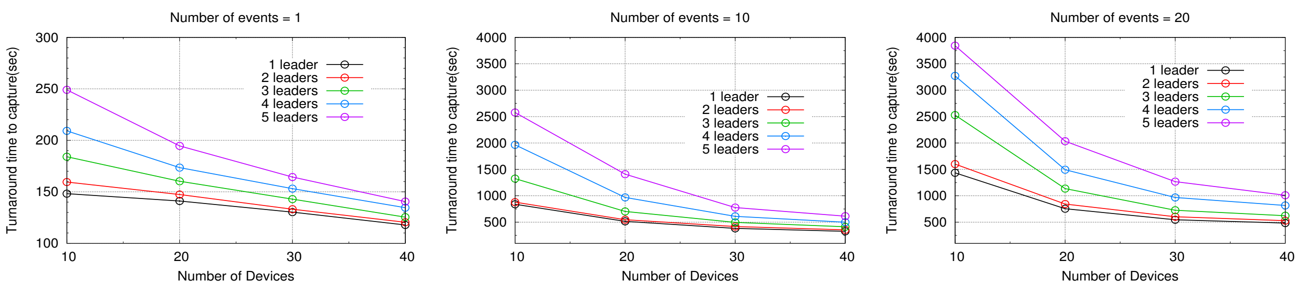

Fig. 4. Comparison of turnaround time based on the number of leaders in a swarm at K-factor 6dB

Summarizing the above, if the devices can identify each event with their beacons, in dynamic multiple swarming in MSC optimized mechanism, each swarm keeps on electing a closest device to an event as a only one leader based on the diverse sensing, where multiple devices in multi-points sense an event's beacon. Diverse sensing removes random error from an event. Continuing to elect the closest single leader in the diverse sensing always causes a swarm to approach an event through in a minimum distance way without random error.

V. Conclusion

We addressed the optimizing mechanism of dynamic multiple swarming in MSC with the number of leaders in each swarm. If such devices can identify each event with their beacons, we showed that a single leader can entice a swarm to approach an event in a minimum way in rice-fading environment.

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