

Modeling and Design of Mobile Surveillance Networks Using a Mutational Analysis Approach*

Amit Goradia and Ning Xi

Department of Electrical and Computer Engineering
Michigan State University
East Lansing, Michigan, 48824, USA
{goradiaa, xin}@egr.msu.edu

Zhiwei Cen and Matt Mutka

Department of Computer Science and Engineering
Michigan State University
East Lansing, Michigan, 48824, USA
{cenzhiwe, mutka}@cse.msu.edu

Abstract—Networked surveillance systems provide an extended perception and distributed reasoning capability in monitored environments through the use of multiple networked sensors. Surveillance can be defined as continuous monitoring and tracking of multiple targets in a region so that they do not leave the field of view of the sensors observing them and maintain discernable resolution for feature identification. Due to the inherent complexity of large networked systems and the diversity of the sensors used, the first challenge is to design an efficient modeling and analysis tool for networks surveillance systems. The next challenge is to devise stable control algorithms for accomplishing the surveillance task. Current feature (point) based visual servoing and tracking techniques generally employed do not provide an optimal solution for the surveillance task. This paper presents a mutational analysis approach for shapes, and shape based control to model and design surveillance mechanisms for such active surveillance systems. Communication is essential for cooperation and coordination of multiple sensor nodes to effectively perform the surveillance task. Due to the large number and heterogeneity of nodes involved and the large amount of information transfer required, designing effective communication techniques for longevity of operation of such mobile surveillance networks is also a major challenge. This paper presents a discussion of the issues related to networking of large scale mobile surveillance networks. Finally, experimental results demonstrate the efficacy of the proposed approach for tracking targets over a large area.

Index Terms—Mobile Surveillance Networks, Mutational Analysis, Visual Surveillance, Hausdorff Tracking

I. INTRODUCTION

Technological advances in wireless networking and distributed robotics have been leading to increasing research on distributed sensing applications using wireless sensor networks. Infrastructure-less surveillance and monitoring are important applications of such rapidly deployable sensor networks. Various types of sensors with varying sensing modalities can be instantly deployed in hostile environments, inaccessible terrain and disaster relief operations to obtain vital reconnaissance information about the area being surveyed. This paper presents the concept of Mobile Surveillance Networks (MSN), which are rapidly deployable infrastructure-less surveillance networks used for continuous monitoring and tracking of multiple targets in a region being surveyed.

MSN's, as shown in figure 1, are comprised of a collection of active sensor nodes equipped with sensing, processing, communication and motion capabilities. The individual sensor nodes can have multiple sensing modalities and surveillance equipment such as cameras, infrared detector arrays, laser rangefinders, omnidirectional acoustic sensors etc. Locomotion and active sensing greatly increase the range and sensing

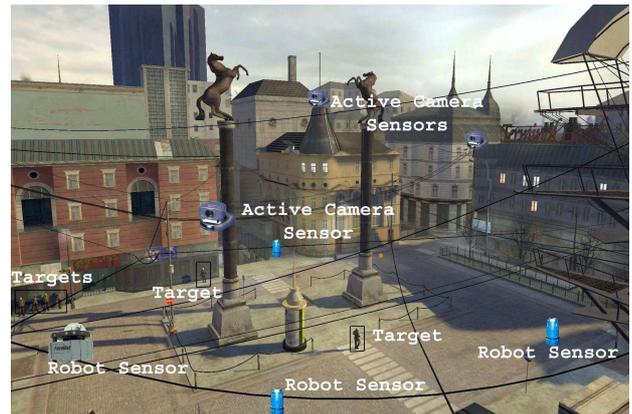


Fig. 1. Mobile Surveillance Network.

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. However these characteristics of MSN's considerably increase the modeling and control complexity of such systems. This paper presents a framework for modeling and control of active sensor nodes used for continuously tracking multiple targets.

A general surveillance task involves keeping multiple moving targets in the active sensing region of the sensors with a certain pre-specified resolution. Research approaches to this problem found in recent literature [1] [2], 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 with certain resolution, effectively and succinctly. 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.

An important characteristic of networked surveillance systems is their capability to pervasively track a target over a large area using multiple sensors. The efficient and timely exchange of information between the individual sensing nodes is imperative for cooperation and coordination of multiple nodes in order to perform pervasive target tracking. Ad-hoc, multi-hop mechanisms are best suited for such mobile infrastructure-less wireless networked systems. Networking and routing mechanisms for distributed wireless sensor networks have attracted a lot of attention in recent literature [5] [6] [7]. These approaches generally assume scalar (low volume) data transfer between the individuals nodes and the sink node (which is just a consumer of the information.) However, surveillance tasks require fast

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and timely transfer of vector (large volume) data, e.g. video data, to the sink and also within the nodes themselves. This scenario may create an unbalanced networking load on the nodes along the optimal relay path, which can be detrimental to the longevity of the network.

In order to solve the active target tracking problem, we propose to use a mutational analysis approach put forward by [8] to describe the evolution of domains. The surveillance task of target coverage and maintaining resolution can be readily expressed in a topological framework using shape analysis and shape functions ([9] [10]). Thus, the variables to be taken into account are no longer vectors of parameters but the geometric shapes (domains) themselves without any regularity assumptions or models known *a priori*. 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 coverage and target domains and further derive feedback control mechanisms to complete the specified task.

In order to aid cooperation and large scale networking for the timely exchange of vector data, we propose to use multi-path routing in wireless ad hoc networks. This paper presents a discussion of some of the underlying issues related to networking and multi-path routing between the nodes for efficient exchange of vector information in multiple target tracking scenarios.

The remaining paper is organized as follows: Section II provides a brief introduction to networked surveillance systems. Section III provides a primer on mutational analysis and other tools for shape analysis. Section IV presents the image based Hausdorff tracking method for tracking targets in the sensor FOV. Multi-sensor collaboration using cooperative Hausdorff tracking and networking issues are discussed in section V. Experimental results of the proposed approach are provided in section VI. Finally, the conclusions and discussions are provided in section VII.

II. NETWORKED SURVEILLANCE SYSTEMS

Networked surveillance systems have received much attention from the research community due to their many pervasive applications [11]. Based on their mobility and rapid-deployment capability, the operation of an MSN’s can be divided into two separate phases, namely deployment and surveillance. Infrastructure-less rapid deployment is an important characteristic of MSN’s and many research efforts have been dedicated to optimally deploy sensor nodes for increasing their total sensing area [12] [13] [14]. A global kinematic representation of a network of connected sensors $\mathcal{R} = \{R_1, R_2, \dots, R_n\}$ using only localization information between one-hop neighbors is suggested in [12]. This relationship between the various nodes is key to sharing meaningful information between them.

Beyond the initial deployment phase, in the surveillance phase there are two major subtasks: target detection and target tracking. Figure 2 the general architecture of a sensor node. The target perception module is responsible for detecting and classifying the various targets in the active field of view (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 [15]. Many approaches such as active background subtraction [2] [16] 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] [16]. 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 the various targets [17].

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 like visual servoing and gaze control [1] [2]. However, these approaches only try to maintain an image feature (point) at the center of the screen and the algorithm used are very sensitive to feature detection and do not express the objectives of the task adequately. They over emphasize the task that can lead to excessive energy consumption due to motion and hence an unacceptable solution when the nodes have limited energy resources. Excessive motion of the camera can also lead to blurring of the image which in-turn is detrimental to feature detection. Further, in [1] the task of ensuring the limits on the size of the image set is accomplished using the prior information on the subject size and is not done based on the feedback from the image.

In this paper we propose the image based Hausdorff tracking method which tries to ensure that the target does not leave the active FOV of the sensor and the size of the target set is maintained at a discernable resolution. Hausdorff tracking can readily express these tasks as a 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 w.r.t. to the motion of the camera/robot is required which is accomplished using mutational equations.

When the target to be tracked is outside the active FOV of the sensor (but in the capable FOV), the node can still ensure that the target is 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 the robot/camera to bring the target in the active FOV of the sensor. 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

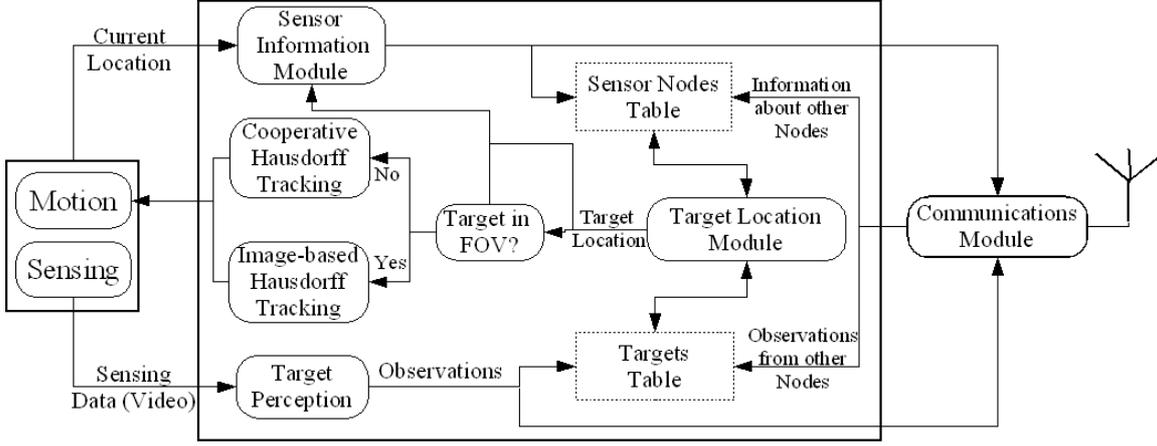


Fig. 2. Architecture of Sensor Node.

be recognized, the sensor will switch over to image based Hausdorff tracking to maintain the target in the active FOV.

The timely exchange of large volume (video) data is imperative for such cooperative tracking scenarios. We assume that the sensor nodes are equipped with geographical location aware devices. Unlike traditional wireless routing protocols, in location based routing each node only needs to know its own position and the position of its one-hop neighbors. This makes location based routing perform well in a dynamic environment such as a mobile surveillance network. The large volume data transmission also put traditional transport protocols into challenge. In our on-going research we are investigating the techniques to build an improved real-time reliable transport service based on forward error correction techniques and multiple routing paths. Multiple paths between the sender and receiver can be used to improve reliability and reduce end-to-end latency. At the same time they also help to leverage the energy consumption in a mobile surveillance network. Forward error correction encodings are applied to certain media streams to further increase their resilience to packet loss.

III. MUTATIONAL ANALYSIS PRIMER

This section provides a basic introduction to shape analysis using mutational equations [18] and relevant concepts useful for developing the theoretical foundation for Hausdorff tracking. The sensor coverage area and the target are readily represented as sets (domains) in $E \subset \mathbb{R}^n$. 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, $d_K(q) = \inf_{o \in K} \|q - p\|$ represents the distance between the point q and domain K .

A. Evolution of a Tube

Tubes are domains evolving with time 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

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

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:

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

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

$$\dot{K} \ni \varphi \quad (3)$$

It should be noted that φ is not a unique representation of the mutational equation which justifies the use of the notation (\ni) [18].

Consider a function $\varphi : \mathbb{R} \times \mathcal{K}(E) \mapsto Lip(E, \mathbb{R}^n)$ as a map associating a Lipschitz map φ to a pair (t, K) . Using this map, we can define the mutation of tube $K(t)$ as:

$$\dot{K}(t) \ni \varphi(t, K(t)), \quad \forall t \geq 0 \quad (4)$$

1) *Controlled Mutational Equations:* A controlled mutational equation can be written as:

$$\dot{K}(t) \ni \varphi(t, K(t), u(t)), \quad \forall t \geq 0 \quad (5)$$

$$u(t) \in U, \quad (6)$$

where, $\varphi : \mathbb{R}^+ \times \mathcal{K}(E) \times U \mapsto Lip(E, \mathbb{R}^n)$ is a continuous map associating a Lipschitz map with (t, K, u) and $u(t) \in U$ is the control input.

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:

$$u(t) = \mathcal{U}(K(t)) \quad (7)$$

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/robot.

B. Shape Functions and Shape Directional Derivative

Shape analysis deals with problems where the variables are not vectors of parameters or functions, but the shapes of geometric domains or sets K contained in a subset $E \subset \mathbb{R}^n$.

1) *Shape Functions*: Shape functions are set-defined maps defined from $\mathcal{K}(E) \mapsto \mathbb{R}$ and provide a “measure” of the deformation of $K \in \mathcal{K}(E)$. 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 . Shape acceptability and optimality can be studied using shape functions J as optimization cost functions as is shown in [9]. Various shape functions can be readily developed which can adequately describe the surveillance task of set coverage or a measure of the size of a set etc.

2) *Directional Derivative of Shape Function* [9]: The directional derivative of the shape function represents the change in the shape function $J(K)$ due to the deformation of the shape K . It can be construed as the analog of the directional derivative in vector spaces and provides us with a measure of the change in the task criterion due to motion of the coverage or target set.

Consider a function $J : H \mapsto \mathbb{R}$ where H is a real Hilbert space such as \mathbb{R}^n . The Gateaux (directional) derivative of J at the point q in the direction of v is defined as:

$$DJ(q)(v) = \lim_{t \rightarrow 0} \frac{J(q + tv) - J(q)}{t} \quad (8)$$

Thus, the Gateaux (directional) derivative involves the point q and the direction v at $t = 0$.

Extending this same concept when q is not an element of a Hilbert space, but a shape (domain) K and v is replaced by φ , which is the direction of mutation of the tube K . Thus the Eulerian semi-derivative (Gateaux directional derivative) is defined as:

$$\dot{J}(K)(\varphi) = \lim_{t \rightarrow 0} \frac{J(\vartheta_\varphi(t, K)) - J(K)}{t} \quad (9)$$

where, $\vartheta_\varphi(t, K)$ is the t reachable tube of K under the mutation φ .

From [18] and [10], the directional derivative of the shape function having the form of

$$J = \int_K f(q) dq \quad (10)$$

can be written as:

$$\dot{J}(K)(\varphi) = \int_K \text{div}(f(q)\varphi(q)) dq \quad (11)$$

C. Lyapunov Theorem for Shapes [19]

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 5. We usually look for assumptions that guarantee the convergence to 0 of $J(K(t))$.

Definition 2: (Shape Lyapunov Function) Consider a subset E of \mathbb{R}^n and a mutational map φ defined on the set E as shown in section 1, a shape functional $J : \mathcal{K}(E) \mapsto \mathbb{R}^+$ and a continuous map $f : \mathbb{R} \mapsto \mathbb{R}$. The functional J is a f -Lyapunov function for the mutational map φ if, for any $K \in \text{Dom}(J)$ we have,

$$J(\vartheta_\varphi(t, K)) \leq w(t), \forall t \leq 0, \quad J(K) = w(0) \quad (12)$$

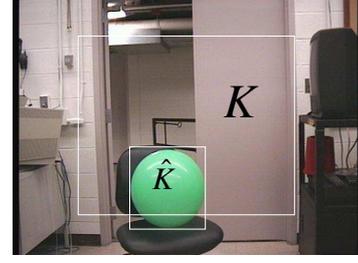


Fig. 3. Target and coverage set for image based Hausdorff tracking.

where, $w(\cdot)$ is a solution of $w' = -f(w)$.

When the solution $w(\cdot)$ converges to 0 as $t \rightarrow \infty$, the shape Lyapunov functional $J(\vartheta_\varphi(t, K))$ also converges to 0.

Using shape derivatives the above definition of Lyapunov functions can be stated as the shape Lyapunov theorem.

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 $\dot{J}(K)(\varphi)$. The functional J is an f -Lyapunov function for φ if and only if, for any $K \in \text{Dom}(J)$, we have

$$\dot{J}(K)(\varphi) + f(J(K)) \leq 0. \quad (13)$$

See [19] for proof. Using the shape Lyapunov theorem we can derive assumptions on the input u , to move the camera/robot, in order to accomplish the surveillance task.

IV. IMAGE-BASED HAUSDORFF TRACKING

Various tasks such as set coverage and maintaining appropriate image resolution can be readily expressed in a set based framework. For example the tasks of keeping the target in the cameras field of view with a certain size can be readily expressed using a shape function as the minimization of a Hausdorff distance based metric or the size of the target etc. The task can be accomplished by reducing the shape function to zero. The task of visual servoing can also be expressed in a set based framework [20]. The shape function essentially represents the error between the desired and actual shapes and reducing it to zero will accomplish the task.

Using the mutational equations, the directional derivative of the shape function which describes the change in the shape function based on the movement of the camera can be calculated as is outlined in section III-B.2. Further, using the shape Lyapunov theorem we can derive an expression for the input u to the camera that will ensure the convergence to zero of the shape function, which in turn would imply task completion.

When the target is located in the active FOV of the sensor, the method of image based Hausdorff tracking can be used to accomplish the surveillance task. The target is detected using image processing algorithms and represented as a collection of pixels (blob) on the image plane. The sensor coverage set is represented as a rectangle centered at the image center and one of the tasks is to maintain the target blob within the sensor coverage set. Another part of the task is to ensure that the target maintains a certain resolution on the image screen so that its features are discernable. The target should also not be too large on the screen, which would make it difficult to identify the target or block other targets from being viewed.

1) *Target, Coverage Sets and Shape Functions*: The target blob is represented as the set K if pixels comprising it and the sensor coverage set is represented as \hat{K} as shown in figure 3. The above task requirements can be mathematically expressed as the following shape function.

$$\begin{aligned} J(\hat{K}) &= J_{FOV}(\hat{K}) + J_{Amin}(\hat{K}) + J_{Amax}(\hat{K}) \quad (14) \\ J_{FOV}(\hat{K}) &= \int_{\hat{K}} d_K^2(p) dq \\ J_{Amin}(\hat{K}) &= \max(\int_{\hat{K}} dq - AREA_MIN, 0) \\ J_{Amax}(\hat{K}) &= \min(AREA_MAX - \int_{\hat{K}} dq, 0) \end{aligned}$$

where, q is a point on the image set \hat{K} and $AREA_MAX$ and $AREA_MIN$ denote the maximum and minimum admissible areas of the target set K for maintaining adequate resolution.

Note that the shape function $J(\hat{K})$ is zero only when set \hat{K} is completely covered by set K and when the area of set \hat{K} is within the limits ($AREA_MIN, AREA_MAX$). Otherwise it is a non-zero positive value.

2) *Shape Directional Derivative*: The deformation of the target set w.r.t. the motion of the camera can be represented using a mutational equation. This deformation can be construed as the summation of two individual components: the motion of the camera and the motion of the target itself. The former can be modeled using the optic flow equations and the latter can be expressed using the estimated velocity of the target.

Assuming that the projective geometry of the camera is modeled by the perspective projection model, a point $P = [x, y, z]^T$, whose coordinates are expressed with respect to the camera coordinate frame, will project onto the image plane with coordinates $q = [q_x, q_y]^T$ as:

$$\begin{bmatrix} q_x \\ q_y \end{bmatrix} = \frac{\lambda}{z} \begin{bmatrix} x \\ y \end{bmatrix} \quad (15)$$

where λ is the focal length of the camera lens [3]. Using the perspective projection model of the camera, the velocity of a point in the image frame with respect to the motion of the camera frame [3] can be expressed. This is called the image jacobian by [3] and is expressed as:

$$\begin{bmatrix} \dot{q}_x \\ \dot{q}_y \end{bmatrix} = \varphi_c(q) = B_c(q) \begin{bmatrix} u \\ \dot{\lambda} \end{bmatrix} = B_c(q)u_c \quad (16)$$

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

where, $u = [v_x, v_y, v_z, \omega_x, \omega_y, \omega_z]^T$ is the velocity screw of the camera motion and $\dot{\lambda}$ is the rate of change of the focal length.

The velocity of the image frame point, q , based on the velocity $v_t = [\dot{x}, \dot{y}, \dot{z}]^T$ of the target point P can be expressed using equation 15 as:

$$\begin{bmatrix} \dot{q}_x \\ \dot{q}_y \end{bmatrix} = \varphi_t(q) = \frac{\lambda}{z} \begin{bmatrix} 1 & 0 & q_x \\ 0 & 1 & q_y \end{bmatrix} v = B_t(q)v_t \quad (17)$$

Using equations 16 and 17, the mutational equation of the target set can be written as:

$$\begin{aligned} \dot{q} &= \varphi(q) = \varphi_c(q) + \varphi_t(q) \\ \dot{\hat{K}} &\ni \varphi(\hat{K}) \end{aligned} \quad (18)$$

3) *Feedback Map u* : The problem now is to find a feedback map u_c such that the shape function J is reduced to zero. For this purpose we need to find the shape directional derivative $\dot{J}(\hat{K})(\varphi)$ of $J(\hat{K})$ in the direction of the mutation $\varphi(\hat{K})$. Assuming a relatively flat object, i.e., the z coordinate of all the points on the target are approximately the same we can derive an expression for $\dot{J}(\hat{K})(\varphi)$ by substituting equations 14 and 18 into 11 as:

$$\dot{J}(\hat{K})(\varphi) = \int_{\hat{K}} \nabla f(q)\varphi(q) + f(q)\text{div}\varphi(q) dq \quad (19)$$

where, $f(q)$ can be construed as the aggregated integrand from equation 14. Equation 19 can be approximated as:

$$\dot{J}(\hat{K})(\varphi) \leq \begin{bmatrix} \frac{1}{z_t} C_1(q) & C_2(q) \end{bmatrix} u_c + \frac{1}{z_t} D(q)\hat{v}_t \quad (20)$$

where, $u_c = [v_x, v_y, v_z, \dot{\lambda}, \omega_x, \omega_y, \omega_z]^T$ and z_t is an estimated minimum bound on the target z position and $z_t > z$ will guarantee the inequality in 20. $C_1(q), C_2(q)$ and $D(q)$ are aggregated terms from equation 19. The \hat{v}_t is an estimate of the target velocity derived from sequential images of the target (derivation of \hat{v}_t is out of scope for this paper).

Using the shape Lyapunov theorem we can find the assumptions on input u_c such that the shape function $J(\hat{K})$ tends to zero as:

$$\begin{bmatrix} \frac{1}{z_t} C_1(q) & C_2(q) \end{bmatrix} u_c \leq -\alpha J(\hat{K}) - \frac{1}{z_t} D(q)v_t \quad (21)$$

The feedback map u_c which is an input to the camera module can be calculated from the above equation 14 using the notion of a generalized pseudoinverse $C^\#(q)$ of the matrix $C = \begin{bmatrix} \frac{1}{z_t} C_1(q) & C_2(q) \end{bmatrix}$ as:

$$u_c = C^\#(\alpha J(\hat{K}) - \frac{1}{z_t} D(q)v_t) \quad (22)$$

It should be noted that the estimate z_t of the target distance 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 pseudoinverse $C^\#$ of matrix C .

V. MULTI-SENSOR COOPERATION AND COLLABORATION

Collaboration among multiple sensors can generally lead to better sensing performance and higher fault tolerance to individual node failure. Coordinating the tracking of multiple targets using multiple sensors can be addressed in two ways:

- 1) Use a central monitoring station to integrate the track information from each node [1].
- 2) Sensor nodes operate autonomously and exchange track information with one another in a geographical vicinity and provide a handover mechanism when the target transitions from one sensor field of view to another [2].

The first approach simplifies track management and communications but is not scalable to large networks due to the limited communication and processing capability of the central monitoring station. Also, the system is not fault tolerant to the failure of the central monitoring station. The second approach is highly scalable and fault tolerant to the failure of nodes but involves significant communication overhead for target track management and disambiguation.

Using the target and sensor node tables mentioned in II, the target location module decides which target to track. This

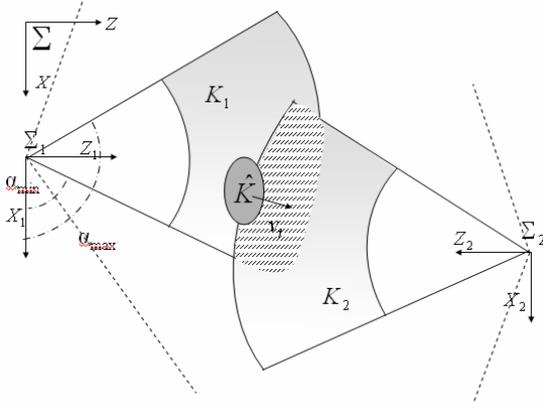


Fig. 4. Target and coverage set for cooperative Hausdorff tracking.

decision process can be expressed as an optimization problem [21] with a cost function based on the relative importance of the detected targets and the information available about the other nodes in the neighborhood. If the target is outside the active FOV (coverage set) of the sensor, it needs to be moved so that the target is within its 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 to transform the image blobs and measurements into a common coordinate system referenced by all the sensors and task the sensors according to the movement of the targets expressed in the common frame of reference. Further, this common representation will be helpful in combining the object detection hypothesis from multiple camera sensors for sensor fusion. It can also be used for designing efficient routing mechanisms and algorithms for communication.

A. Cooperative Hausdorff Tracking

1) *Target location and representation:* Determining the object 3D location from single sensor reading requires some prior knowledge of the scene or the object. Collins[1] used the geographical location information in the form of a digital elevation map. We propose to use the prior statistical knowledge of object attributes e.g., size, width etc., for this purpose. For example in tracking human visages, we generally have knowledge about the statistical properties such as mean and deviation of the size of a human head. Another example can be tracking automobiles where the approximate size of the automobile is known in advance. Assuming a gaussian distribution with mean m_w and variance σ_w^2 for the width of the object being tracked, the distance to the object can be calculated as a gaussian variable:

$$m_z = \lambda \frac{m_w}{w_i}, \quad \sigma_z^2 = \frac{\lambda^2 \sigma_w^2}{w_i^2} \quad (23)$$

(m_z, σ_z^2) represent the z coordinate of the target as a gaussian variable. Sensing errors resulting from camera calibration and lens aberrations should also be accounted for in the estimate of the location of the centroid of the target. The location of the centroid can be expressed using a two dimensional gaussian estimate as is shown in [22]. We represent the target as a

region of invariance (ROI) for the existence of the target. This can be done by representing the 2D gaussian variable of the centroid location as set \hat{K}_c of points with a certain confidence interval. Similarly the size of the object is also represented as a set \hat{K}_s . The region of invariance can be calculated as a structural dilation of the set \hat{K}_c with the set \hat{K}_s and can be calculated using binary morphological operators [18]. Further we calculate a bounding box for the ROI of the target set and use that as the geometric representation of the target set \hat{K} .

2) *Coverage Set:* The coverage set can be construed as the set of points that satisfy the viewing constraints of the camera. It can be defined as the active field of view of the camera after incorporating the depth of field constraints such as the maximum and minimum focus distances. Consider a point $q \in \mathbb{R}^2$ defined as:

$$\begin{bmatrix} q_x \\ q_z \end{bmatrix} = \begin{bmatrix} x + r \cos(\rho) \\ z + r \sin(\rho) \end{bmatrix} \quad (24)$$

where $[x, z, \theta]^T$ are the coordinates of the robot and r, ρ are the polar coordinates of point q with respect to the robot coordinates. Using equation 24, the coverage set for the focusing constraint can be written as:

$$K = \{q \mid r \in (D_{min}, D_{max}), \rho \in (\alpha_{min}, \alpha_{max})\} \quad (25)$$

where D_{min}, D_{max} are the minimum and maximum focus distances and $\alpha_{min}, \alpha_{max}$ are the minimum and maximum angles of the view lines as shown in figure 4. The motion of each point in the coverage set can be written as:

$$\begin{bmatrix} \dot{q}_x \\ \dot{q}_z \end{bmatrix} = \begin{bmatrix} 1 & 0 & -r \sin(\rho) \\ 0 & 1 & r \cos(\rho) \end{bmatrix} u \quad (26)$$

$$\dot{q} = \varphi(q) = B u$$

where $u = [\dot{x}, \dot{z}, \dot{\theta}]^T$ is the velocity input to the camera. Using equation 26, the mutational equations for the motion of the coverage set can now be written as:

$$\dot{K} \ni \varphi(q) \quad (27)$$

3) *Shape Function and Shape Directional Derivative:* The objective is to cover the target set \hat{K} with the coverage set K such that $K \subset \hat{K}$. This condition can be written as:

$$J(K) = \int_{\hat{K}} d_K^2(p) dp \quad (28)$$

The directional derivative of F is given as [20]:

$$\dot{J}(K)(\varphi) = 2 \int_{\hat{K}} \inf_{q \in \Pi_K(p)} \langle (q - p), \varphi(q) \rangle dp \quad (29)$$

where, $\Pi_K(q)$ is the projection of the point q on the set K defined as the set of points in K having the same distance ($d_K(x)$) from point x and is defined as:

$$\Pi_K(q) = \{p \in K \mid \|p - q\| = d_K(q)\} \quad (30)$$

4) *Feedback Map:* Using the shape Lyapunov theorem assumptions on the feedback map u can be obtained in order to drive the shape function to zero. The assumption on u can be written as:

$$u \leq -\frac{1}{2} \alpha C(K) \# J(K) \quad (31)$$

$$C(K) = \int_{\hat{K}} \inf_{q \in \Pi_K(p)} B(q)^T (q - p) dp \quad (32)$$

where $C(K)^\#$ is the generalized pseudo inverse of the matrix $C(K)$. The null space vector for calculating the pseudo inverse $C^\#(K)$ will decide the gain distribution between the various redundant control inputs.

Using the feedback map u , $J(K)$ can be reduced to zero which implies that the coverage set covers the target set. 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 IV.

B. Networking and Related Issues for MSN's

The networking component of each node is responsible for delivering required messages among the peer nodes. It is reasonable to assume that the sensor nodes are equipped with geographical location aware devices. Extensive research has been done regarding forwarding packets in a wireless network based on the geographical location of the nodes [23]. Unlike traditional wireless routing protocols, in location based routing each node only needs to know its own position and the position of its one-hop neighbors. This makes location based routing ideal for dynamic environments such as a MSN. Building a transport service for a mobile surveillance network is challenging task because (1) The data link layer and network layer of most ad hoc networks are not able to provide QoS guarantee; and (2) possible frequent topology changes, wireless signal attenuation and other constraints cause many uncertainties in the wireless ad hoc networks.

In our on-going research we are investigating the techniques to build an improved real-time reliable transport service over ad hoc networks. Multiple disjoint paths between the sender and receiver are used to improve reliability and reduce end-to-end latency. Forward error correction encodings are applied to certain media streams to further increase the resilience over packet loss. FEC is traditionally used in the link layer to avoid unnecessary retransmissions. The advancement of encoding techniques allow redundancy to be added into the transmission data without increasing the volume of the data significantly. For example, a class of erasure codes called digital fountain code [24] enable the transport layer to provide a reliable service and at the same time reduce the frequency of acknowledgments and retransmissions. This is especially meaningful in an unstable networking condition like the mobile surveillance network. In our proposed approach, p packets of source data can be encoded into αp packets, where α ($\alpha \geq 1$) is the stretch factor. The encoded data packets can be scheduled to be transmitted over multiple routing paths. As soon as the receiver collects p distinctive encoded data packets, the decoding algorithm can reconstruct the original message. By using multiple paths overlay a mobile network, we can also adjust the global energy consumption of the whole network based on the QoS requirements and energy levels of the sensor nodes. For example, by diverting the traffic over multiple paths we can avoid energy depletion in some nodes that are in the intersection of the most popular paths.

Traditional approaches have explored the possibilities of using multiple paths in a wireless network to improve QoS, such as AODVM [25] and Split Multi-path Routing (SMR [26]). However, none of the existing approaches will fit into the MSN paradigm due to the QoS requirements and time sensitivity of the surveillance tasks.

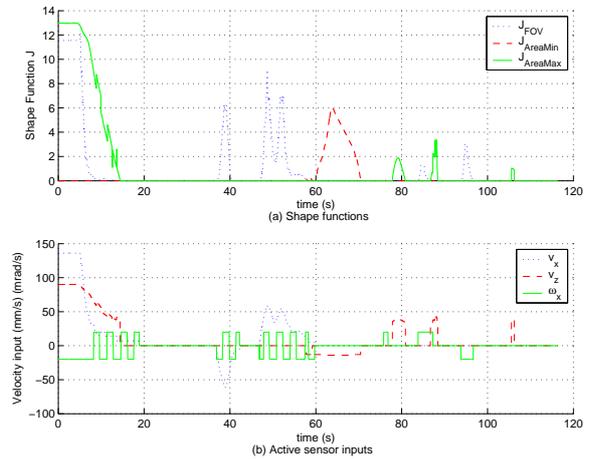


Fig. 5. Image based Hausdorff tracking using active camera

VI. EXPERIMENTAL IMPLEMENTATION AND TESTING

The theoretical results were experimentally verified using active vision sensors mounted on mobile robots. The experimental setup consists of three Sony EVI-D30 active PTZ (pan-tilt-zoom) cameras mounted on a Nomad XR 4000 mobile robot. *CMVision* was used for color analysis and blob detection and merging [27]. Two different experiments were carried out to verify the image based and task based Hausdorff tracking scenarios. The target to be tracked was a solid color ball approximately the size of a human face.

A. Image Based Hausdorff Tracking

The surveillance task is to maintain the target in the active FOV while maintaining a discernable resolution of the target on the image plane. The task is described mathematically using equation 14. The target was a ball that was manually moved around in 3D space during the duration of the experiment. 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 on this grid. Assumptions on the input $u = [\dot{x}, \dot{z}, \omega_x, \omega_y, \dot{\lambda}]^T$ to the robot and camera system were derived using equation 22. The target was initially placed where the task criterion were not satisfied and then the target moved around manually, which generated a disturbance input to the system and the system immediately tried to reduce the value of the shape function to zero.

Figure 5 depicts the results of the image space Hausdorff tracking task using an active camera. The shape functions $J_{FOV}(\hat{K})$, $J_{AreaMin}(\hat{K})$ and $J_{AreaMax}$ and inputs $u = [\dot{x}, \dot{y}, \omega_x]^T$ are plotted in 5 (a) and (b), respectively. The figure shows that the system is stable and that the target is maintained in the camera field of view with a desired resolution despite the seemingly random motion of the target.

B. Cooperative Hausdorff Tracking

The cooperation between nodes to continuously track a target by directly tasking various sensors can be done using cooperative Hausdorff tracking as explained in section V-A. Figure 6 depicts the experimental results of this tracking scenario which involves multiple nodes observing different areas of a locality with an overlapping total capable FOV as shown in figure 4. The target is being actively tracked by node A and is moving out of its capable FOV as is depicted by the

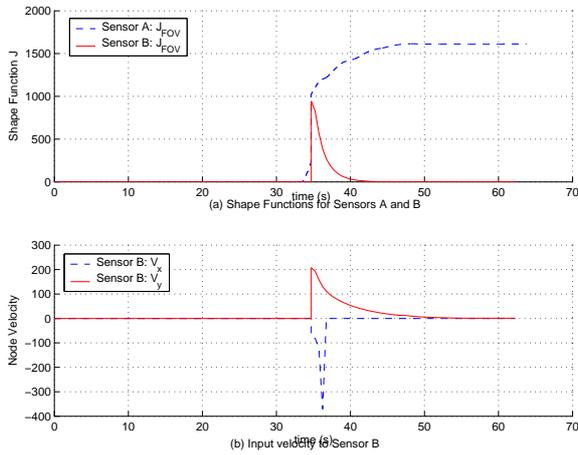


Fig. 6. Cooperative Hausdorff tracking using multiple sensors

shape function Sensor A: J_{FOV} . At $t = 35s$ the target moves very close to the edge of the capable FOV of sensor A. At this time, sensor A sends out a request to peer sensor B to take over the tracking of the target based on the entries in the sensor nodes table. Sensor B responds with an affirmative reply accepting the request and begins to track the target using the cooperative Hausdorff tracking method whereby it tries to reduce the value of its shape function J_{FOV} to zero by moving its active FOV. Once the target appears in the active FOV, it is recognized by the vision module as the target it is supposed to track, which switches the tracking mechanism to image based Hausdorff tracking. Multiple runs of these experiments were carried out with various scenarios to verify the validity of the operation.

VII. CONCLUSIONS

This paper proposes a mutational analysis based topological framework for modeling and design of mobile 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 continuous target tracking while maintaining appropriate image resolution. This paper presents the design of a surveillance task using image based Hausdorff tracking used when the target is in the active field of view of the sensor. It further elaborates on cooperative Hausdorff tracking used to track targets which are outside the active field of view of the sensor using the observations from other sensors. A discussion on the networking and routing issues related to communicating multi-modal vector (large volume) sensor data is also provided, which describes the direction of our current work for using multipath routing for timely information exchange for surveillance tasks and increasing the longevity of the network. Various experimental tracking scenarios were performed and the experimental results validated the soundness of the proposed approaches.

REFERENCES

- [1] R.T.Collins A.J.Lipton H.Fujiyoshi and T.Kanade, "Algorithms for Cooperative Multisensor Surveillance," *Proceedings of the IEEE*, vol. 89, pp. 1456–1477, 2001.
- [2] T.Matsuyama and N.Ukita, "Real-Time Multitarget Tracking by a Cooperative Distributed Vision System," *Proceedings of the IEEE*, vol. 90, no. 7, pp. 1136–1150, 2002.

- [3] S. Hutchinson G. Hager and P.I. Corke, "A Tutorial on Visual Servo Control," *IEEE Transactions on Robotics and Automation*, vol. 12, no. 5, pp. 651–670, 1996.
- [4] C.M. Brown, "Gaze Control with Interactions and Delays," *IEEE Transactions on Systems Man and Cybernetics*, vol. 20, no. 1, pp. 518–527, 1990.
- [5] Chalermek Intanagonwiwat, Ramesh Govindan, Deborah Estrin, John Heidemann, and Fabio Silva, "Directed Diffusion for Wireless Sensor Networking," *IEEE/ACM Transactions on Networking*, vol. 11, no. 1, 2003.
- [6] D. Braginsky and D. Estrin, "Rumor Routing Algorithm for Sensor Networks," *Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications*, pp. 22–31, 2002.
- [7] Haitham S. Hamza and Shasha Wu, "RAODV: an Efficient Routing Algorithm for Sensor Networks," *Proceedings of the 2nd International Conference on Embedded Networked Sensor Systems*, pp. 297–298, 2004.
- [8] Jean-Pierre Aubin, "Mutational Equations in Metric Spaces," *Set-Valued Analysis*, vol. 1, pp. 3–46, 1993.
- [9] J. Cea, "Problems of Shape Optimal Design," *Optimization of Distributed Parameter Structures vol. I and II*, pp. 1005–1087, 1981.
- [10] Jan Sokolowski and Jean-Paul Zolesio, *Introduction to Shape Optimization: Shape Sensitivity Analysis*, Computational Mathematics. Springer-Verlag, 1991.
- [11] C.S. Regazzoni, V. Ramesh, and G.L. Eds. Foresti, "Special Issue on Third Generation Surveillance Systems," *Proceedings of the IEEE*, vol. 89, Oct. 2001.
- [12] J. Tan, N. Xi, W. Sheng, and J. Xiao, "Modeling Multiple Robot Systems for Area Coverage and Cooperation," in *ICRA*, 2004.
- [13] S.A. Stoeter, P.E. Rybski, M.D. Erickson, M. Gini, D.G. Hougen, D.G. Krantz, N. Papanikolopoulos, and M. Wyman, "A Robot Team for Exploration and Surveillance: Design and Architecture," in *Proceedings of the Intl. Conf. on Intelligent Autonomous Systems*, 2000, pp. 767–774.
- [14] J. Cortes, S. Martinez, T. Karatas, and F. Bullo, "Coverage Control for Mobile Sensing Networks," in *ICRA*, 2003.
- [15] K. Toyoma, J. Krumm, B. Brumitt, and B. Meyers, "Wallflower: Principles and Practice of background Maintenance," in *International Conference on Computer Vision*, 1999, pp. 255–261.
- [16] T. Boulton, R. J. Micheals, Xiang Gao, and M. Eckmann, "Into the woods: Visual Surveillance of Noncooperative and Camouflaged Targets in Complex Outdoor Settings," *Proceedings of the IEEE*, vol. 89, Oct. 2001.
- [17] R.R. Brooks, C. Griffin, and D.S. Friedlander, "Self-Organized Distributed Sensor Network Entity Tracking," *International Journal of High Performance Computing*, vol. 16, no. 2, 2002.
- [18] Jean-Pierre Aubin, *Mutational and Morphological Analysis: Tools for Shape Evolution and Morphogenesis*, Birkhäuser, 1999.
- [19] Luc Doyen, "Shape Lyapunov Functions and Stabilization of Reachable Tubes of Control Problems," *Journal of Mathematical Analysis and Applications*, vol. 184, pp. 222–228, 1994.
- [20] Luc Doyen, "Mutational Equations for Shapes and Vision-based Control," *Journal of Mathematical Imaging and Vision*, vol. 5, no. 2, pp. 99–109, 1995.
- [21] D. Song and K. Pashkevich, A. Goldberg, "ShareCam Part I and II," in *International Conference on Intelligent Robots and Systems*, 2003, pp. 1080–1093.
- [22] A. Stroupe, M. Martin, and T. Blach, "Distributed Sensor Fusion for Object Position Estimation by Multi-Robot Systems," in *ICRA*, 2001.
- [23] Martin Mauve, Jorg Widmer, and Hannes Hartenstein, "A Survey on Position-Based Routing in Mobile Ad-Hoc Networks," *IEEE Network Magazine*, vol. 15, no. 6, pp. 30–39, 2001.
- [24] John W. Byers, Michael Luby, Michael Mitzenmacher, and Ashutosh Rege, "A Digital Fountain Approach to Reliable Distribution of Bulk Data," in *SIGCOMM*, 1998.
- [25] Zhenqiang Ye, Srikanth V. Krishnamurthy, and Satish K. Tripathi, "A Framework for Reliable Routing in Mobile Ad Hoc Networks," in *INFOCOM*, 2003.
- [26] S.-J. Lee and M. Gerla, "Split Multipath Routing with Maximally Disjoint Paths in Ad Hoc Networks," *IEEE International Conference on Communications*, vol. 10, 2001.
- [27] J. Bruce, T. Balch, and M. Veloso, "Fase and Inexpensive Color Image Segmentation for Interactive Robots," in *IROS*, 2000.