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Establishing an emergency communication network and optimal path using multiple autonomous rover robots

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Summary

The natural calamity or disaster may destroy all communication networks especially a cellular network that relies on a tower. Although many solutions to an ad hoc wireless network have been proposed, forming a network covering a respective region with mobile robots toward optimal coverage remains to be an open problem. In this paper, we take the initiative to handle the optimal network coverage and path selection in disaster region with the help of multiple movable/rover robots. This paper consists of load balance distribution algorithm and optimal coverage algorithm applied to find the next optimally possible node location for all robots. Next, the robots maneuvering in an unknown disaster environment to identify the optimal path between the source and destination by using a particle swarm optimization algorithm. Finally, simulated results show that the algorithms can significantly improve the network coverage in the entire region, and the optimal path can effectively identify the optimal solution for all rover robots.

KEYWORDS

autonomous maneuvering, disaster management, load balancing algorithm, optimal coverage algorithm, particle swarm optimization algorithm

1 | INTRODUCTION

The existence of natural calamity is a noteworthy problem in every place in the world. Some serious physical extent of the disaster makes restriction to access the disaster place. Nowadays, the wireless sensor network and the multi-UAV (Unmanned Arial Vehicle) scheme plays a vital role in disaster management systems.[1] Optimal coverage of wireless sensor network is the main objective to design effective wireless sensor networks and is achieved by avoiding the networks in an unnecessary place and optimal coverage in all the disaster areas.[2] The sensor node is classified in to two types, ie, static node and dynamic node. The static nodes are used for the optimal coverage in case of artificial deployment, and the robot as dynamic nodes are used for gathering data from a specialized area.[3]

Path planning and execution of the rovers to the disaster place are very important and difficult. The robot has to achieve the following activities: task planning, area modeling, path planning, sensory fusion, path execution, and localization of the robot inside the environment.[4-6] The task planning activity can be executed from the task given to the robot and intelligent to do it.[7] The robot can get the information around the environment modeling using numerous types of sensor.[8] The other issue in the sequence figuration will be the cause for the robot to move from the initial point to its destination.[9] The conventional path planning has been classified into two types, which are online path planning and offline path planning. The offline path planning will create the entire map for the surrounding area before starting the movement, and this approach uses all the information about the environment space that is required to compute the optimal solution.[10]

Hao and Agarwal introduce the framework for optimal path planning for unmanned ground vehicle to the destination using Lyapunov stability controller to keep the robot trajectories.[11] The challenge in a multifaceted interaction between the dynamic environment and robot does exist.[12,13] The author highlighted the problem in NARMAX modeling to calculate the desired root of the robot and produce a code by a task protest.[14] Das and colleagues[15] proposed an optimal path optimization for a multi-robot system in a dynamic environment using gravitational search algorithm, and it provides the best path in a very earlier time than the previous algorithm.

2 | LITERATURE REVIEW

Erdelj et al[1] proposed the important join role of multi-UAV system and WSN in natural disaster management. In this paper, they discussed about various problems in disaster management like coverage, mobility, connectivity and reliability. Examining the present state of WSN and multi-UAV will lead to identify the challenge and issue in the disaster management system.[1]

Papageorgiou et al[16] introduced the mission critical mobility model for an ad hoc network. They highlighted the important characteristics of mission critical model that acquires real time environmental data that are affecting the physical movement of obstacle and signal transmission. The possessions of the planned model have been analyzed in terms of node distribution using simulation studies. The result assures that the planned model provides distinct features with respect to other model.[16]

Wichmann et al[17] proposed the wireless sensor and robot network with telephone to characterize the interaction between the robots or components of the WSNRT and considered many issues related to coordination mechanism among the robots and communication. The main challenge in the WSNRT is the degree of autonomy of the robot varying the lifetime and throughput of the network. The multiple degrees of autonomous lead to requirements in different data should be collected and communicated over the network. This system is used to replace the human interaction in dangerous areas.[17]

Wichmann and Korkmaz[18] studied how to reduce the physical collection delay over the flexible and slow mobile link in a large scale WSRN. From this study, they identified that such sink requires smooth and optimal path. Then, they developed an algorithm that obtained a smooth and optimal path for the TSP tour and adjusted the smooth path based on the amount of data collected in the node to create the more efficient path. Simulation also showed that the mobile sink is able to save throughput energy using the SPC algorithm.[18]

Bhuvaneswari et al[19] implemented autonomous rovers that can detect and intimate optimal ways in the place where sudden change in the surrounding environment due to natural and other disaster. The natural calamity will change the traveling path so that reaching the disaster place is a very tough task. The inertial sensors of the smart phone used to notice the surrounding environment and enables the robot to work with conservation to the satellite. The communication among the robot will increase the efficiency in optimal path identification to a disaster place. This discussed method reduces the cost of using satellite and increases the availability of easy access service.[19]

Fakoor et al[20] have proposed the method based on Markov decision processes and fuzzy inference systems for optimal path planning for humanoid robots in unknown complex environments. The cost function has been identified using Bellman equation without the exact destination and obstacle's shape. In the discussed method, locomotion and path planning are fully autonomous, which reduce human interaction in unknown environment. The autonomous path planning ensures that the robot can work effectively in real world applications. They have used humanoid robot (NAO H25 V4) to implement and develop the method successfully.[20]

Wang et al[21] have proposed multinode collaboration of internet of things and optimization algorithm for WSN using particle swarm optimization with current position and velocity. In this work the velocity of the particle plays vital role for network coverage. This work described four main contributions; those are global optimal solution, optimal objective function, local optimal solution and introduction of coherent velocity to explore better solution.[21]

Han and Seo[22] dealt with a complex environment using SPS and PI_FLP for node generation and generate the points in optimal space. The SPS algorithm generated the node and finalized without any variation in the solution, unless environment itself changed; moreover, PI_FLP algorithm is used to find the velocities and identified the optimal point in related space, which is having more obstacle. Finally, the optimal path has been planned to a disaster place and ensured safety in rovers involved in path identification.[22]

Huang and Savkin[23] proposed the shortest feasible path planning algorithm for path planning robots in a field with many obstacle. They formulated the problem in a shortest path planning for a single robot with variant DTSPN and further considered the shortest feasible path planning for multiple robot that presented k-shortest feasible path planning algorithm. Various simulations have been conducted with different robot speed, which distributed data loads to highlight the performance of SFPP and K-SFPP algorithm. Finally, they found that proposed algorithms were very effective to plan the path for robot with limited angular velocities.[23]

Bakdi et al[24] proposed and implemented an offline Kinect-based optimal collision-free path planning for a differentially driven indoor mobile robot. This robot performed many tasks like modeling and perception of environment around its surroundings; in addition, it finds the best collision-free path for determining the position and orientation to execute the generated path using genetic algorithm. Addition to that information are collected image processing techniques.[24]

Nie et al[25] proposed a non-linear inertia and annealing PSO algorithm to overcome the shortcomings of the basic PSO algorithm, and they are simulated both in simple and complex environments to check the effectiveness of proposed algorithm and it is compared with the basic PSO algorithm.[25]

Sheikhattar and Kalantari[26] proposed a distributed load balancing protocol based on ADMM iterations for general network configuration. This protocol provides a fully distributed framework where the three-step iterative scheme converges to the minimum l-p solution of network flow. Minimizing the p-norm yields balanced load distribution throughout the network.[26]

In this paper, the basic algorithm is extracted and improvements in PSO are tried to optimize the PSO parameters accordingly. Parameters are optimized empirically with trial and error method (see the work of Koohi and Groza).[27]

3 | BACKGROUND ANALYSIS

In this section, we present the structure of the PSO algorithm and provide a background on the load distribution algorithm for a communication network. The aim of this section is to introduce the basic concepts, which are later used to build up the rest of the work in this paper.

3.1 | Analysis of PSO

The particle swarm optimization (PSO) algorithm was derived from the predation of birds' group. The swarm makes its goals by the collective cooperation of particles. The algorithm is simple, robust, and has good optimization ability, and it was widely used to solve optimization problems. In recent years, some scholars introduced PSO to the path planning.[28] Particle moves to better position in the problem space to search for the best solution according to beneficial experience of its own and its neighborhood. It is iterative optimization and each possible solution of the optimization is a particle of the swarm. The direction of the current iteration (such as particle velocity) is determined by particle's own memorized optimization and sharing information between particles. The iteration terminates until the optimal solution is found to meet the conditions. Let the size of particle swarm population be n, and the internal dimension of the particle d. Then, the position of particle i ($1 \le i \le n$) is expressed as Xi = (xi1, xi2, … , xid), the speed as Vi = (vi1, vi2, … , vid), the optimal own position as Pi = (pi1, pi2, … , pid), the optimal value as Pibest, the global optimal position as G = (g1, g2, … , gd), and the global optimal value as Gbest.

Use f(x) to represent the fitness function of particles. Then, the best position and its optimal value of the particle can be updated by the following formula:

$$Pi(k+1) = \begin{cases} Pi(k) & f(Xi(k+1)) \ge f(Pi(k)) \\ Xi(k+1) & f(Xi(k+1)) < f(Pi(k)) \end{cases} \tag{1}$$

$$P_{ibest}(k+1) = \begin{cases} P_{ibest}(k) & f(Xi(k+1)) \ge f(Pi(k)) \\ f(Xi(k+1)) & f(Xi(k+1)) < f(Pi(k)). \end{cases} \tag{2}$$

After each particle reaches its own optimal position, the particle swarm will update its global optimal value by formula (3). Then, every particle's velocity and actual position can update by formula (4) and (5), ie,

$$G\_best = \{Pj(k)\,|f(Pj(k)) = min(f(P1(k)), f(P2(k)) \dots .\neg f(Pd(k)))\} \tag{3}$$

$$Vi(k+1) = w * Vi(k) + c1 * rand1 * (P(k) - Xi(k)) + c2 * rand2 * (G(k) - Xi(k)) \tag{4}$$

$$Xi(k+1) = Xi(k) + Vi(k), \tag{5}$$

where the velocity that updates formula (4) is the core of the particle swarm algorithm, which consists of three parts. The first part reflects the inertia of the particle, the second part represents the influence from itself, and the third part represents the influence from the whole particle swarm. There are three parameters in this formula: w is the inertia weight coefficient, and c1 and c2 are the self-learning factor and social learning factor, respectively. These are the important factors affecting the efficiency and performance of the PSO, which determine the global and local search ability and accuracy.

The memory component of the particle is given by its personal best value and it is called the cognitive component. In order for the particle to move to its best region in the space, it also uses its social group best component too. Figure 1 describes the steps of PSO optimization search. The algorithm initializes the particle positions at first and then run the application as many times as necessary to find the G_{best} weight vector. In each iteration, Pi_{best} and G_{best} vectors are updated to calculate the velocity vector of each particle. Once the velocity for each particle is calculated, each particle's position is updated by applying the new velocity to the particle's previous position. This process is repeated until the stopping condition is met.

3.2 | Load balancing distribution algorithm

Effective load balancers logically determine which device within a given server farm is best able to process an incoming data information. Doing so requires algorithms programmed to distribute loads in a specific way. Algorithms vary widely, depending on whether a load is distributed on the networks. Algorithm selection impacts the effectiveness of load distribution mechanisms and performance. Here, we will be discussing the pros and cons of several widely used algorithms found in communication network load balancing solutions.

We consider a network model based on a connected directed graph G = (V, E) with $V = \{1, 2, ..N + 1\}$ as the set of vertices and $E \subset V \times V$ as the set of edges. In this model, network nodes and communication links are represented by vertices and edges, respectively. Each edge is denoted by $(i, j) \in E$, with $i < j$, means that nodes i and j are neighbors that can exchange information directly. The set of one-hop neighbors of node i is denoted by Ni; the cardinality of this set, di = |Ni|, is defined as the degree of node i. Assume that there is M links available in the network graph. We assume that the network topology has no change or changes slowly giving enough time to optimally balance the traffic.

Let f be the flow vector containing network flows fm, m = 1, 2, … M, streaming on the links. The sign of flow fm corresponding to the link (i, j) determines the direction of flow from node i to node j, with fm < 0 meaning that flow is streaming in the opposite direction. The source vector b = [b1, b2, … bN] contains information rates generated at each node. The sign of component bi determines the role of node in the network with positive sign as the source node, negative sign as the sink node, and zero-valued for intermediate relay nodes. It is obvious that the total generated flow would be routed through the sink node, Pi ∈V bi = 0.

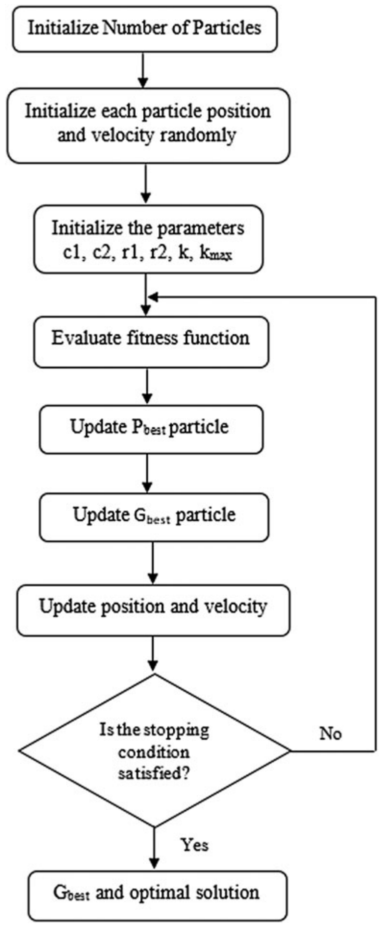

FIGURE 1 Flowchart for PSO Algorithm

The basic feasibility condition for our network flow model is the flow conservation law. This implies that the sum of input flows to a node, including the generated flow at that node, is equal to zero. The flow conservation can be written in the compact form, Kf ~ = ~b, where matrix K~ is the incidence matrix of size (N + 1) × M for the network graph. This matrix contains all the information about the node-edge relationship and show how node i is related to edge m by the K~ in the element of matrix. It means that the total generated flow at any arbitrary set of nodes should not exceed the total capacity constraint of their corresponding minimum cut set to the sink. Load balancing should take place when the load situation has changed. There are some particular activities that change the load configuration in the environment.

4 | RESEARCH METHODOLOGY

In this research, we develop an intelligent system based software for the restoration of communication network in a disaster-struck area done in autonomous manner using the rover robot as focusing in acquiring the optimal coverage for the communication network as a part of the mitigation process in the disaster management. Here, the robots have to take one of the two forms based on their actions. One is a network coverage robot. In this form, the robot is considered as the communication node, which has to move slower in order to conserve the energy for network communication. Another form is a highly mobile, which can spend more energy on moving to find optimal path and tracking. The network coverage robots are inter-connected with the mesh topology but not fully connected to each other. The communication network is established with the help of forming ad hoc wireless network covering the entire disaster region with the help of multiple movable/rover robots. Network coverage in a disaster area has been implemented using a balanced load distribution algorithm by deploying multiple robots because natural disaster will destroy the cellular network. The network rover distribution to the area is based on the number of users available in that area. Next is to maneuver an autonomous rover robot in an unknown disaster environment and to identify the optimal path between the source and destination using the particle swarm optimization (PSO) algorithm.

The various steps involved in the algorithm of proposed methodology are as follows:

Step 1: Initialize the number of user in each region and decision variables. Fix the maximum number of iterations and population size.
Step 2: Initialize the position for creating random solution. The velocity and position of all particles are randomly set to within pre-defined ranges.

Step 3: At each iteration, the velocities of all particles are updated according to p_{best} and g_{best}, which is the position with the "best" objective value found so far by particle i and the entire population respectively; w is a parameter controlling the dynamics of flying; c1 and c2 are the factors controlling the related weighting of corresponding terms. The random variables help the PSO with the ability of stochastic searching.

Step 4: The positions of all particles are updated according to particle velocity. It should be checked and limited to the allowed range.

Step 5: After updating the position and velocity, the best cost and solution for each iteration of swarm particle velocity and position should be calculated.

Step 6: Repeat steps 2 to 4 until the maximum number of iterations gets the best cost. It reports the values of g_{best} and $f(g_{best})$ as its best solution.

Step 7: PSO utilizes several searching points and the searching points gradually get close to the global optimal point using its p_{best} and g_{best}. Initial positions of p_{best} and g_{best} are different. However, using the different directions of p_{best} and g_{best}, all agents gradually get close to the global optimum.

All of particles have fitness values, which are evaluated by the fitness function to be optimized and have velocities that direct the particles. The particles are optimized through the problem space by following the current optimum particles. PSO is initialized with a group of random particles and then searches for optima by updating generations. In every iteration, each particle is updated by following the two "best" values. The first one is the best solution (fitness) it has achieved so far. This value is called p_{best}. Another "best" value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population. This best value is a global best and called g_{best}. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called l_{best}.

In order to show the influence of PSO with balancing distribution in communication network application, we followed a two-phase approach. First, we have fix the problem and initialize the parameter like number of handle points, number of decision variables, and size of decision matrix, respectively. Next, the swarm size and iterations are defined for the PSO algorithm, and we fix the particle position and velocity randomly. Particle velocity represents the maximum ability of the rover robot to move in a direction. Although the velocity for each robot varies in practical scenario, in our simulation, it is considered as fixed for all the path detection rovers. For network coverage rovers, the particle velocity is set to low and also considered for PSO. In our proposed system, the particle's best position, cost and solution, respectively, are evaluated. For each iteration, the swarm particle velocity and position are varied with respect to the best cost by using PSO algorithm. Finally, we illustrated the particle's cost and solution by the cost function of particle position.

For the global best cost of iteration, the optimized path identified by maneuvering an autonomous rover robots that use particle swarm optimization is observed. The rover robots are provides the network coverage for neighborhood by load balancing distribution in the unknown disaster environment.

5 | RESULTS AND DISCUSSION

This section discussed the experimental evaluation of the proposed method algorithm. The experiment is performed in the environment of MATLAB software. The simulated results are used to optimize the robot path planning in a disaster environment. Table 1 shows the values of the parameter for the proposed simulations. There are no many parameters need to be tuned in PSO. The number of nodes is considered as the number of particles in PSO. The stop condition for PSO algorithm iteration is until any of the particles reaches the destination assumed. The inertia weight damping is to control the velocity of the node as the rover robot's ability to move from rest is little lower than normal. So, it is assigned a little lower to normal. Inertia weight damping controls the velocity of the particle as rover's speed is limited.

We initialize the position for all the autonomous rover robots, and we consider three cases for path optimization.

5.1 | Case 1

We consider the number of users in five different regions such as A1 = 14, B1 = 1, C1 = 5, D1 = 5, and E1 = 0, respectively. The total number of rovers available for network coverage is num = 5, and the number of rovers or nodes is moving toward A1 = 3, B1 = 0, C1 = 1, D1 = 1, and E1 = 0. Finally, we get the best cost for moving rover robots and evaluated the optimal path toward destination, as shown in Figure 2.

TABLE 1 Simulation parameters

Parameter	Value
Number of maximum user per node	5
Population size	150
Number of node	50
Dimension area	100 m x 100 m
Inertia weight damping	0.98

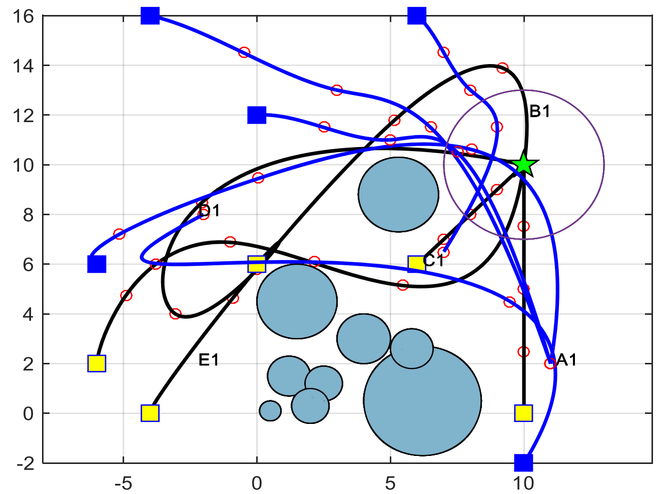

FIGURE 2 Case 1 – Best cost path optimization

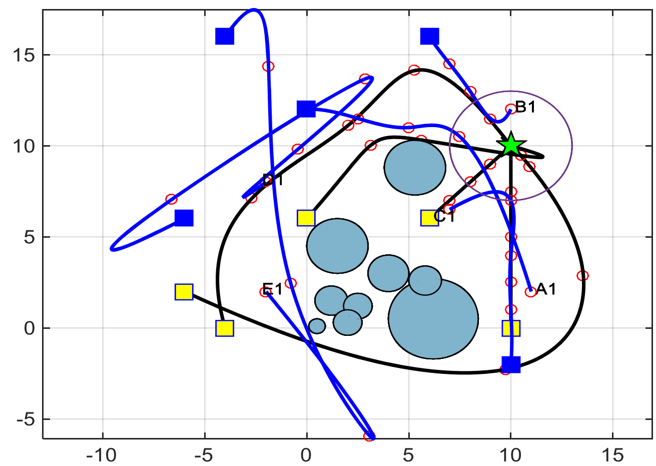

FIGURE 3 Case 2 – Best iteration cost for optimal path

5.2 | Case 2

We consider the number of users in five different regions such as A1 = 5, B1 = 5, C1 = 5, D1 = 5, and E1 = 5, respectively. The total number of rovers available for network coverage is num = 5, and the number of rovers or nodes is moving toward A1 = 1, B1 = 1, C1 = 1, D1 = 1, and E1 = 1. Finally, we get the best cost for moving rover robots and evaluated the optimal path toward destination, as shown in Figure 3.

5.3 | Case 3

We consider the number of users in five different regions such as A1 = 24, B1 = 0, C1 = 1, D1 = 1, and E1 = 1, respectively. The total number of rovers available for network coverage is num = 5 and the number of rovers or nodes is moving toward A1 = 5, B1 = 0, C1 = 0, D1 = 0, and E1 = 0. Finally, we get the best cost for moving rover robots and evaluated the optimal path toward destination, as shown in Figure 4.

In the simulated Figures, the yellow and blue boxes are the initial location of network coverage and path detection rovers, black lines are the path of optimal path detection rovers, blue lines are the path of network coverage rovers, and star and blue circles are the destination of optimal path and obstacles, respectively. It is not difficult to recognize the approximate proportional relation between the best iteration and the running time; and then, the coherent velocity introduced into particle swarm optimization for network coverage does not consume more time but saves running time. It is because the coherent velocity improves the ability of a node to find the optimum position in a local area.

The network node or network robot is allowed to travel a little distance to conserve energy for communication and also to preserve the network topology. If the topology has a change, the load balancing distribution algorithm has to be run again.

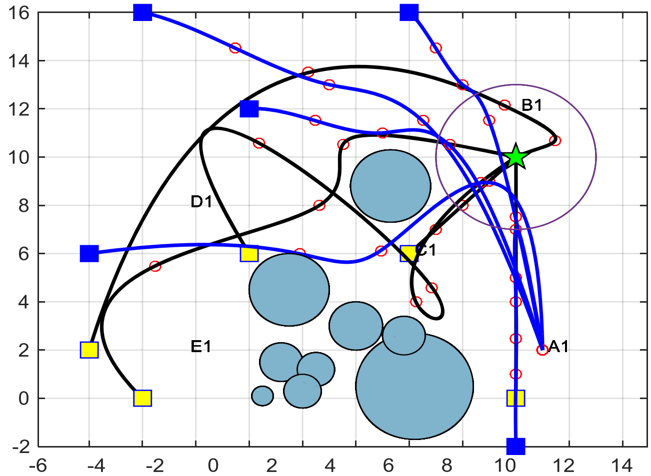

FIGURE 4 Case 3 – Best iteration cost for optimal path

6 | CONCLUSIONS

A network coverage and optimal path of communication networks are proposed based on particle swarm optimization and balancing distribution with rover robots. The experiments verify the effectiveness of the algorithm; the particle's velocity plays an important role to improve network coverage. The main contributions are as follows: the global optimal solution into the local optimal solution by the best cost of iterations, the node and area coverage models are provided as optimal objective function, and network coverage done by the distribution algorithm of networks is a detailed description using particle swarm optimization. Finally, we have a potential method to identify the optimal path by PSO to maneuver an autonomous rover in an unknown disaster environment.

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