Active Cameras Resources Management Assisted by Wide Field of view Fixed Cameras for the Surveillance of Multiple Moving Targets

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Abstract—**In this paper, we propose a novel approach to manage an active resources for a centralized active vision system assisted by a wide field of view fixed cameras (WFOV-FC). Indeed, since the WFOV-FC can provide only large coverage with low resolution, these later are used to generate spatiotemporal observation requests from all detected and tracked target in the surveillance zone. The information gathered will be used to schedule the set of active Pan-Tilt-Zoom cameras (PTZ-AC) in order to collect high-resolution videos suitable for further biometric analysis. Based on the output of this biometric analysis, the same used set of active cameras is requested to maximize at the same time the coverage with close-up views of every target identified as a threat. We formulate PTZ multi-cameras assignment and handoff as a planning problem whose solution achieves optimal cameras assignment in real time. Simulation results, show the efficiency of the proposed policy in satisfying both objectives at the same time**

Keywords-Multi-cameras systems; active and fixed cameras; assignment; online scheduling

I. INTRODUCTION

There is an ever increasing demand for security monitoring systems in the modern world. Visual surveillance is one of the most promising areas in security monitoring for several reasons. It is easy to install, easy to repair, and the initial setup cost is inexpensive when compared with other sensor based monitoring systems, such as audio sensors, motion detection systems, thermal sensors, etc. [1].

Video surveillance systems are installed in locations ranging from multinational banking organizations to public institutions to small local stores, and there is a similar disparity in the level of sophistication of installed systems. The use to which these systems are put also varies widely with the intentions of the operators and the budget available for the implementation of the system.

Earlier works in the field of cameras and videos technologies have made it possible to network numerous video cameras together by an operator in order to provide visual coverage of small and medium spaces such as banks and shops. However, as the size of the multi-cameras system grows and the level of activity in the public space increases, it becomes infeasible for human operators to monitor the multiple video streams and identify all events of possible interest, or even to control individual cameras in performing advanced surveillance tasks, such as zooming on a moving subject of interest to acquire one or more facial snapshots. Moreover, the cost of employment of a human operator outpaces the cost of installing and maintaining the multi-camera systems. Consequently, a timely challenge for computer vision researchers is to design multi-cameras systems capable of performing visual surveillance tasks automatically or at least with minimal human intervention. We regard the design of an autonomous multi-cameras system as a problem of resource allocation and scheduling, where the cameras are treated as resources required to complete the desired sensing tasks.

Autonomous multi-cameras systems using only WFOV-FC can provide large, low resolution coverage of the scene. However, recognition and identification of targets usually require close-up views at high resolution which need PTZ-AC. The resulting proposed autonomous multi-cameras system is based on a set of WFOV-FC’s and a set of PTZ-AC’s as illustrated in Figure 1. The major challenge in this work is the control and scheduling of the set of PTZ-AC so that satisfying the tradeoff between three competing objectives:

- Capture high quality video for as many as possible, preferably all, of the targets in the scene
- Observe each target for as long or as many times as possible, since the chances of identifying and classifying a target improve with the amount of data collected about that target.
- Maximize the coverage time of targets identified as a threats during their stay in the surveillance zone.

Not considering one of the three objectives will conduct to the situation where each camera follows a single target for their entire stay in the scene, ignoring all other pedestrians. The second situation is that a camera briefly observes every target in turn and repeatedly, thus spending most of the time transitioning between different pan, tilt, and zoom settings. The third one leads to ignore appeared threats.

This paper is organized as follows. Section II gives comprehensive background of the current and emerging approaches for camera selection and handoff. This is followed by presenting the adopted system architecture for an accurate autonomous video surveillance. In Section IV, we present the formulation of the challenge targeted as a machine scheduling problem. We next propose our scheduling policy in Section V. Finally, we describe simulation setup and results in Section VI and conclude the paper in Section VII.

II. Related Work

Previous work on multi-camera systems has dealt with issues related to low and medium-level computer vision, namely identification [2, 3], recognition [4, 5], detection and tracking of moving objects [6-13]. The importance of accurate detection, tracking, and data association is obvious, since tracking information is needed as the initial stage for controlling one or more PTZ cameras to acquire high-resolution imagery.

However, in addition to detection and tracking, the acquisition of high-quality imagery, particularly for biometrics purposes, requires accurate calibration between the fixed and PTZ cameras in order to focus attention on interesting events that occur in the scene. The control or the schedule of active cameras set when there are more objects to be monitored in the scene than the active cameras is also a challenge for many researchers. Some of themes employ a WFOV-FC to control an active tilt-zoom camera. This configuration is often termed in the literature as master–slave. Many researchers use a master–slave camera configuration with two or more [19] cameras. In particular, most of the methods strongly rely on a direct camera calibration step. Basically these approaches are not autonomous since they need a human to deal with calibration marks. Nevertheless, few exceptions are discussed, where in order to track targets across a fixed and a PTZ camera, they used an affine transformation between consecutive pair of frames for stabilizing moving camera sequences, and an homography transformation for registering the moving and stationary cameras with the assumption that the scene is planar.

A camera scheduling algorithm [14], would typically utilize tracking information, provided by one or more fixed cameras performing detection and tracking [16, 17], for computing a schedule that controls the assignments of targets to PTZ cameras over time. Each PTZ camera would then servo, based on calibration data, to aim itself at different targets in a timely fashion as specified by the schedule.

A similar approach involving calibrated static and pan/tilt cameras is presented in [9]. Data from multiple static cameras is fused to estimate the 3D location of the pedestrian. An active camera uses calibration information to bring the target into the center of its view. After initial repositioning, the active camera autonomously tracks the target [6, 7], thereby avoiding the communication overhead associated with master-slave configurations. The active camera periodically sends its pan/tilt settings to the static cameras. The static cameras can use this information to decide whether or not the active camera is tracking the correct target. If it is not, the active camera is repositioned.

Other authors, such Lim et al. [20], have proposed a number of different camera scheduling algorithms designed for different application goals, where they include, for example a scheme for scheduling available cameras in a task-dependent fashion , static and non static priority policies [15].

The work presented here, differs from the previous existing scheduling multi-cameras works in the following points:

It can handle several PTZ-AC's

The different PTZ-AC's are modeled as autonomous agents that are not driven by the WFOV-FC's.

The scheduling strategy supports both high quality videos recording and coverage insurance of targets and threats.

III. System Architecture

Figure 1 shows the architecture of the system. The system considered consists of "N_a"($N_a > 1$) PTZ-AC's and WFOV-FC's. The WFOV-FC's detect and label all moving objects in the scene. The states of the objects (e.g., size, position and velocity) in the 2D image space are tracked and predicted. Based on the prediction, the different observation requests are generated. Then the request assignment process assigns a subset of the targets/requests to each PTZ-AC by computing the relevance of the different PTZ-AC's to the observed targets in the surveillance zone. Each PTZ-AC camera tracks the objects assigned to it by selecting the PTZ-AC parameter settings that best satisfy these requests to capture high resolution images/videos of the targets.

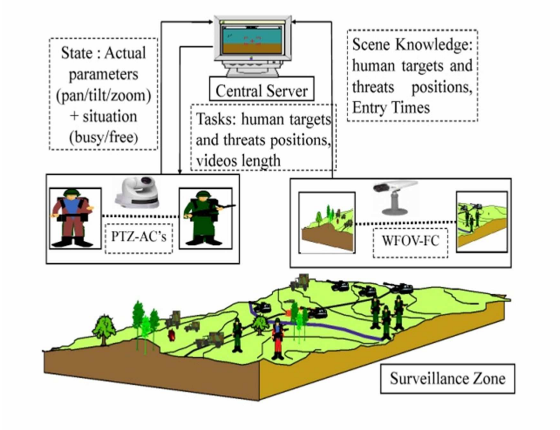

Figure 1. System Overview

IV. Problem Statement

We consider a multi-cameras system including "N_f"calibrated WFOV-FC's and "N_a" PTZ-AC's.

Let $O = \{o_i \backslash i = 1,2, \dots\}$denote the set of targets observed at a given time by the multi-cameras system. At that time, the state of a target is given by $o_i^t = (x_i^t, v_i^t)$ where "x_i" and "v_i" represent the position and velocity, respectively, of observed target *i*.

Let each PTZ-AC be described by a tuple $(P, \alpha_{min}, \alpha_{max}, \beta_{min}, \beta_{max}, Z_{min}, Z_{max})$. We assume therefore that the "3D position P of each PTZ-AC is known a priori. $[\alpha_{min}, \alpha_{max}]$, $[\beta_{min}, \beta_{max}]$ and $[Z_{min}, Z_{max}]$ represent the pan tilt and zoom limits, respectively, for each PTZ-AC.

The problem is to find a schedule on "N_a" PTZ-AC that minimizes the total unit penalty when target "I" with deadlines "d_i" are released at time "r_i" The targets require arbitrary processing times and pre-emption (pmtn) is

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allowed. So, minimizing the total unit penalty is akin to maximizing the number of targets successfully recorded prior to their deadlines.

We can describe the camera scheduling problem proposed as:

$$E^* = argmax\ q(E_i^t) \quad (1)$$

$$E_i^t \in E_a$$

$$E_a = \{E_i^t / t \in [t_{current_{time}}, t_p], i \in [1, N_a]\} \quad (2)$$

where E denote a feasible event defined as follows:

$$E = R(c_i^{PTZ}, o_i) \cup R(c_i^{PTZ}, ot_i) \quad (3)$$

$R(c_i^{PTZ}, o_i) -$ The recording of human target by a PTZ-AC.

$R(c_i^{PTZ}, ot_i) -$ The recording of human target identified as a threat by a PTZ-AC.

$t_p -$ Preset time that indicates the number of predicted plans depending on the predicted states of humans targets observed.

The complexity of problem (1) is NP-hard [18]. Hence, we resort to a greedy algorithm for scheduling cameras to observe targets.

The obvious non-clairvoyant online algorithms are Round Robin (RR) and Shortest Elapsed Time First (SETF). The idea of the RR is to devote identical processing resources to all jobs, whereas SETF devotes all resources to the job that has been processed the least. As SETF is known to perform poorly when jobs are not fully parallelizable [19], we used the weighted RR.

The policy of using a weighted RR scheduling scheme is to assign jobs to multiple processors with different load capacities. Each processor is assigned a weight indicating its processing capacity and more jobs are assigned to the processors with higher weights.

We model each PTZ camera as a processor whose weights, which quantify the suitability of a camera with respect to observing a target, are adjusted dynamically.

These weights are assimilated to a combination of several quality measures.

The computation of the relevance of a PTZ-AC to the task of recording close-up videos of selected targets for further identification and/or classification process, encodes an intuitive observation which is formalized by describing the relevance of a PTZ-AC to the task of observing a target in terms of quality factor"q". omitting superscripts t, i and E , the global quality is expressed as follows:

$$q = \begin{cases} 1 & \text{if } c_i^{PTZ} \textit{ is idle} \\ q_{\alpha\beta Z} \cdot q_o \cdot q_d \cdot q_\sigma \cdot q_c \end{cases} \quad (4)$$

where the different sub qualities are defined in the following subsections:

A) PTZ limits "$q_{\alpha\beta Z}$" :

The turn and zoom limits of cameras should be taken into account when assigning a camera to observe a target. A camera that has more leeway to turn and zoom may be able to follow a target for a longer period of time. The mechanical limitation for each PTZ camera on its Pan Tilt Zoom parameter range is defined by:

$(\alpha_{min}, \alpha_{max}, \beta_{min}, \beta_{max} Z_{min}, Z_{max})$.

$$q_{\alpha\beta Z} = \exp\left(-(\alpha - \hat{\alpha})^2 - (\beta - \hat{\beta})^2 - (Z - \hat{Z})^2\right) \quad (5)$$

$$\hat{\alpha} = \frac{(\alpha_{min} + \alpha_{max})}{2} \quad (6)$$

$$\hat{\beta} = \frac{(\beta_{min} + \beta_{max})}{2} \quad (7)$$

where: "α" and "β" are respectively, the pans, tilts angles corresponding to the location of the target.

"Z", is the actual zoom setting of a given camera.

"$\hat{Z}$", is the desired zoom to record close-up videos.

B) Observational range "q_o":

It reflects the observational constraints of a camera. It is set to 0 when the human target is outside the observational range of a camera; otherwise, it is set to 1.

$$q_o = \begin{cases} 1 & \text{if } \alpha \in [\alpha_{min}, \alpha_{max}] \text{ and} \\ & \beta \in [\beta_{min}, \beta_{max}] \text{ and} \\ & Z \in [Z_{min}, Z_{max}] \\ 0 & \end{cases} \quad (8)$$

where: $[\alpha_{min}, \alpha_{max}]$, $[\beta_{min}, \beta_{max}]$ and $[Z_{min}, Z_{max}]$ are the external vertical, horizontal rotations, and zoom factor.

C) Target-Camera Distance "q_d"

Tracking becomes harder as camera-to-target distance grows. The quality of captured imageries generally degrades as the distance"d_{tc}", between the target and the camera increases or decreases consequentially. Hence, this quality measure is only based on "d_{tc}".

$$q_d = \exp - \left((d_{tc} - \hat{d})^{\wedge 2}\right) \quad (9)$$

where $\hat{d}$ is the desired distance of a target to a camera that allows recording close-up videos.

D) View Angle "q_σ"

It is more desirable to select a camera that has frontal view of a target, in order to record high quality videos that will serve for identification purposes. This later is defined as it is the angle between the velocity vector of the target and the optical centre of a camera.

$$q_\sigma = \exp(-\sigma) \quad (10)$$

where σ is defined as the angle between the velocity vector of a target and the line that join the position of that target and a selected camera.

E) Handoff candidate"q_c"

Handoff candidate quality gives preference to handoff candidates in the vicinity of the camera currently observing the target. The idea is that nearby cameras have similar viewpoints, making appearance based target signature more relevant for the candidate camera.

$$q_c = \exp(-\delta) \quad (11)$$

where δ is the angle between the fixation vector of camera c_i^{PTZ} and the fixation vector of the camera currently observing the target.

V. MULTI-CAMERAS SCHEDULING ALGORITHM

In this section, we describe the scheduling policy for scheduling a set of PTZ-AC's in order to achieve the above cited challenge. Finding an optimal event that fits with the movement horizon of the targets/ threats, while maximizing the objective function (1) is a combinatorial problem. Our policy is based on some modifications in the well known Round Robin algorithm which yields to a novel heuristic able to satisfy the three points of our challenge. Algorithm 1 outlines our policy strategy:

Data: set of PTZ-AC's currently assigned to the different targets"$V_{Busycam}$" . Set of PTZ-AC's cameras that are currently available"$V_{Freecam}$". Set of targets that are currently not assigned a PTZ-AC "$V_{Unsched\_o}$". Set of targets that are currently being followed by PTZ-AC's "V_{sched_o}". Set of threats that are currently not assigned a PTZ-AC "$V_{Unsched\_ot}$". Set of threats that are currently being followed by PTZ-AC's "V_{sched_ot}".

Begin:

Set V_{Busycam}, $V_{\text{Unsched\_o}}$, V_{sched_o}, $V_{\text{Unsched\_ot}}$ and V_{sched_ot} to $\{\emptyset\}$.

$V_{\text{Freecam}} = \{c_i^{PTZ} / i = 1, \dots, N_a\}$

For t= 1: t_p: ….. **do**

Remove targets and threats that appears to have left the scene from $V_{\text{Unsched\_o}}$, V_{sched_o}, $V_{\text{Unschedot}}$ and V_{Lsched_ot}. Move the corresponding cameras from V_{Busycam} to V_{Freecam}

For all New arrivals "o_i" **do**

Set "$t_{s\_o_i} = 0$" (the timestamp of"o_i"). Set "$t_{rc\_o_i} = 0$" (times-recorded count on"o_i"). Add "o_i" to V_{Lsched_o}

End for

For all Cameras "c_i^{PTZ}" in the V_{Busycam} **do**

if $t_{s\_o_i}$ by a "c_i^{PTZ}" is equal to $t_{préemption}$ **then** Set "$t_{s\_o_i} = 0$". Increment "$t_{rc\_o_i}$". Move "c_i^{PTZ}" from V_{Busycam}toV_{Freecam}. Move "o_i" from V_{sched_o} to $V_{\text{Unsched\_o}}$

else if("$t_{s\_o_i}$" by a Camera "c_i^{PTZ}" is>= $t_{préemption}$ **and** ($V_{\text{Unsched\_o}} \neq \{\emptyset\}$ or $V_{\text{Unsched\_ot}} \neq \{\emptyset\}$) **and** (Camera "$c_i^{PTZ}$" is relevant to at least one of the targets in $V_{\text{Unsched\_o}}$ or threats in $V_{\text{Unsched\_ot}}$) **or** ("o_i" times-recorded count ≥1 and a target "$o_j, j \neq i$" in $V_{\text{Unsched\_o}}$ has times-recorded count equal to 0 and Camera "c_i^{PTZ}" is relevant to "o_j") **or** threat "$ot_j, j \neq i$" in $V_{\text{Unsched\_ot}}$ has times-recorded count equal to 0 and Camera "c_i^{PTZ}" is relevant to "ot_j")**then**

(Set "$t_{s\_o_i} = 0$" and Move "c_i^{PTZ}" fromV_{Busycam} to V_{Freecam} and Move "o_i" from $V_{\text{sched_o}}$to $V_{\text{Unsched\_o}}$) **or** (Move "c_i^{PTZ}" from V_{Busycam} to V_{Freecam} and Move "ot_i" from $V_{\text{sched_ot}}$to $V_{\text{Unsched\_ot}}$)

End if, End for

For all Cameras "c_i^{PTZ}" in V_{Freecam} **do**

Compute $V_{\text{relevant\_o}}$ which consists of the targets in $V_{\text{Unsched\_o}}$ that are relevant to "c_i^{PTZ}".

Compute $V_{\text{relevant}_{\text{ot}}}$ which consists of the targets in $V_{\text{Unsched}_{\text{ot}}}$ that are relevant to "c_i^{PTZ}"

If $V_{\text{relevant\_ot}} = \{\emptyset\}$ **then**

If $V_{\text{relevant\_o}} = \{\emptyset\}$ **then** Continue

Elseif $V_{\text{relevant\_ot}} = \{\emptyset\}$ and $V_{\text{relevant\_o}} \neq \{\emptyset\}$ **then** Pick target "o_i" from $V_{\text{relevant\_o}}$ with the highest probability of threat. Assign "c_i^{PTZ}" to "o_i". Move "c_i^{PTZ}" from V_{Freecam} to V_{Busycam}. Move "o_i" from V_{Unsched} to V_{sched}

Elseif ($V_{\text{relevant\_ot}} \neq \{\emptyset\}$ and $V_{\text{relevant\_o}} = \{\emptyset\}$) **or** ($V_{\text{relevant\_ot}} = \{\emptyset\}$ and $V_{\text{relevant\_o}} = \{\emptyset\}$) **then** Pick target "ot_i" from $V_{\text{relevant\_ot}}$ with the highest probability of threat. Assign "c_i^{PTZ}" to "ot_i". Move "c_i^{PTZ}" from V_{Freecam} to V_{Busycam}.

End if, End for, End for

Algorithm 1. Sheduling policy

VI. SIMULATION RESULTS

We simulate a monitoring area with up to 15 autonomous targets that enter, travel for free inside, and leave the monitoring area of their own volition. We tested the scheduling strategy in various scenarios using from 1 to 5 PTZ active cameras.

Each target spends anywhere from 40 to 150 seconds in the monitoring space. The processing time judged satisfactory to capture sufficient frame for identification and classification purpose is set to 30 seconds, while the preemption cut-off time is set to 5 seconds. The targets are assumed to enter the monitoring area randomly. The simulation time is set to 180 seconds.

As expected, we can see from Figure 2 that the probability of correct recording depends to the ratio between the number of targets and available cameras. However, we judge that the results are acceptable since the majority of obtained values are superior to 0.5. This is due in part to the use of the quality measure which exhibits high success rate for recording close up video and lower average lead time required by a PTZ-AC to fixate on a target and initiate video recording.

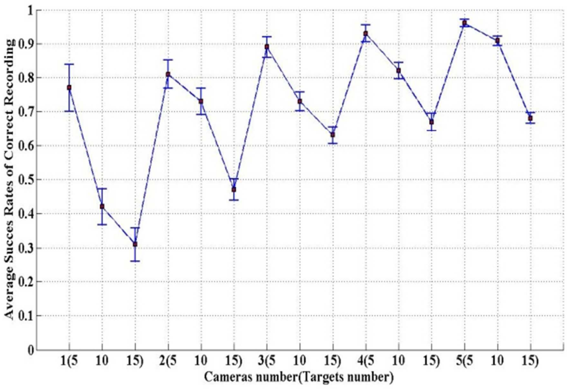

Figure 2. Average succes rate of correct recording

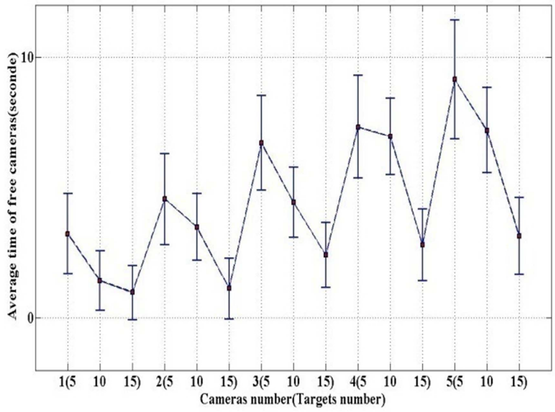

Figure 3. Average time of free cameras

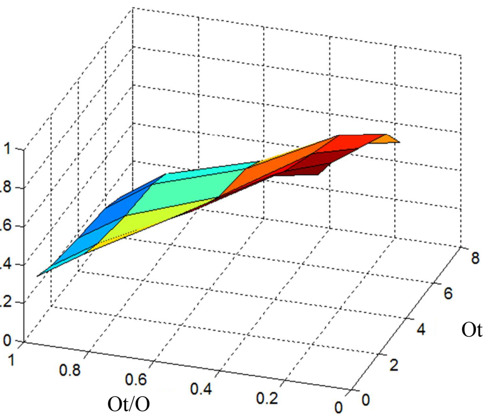

Figure 4. Average succes rate of total threats covrage versus number of targts

Figure 3 shows that average time of free cameras depends also to the above cited ratio. We can remark that the results are very encouraging since the highest obtained time which corresponds to the worst result; present an approximate rate of 0.04 in the total considered simulation time.

Figure 4 represents the success rate of assuring total coverage of a number of threats (up to 7) while using 5 cameras. We can remark that this rate decrease as the number of total target increase. Nevertheless, this result confirms the capacity of the elaborated policy to target several objectives at the same time and return an optimal scheduling solution at every time step.

VII. CONCLUSION AND FUTURE WORK

We have presented a novel approach to control multiple PTZ-AC's assisted by a set of WFOV-FC in order to satisfy three main objectives in real time. The main novelty of our approach lies in capturing high quality video for as many as possible of the targets in the scene, while observing each target for as long or as many times as possible and at the same time maximizing the coverage time of targets identified as a threats during their stay in the surveillance zone. The problem was solved by using a probabilistic objective function that encapsulates a set of quality measures. The reported simulations demonstrate the effectiveness of the proposed policy in satisfying the above objectives in the same time. We are interested in conducting more detailed quantitative performance evaluation in the future by validating imageries captured online with biometrics tasks such as face detection or recognition that can be conducted offline.

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