Cooperative Multi-Target Surveillance Using a Mutational Analysis Approach*

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***Abstract*— Networked surveillance systems provide an extended perception and distributed sensing capability in monitored environments through the use of multiple networked sensors. The task of tracking multiple targets in a surveillance network is a challenging problem because of the following reasons: (1) multiple targets need to be monitored and tracked continuously so that they will not leave the view of at least one of the sensors; (2) the view of the sensors needs to be optimized so that at a given time the targets are observed with a discernable resolution for feature identification; (3) it is important to devise stable control algorithms for accomplishing the surveillance task. Current feature (point) based visual surveillance and tracking techniques generally employed do not provide an adequate framework to express a surveillance task. This paper presents a mutational analysis approach for shape based control to model a multi-target surveillance scenario. It further presents an optimal multiple sensor task planning algorithm based on the target resolution and priority, to achieve optimal coverage of multiple targets in the sensing region of the surveillance network. Finally, experimental results demonstrate the efficacy of the proposed approach for tracking multiple targets over a large area.**

***Index Terms*— Surveillance Networks, Mutational Analysis, Visual Surveillance, Hausdorff Tracking, Target Tracking.**

I. Introduction

In a wireless surveillance network, the surveillance nodes are equipped with sensors and wireless communication capabilities. Due to the infrastructure-less architecture, the surveillance network can be deployed into hostile or ad hoc environments and hence have many advantages in carrying out area surveillance, reconnaissance or object tracking tasks in widely varying environments. The individual sensor nodes can have multiple sensing modalities such as cameras, infrared detector arrays, laser range finders, omnidirectional acoustic sensors, etc. Locomotion and active sensing greatly increase the range and sensing capability of the individual sensor nodes. Multiple nodes also facilitate simultaneous multi-view observation over a wide area and can aid in reconstruction of 3D information about the tracked targets. This paper presents a framework for modeling and control of active sensor nodes used for continuously tracking multiple targets.

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A surveillance task implies that the targets are continuously maintained in the active sensing region of the sensor. Research approaches to this problem found in recent literature [1], [2], [3] generally use visual servo control [3] or gaze control [4], which mainly involve feature (point) based tracking and fail to describe the basic task of maintaining the target in the sensor's active field of view effectively and succinctly. These approaches cannot address the problem of ensuring the coverage of multiple targets using a single sensor. Further, these approaches result in excessive camera motion that may result in blurring and other undesired effects, which in turn have detrimental effects on the surveillance task.

In order to solve the active target tracking problem, we propose to use a mutational analysis approach [5]. Multiple target coverage can be readily expressed in a set based topological framework using shape analysis and shape functions ([6] [7]). Thus, the variables to be taken into account are no longer vectors of parameters but the geometric shapes (domains) themselves. Unfortunately, due to the lack of a vectorial structure of the space, classical differential calculus cannot be used to describe the dynamics and evolution of such domains. Mutational analysis endows a general metric space with a net of "directions" in order to extend the concept of differential equations to such geometric domains. Using mutational equations, we can describe the dynamics (change in shape) of the sensor field of view (FOV) and target domains and further derive feedback control mechanisms to complete the specified task.

Multi-sensor collaboration is essential for achieving the task objectives of such large scale networks. Various approaches have been suggested for tasking such networks right from completely centralized [1] to highly decentralized approaches [2]. Centralized approaches are not fault tolerant and do not scale well with the number of nodes. On the other hand, completely decentralized approaches need to assume a very high density of sensors in order to pervasively track multiple targets and do not scale well with the number of targets. In this paper we propose to use a grouping architecture that combines the advantages of both centralized and decentralized approaches to pervasively track multiple targets in a surveillance network.

The remaining of the paper is organized as follows: Sec-

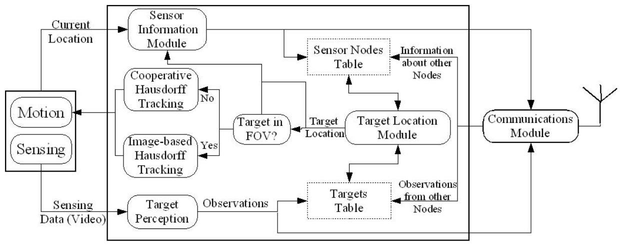


Fig. 1. Architecture of Sensor Node.

tion II provides a brief introduction to networked surveillance systems. Section III presents the method of Hausdorff tracking using mutational analysis. Multi-sensor collaboration and sensor tasking problems are presented in IV. Experimental results of the proposed approach and conclusions are provided in section V and VI respectively.

II. Networked Surveillance Systems

Networked surveillance systems have received much attention from the research community due to their many pervasive applications [8]. A surveillance task can be divided into two major subtasks, namely target detection and target tracking. Figure 1 depicts the architecture of a sensor node. The target perception module is responsible for detecting and classifying the various targets in the active FOV of the sensor and performing temporal consolidation of the detected targets over multiple frames of detection. Moving target detection and classification is known to be a difficult research problem [9]. Many approaches such as active background subtraction [2] [10] and temporal differentiation have been suggested for detecting and classifying various types of moving targets including single humans and human groups to vehicles and wildlife [1] [10]. The next problem would be to classify and associate the various detected image blobs to discernable targets and maintain their temporal tracks in order to pervasively track them. Various approaches such as extended Kalman filtering, pheromone routing and Bayesian belief nets have been suggested for maintaining the track of targets [11]. The individual sensor nodes maintain information regarding the observations of their neighboring nodes and broadcast (within their locality) their own observations. Based on the combined observations, each node develops a list of targets being actively tracked and the status of its peer nodes and stores this information in the targets table and the sensor nodes table, respectively. In the targets table, the native as well as observed characteristics of the target objects, observed by the respective sensors are stored. The targets table also stores information indicating the node that sensed these characteristics. Nodes also store peer information, such as location, active FOV and total capable FOV of the peer.

When a target is recognized in the active FOV of a sensor, it can be tracked using image based tracking methods such as visual surveillance and gaze control [1] [2]. However, these approaches over emphasize the task that can lead to excessive motion which can lead large energy consumption and blurring of the image, which in-turn is detrimental to feature detection. Further, these approaches cannot describe the task of tracking multiple free moving objects using a single sensor and hence are not feasible for use in environments with high target density [1].

In this paper we propose the image based Hausdorff tracking method that tries to ensure that multiple targets can be tracked in the sensor active FOV. Hausdorff tracking can readily express these tasks as the minimization of an error (shape function) and accomplish them using feedback directly from the image analysis. In order to develop the feedback map $u(t)$ to the motion module, the motion of the target set with respect to the motion of the camera/robot is required which is accomplished using mutational equations.

When the targets to be tracked are outside the active FOV of the sensor (but in the capable FOV), the node can still ensure that the targets are acquired in the active FOV using target location information available from other sensors in the targets table. This paper proposes the method of cooperative Hausdorff tracking for deriving assumptions on the input u to move the sensor such that the targets are located in its active FOV. Using the cooperative Hausdorff tracking method the target can be brought into the active FOV of the sensor and assuming that the visual characteristics of the target can be recognized, the sensor will switch over to image based Hausdorff tracking to maintain the target in the active FOV.

In most surveillance tasks, spatial proximity of sensor nodes is a vital characteristic of sensor networks. In order to take advantage of the proximity of the nodes to conserve energy or enable efficient and sensing and information processing, sensors are often organized into local collaborative groups. Groups are formed based on proximity and the members in a group communicate their observations to each other. The problem of assigning sensors to a task can then be performed by solving an optimization problem which will assign the sensors the targets to track. Each sensor can potentially view multiple targets which can be tracked within the sensor view. The proposed mutational analysis approach allows us to address the problem of multiple target tracking using a single sensor which will enable efficient target tracking in environments having a high target density.

III. Hausdorff Tracking

The surveillance task of maintaining multiple targets in the active field of view can be readily expressed in a set based framework. This task can be expressed using a shape function [6] as the minimization of a Hausdorff distance based metric or the size of the target etc. The task of visual servoing can also be expressed in a set based framework [12]. The shape function essentially represents the error between the desired and actual shapes and reducing it to zero will accomplish the task.

A. Mutational Analysis

The sensor coverage area and the target are readily represented as sets (domains) in $E \subset \mathbb{R}^n$. In order to develop the feedback map $u(t)$ to move the sensor, the motion of the target set with respect to the motion of the camera/robot needs to be expressed. In order to study the motion of these domains we need to define a differential calculus on the space of all compact, non-empty subsets $\mathcal{K}(E)$ of the closed set E. The mathematical framework of mutational analysis allows us to extend the concept of differential equations to the metric space $\mathcal{K}(E)$. For defining mutational equations, we supply the space $\mathcal{K}(\mathbb{R}^n)$ with a distance d, for example the Hausdorff distance between domains $K_1, K_2 \in \mathcal{R}^n$ defined by $d(K_1, K_2) = \sup_{q\in\mathbb{R}^n} \|d_{K_1}(q) - d_{K_2}(q)\|$, where, $d_K(q) = \inf_{p\in K} \|q - p\|$ represents the distance between the point q and domain K. Let the sensor coverage area be represented as the set $K := \{q\}$ and the target as the set $\hat{K} := \{p\}$.

Domains evolving with time are called tubes and can be defined as a map $K(\cdot) : \mathbb{R}^+ \mapsto \mathcal{K}(E)$. The deformation (motion) of the coverage and the target sets can be represented using tubes. The evolution of a tube can be described using the notion of a time derivative of the tube as the perturbation of a set. Associate with any Lipschitz map $\varphi : E \mapsto E$, a map called the transition $\vartheta_\varphi(h, q) := q(h)$, which denotes the value at time h of the solution of the differential equation: $\dot{q} = \varphi(q),\ q(0) = q_0$. Extend this concept of a transition to the space $\mathcal{K}(E)$ by introducing the reachable set from set K at time h of φ as

$$\vartheta_\varphi(h, K) := \{\vartheta_\varphi(h, q_0)\}_{q_0\in K} \tag{1}$$

The curve $h \mapsto \vartheta_\varphi(h, K)$ plays the role of the half lines $h \mapsto x + hv$ for defining differential quotients in vector spaces. Using the concept of the reachable set the time derivative of a tube can be defined as a mutation:

Definition 1: (Mutation) Let $E \subset \mathbb{R}^n$ and $\varphi : E \mapsto E$ be a Lipschitz map ($\varphi \in Lip(E, \mathbb{R}^n)$). If for $t \in \mathbb{R}^+$, the tube $K : \mathbb{R}^+ \mapsto \mathcal{K}(E)$ satisfies:

$$\lim_{h\to 0^+} \frac{d(K(t + h), \vartheta_\varphi(h, K(t)))}{h} = 0, \tag{2}$$

then, φ is a mutation of K at time t and is denoted as:

$$\mathring{K}(t) \ni \varphi(t, K(t)),\ \ \forall t \geq 0 \tag{3}$$

We can further define controlled mutational equations as:

$$\mathring{K}(t) \ni \varphi(t, K(t), u(t)),\ \ \forall t \geq 0,\ u(t) \in U \tag{4}$$

A feedback law can be defined as a map $\mathcal{U} : \mathcal{K}(E) \mapsto U$ associating a control u with a domain $K(t)$ as: $u(t) = \mathcal{U}(K(t))$. Using a controlled mutational equation, we can model the motion of the target and coverage sets due to the motion input u to the camera as:

$$\mathring{K}(t) \ni \varphi(K, u) := \{\dot{q} = B(q)u | q \in K\} \tag{5}$$

Problems involving variables which are not vectors of parameters or functions, but shapes of geometric domains or sets K contained in a subset $E \subset \mathbb{R}^n$ can be addressed using shape analysis. Shape functions are set-defined maps defined from $J(K) : \mathcal{K}(E) \mapsto \mathbb{R}$ [6]. They provide a “measure” of the deformation of $K \in \mathcal{K}(E)$ and can be used to study shape acceptability and optimality. For example we can use a shape function to check the distance of the set K to another set $\hat{K}$, or whether the reference set $\hat{K}$ is contained within the current set K. An example of such a coverage function is:

$$J(\hat{K}) = \int_{\hat{K}} d_K^2(p)dp, \qquad q \in K, \quad p \in \hat{K} \tag{6}$$

The change in shape function $J(K)$ due to the deformation of the shape K can be represented using the directional derivative of the shape function which can construed as the analog of the directional derivative in vector spaces and provides a measure of the change in the task criterion due to motion of the coverage or target set. The Eulerian semi-derivative of the shape function $J(K)$ in the direction of the mutation $\varphi(K, t, u)$ is defined as [6]:

$$\mathring{J}(K)(\varphi) = \lim_{t\to 0} \frac{J(\vartheta_\varphi(t, K)) - J(K)}{t} \tag{7}$$

where, $\vartheta_\varphi(t, K)$ is the t reachable tube of K under the mutation φ. It can be construed as the analog of the Gauteaux directional derivative in a Hilbert space. For the shape function described in equation 6, the shape directional derivative can be written as [7], [12]:

$$\mathring{J}(K)(\varphi) = 2\int_{\hat{K}} \inf_{q\in\Pi_K(p)} \langle (q - p), \varphi(q)\rangle dp, \tag{8}$$

$\Pi_K(p)$ denotes the projection of the point p on set K.

The asymptotic behavior of the measure $J(K(t))$ of the deformation of the set K can be studied using the shape Lyapunov theorem. The deformation is described as the reachable tube $K(t)$ and is the solution to the mutational equation in equation 4. We can now state the shape Lyapunov theorm which provides the conditions to guarantee the convergence of $J(K(t))$ to 0.

Theorem 1: Consider $E \subset \mathbb{R}^n$ and a mutational map φ defined on the set E, a shape functional $J : \mathcal{K}(E) \mapsto \mathbb{R}^+$ and a continuous map $f : \mathbb{R} \mapsto \mathbb{R}$. Let the Eulerian semi-derivative of J in the direction φ exist and be defined as $\mathring{J}(K)(\varphi)$. The functional J is an f-Lyapunov function for φ if and only if, for any $K \in \mathrm{Dom}(J)$, we have

$$\mathring{J}(K)(\varphi) + f(J(K)) \leqslant 0. \tag{9}$$

See [13] for proof. Using the shape Lyapunov theorem and equation 5, we can derive assumptions on the input u, to move the camera, in order to accomplish the surveillance task as:

$$\langle \int_{\hat{K}} \inf_{q\in\Pi_K(p)} B(q)^T(q - p)dp, u\rangle \leq -\frac{1}{2}\alpha J(K) \tag{10}$$

Any u which satisfies the above equation will ensure coverage. In order to find a u, let us denote:

$$C(K) = \int_{\hat{K}} \inf_{q\in\Pi_K(p)} B(q)^T(q - p)dp. \tag{11}$$

Let $C(K)^\#$ be the pseudo inverse of $C(K)$. Thus, the conditions on u to guarantee coverage can be written as:

$$u = -\frac{1}{2}\alpha C(K)^\# J(K). \tag{12}$$

Assuming $C(K)^T$ is non-singular, the input u for the camera which provides coverage can be calculated using equation 12.

B. Image based Hausdorff tracking

Image based Hausdorff tracking can be used when the targets to be tracked are visible in the sensor field of view. Using the method developed in the previous section, the condition on the input u for task accomplishment can be derived. The coverage set K is the set of points on the image plane (X, Y), within which we require the targets to be maintained. Generally it is taken as a rectangle centered in the image plane. The target $\hat{K}$ is defined as the union of the individual image plane blobs(sets of pixels) formed by the multiple (n) targets as: $\hat{K} = \bigcup_{i=1}^{n} \hat{K}_i$. The coverage task can be represented as using a shape function in equation 6. Based on the definition of the coverage set, we can see that the coverage set is invariant to the motion of the camera. the target blobs however move on the image plane due to the camera motion. The mutational equation representing this relation between the movement of the camera and the target blobs can be derived using the optical flow equations as is shown in [3]. The mutational equation can be written as:

$$\begin{bmatrix} \dot{q}_x \\ \dot{q}_y \end{bmatrix} = \varphi_c(q) = B(z,q) \begin{bmatrix} u \\ \dot{\lambda} \end{bmatrix} = B(z,q) u_c \tag{13}$$

$$B(z,q) = \begin{bmatrix} -\frac{\lambda}{z} & 0 & \frac{q_x}{z} & \frac{q_x q_y}{\lambda} & -\frac{(\lambda^2+q_x^2)}{\lambda} & q_y & \frac{q_x}{\lambda} \\ 0 & -\frac{\lambda}{z} & \frac{q_y}{z} & \frac{\lambda^2+q_y^2}{\lambda} & -\frac{q_x q_y}{\lambda} & -q_x & \frac{q_y}{\lambda} \end{bmatrix}$$

where λ is the focal length of the lens, (q_x, q_y) is a point on the image plane of the point (x, y, z) and $u = [\dot{x}, \dot{y}, \dot{z}, \omega_x, \omega_y, \omega z, \dot{\lambda}]^T$ is the input velocity applied to the camera. Note that we apply only a pan and tilt velocity ($u = [\omega_x, \omega_y]^T$) to the camera but if other inputs are acceptable, we can derive them using above equation.

Using the shape Lyapunov theorem, we can derive the input u to accomplish the task as is shown in equation 12. It should be noted that the estimate z of the target distance in equation only affects the gain of the control and not its validity. Further it is important to note that the gain distribution between the various redundant control channels depends on the selection of the null space vector when calculating the generalized pseudo-inverse $C^{\#}$ of matrix C.

C. Cooperative Hausdorff tracking

Collaboration among multiple sensors can generally lead to better sensing performance and higher fault tolerance to individual node failure. A sensor allocation module (section IV) decides which targets are supposed to be tracked by the sensor. If the specified targets are outside the active FOV (coverage set) of the sensor, the sensor needs to be moved in order to accommodate the targets within it's active sensing region. Cooperative Hausdorff tracking can be used for this purpose. Once the target is detected in the active FOV, the sensor switches to image based Hausdorff tracking to perform the surveillance task. For establishing cooperation of multiple sensors, which may not be able to observe the same object simultaneously, there is a need transform local measurements into a global reference frame. Using prior information about the size of the object and knowledge about the sensor locations, the global 3D coordinates of the targets can be estimated as is done in [14].

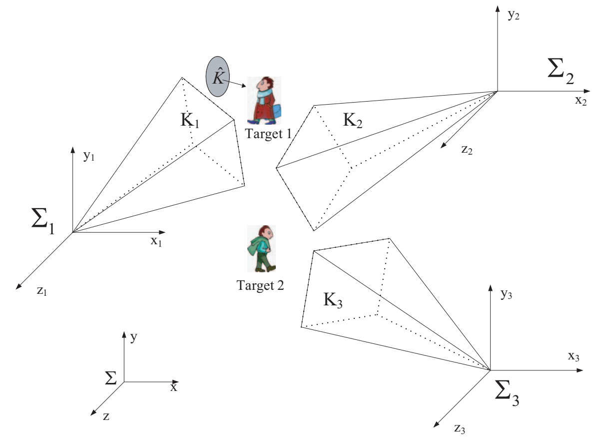


Fig. 2. Target and coverage set for cooperative Hausdorff tracking.

The coverage and target sets are defined as shown in Figure 2. The coverage set can be specified as the set of points which satisfies the viewing constraints of the sensor and can be defined as the active FOV of the camera after incorporating the depth of field constraints such as the maximum and minimum focus distances. Consider a point $q \in \mathbb{R}^3$ in the sensor coordinate frame defined as:

$$\begin{bmatrix} q_x \\ q_y \\ q_z \end{bmatrix} = \begin{bmatrix} r\cos(\theta)\sin(\phi) \\ r\cos(\phi) \\ r\sin(\theta)\sin(\phi) \end{bmatrix} \tag{14}$$

where (r, θ, ϕ) are the polar coordinates of the point q in the sensor frame. Using the above equation, the coverage set can be defined as :

$$K = \{q \mid r \in (D_{min}, D_{max}), \theta \in (\alpha_{min}, \alpha_{max}), \\ \phi \in (\beta_{max}, \beta_{min})\} \tag{15}$$

where, (D_{min}, D_{max}) represent the depth of field and $(\alpha_{min}, \alpha_{max}), (\beta_{max}, \beta_{min})$ are the view angles for the sensor. The global coordinates of the target set $\hat{K}$ can be transformed to the local sensor coordinates using the localization information available.

The mutational equation for the motion of the coverage set can be written as:

$$\begin{aligned} \begin{bmatrix} \dot{q}_x \\ \dot{q}_y \\ \dot{q}_z \end{bmatrix} &= r \begin{bmatrix} \cos(\theta)\cos(\phi) & -\sin(\theta)\sin(\phi) \\ \sin(\phi) & 0 \\ \sin(\theta)\cos(\phi) & \cos(\theta)\sin(\phi) \end{bmatrix} u \\ \dot{q} &= \varphi(q) = B\ u \end{aligned} \tag{16}$$

where $u = [\omega_x, \omega_y]^T$ is the velocity input to the camera. The objective is to cover the set of targets $\hat{K}$ with the coverage set K such that $K \subset \hat{K}$. This condition can be written using a shape function as:

$$J(K) = \int_{\hat{K}} d_K^2(p)\ dp \tag{17}$$

Using the procedure outlined in section III-A conditions on the feedback map u for task accomplishment can be derived.

Assuming that the target can be recognized once it is in the sensor active FOV, further tracking can be performed using image based Hausdorff tracking described in section III-B.

IV. Optimal Sensor Allocation

For successful completion of the surveillance task, it is important to allocate the sensors to the targets that are actively being tracked. Generally, each target should be tracked by the sensor that can view it at an optimal resolution for best visibility of that target. However, when the system is heavily loaded, that is, the target density in a particular region with a limited number of sensors is high, one sensor might need to track multiple targets. Even when the system is underloaded, multiple target tracking by individual sensors is highly desirable as viewpoint redundancy will lead to better estimates of the target coordinates and also present the viewer a clearer view of all the targets that are being tracked. In this section we propose a heuristic method to determine an optimal sensor allocation strategy.

At each system interval, the leader node computes a cost and visibility weight for the targets being tracked. Assume m sensors with cameras were setup in the system and there are n targets that need to be covered. One camera can cover from 0 to up to n targets, so for each camera, the number of possible coverage sets is $\sum_{k=0}^{n}\binom{n}{k} = 2^n$. In order to determine the optimal coverage set for each camera, we set up a weight matrix W for the coverage options. An element of the matrix W is defined as ($i \in [1, m]$ and $k \in [0, 2^n - 1]$):

$$w_{ik} = \sum_{s=1}^{\mathcal{C}(L(k))} V_{i,L(k)} \cdot (R_{s,i,L(k)} \cdot w_v + P_s \cdot w_p) \quad (18)$$

The following parameters are explained as follows:

- $L(k)$ is the k^{th} combination of the set $[1, n]$.
- $V_{i,L(k)}$ is a binary value (either 0 or 1) that indicates the ability for the sensor node to cover all the targets in the set $L(k)$.
- $R_{s,i,L(k)}$ is the resolution of target s viewed by sensor node i when all the targets in the set $L(k)$ are covered by sensor node i. The resolution is calculated as follows:

$$R_{s,i,L(k)} = \lambda \frac{x_s}{z_{s,i}} \quad (19)$$

  where x_s is the width of the target s and $z_{s,i}$ is the distance between target s and sensor node i. $\lambda \in (\lambda_{min}, \lambda_{max})$ is the zoom factor (focal length) of the camera of sensor node i.
- P_s is the preassigned priority of target s in the tracking system.
- w_v and w_p are adjustable parameters to reflect the importance of resolution and priority in the coverage weight.

For each row of the matrix, a larger value will indicate a more desirable target assignment. However, it is required that all targets should be covered by the sensor nodes. Thus, an optimal solution of the problem can be defined as $\{(y, L_y) | y \in [1, n]$and $L_y$is a combination of the set $[1, n]\}$ which satisfies that $\sum_{y=1}^{n} L_y$ is the largest among all the possible coverage set for each camera.

By brute force the complexity of the algorithm is $O(2^{mn})$. When n and m are large, heuristic algorithms are needed to find the optimal assignment. In reality, many heuristic approaches can be taken into account when solving the problem. For example, we can prove that under normal target density, the coverage matrix will be a sparse matrix, where most of the elements are zero. Further, in most cases, we do not need to find the optimal solution. Finding a sub-optimal solution would reduce the complexity of the algorithm dramatically. For example, after setting a threshold of the acceptable weight, we can take the first solution encountered as long as all the targets are covered.

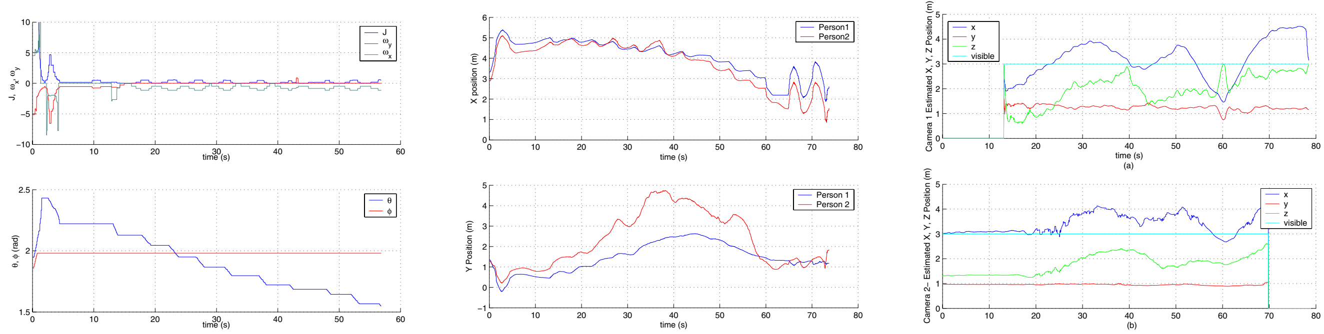
V. Experimental Implementation and Testing

The theoretical results were experimentally verified using active vision sensors located in an indoor environment. The experimental setup consists of three Sony EVI-D30 active PTZ (pan-tilt-zoom) cameras placed at different locations in a room. Two cameras were actively tasked for tracking and one sensor was tasked for monitoring and detecting new objects entering the environment.*CMVision* was used for color analysis and blob detection and merging [15]. Two experiments were carried out to verify the image based and cooperative Hausdorff tracking scenarios. The targets to be tracked were humans (wearing solid color clothes), which could be segmented from the background. The size of the detected object was assumed to have a mean and variance of the human being.

A. Image Based Hausdorff Tracking for Multiple Humans

The surveillance task is to maintain the multiple targets in the active FOV of the sensor. The targets were two humans moving around and interacting with each other. The image was taken as a regular grid of 128x96 pixels evenly spread over the 640x480 original image in order to reduce the computation load. The target set K was approximated as occupying a certain number of pixels (in multiple disjoint locations) on this grid. Assumptions on the input $u = [\omega_x, \omega_y]^T$ to the camera system were derived using equation 12. The targets were initially located such that they were out of the field of view of camera. The targets were detected by the monitor and the sensor was tasked to cover the two targets simultaneously. At, $t = 0$, the targets are just in the active FOV of the sensor and task criterion is not satisfied. The camera then moves to reduce the shape function J to zero so the targets are now covered. The targets then randomly move around the room and the camera tries to maintain both targets continuously in the active FOV.

Figure 3(a) depicts the J and the input velocities ($u = [\omega_x \omega_y]^T$ applied to the camera. Notice the initial large value of the shape function J, which is quickly reduced to zero. Figure 3(b) depicts the position X, Z estimated of the two targets. We see that despite the seemingly random motion of the two targets, the camera always tries to keep both of them in the active FOV. Further, the energy efficiency of the



(a) Image based Hausdorff tracking

(b) Image based Hausdorff Tracking: Estimated position of targets

(c) Cooperative Hausdorff tracking: Estimated position of targets

Fig. 3. Experimental Results

proposed method is demonstrated by the relatively infrequent input applied to the camera only when one of the objects escapes the active FOV.

B. Multisensor Cooperative Tracking

Pervasive surveillance using the proposed multi-sensor coordination mechanism was rigorously tested. The task of tracking a target over multiple sensor coverage regions was carried out. The target moved a large distance spanning the capable viewing regions of multiple sensors. Figure 3(c) depicts the results of the tracking scenario. Initially, sensor 2 can see the complete object but it is out of the active FOV of sensor 1, which is depicted by the target visible flag. Based on the solution of the optimization, sensor 1 is tasked to track the object. It uses cooperative Hausdorff surveillance to cover the target. The global coordinates of the target for cooperative Hausdorff tracking are provided by sensor 2.

Once it acquires the target, it switches to image based Hausdorff tracking to ensure target coverage. The target then randomly moves around in the active FOV of both the sensors, which keep continuously tracking it. Notice the robust tracking performance of the image based tracking scenario despite the minor differences in the estimation of the object location. The target then starts to move out of the tracking range of sensor 2 that again triggers the optimization planning problem, which assigns sensor 1 to keep continuously tracking the target.

VI. Conclusion

This paper proposes a mutational analysis based topological framework for modeling and design of surveillance networks, which find applications in myriad infrastructure-less, rapidly deployable pervasive multi-target surveillance and monitoring scenarios. Using the concept of mutations of domains and shape analysis we can derive the conditions for accomplishing various surveillance tasks such as pervasive target tracking over a large area. This paper presents the design of a surveillance task of tracking multiple targets using image based Hausdorff tracking, used when the targets are in the active field of view of the sensor. It further elaborates on cooperative Hausdorff tracking used to track targets that are outside the active field of view of the sensor using the observations from other sensors. Various experimental tracking scenarios were performed for the proposed Hausdorff tracking methods and the experimental results validated their soundness. Using the proposed approach, multiple targets can be tracked in relatively large environments.

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