AERIAL CAMERA NETWORK FOR OBSERVING MOVING TARGETS

Seminar Report

submitted in partial fulfillment of the requirement
for award of Degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

of

APJ Abdul Kalam Technological University

Submitted by

REVATHY SURENDRAN

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CERTIFICATE

This is to certify that the report entitled **Aerial Camera Network for Observing Moving Targets** *submitted by* **Ms. REVATHY SURENDRAN**, *Reg.No.***MAC15CS049** *towards partial fulfillment of the requirement for the award of Degree of Bachelor of Technology in Computer science and Engineering from APJ Abdul Kalam Technological University for December 2018 is a bonafide record of the seminar carried out by her under our supervision and guidance.*

Prof. Joby George	**Prof. Neethu Subash**	**Dr. Surekha Mariam Varghese**
Faculty Guide	***Faculty Guide***	***Head of the Department***

Date: Dept. Seal

ACKNOWLEDGEMENT

First and foremost, I sincerely thank the 'God Almighty' for his grace for the successful and timely completion of the seminar.

I express my sincere gratitude and thanks to Dr. Solly George, Principal and Dr. Surekha Mariam Varghese, Head Of the Department for providing the necessary facilities and their encouragement and support.

I owe special thanks to the staff-in-charge Prof. Joby George and Prof. Joby Any Mathew for their corrections, suggestions and sincere efforts to co-ordinate the seminar under a tight schedule.

I express my sincere thanks to staff members in the Department of Computer Science and Engineering who have taken sincere efforts in helping me to conduct this seminar.

Finally, I would like to acknowledge the heartfelt efforts, comments, criticisms, co-operation and tremendous support given to me by my dear friends during the preparation of the seminar and also during the presentation without whose support this work would have been all the more difficult to accomplish.

ABSTRACT

An aerial camera network (ACN) is used for observing moving targets. An algorithm for decentralized and cooperative motion planning of these cameras in 3D environment is proposed. The algorithm enables ACN to observe targets from different elevations with the objective of jointly maximizing duration and quality of observation for each target. The multi-scale observation depends on field of view of aerial camera. Quality of observation depends on the elevation level of camera. The algorithm uses quad-tree data structure to model the discrete movement decisions of cameras in 3D environment, variations in field of views and quality of observation. The use of artificial forces allows the aerial cameras to avoid collisions. It also shares the workload of assigning locations and targets to cameras.

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LIST OF ABBREVIATION

ACN	Aerial Camera Network
FOV	Field-of-View
CMOMMT	Cooperative Multirobot Observation of Multiple Moving Targets
A-CMOMMT	Approximate CMOMMT
P-CMOMMT	Personified CMOMMT
B-CMOMMT	Behavioral CMOMMT
UAV	Unmanned Aerial Vehicle
MAV	Micro Aerial Vehicle
MPC	Model-Predictive Control

Introduction

Many search, reconnaissance and surveillance tasks require a set of networked cameras (camera network) to work as a team and to perform cooperative observation of multiple moving targets[1][2][3]. Other applications of such cooperative observation of multiple moving targets can be found in sports[4], crowd and social movement monitoring[5], wildlife research[6] and disaster management[7]. Existing approaches have mostly focused on either stationary camera network or mobile ground camera network on the ground where homogeneous ground robots (unmanned ground vehicles)[8] equipped with cameras are used as mobile cameras.

The recent developments in ease of deployment, versatility and reduction in cost and size of Unmanned Aerial Vehicles (UAVs) have revolutionized aerial robotics, camera networks and the aerial observation of ground or bird's-eye view[5]. These small-scale and autonomous UAVs such as Micro Aerial Vehicles (MAVs) or quad-rotors are equipped with cameras and networked,to form an Aerial Camera Network (ACN) where each UAV works as a smart aerial camera[2][3][6]. A key research problem related to ACN is the dynamic placement of these smart aerial cameras to maintain the best view of each moving target in the environment. To maintain the best view, we consider maximizing both the duration and the quality (i.e., resolution) of observation for each moving target.

The use of a mobile ground camera network for observing multiple moving targets, also known as Cooperative Multirobot Observation of Multiple Moving Targets (CMOMMT), is an NP-hard problem and was rst presented in 1997[1]. CMOMMT considers a greater number of targets than cameras and develops a dynamic placement strategy for mobile ground cameras to maximize the collective time during which each target is observed. CMOMMT using local force vectors for coordination among cameras was upgraded to Approximate CMOMMT (A-CMOMMT) by including weighted local force vectors[1] and P-CMOMMT by reducing the overlap of observation of a single target by multiple cameras. Behavioral CMOMMT (B-CMOMMT)[8] added help calls to increase the performance of the CMOMMT. A similar approach was also proposed in by assigning different priority weights to targets. Instead of using local force vectors and help calls, exible formation of cameras and modelpredictive control strategies can be used in CMOMMT. The degree of decentralization in camera network and the minimization of the time of initial contact with a newly appeared target have also been considered in this domain.

More recent methods of CMOMMT use ACN to enable the movement of aerial cameras in 3D environments for observing multiple ground moving targets and even ying targets. A recent survey on multi-robot cooperative observation of moving targets discusses the details in this regard. While ground camera has to cope with the difcult movements over uneven surfaces and collision avoidance in cluttered environments, an aerial camera can easily move in a less cluttered 3D space with increased movement options. Aerial cameras can observe more region on the ground with less occlusion. Additionally, aerial cameras can also get access to parts of the region where ground cameras cannot move. However, the existing ACN-based CMOMMT approaches are restricted only to uniform FOV and uniform resolution observations.

An important characteristic of the smart aerial camera, which is variation in FOV with respect to varying zoom levels or distances (altitudes) from the scene, has not been considered in the literature. Variable zoom lenses and altitudes of the aerial cameras present an opportunity to adapt the FOVs, leading to a trade-off between coverage and quality of observation. When aerial cameras in ACN can adjust their FOVs, one must determine their optimal FOVs that minimize the redundancy in observed areas while maximize the quality of observation. The problem in the existing techniques is that none of them can maximize the number of targets that are being observed throughout the mission time by a network of mobile aerial cameras (sensors) with variable FOVs (multiscale observation).

Although, the work on multi-scale observation using variable FOVs of an aerial camera exists, it is only limited to the single camera system, observation of stationary targets or observation of static environments without any target. It has already been shown that tracking all ground moving targets while maintaining optimum aerial view at all times is not feasible. In our previous work, we have presented a centralized system for dynamic placement of aerial cameras to maintain the best view of each moving target in the environment. In this report, we extend existing work by presenting a decentralized system with collision avoidance among the aerial cameras for the same purpose. This has some elements in common with the work on guiding the formations of ground moving robots using aerial cameras which presents a partially distributed algorithm for moving aerial cameras. We specically address the challenges of mobility and coordination in smart aerial camera network

The main contributions of this report are as follows:

1) A decentralized system for dynamic placement of networked aerial cameras to maintain the best view of each moving target in the environment.

2) The modication of the conventional CMOMMT objective function by including a term that accounts for the quality (resolution) of observation.

3) We use quad-tree data structure to model not only the 3D environment but also the variable FOVs or the observations at large spatial scales (low resolution) versus observations at a small spatial scales (high resolution). This kind of modeling helps us in dening the trade-off between the visibility and the quality of observations of moving targets.

4) We include collision avoidance among the aerial cameras in our proposed algorithm.

5) We use articial forces to guide the movement of aerial cameras on the nodes of the quad-tree.

6) We present simulation results for several scenarios.

Related work

The most basic version of the target observation problem is the art gallery problem, a well know problem in computational geometry. The task is to find locations for cameras in a polygonal environment such that any point in the polygon at any time can be observed with least number of cameras possible. The problem is NP-hard in general, but special cases allow to compute solutions efficiently. Also of interest, in particular for seeking new targets, is the problem of finding the shortest route for a watchman to once see the entire polygon.

CMOMMT has been formalized by Parker in 1997. The objective of CMOMMT is to maximize the collective time of observation. CMOMMT considers greater number of targets than robots and develops a dynamic placement strategy for mobile ground cameras to maximize the collective time during which target is observed. Each robot operates either in search or track mode. When a robot finds more targets in its FOV, it tracks them and moves towards the virtual center of mass of moving targets. The robot switches back to search mode when there are no targets in its FOV.

CMOMMT using local force vectors for coordination among robots was upgraded to A-CMOMMT by including weighted local force vectors for better coordination among the robots and P-CMOMMT by reducing the overlap of observation of single target by multiple robots. To reduce the risk of losing a target, B-CMOMMT adds a third mode of operation, help mode, a robot that is about to lose a target broadcasts a help request to other robots. The robot that is in search mode respond to this request by approaching the robot that made the request.

In the next approach instead of using local force vectors and help calls, flexible information of robots and predictive control strategies were used in CMOMMT. More recent methods use MAVs to increase the observation of moving targets. Existing MAV based observation of moving targets are based on uniform FOV and uniform resolution observation.

Most recent method of CMOMMT uses ACN to enable the observation of multiple ground moving targets. Aerial camera can move in less clustered 3D space with increased movement options. They can observe more region on ground with less occlusion. They can also get access to those areas which are restricted to ground cameras. But existing methods are restricted to uniform FOV and uniform resolution observations.

The work on multi-scale observation using variable FOVs exists, it is limited to single camera system, observation of stationary target or observation of static environment without any targets. In these methods, we had centralized system for dynamic placement of aerial cameras to maintain the best view of each moving target in the environment.

Proposed method

3.1 Problem formulation

Let us consider a rectangular, bounded and obstacle free region $\Omega \in$ R^2 on the ground with even surface and known dimensions (length l and width w). Let G = $\{G_1, G_2, ..., G_B\}$ be the set of B independently moving, uniquely identiable, cooperative and non-evasive ground targets in Ω. The value of B is assumed to be known and constant (targets do not disappear or leave/enter Ω) for the duration of the mission. The state of the i^{th} target at time step t is assumed to be known (e.g., GPS coordinates) and is denoted by

X$_i^t$=(x_i^t,$\dot{x}_i^t$,y_i^t,$\dot{y}_i^t$) (Equ:3.1)

where (x_i^t,y_i^t) and ($\dot{x}_i^t$,$\dot{y}_i^t$) are the location and velocity of the target. The motion of G_i is

x$_i^{t+1} = \phi x_i^t$+γ_i (Equ:3.2)

where Φ is the state transition matrix with process noise $\gamma_i \sim \eta(0, Q)$ and process noise covariance matrix Q.

Let C = $\{C_1, C_2, ..., C_A\}$be a set of A mobile, homogeneous,synchronized and networked aerial cameras.We assume that each aerial camera is a quad-copter equipped with a downward-looking camera, a position sensor (e.g., GPS), a wireless communication unit to exchange information, and a computing unit to perform updates and local control actions. We assume that the value of A is known and A $\ll B$. These aerial cameras with hovering capabilities and zero degrees of yaw, roll and pitch can move above the region in discrete time steps t.

The state of the j^{th} aerial camera at time step t is denoted by

$$Y_j^t=(x_j^t,y_j^t,z_j^t) \qquad \text{(Equ:3.3)}$$

where(x_j^t,y_j^t,z_j^t) are (x,y,z) co-ordinates in space which defines the location of the aerial camera C_j in space. The aerial cameras are assumed to move above the region Ω with no restrictions on their altitude and thus the (x,y) components of $y_j^t \in R^3$ coincide with (x,y) $\in$ Ω . Two or more cameras collide when they move to the same location at the same time step. Each aerial camera executes the following three actions at time step t: takes observation, coordinates with other aerial cameras for motion planning, and moves to the new location. The duration of the time step is constant and sufcient for each aerial camera to perform the three actions. We assume that the speed of each aerial camera is higher than that of the fastest target.

The FOV of each aerial camera, which is assumed to be a square, depends on its zoom level and its altitude (z_j) from the surface of the region Ω. For a given zoom level, the aerial camera C_j has a distinct FOV $F_j \in \Omega$ which depends on y_j^t. Reduction in the value of z_j^t reduces the FOV (F_j^t) of aerial camera C_j. Similarly, for a given location (constant altitude) the aerial camera can vary its FOV by varying its zoom level. However, we assume for the sake of simplicity that zoom level of the aerial camera is constant.

A target is considered under observation when it is in the FOV of at least one aerial camera. We assume an aerial camera as a perfect sensor with no observation noise. The observation of target G_i by aerial camera C_j at time step t is defined as

$$\odot_{ij}^t = \begin{cases} 1 & if(x_i^t, y_i^t) \in F_j^t \\ 0 & otherwise \end{cases} \qquad \text{(Equ:3.4)}$$

(x_i^t, y_i^t) denotes location of target; F_j^t denotes FOV of camera.

A single aerial camera can observe multiple targets and multiple aerial cameras can observe a single target. However, the simultaneous observation of a single target by multiple aerial cameras in a single time step is of no advantage to us as A$\ll$ B and we are not involved in multi-view analysis, depth perception or in obtaining accurate location estimate of the target.

The standard CMOMMT[8] problem uses the following objective function to maximize the collective time of observation

$$\Upsilon = \frac{1}{B\Gamma}\sum_{t=0}^{\Gamma}\sum_{i=1}^{B}\bigvee_{j=1}^{A}\odot_{ij}^{t} \qquad \text{(Equ:3.5)}$$

where Γ represents the total time of the mission; B denotes number of targets; A denotes number of cameras.

We extend this objective function by including variable quality (multiple scales) of observations and refer to this problem as cooperative multi-scale observation of moving targets. We represent the multiple scales of observation in terms of the vertical distance (altitude z_j) from the target to the downward looking aerial camera. Thus, z_j is the scale parameter that determines the multiple scales of observation. Increasing the z_j of an aerial camera C_j increases its FOV but reduces its scale (quality or resolution) of observation i.e., the spatial scale at which the target is being observed at. At a higher altitude, an aerial camera can observer (at large spatial scale) larger region on the ground at the cost of quality of observation (cannot see smaller details). Reduction in the altitude of the aerial camera reduces the (spatial scale) observed region on the ground but increase the quality of observation (small details can be seen). By including multiple scales, the expression of observation in (Equ:3.4) becomes

$$\bigodot_{i\,j}^{t} = \begin{cases} \frac{1}{z_j} & if(x_i^t, y_i^t) \in F_j^t \\ 0 & otherwise \end{cases} \qquad \text{(Equ:3.6)}$$

where $0 \leq \bigodot_{i\,j}^{t} \leq 1$ now denes the quality of observation;z_j denotes z co-ordinate of camera.

We obtain highest quality observation of target G_i at time step t ($\bigodot_{i\,j}^{t}$= 1) when the aerial camera C_j is observing it from the lowest allowed altitude z_j^t=1.

In addition to maximizing the number of targets under observation and their duration of observation, we need to maximize the collective quality (resolution) of observations. This corresponds to maximizing the following objective function:

$$g=\frac{1}{B\Gamma}\sum_{t=0}^{\Gamma}\sum_{i=1}^{B}\bigodot_{i\ j}^{t} \qquad \text{(Equ:3.7)}$$

where g $\in$ [0,1]; B is number of targets; Γ is time of mission; $\bigodot_{i\ j}^{t}$ is quality of observation .

In (Equ:3.7), g = 0 implies that no target is under observation throughout the mission and g = 1 implies that all the targets are under highest quality observation throughout the mission. With limited number of aerial cameras (i.e., A $\ll$ B) it is not possible to observe all the targets with high quality all the time. The objective can be restated as to minimize both the total time in which targets escape observation and the distance from aerial camera to target.

It is difcult to get g = 1 for a large number of elevations, as targets will easily escape the smallest FOVs. The multi-scale multi-camera coverage problem at hand is dynamic where the coordinated movement approach should determine at each time step:
(i) the aerial camera to observe,

(ii) the part of the region to observe, and

(iii) the quality of observation.

We focus on developing a decentralized cooperation and movement strategy for ACN to maximize g and to avoid collisions among the aerial cameras. We assume that the trajectory of an aerial camera is not known or calculated in advance and the camera chooses autonomously its trajectory. The dynamic, distributed and coordinated motion planning approach of the cameras should determine at each time step, the next location and the FOV for each camera. It exposes many signicant issues including problems of coordination, navigation and planning in highly dynamic environments.

3.2 Quad-tree based space discretization

In a continuous 3D space there are innite number of locations for the movement of aerial cameras and thus innite number of different overlapping FOVs even for a single aerial camera. The innite number of movement locations and FOVs with overlapped regions make it very complex for the aerial cameras to coordinate their movement decisions and to map their movements with different FOVs. In order to reduce the number of allowable locations and overlapping FOVs for the aerial cameras to a level considered negligible for adversely affecting the performance of coordinated motion planning some discretization is required.

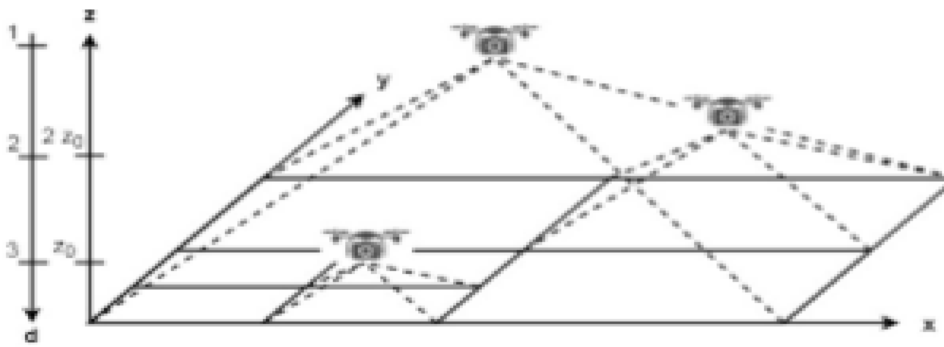

Figure 3.1: Model for movement of aerial camera

We discretize the 3D space for the movement of aerial cameras and model it as a quad-tree τ [9]with nodes, as shown in Fig. 3.1. Let k = $\{1, 2, ..., \}$ denote the index of the nodes and d denote the depth of the quad-tree where the root node (k = 1) of τ is at d = 1 and the leaf nodes of are at maximum depth of d = ϵ. Similarly, the indices of the nodes at d = 2 are k = 2,k = 3,k = 4, and k = 5 and there are $(2^{d-1})^2)$ nodes at depth d. E = $\{1, ..., (2^{d-1})^2)\}$ denotes the set of nodes at depth d. We consider the topology of the τ as xed (nodes cannot be added or deleted) and complete (all its leaves are at the same depth). Except the root and the leaf nodes, each node k of the τ has ve adjacent nodes, i.e., k0 (parent node) and four children nodes k1 (north west), k2 (north east), k3 (south east), k4 (south west) as shown in Fig.3.2.

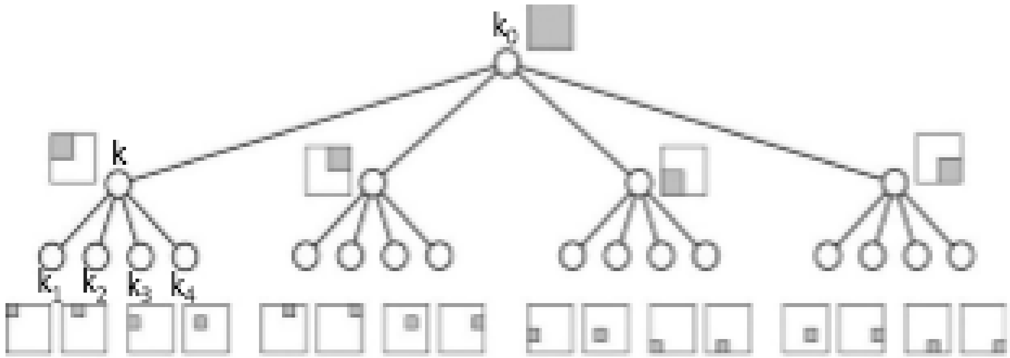

Figure 3.2: Model for FOV of aerial camera

Each node represents an allowable location y for the movement of aerial cameras, such that

$$y_j^t \longrightarrow k \tag{Equ:3.8}$$

for k = $\{1, 2, ..., k\}$ where y_j^t denotes location of camera and k denotes node of quad-tree . An aerial camera can only take observation when located at a node of τ as shown in Fig. 4.1. An aerial camera can be located only at a single node at a given time step. A node having an aerial camera is known as occupied node while other are known as free nodes. Every node k is associated with a specic FOV F_k which represents the FOV of a downward-looking aerial camera located at node k. The root node (k = 1) of the τ is centered with some altitude at Ω , such that F1 = Ω and leaf nodes of the τ are at minimum altitude. The FOV of aerial camera C_j that hovers at node k is denoted as $F_j = F_k \in \Omega$. If k is an internal node and $k_1, ..., k_4$ are its four children nodes, then the four FOVs F_km are obtained by splitting the FOV F_k into four equally sized squares. Therefore F$_k$ $= Um = 1, 2, 3, 4$F$_{km}$ and $F_{km} \bigcap F_{kn}$ = ϕ (non-overlapping FOVs of aerial cameras located at same altitude) where k_m and k_n are siblings (m $\neq$ n). It is obvious that the aerial camera C_j at node k having FOV $F_j = F_k$ is already observing $F_{k1}, F_{k2}, F_{k3}, F_{k4}$ with quality $\odot_j = \frac{1}{z_j}$. The number of targets within the FOV F_k is represented as B_k where 0 $\leq$ Bk $\leq$ B and B1 = B.

Let $G_k = G_1, G_2, ..., G_{Bk}$ be the set of B_k targets where $G_k \in GandG_k = \phi$ if F$_k$ $=$ $\phi(B_k = 0)$. The leaf nodes with d =ϵ are set at altitude z_0 from the $\Omega, where$z$_0$ is the minimum allowed altitude of an aerial camera. Reducing the altitude of an aerial camera below z_0 may cause the camera to hit the target. The levels of the quad-tree are related to z_0 as z = 2$^{\epsilon - d}z_0$.

By modeling the 3D space into a quad-tree, the best quality observation of target G_i^t defined earlier becomes

$$\bigodot_{i\,j}^{t} = \begin{cases} d_j^t & if(x_i^t, y_i^t) \in F_j^t \\ 0 & otherwise \end{cases} \qquad \text{(Equ:3.9)}$$

where d_j^t is depth in quad-tree where camera is located; (x_i^t, y_i^t) location of target and F_j^t FOV of camera.

We normalize this best quality observation to obtain

$$\bigodot_{i\,j}^{t} = \begin{cases} \frac{d_j^t}{\epsilon} & if(x_i^t, y_i^t) \in F_j^t \\ 0 & otherwise \end{cases} \qquad \text{(Equ:3.10)}$$

where $\frac{1}{\epsilon} \leq \bigodot_i^t \leq 1$.

This quad-tree is used not only to model the 3D space for the movement of aerial cameras and to model variable FOVs but also as a coordination mechanism among these cameras to form an aerial camera network. This modeling leaves a large 3D volume, especially between the upper levels of the quad-tree, unused, which can increase the efciency of motion planning algorithms by reducing the movement options. In addition to representing a location in the 3D space, each node of the tree keeps a record of targets visible from that node, the aerial camera located at that node and other information required for the motion planning of the aerial cameras. A copy $\tau_j of the \tau is stored in local memory of \mathrm{C}_j$. The key purpose of the quad-tree is to reduce the movement options from innite in an analogue space and even from twenty seven in an unconstrained discrete neighborhood cube to only six (including the current location). These six nodes (locations) include the current node k and the ve adjacent nodes. The exceptions are the root node (5 movement options) and the leaf nodes (2 movement options). These six movement options for an aerial camera located at node k are shown in Fig. 4.2. We do not need uniform number of movement options at each level of τ, because increasing the altitude reduces the number of movement locations as

$$\bigcup_{e \in E} F_e = \Omega \qquad \text{(Equ:3.11)}$$

where F_e denotes FOV of camera and Ω is 3D space.

3.3 Cooperative movement of aerial cameras

The objective of the proposed distributed cooperative movement is the identication of nodes on the τ and the assignment of these nodes to aerial cameras in such a way that maximizes the number of targets under high quality observation. The aerial cameras should jointly coordinate to identify and to assign nodes as next way-points for their movement at each time step. This cooperative movement of aerial cameras has to avoid collision among the cameras during their movement. Moreover, the cooperative movement of aerial cameras has to discourage the movement of an aerial camera to higher altitudes as it results in great loss of camera's power and low resolution observation. We call the proposed approach as Multi-Scale Cooperative Multi-Robot Observation of Multiple Moving Targets (Multi-Scale CMOMMT).

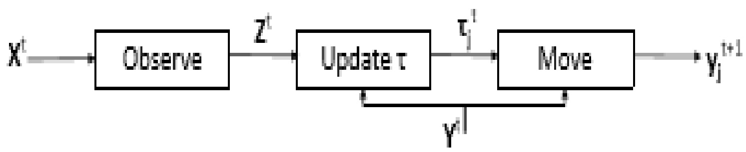

Figure 3.3: Block diagram of the overall process followed by each aerial camera in a single time step

Fig.3.3. shows the overall process of cooperative movement followed by each aerial camera in a single time step. The aerial camera C_j located at node k receives the targets' actual states X^t at time step t where it directly observes G_k targets. Information about the target locations X_t and current states of all the aerial cameras Y_t at time step t are shared and used to update the local copy of the quad-tree τ_j. The aerial camera C_j at time step t then uses its updated local copy of the quad-tree τ_j to decide one of the six locations for its movement. We use heuristic approach to optimize the objective function. In our proposed algorithm (Multi-Scale CMOMMT), the aerial cameras use articial forces on quad-tree for cooperative motion planning and token passing protocol for conflict resolution.

3.3.1 Artificial forces on quad-tree

We are using a concept similar to articial potential eld for the cooperative motion planning of aerial cameras. Articial potential eld related methods are based on the application of articial forces for motion planning. These methods simultaneously consider the problem of obstacle avoidance and that of trajectory planning. Preferably, these articial forces should be generated in the conguration space of the aerial cameras and each camera should move in a eld of forces. In our proposed algorithm, each node of the applies an articial force to attract/repel a nearby camera. These articial forces provide a mechanism of cooperation for the aerial cameras. As a result (under the inuence) of these articial forces, cameras cooperatively move to different nodes of the . The total articial force at node k is denoted by

$$\mathrm{f}_k = \theta_k - \phi_k \qquad \text{(Equ:3.12)}$$

which is a combination of two articial forces: attractive force (θ_k) and repulsive force (ϕ_k). The free nodes, considered as goal locations, generate attractive forces which make the mobile aerial cameras move towards these locations. Occupied nodes, considered as mobile obstacles, generate repulsive forces which repel other aerial cameras. Consequently, the aerial cameras move away from each other towards the nodes of the where targets are observable at relatively high quality.

The attractive force k at node k is dened as

$$\theta_k = \begin{cases} \sum_{i=1}^{B_k} \theta_{ki} & if B_k > 0 \\ 0 & otherwise \end{cases} \qquad \text{(Equ:3.13)}$$

where θ_{ki} is the attractive force at node k contributed by target $G_i \in G_k$ and is defined as

$$\theta_{ki} = \begin{cases} \frac{d_k}{\bigodot_i} & if \bigodot_i \neq 0 \\ \epsilon & otherwise \end{cases} \qquad \text{(Equ:3.14)}$$

where d_k is depth of location of node k in quad-tree; $\bigodot_i$ is quality of observation of target i and ϵ is maximum depth of quad-tree.

Each target that can be observed from node k applies an attractive force and contributes to the total attractive force θ_k. The attractive force θ_k at node k increases with increase in the number of targets visible from node k and increase in the depth of node k . A node at lower altitude (higher value of d_k) with more targets to observe applies more attractive force as compared to a node at higher altitude (lower value of d_k) with the same or less number of targets to observe. The node k applies no attractive force if there are no targets within the FOV (F_k) associated with it (B_k = 0). The quality of current observation of the target G_i, which is $\bigodot_i$, adversely affects the attractive force θ_{ki}. The reason for this adverse affect is to reduce the attractive force at node k contributed by a target which is already being observed with high quality. The target $G_i \in G_k$ contributes less attractive force if it is already being observed with high quality (under the observation of an aerial camera located at a leaf node). The target $G_i \in G_k$ contributes more attractive force if it is not under the observation of any aerial camera ($\theta_{ki} = \epsilon$in Equ:3.14). We normalize the value of attractive force θ_k to $0 \leq \theta_k \leq 1$ by using $\frac{\theta_k}{max1,...,k}$. Fig. 3.4 shows an example of how to calculate k at node k.

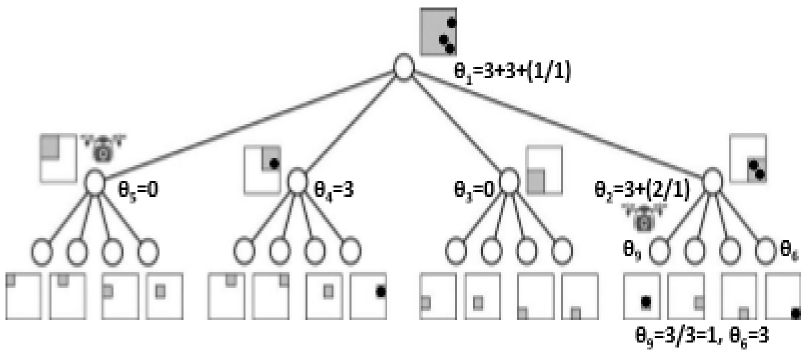

Figure 3.4: calculation of attractive force

The repulsive force, which depends only on the location of an aerial camera, is used to avoid collisions among the aerial cameras. The repulsive force at node k due to aerial camera C_j is inversely proportional to Euclidean distance $\|p_{kj}\|$ between the node k and the location of C_j. The repulsive force by A-1 aerial cameras on C_j located at node k is defined as

$$\phi_k = \sum_{l=1}^{A} \frac{1}{\|p_{kl}\|} \qquad \text{(Equ:3.15)}$$

An occupied node applies maximum repulsive force. Increase in the collective distance of aerial cameras from a node reduces the value of repulsive force contributed by that node. We normalize the value of $\phi_k to0 \leq \phi_k \leq 1$ by using

$\frac{\phi_k}{max\{\phi_1,...,\phi_k\}}$

These articial forces depend on the goal states of the motion planning and the locations of the cameras in the environment. The goal states are those nodes of the τ at higher values of d where an aerial camera can observe targets. These states are dynamic and changed with the movement of targets at each time step. The movement decision takes into account two sub-goals, namely maximization of the number of targets under observation and resolution maximization. While the aerial cameras can be trapped in a local maximum, the effects of this local maximum are likely to be temporary as targets move and goal states are changed. Global/local minima and global/local maxima problems of conventional articial potential eld method does not affect our algorithm as the setting is very dynamic and the forces are changed each time step.

3.3.2 Movement on quad-tree

Each time step the aerial camera C_j updates its local copy of the τ, which is τ_j, by computing new values of the force f_k for $1 \leq k \leq \epsilon. The aerial camera$C$_j$ then uses its τ_j with updated values of articial forces to select the node for its next move. It is possible that multiple cameras select a common node for their movement in a single time step. This will cause a collision of aerial cameras. In order to resolve this conflict, we use token passing protocol. Each aerial camera updates its τ_j and makes its movement only when it receives the token. The token authorizes the camera to update its τ_j and to make its movement decision. When its movement decision is complete, the aerial camera passes the token along to the next aerial camera in the team.

Each aerial camera determines its new location in a distributed way for itself, as presented in Algorithm 1 and Algorithm2.At each time step t,aerial cameras are waiting for the token. As soon as the aerial camera C_j receives the token it determines its new location, moves and passes the token. The token is initially assigned to a randomly selected aerial camera, denoted as C_1. An aerial camera may take longer to move between the upper levels of the quad-tree and variation in the scale of the time step would affect the performance of the proposed method. However, we are not addressing temporal scales and consider a constant duration time step which is sufcient for an aerial camera to move between any two levels of the quad-tree. To determine the new location, the aerial camera C_j requires the following two steps (Algorithm 1 and Algorithm 2).

First, states for the targets X^t and aerial cameras Y^t are recorded to update the local copy of the quad-tree (Algorithm 1). States of the targets can be received either by direct observation or through wireless communication. The states of the aerial cameras are received directly from the aerial cameras using onboard wireless communication. These measurements are used to calculate and update the value of f_k at each node in τ_j (line 8 to line 13 in Algorithm 1). This rst step of updating τ_j is the main source of cooperation among the aerial cameras. Second, the aerial camera C_j determines one of its neighboring node as its new location y^{t+1}_j (Algorithm 1). This new location is one of six adjacent locations (if y^t_j is not root or leaf node), including the current node k, that has the maximum value of articial force f (line 10 to line 11 in Algorithm 2). If more than one neighboring node has the same value of f_k, priority is given to the node at higher depth level (to reduce the altitude of the aerial camera). If more than one node on child level of the quad-tree has same value of f_k, priority is given to the node that comes rst in the anti-clockwise direction. These priorities are taken into account in line 10 and line 11 of Algorithm 2 by sorting the six nodes around node k into a temporary array temp. If y^t_j is root node then adjacent locations are ve (temp $\leftarrow$ [k1, k2, k3, k4, k] in line 11 of Algorithm 2) and if y^t_j is leaf node then the adjacent locations are only two (temp $\leftarrow$ [k, k0] in line 11 of Algorithm 2). An aerial camera can move only upward if it is not observing any target (line 7 and line 8 of Algorithm 2). The node in temp with a maximum value of f is determined as the new location for aerial camera C_j. Once the aerial camera C_j selects and moves to its new location, it passes the token. It then takes the observation of Ω and starts waiting for the token. After each time step, all the aerial cameras are located at their new locations Y^{t+1}.

3.4 Algorithms

Algorithm 1 Updating local copy of the quad-tree

1: A:number of aerial cameras

2: B: number of targets

3. X^t: states of targets at time step t

4. Y^t: states of aerial cameras at time step t

5. G_k: set of targets visible from node k

6. B_k: number of targets visible from node k

7. Initialize quad-tree τ by setting f_k=0 for k=1,2,...k

8. procedure UPDATETREE(τ, X^t, Y^t)

9. for k=1 : k do

10. calculate G$_k$ =/G1,G2,...,G$_{Bk}$/, 0 $\leq$ B$_k\leq$ B

11. calculate θ_k (Equ:3.13)

12. calculate ϕ_k (Equ:3.15)

13. $f_k = \theta_k - \phi_k$

14. end for

15. end procedure

Algorithm 2 Movement decision of an aerial camera

1: y_j^t: state of aerial camera C_j at time step t

2: F_j: FOV of aerial camera C_j

3. temp: array to store nodes priority-wise

4. k: node to store current state y_j^t

5. procedure MOVE(τ, y_j^t)

6. k $\leftarrow$y$_j^t$

7. if F_j== ø & k_0 is free then

8. $y^{t+1}{}_j \leftarrow k_0$

9. else if F$_j\neq$ ø then

10. temp $\leftarrow$ [k$_1, k_2, k_3, k_4, k, k_0$]

11. $y^{t+1}{}_j$ $\leftarrow$ node in temp with maximum f

12. else

13. $y^{t+1}_{j} \leftarrow$ k
14. end if
15. end procedure

The complexity of Algorithm 1 is O(k^2) as the loop in line 9 iterate times and calculations in line 11 and line 12 also need iterations. The complexity of Algorithm 2, which selects only one out of six possible options, is constant i.e., O(1) . Thus total number of nodes in the quad-tree is the dominating factor in determining the complexity of the proposed algorithms.

3.5 Performance evaluation

The effect of changing the number of aerial cameras and targets (ratio of A to B) on the performance measure is shown in Fig. 3.5. The gure shows how the approach scales with the number of aerial cameras and targets. We perform simulations for varying numbers of targets and aerial cameras starting from A/B = 1/1 to A/B = 4/40. Increase in the number of aerial cameras for given values of B and always increases the resolution of observation (g). While increasing the number of targets (B) for given values of A and ϵ reduces the value of g. Except for A = 1, we notice a sharp decrease in the value of g as we reduce the value of ratio A : B (for lower values of A/B). The g attains nearly a uniform value for further reduction in the ration A to B. It is clear from Fig. 3.5.that the value of g, for a given value of ratio A to B, increases with increase in density of targets and aerial cameras.

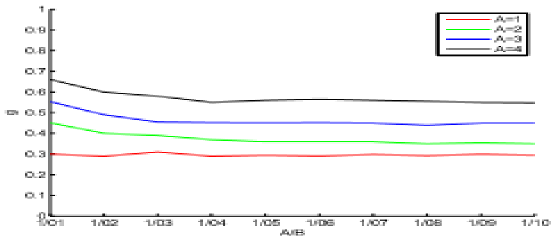

Figure 3.5: The effect of the ratio A/B on g (quad-tree τ of ϵ = 3 levels).

Increase in the size of the quad-tree gradually decreases the performance. We nd that allowing more locations at different resolutions reduces the value of g . The reason is the frequent escape of the targets from the reduced-size FOVs associated with the nodes at lower levels of τ. The aerial cameras cannot stay longer at the leaf nodes(d = ϵ)to take the high resolution observation of targets. In most of the cases when targets are spread in the Ω, aerial cameras don't even reach the leaf nodes to take high resolution observations.

For lower velocities of targets the aerial camera nds it easy to reach the leaf nodes and take high resolution observation for longer time duration. This results in higher values of g. As we increase the velocity of targets they frequently move from one FOV associated with a node at higher value of d to another. With higher velocities of targets, the aerial cameras nd it difcult to reach leaf nodes and stay longer over there, which reduces the value of g.

The location initialization of aerial cameras also affects the performance of our proposed approach. We perform one set of simulation runs by initializing all the aerial cameras at the upper nodes of τ starting from the root node and one set of simulation runs by initializing all aerial cameras at randomly selected leaf nodes. We plot the following metric

$$\mathrm{g}_t = \frac{1}{B} \sum_{i=1}^{B} \bigodot_i^t \qquad \text{(Equ:3.16)}$$

where B is number of targets and $\bigodot_i^t$ is quality of observation of target i.

to show the instantaneous performance of our proposed approach for the two types of location initialization. The value of g_t represents the quality observation of all the targets at each time step t. As time passes, performance due to both types of initialization converges to the same value of g_t. It shows that aerial cameras can optimize their movement pattern to maximize the quality observation of all the targets provided that sufcient amount of time is available. This optimal movement pattern is independent of the initial locations of the aerial cameras. In both the cases, the value of g at the end of the simulation remains the same.

Fig.3.6. shows the results of multi-scale CMOMMT in comparison to those obtained by A-CMOMMT, BCMOMMT and recently developed decentralized Mixed Integer Model-Predicitve Control (MPC) approaches. In order to compare our multi-scale approach with the existing xed and single-scale approaches, we restrict the movement of aerial cameras in the existing approaches to a horizontal plane corresponding to leaf nodes of the quad-tree. Fig.7.1. shows that the proposed multi-scale CMOMMT outperforms the existing approaches. Superiority of the multi-scale CMOMMT approach becomes even more obvious for lower values of camera-target ratio A/B. An improvement of approx. 22% compared to Mixed-Integer MPC method is achieved for A/B = 1/10.

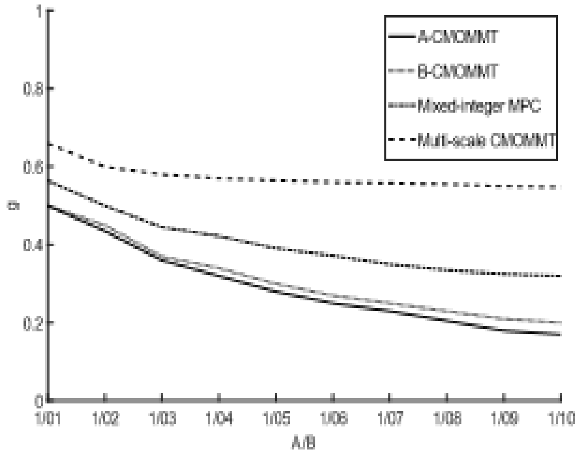

Figure 3.6: Comparison of the simulation results obtained from the proposed Multi-scale CMOMMT approach and from ACMOMMT, B-CMOMMT and Mixed Integer MPC approaches. The higher values of g show better performance (quad-tree τ of ϵ = 3 levels).

Conclusion

We presented a quad-tree based distributed and cooperative movement strategy for a wireless and mobile aerial camera network to maximize the collective time and quality of observation for multiple moving ground targets. This cooperative movement strategy enables the individual aerial cameras in the aerial camera network to work together towards a common goal of maximizing the high quality observation of large group of moving targets. The proposed method enables the dynamic and simultaneous assignment of locations and FOVs to aerial cameras in the network. This work is suitable not only for aerial camera network that can move in 3D space, but also for networked sensors that can control the location and zoom level of their FOVs. We have found that the quality of observation depends not only on the number of targets and aerial cameras but also on the levels of quality (elevations). We have also found that the performance measure deteriorates with increase in the levels of qualities for observation in a highly dynamic setting. Several variations of this dynamic sensor coverage problem are possible, such as considering distributed coordination, heterogeneity of sensors (including pan-tilt-zoom and other parameters of the sensor), the characteristics of the terrain and the cost of movement.

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