Coactive learning for multiple robot search and coverage problem

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Abstract

In this research program we will apply machine learning techniques for solving the problem of finding desired location of node for managing effective communication within the assigned cost. The purpose of this paper is to improve the functionality and tasks performance of the multiple robots by applying coactive learning algorithm. The focus should be given to the challenges and issues which exist with the coverage system such as hostility of the set targets, change of environment, localization of resources and other equipment, occurrence of collision, and cooperation among competitive agents. The algorithm is designed for solving the team orienteering problem which is based on greedy algorithm. It can be concluded that the Swapping and add functions are used for getting the desired location of the random points.

I. Introduction:

Background:
The coactive learning techniques are applied to the robots which are developed for assisting the humansThe performance of the robots can be improved by applying the coactive learning algorithm for giving weightage and priority to the environmental variables [1]. The performance of the human can be improved by providing optimal solution to the human to diagnose the real time problems and provides with effective solution to resolve the complex scenario [2]. The coactive learning framework is used to define the cooperation between various sources so that structured data mining can be effectively done [3]. The multiple robots which are used in the scenario are having different skills and quality of sensor cameras used in them. The cost function is designed for improving alternatives provided for the functioning of the robots so that cost factors can be minimized [4].

Research Aim:
The aim of the research is to provide solution to the problems which commonly occurred in implementing coverage planning. In this research program we will apply machine learning techniques for solving the problem of finding desired location of node for managing effective communication within the assigned cost.

Problem domain
The tasks performed by robots requires maximum energy for completing their given action plan. The problem is faced in managing the behaviour and skills of different robots which are undertaken because it is difficult to manage the integration between multiple robots which are equipped with varying hardware and software used.

Research Questions
Primary Question: How the coactive learning approach facilitates the multi-robot search and Coverage problem?

II. Chapter 2: Literature Review

The designing of the functional program of multiple robots is based on coverage system for overcoming the challenges faced in the development of tasks interdependence environment. The challenges which are commonly faced in the working program of the multiple robots are setting hostility of the targets, environmental changes within the fraction of micro-seconds, local distribution of the resources, and occurrence of collision, decreasing cooperation and coordination between the common agents.

Team orienteering problem is the general problem which occurs in setting targets and locations of the multiple robots [5]. N number of agents are used for visiting target locations so that cost spend in finding the location can be minimized.

Planning of solving the path problems helps in measuring the area covered by the multi-robots. The coverage planning is required for rescue operations to overcome the problems which are created by the disaster occurrence. The exploration of the multi-robot is done because of heuristic hostile environment [6]. It is recommended to decompose the team orienteering problems so that solution can be drawn within time and cost [7]. The coactive learning program is helpful in tracing the static location of the robots sites for travelling of the agents.

The real time information is collected by monitoring the pathway of the robots for communication so that disasters can be minimized by taking effective rescue operation before the occurrence of uncertainty [8].

The interaction between the human and robots can be improved by using the coactive learning [9]. The weightage is given to the location so that optimal solution can be drawn by deploying the utility function [10]. The macros are used for providing abstraction to the tasks [11]. The macros are used for increasing the performance of the robots by specifying the teachings of the human.

III. Chapter 3: Research Methodology

<u>Research Framework</u>

The research methodology is completed in 6 steps which are summarised in the table below:

Steps	Description
Defining Research problems	The research is carried on solving the team orienteering problem which occurs due to the set of random location so it is difficult for the multiple robots to find the desired location.
Data collection	The data is collected from online and offline sources so that required data can be collected for imposing the experimental set up so that accuracy of the proposed model can be identified
Proposed system model	The focus is given on finding the shortest distance to get visibility of the desired location from the set of random location within the minimum cost associated with the movement of the robots for each search.
Experimental Set up	The performance of the designed algorithm is tested by comparing with other algorithm such as sequencing protocol, and others.
Result Analysis	The analysis of the experiment helps in finding that the implication of MIPP protocol is facing the drawback that it cannot access the visibility of set which is having more than 90 random locations.

<u>Problem Statement</u>

Team orienteering is the major problem which exist with the Robotic system environment because it is difficult to search location from the set of random location and multiple robots are visiting the location.

The locations are predefined in the landscape. The probability of finding the landscape is defined as $P : X \rightarrow [0,1]$

The robot is not able to find the location X whereas Y is the reachable positions for the robot. There are multiple robots placed in the landscape for finding the desired location. R_i is used for representing the Robot [12].

The starting and ending locations is denoted as s_i and e_i. B_i is the energy constraint. The utility function can be visible by defining the probability of location which is define as

$$O_i : \mathcal{Y} \times \mathcal{X} \rightarrow [0,1]$$

The cost function for given utility function can be defined as

$$C_i : 2^{\mathcal{Y}} \rightarrow \mathbb{R}^+$$

The total cost of the function can be defined as

$$\Gamma_i : \mathcal{Y} \rightarrow \mathbb{R}$$

The performance of the multiple robots is depends on coverage location and minimizing the energy constraint. The location of the target can be calculated by measuring the visibility of the function [13]. Observation cost can be calculated by defining the following formula:

$$\begin{aligned} Cost(T) &= \sum_{i=1}^{n} Cost(T_i) \\ &= \sum_{i=1}^{n} \left[\sum_{(y_j, y_{j+1}) \in T_i} C_i(y_j, y_{j+1}) + \sum_{y \in T_i} \Gamma_i(y) \right] \end{aligned}$$

The set of observation value is defined as

$$V_{\mathcal{R}}(S) = V(\mathcal{R}) - V(S \cup \mathcal{R})$$

IV. Chapter 4: Proposed System Model

The coverage problem which is associated with the robots of finding the exact location by taking number of observation can be resolved by deploying the information planning for the multiple robots. From the literature analysis, we have found that multi-robot information path planning (MIPP) is not effective in solving the complex and large problem. The greedy algorithm is suitable for solving the coverage problem. The heuristic planning is helpful in measuring and identifying the location within the approved cost and budget [14].

<u>Algorithm: Multi-Robot greedy heuristic Algorithm</u>

```
function MIPP({(s_1,e_1),...,(s_k,...,e_k)},{B_1,...,B_k})    ▷ Parameters for k robots
    R ← ϕ
    for i ∈ {1,...,k} do
        iter ← CEIL(log_2(2 2̄B_i))
        P_i ← SPP(s_i,e_i,B_i,R,iter,α)
        R ← R ∪ P_i
    end for
    return {P_1,...,P_k}
end function
```

The auction based planning helps in controlling and finding the locations by the multiple robots. The locations point can be swapped for managing the budget [15]. Cost of utility function depends on the utility function. The algorithm given below shows the

<u>Auction based algorithm:</u>

function AUCTION($\mathcal{X}, \mathcal{Y}, n$)
    $\mathcal{R} \leftarrow \phi, \mathcal{T} \leftarrow \phi$
    $c \leftarrow$ TRUE
    while $c =$ TRUE **do**
        while TRUE **do**
            $(k, p) \leftarrow$ arg- $\max_{k \in \{1 \dots n\}, p \in \mathcal{Y}}$ GETBID($\mathcal{X}, \mathcal{R}, k, p$)
            if $(k, p) =$ NULL **then**
                break
            end if
            ALLOCATE($\mathcal{T}, k, p$)
            $\mathcal{R} \leftarrow \mathcal{R} \cup \{p\}$
        end while
        $c \leftarrow$ IMPROVE($\mathcal{X}, \mathcal{Y}, n, \mathcal{T}$)
    end while
    return $\mathcal{R}$
end function

Multi-Robot information distribution Algorithm:

function MIPP($\{(s_1, e_1), \dots, (s_k, \dots, e_k)\}, \{B_1, \dots, B_k\}$) ▷ Parameters for k robots
    $\mathcal{R} \leftarrow \phi$
    for $i \in \{1, \dots, k\}$ **do**
        $iter \leftarrow$ CEIL($\log_2(2\ \bar{2}B_i)$)
        $\mathcal{P}_i \leftarrow$ SPP($s_i, e_i, B_i, \mathcal{R}, iter, \alpha$)
        $\mathcal{R} \leftarrow \mathcal{R} \cup \mathcal{P}_i$
    end for
    return $\{\mathcal{P}_1, \dots, \mathcal{P}_k\}$
end function

The auction based planning is effective for controlling the robots and helps in finding the desired location. The robot is assigned with maximum bidding value for finding the desired location [16]. Value of utility function and bidding method is used for measuring the number of observations [17]. The new location is finding out by identifying the maximum number of bidding value of the robots. The budget is spend in finding the desired location and do movement in getting the final location [18]. The ratio of cost spent and the value of utility function helps in finding the observation value:

$$\frac{V_{\mathcal{R}}(\{p\})}{C_k(\mathcal{R} \cup \{p\}) - C_k(\mathcal{R})}$$

Where R represents the set of observations

The robot moves to the new location if in one view the cluster of node is not observed. The spatial closeness of the clusters helps in finding the desired location in the single view [19]. The heuristic approach is deployed for finding the unobserved locations. Utilization of the budget should be planned so that sequencing of finding the location can be evaluated within the fixed interval of time [20].

The observation points are preserved in S set. T identifies the plan taken to get the accurate result. The utility functions are created to get preferences to the human [21]. The utility functions are represented as V (T). W is used for representing the preference vector to the human ideas and E shows the characteristics and plan of the human perception. $\vec{\mathbf{W}}\vec{\mathbf{E}}_T$ is used for representing the perception of the human experts.

<u>Coactive Learning function in the auction based planning algorithm:</u>

```
function CoactiveLearnUpdate(T_s, T_e, C_e)
    if C_e > 0 then
        Δ_t ← E(T_e) − E(T_s)
        W_{t+1} ← W_t + λ_t Δ_t          ▷ λ_t depends on learning algorithm
    end if
end function
```

The utility function is expressed as:

$$\mathcal{V}(T) = w_0 V(T) + \vec{\mathbf{W}}'\vec{\mathbf{E}}_T$$

The decomposition of the characteristics in edges and vertex than the designing of the utility function is changed as

$$\mathcal{V}(T) = \left[\sum_{x\in X} w_0 P(x) \prod_{y\in S}(1 - O(y,x))\right] + \sum_{\langle y_i, y_{i+1}\rangle\in T} \vec{\mathbf{W}}' E(y_i, y_{i+1}) + \sum_{y_i\in T} \vec{\mathbf{W}}' F(y_i)$$

The utility function of the solver is represented by

$$\mathcal{V} : 2^{\mathcal{Y}} \rightarrow \mathbb{R}$$

The utility function of the human perception is represented by

$$\mathcal{U} : 2^{\mathcal{Y}} \rightarrow \mathbb{R}$$

The working of the operator is represented by

$$\omega_i : 2^{\mathcal{Y}} \rightarrow 2^{\mathcal{Y}}$$

The modification in the plan is done by developing the set of operators which is represented by

$$\Omega = \{\omega_1, \omega_2, \ldots\}$$

The efficiency of the human efforts can be evaluated by identifying the number of operators used for finding the relevant solution to the problem. The edge characteristics are represented as

$$E(y_i, y_{i+1})$$

The vertex characteristics is represented by

$$F(y_i)$$

The utility function is decomposed in edge and vertex characteristics for evaluating the locations.

Perceptron: The uniformity in the instances can be identified by applying coactive learning rate when probability is equal to 1:

$$\lambda_t = 1$$

Passive aggression perceptron:

The passive aggression perceptron is used for sensing the allocation of weights to the vectors for improving the value of utility function. The probability of missing the target is minimized. It can be evaluated as:

$$\lambda_t = \frac{1 - \vec{\mathbf{W}}_t \vec{\Delta}_t}{||\vec{\Delta}_t||^2}$$

Cost Sensor perceptron:

The cost of the perceptron should be updated with each move of robots in finding the location. The scaling of the cost can be done as

$$\lambda_t = C_e$$

Cost sensor passive aggression perceptron:

The value of the utility function can be improved by defining the following function

$$\lambda_t = \frac{C_e - \vec{\mathbf{W}}_t \vec{\Delta}_t}{||\vec{\Delta}_t||^2}$$

The performance of finding the location can be improved by deploying the parameters of coactive learning.

Cost bound

The overrunning of the algorithm in finding the location will increase the cost limits and decreases the quality of service provided to the human by accelerating the allocated budget of the searching program.

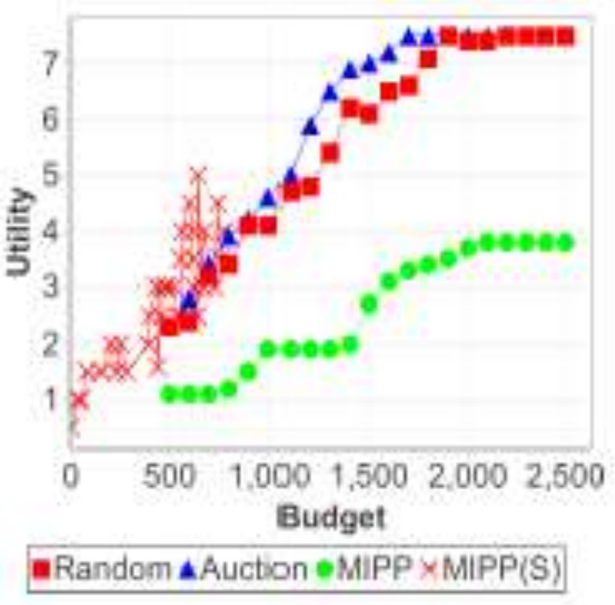
Experiment set up:
The experimental setup helps in estimating the allocation of the cost by inducing the sequential access of location. The usage of budget and managing the running time of robots can be improved by deploying the auction based planning algorithm. The feasibility of the algorithm can be measured by calculating the bidding value of the robots. MIPP protocol is used for measuring the utility value. 30 random points are chosen. Distance between the random points is approximately 25 units of the map. The visibility value of the function is more than 25 units of distance. Scaling of the visible function should be within the allocated budget.

V. Chapter 5: Analysis and Result

The proper utilization of the budget fails in deploying sequential approach for finding of location. Time complexity increases by scheduling the robotic search in sequence approach. The graph below is plotted between the utility function value and the cost associated with finding desired location:

Experimental Results

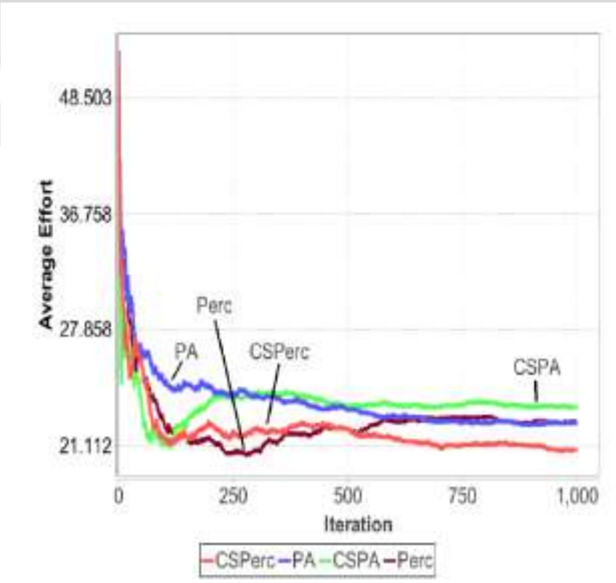
The experimental set up helps in finding out the comparison between three different algorithms which are implemented for finding the location by the multiple robots which are named as auction based planning algorithm, MIPP protocol, and random allocation of the location. The base line is set for selection of the allocation point for planning of accurate budget. 1000 * 1000 sq. units are used for mapping the random locations. The graph below show the value of utility function when equal to 30 for three different algorithms which are used finding the desired location by the multiple robots:



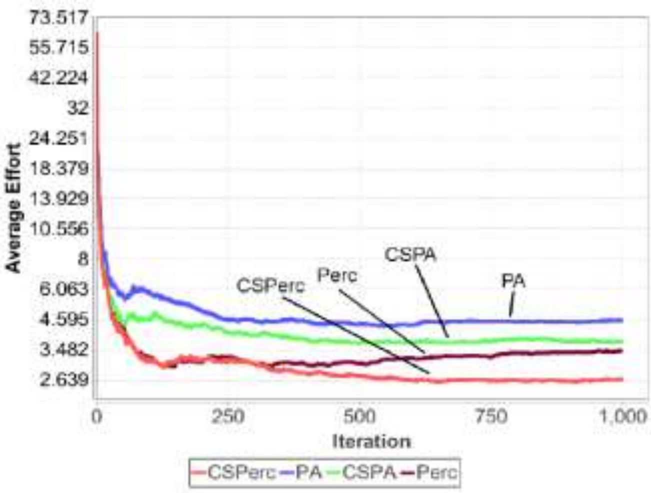
Coactive Learning Experiment Result

In Coactive learning approach, sparse distribution of the random location means that most of the random locations are the non-zero values. The dense weight of the graph shows that it does not contain any zero components. The Swapping and add functions are used for getting the desired location of the random points. The swapping function is used for swapping the values of the allocated location to the unallocated locations

The graph below shows the random location in sparse distributed maps.



The graph below shows the features of the random location in dense mapping environment.



VI. Chapter 7: Conclusion

It can be concluded that the Swapping and add functions are used for getting the desired location of the random points. The swapping function is used for swapping the values of the allocated location to the unallocated locationsThe coactive learning framework is used to define the cooperation between various sources so that structured data mining can be effectively done. The automation in solving the problems improves experiences of the programmer to earn learning efficiency.

VII. References

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