Distributed Signal Processing and Data Fusion Methods for Large Scale Wireless Sensor Network Applications

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Abstract. In this PhD dissertation we study the problem of continuous object tracking using large scale WSNs. We propose a novel practical WSN-based scheme that is able to track and predict the evolution behavior of a continuous object's boundary under realistic assumptions. The proposed scheme consists of two main components: a) A collaborative in-network WSN algorithm that estimates the local evolution parameters (orientation, direction and speed) of an evolving continuous object, and b) a novel algorithm which combines the produced local estimates, as they become available to a fusion center, to reconstruct the overall continuous object's boundary. Extensive computer simulations demonstrate the ability of the proposed collaborative algorithm to estimate accurately the evolution characteristics of complex continuous objects (e.g. with time-varying evolution rates and/or irregular boundary shapes) using reasonably dense WSNs. Moreover, it shown that the algorithm is robust to sensor node failures and communication link failures which are expected in harsh environments. Finally, we show that the proposed boundary reconstruction algorithm is able to track with accuracy the evolution of different types of continuous objects, using a small number of local front estimates that may be distorted with error.

Keywords: machine learning, distributed estimation, Bayesian estimation, continuous object tracking, environmental hazards, wireless sensor networks.

1 Introduction

Wireless Sensor Networks (WSNs) is a rapidly maturing technology with a wide range of applications (e.g. target tracking, surveillance, environmental monitoring, patient monitoring to name a few). A WSN typically consists of a large number inexpensive autonomous electronic devices (sensor nodes) which are deployed over a geographical region and monitor physical or environmental parameters. Apart from "sensing" the environment, WSN nodes are also able to process

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data and exchange information. Recent advances in microelectronics and wireless communication have made WSN technology an ideal candidate for large-scale decision and information-processing tasks.

Tracking objects (i.e. determining their location over time) has been a well studied problem with numerous civilian and military applications. Apart from finding the trajectory of the objects, it is also important to estimate their motion characteristics (i.e. direction and speed) in real time, since this information can be used to predict their future locations and understand their evolution behavior.

Wireless sensor network technology has been extensively used for single and multiple target tracking applications. Due to the rapidly dropping cost of the sensor nodes, WSNs are also gaining popularity in environmental monitoring applications. Recently, sensor network-based methods have been proposed for detecting the boundaries of diffusive hazardous phenomena [1–3], modeled as "continuous objects" (such as expanding wildfires, oil spills, diffusing bio-chemical materials etc.). Continuous objects are usually spread in large regions and their size and shape is dynamically changing with time. The ability to track and predict, with reasonable accuracy, the location of a diffusive hazard's boundary is of paramount importance since it helps the authorities to organize efficiently their responses (hazard suppression, possible evacuation etc).

The key idea behind the reported WSN-based continuous object tracking methods has been an attempt to identify over time the sensor nodes located closest to the evolving object's front line (boundary nodes). Although these methods can estimate implicitly the boundaries of a continuous object (evolving hazard) using the locations of the boundary nodes, they have important limitations that renders them impractical for the development of real world application systems for hazard tracking.

The main limitations that appear in almost all reported WSN-based continuous object tracking schemes are:

L1: They require unrealistic sensor nodes densities (thousands sensors per km^2) to determine with reasonable accuracy the boundary of an evolving continuous object. Although, the cost of the sensor nodes has been significantly reduced, it still remains prohibitive to cover large geographical regions (many km^2) with high density WSNs.

L2: They do not consider node or communication failures. However, these failures are certainly expected in large scale WSNs applications, and especially in the harsh environments created by the evolving hazardous phenomena (e.g. wildfires).

L3: They require synchronization between the sensor nodes, a capability that is difficult to achieve even in small scale WSNs.

L4: They assume an idealized sensing mechanism (i.e. fixed sensor nodes detection distance, do not consider sensing functionality disruptions etc) that renders them impractical for hazard tracking.

L5: They are incapable to provide information about the spatiotemporal evolution characteristics (e.g. direction and speed) of the continuous object's boundary. This limitation makes them incapable to be used for predictive modeling as part of decision support systems.

L6: They are incapable to assess the processing, memory and energy requirements before a real field deployment.

L7: They propose naive techniques to reconstruct the continuous object's boundary or are incapable to reconstruct it without using the human ability to identify the boundary's shape from the boundary nodes locations.

The main contribution of this dissertation is the conception, design and development of a WSN-based continuous object tracking scheme that addresses all the aforementioned limitations. We have to mention that most parts of the doctoral dissertation have been published in peer reviewed scientific journals and high quality referred Conferences Proceedings at the time of its writing.

2 Modeling Detection Distance Uncertainty

It is usually assumed that a sensor node can detect an event inside a disk area of radius R_d. Although this may not always hold in real applications, it is frequently adopted since it simplifies the analysis. Many disk based sensing models have been proposed in the literature e.g. the binary, staircase, probabilistic, etc. Among the most popular ones is the probabilistic sensing model given below,

$$p(x) = \begin{cases} 1 & x \leq R_s \\ e^{\lambda(x-R_s)^\gamma} & R_s < x < R_d \\ 0 & x \geq R_d \end{cases} \tag{1}$$

where the probability for a sensor node to detect an event is exponentially decreasing with distance x in the range $[R_s, R_d]$ and it is assumed that the sensor will detect an event with probability 1 (perfect sensor) if it occurs within the inner circle of radius R_s (see Figure 1a). The value of R_s (in the range $[0, R_d]$) is application dependent. The parameters γ and λ in equation (1) control the rate of probability decrease and can be determined considering the physical properties of the sensor, the noise in sensor measurements, the characteristics of the sensed physical quantity etc.

We introduce a novel variation of the probabilistic sensing model which, in addition to describing the detection distance uncertainty, it also accounts for the real possibility of a sensor node malfunctioning in a harsh environment as the hazard's front gets closer. This sensing model variation was inspired by the analysis of real WSN data collected from two outdoor experimental burns that took place at Gestosa's experimental field site in Portugal [4]. The data analysis has shown that in many cases the sensors were unable to detect the approaching fire front since abrupt increases in temperature (usually due to sudden flame fluctuations) destroyed the sensors before they detected the phenomenon (their measurements overcome a predetermined threshold).

The sensing range of a node S_i is assumed to be a circular region of radius R_d (see dotted circle in Figure 1b) centered at the sensor's location (L_i), as for

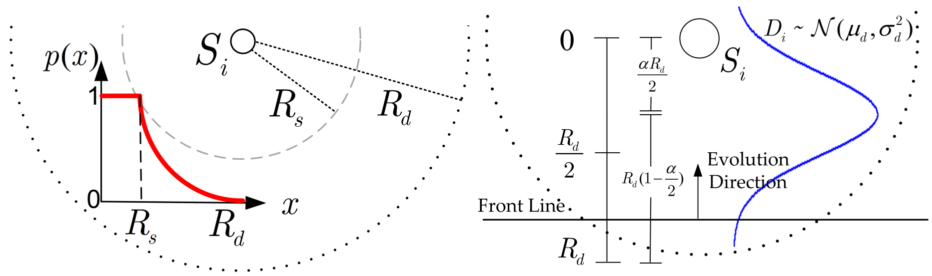

Fig. 1: Sensing Modeling: (a) Probabilistic exponential sensing model. (b) The proposed shifted Gaussian sensing model.

the probabilistic model. The value of R_d is hazard specific and depends on: (i) The sensor's technical specifications (e.g. its sensitivity), (ii) how the monitored phenomenon affects the physical quantity measured by the sensor. Using this information we can estimate the expected distance at which the evolving front is detected by the sensor [5]. We set this distance equal to $\frac{\alpha R_d}{2}$, where $0 \leq \alpha \leq 1$ (see Figure 1b). However, due to the stochastic nature of a hazard's detection this distance may actually deviate from its expected value. To account for this stochasticity we treat the detection distance as a normally distributed random variable, $D_i \sim \mathcal{N}(\mu_d, \sigma_d^2)$, with parameters:

$$\mu_d = \frac{\alpha R_d}{2}, \qquad 3\sigma_d = R_d(1 - \frac{\alpha}{2}) \Rightarrow \sigma_d = \frac{R_d}{3}(1 - \frac{\alpha}{2}). \tag{2}$$

In setting the standard deviation as in (2) above we assumed that the probability for a sensor to detect the approaching diffusive phenomenon at a distance larger than R_d is negligible.

As observed in Figure 1b the probability of detection increases monotonically as the distance of the local front from the sensor decreases in the range $\left[\frac{\alpha R_d}{2}, R_d\right]$. However, in close range $\left[0, \frac{\alpha R_d}{2}\right]$ the probability of detection decreases. This modeling decision is justified considering that the inability of a sensor to detect the approaching front at the expected detection range $\left[\frac{\alpha R_d}{2}, R_d\right]$ is an indication of a potential hazard-induced malfunction reducing the probability of detecting the hazard as it gets closer to the sensor node. This simple and realistic, sensing model in the presence of propagating hazards allows us to capture both the inherent stochasticity associated with the detection distance as well as the sensor node's increasing probability to malfunction as the hazard gets in close range. Importantly, it does not harm at all the generality since by setting the parameter $\alpha = 0$ in equation (2) (i.e. $\mu_d = 0$) we can relax the assumption that a node may malfunction and revert back to a monotonic probabilistic sensing model centered at the sensor node's location. The proposed "shifted" Gaussian model is therefore very flexible since it can cover both scenarios: diffusive hazards which may, or may not, affect the functionality of deployed sensor nodes. This is in contrast to the classical monotonic probabilistic model which ignores the real possibility of sensing mechanism failures as the hazard propagates in close range.

3 Collaborative WSN algorithm for estimating the spatiotemporal evolution characteristics of a continuous object

In this section we present the collaborative WSN algorithm for estimating and tracking the local evolution characteristics of continuous objects [6–8].

The key idea of the proposed in-network collaborative algorithm is the following: As soon as the deployed sensor nodes detect the evolving front line of a propagating hazard they are dynamically organized into ad-hoc local clusters (see Figure 2a) of 3 nodes *(triplets)*. Each triplet consists of a Master sensor (S_i^M) who initiates cluster formation and two Helper sensors $\{S_j^H, S_k^H\}$ that the Master selects among the nodes in its neighborhood and uses (without them knowing it!) to update its current (prior) local front evolution belief model. The parameters of the updated (posterior) model (speed, orientation and evolution direction) are then propagated forward to other sensor nodes residing in the area where the evolving phenomenon is moving into.

3.1 Model Updating

In our example we assume *w.l.o.g.* that S_i^M has notified by its Helper neighbors $N_i^H = \{S_j^H, S_k^H\}$ (see Figure 2c) that they have detected the evolving front at time instances t_{ij} and t_{ik} respectively, where *w.l.o.g.* $t_{ij} < t_{ik}$. When the Master S_i^M receives the notifications from the pair of Helpers, initiates the model updating procedure described below.

The updating starts with the calculation of the "new" (posterior) local front speed model parameters ($U_i^* \sim \mathcal{N}(u_i^*, s_i^{*2})$). Master node S_i^M uses the expressions in (3) and calculates the parameters of the Normal speed models $U_{ih} \sim \mathcal{N}(u_{ih}, s_{ih}^2)$ of the two Helper projection points p_{ih} where $h = \{j, k\}$.

$$u_{ih} = \frac{\mu_{ih}}{t_{ih}} = \frac{2d_{ih} - \alpha R_d}{2t_{ih}}, \qquad s_{ih} = \frac{\sigma_{ih}}{t_{ih}} = \frac{R_d(1 - \frac{\alpha}{2})}{3t_{ih}} \tag{3}$$

By substituting these parameter values in (4), S_i^M calculates the Gaussian mixture weights w_{ij} and w_{ik}.

$$w_{ij} = \frac{1}{1+C}, \quad w_{ik} = \frac{C}{1+C}, \quad C = \frac{s_{ij}|u_i - u_{ij}|}{s_{ik}|u_i - u_{ik}|}. \tag{4}$$

Then, by applying the resulting mixture weight values into (5) and (6) the Master calculates the parameters ($\hat{u}_i$ and $\hat{s}_i$) of the Normal distribution that best approximates the Gaussian mixture (see equation (7)).

$$\hat{u}_i = w_{ij}u_{ij} + w_{ik}u_{ik} \tag{5}$$

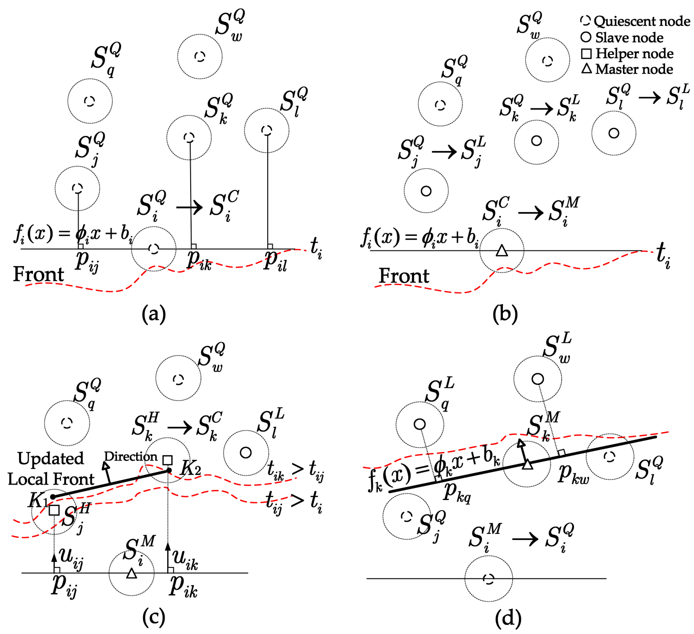

Fig. 2: Local front model updating procedure: (a) Node S_i becomes Master candidate and checks if it satisfies the conditions to become a Master, (b) node S_i becomes a Master and "enslaves" its neighbors S_j, S_k and S_l, (c) Master S_i^M uses the information received from its two Helpers (S_j^H and S_k^H) and updates the local front's line parameters, (d) node S_k becomes the new Master and S_i releases its slaves.

$$\hat{s}_i^2 = w_{ij}s_{ij}^2 + w_{ik}s_{ik}^2 + w_{ij}w_{ik}(u_{ij} - u_{ik})^2 \tag{6}$$

$$p(u) = \sum_{h \in \{j,k\}} w_{ih}\mathcal{N}(u|u_{ih}, s_{ih}^2), \tag{7}$$

Having available these parameters ($\hat{u}_i$ and $\hat{s}_i$), along with the prior model parameters (u_i, and s_i), S_i^M applies them to equation (8) to obtain parameters (u_i^*, s_i^{*2}) of the posterior speed model.

$$u_i^* = \frac{u_i\hat{s}_i^2 + \hat{u}_i s_i^2}{\hat{s}_i^2 + s_i^2}, \quad s_i^{*2} = \frac{\hat{s}_i^2 s_i^2}{\hat{s}_i^2 + s_i^2} \tag{8}$$

Next, Master S_i^M estimates the local front's orientation, ϕ_i^*. To update this parameter the Master finds the coordinates of two points, $K_1 = (x_1, y_1)$ and $K_2 = (x_2, y_2)$, which are expected to lie on the "new" local front line (see Figure 2c) and applies them directly to equation (9).

$$\phi_i^* = \frac{y_2 - y_1}{x_2 - x_1}. \tag{9}$$

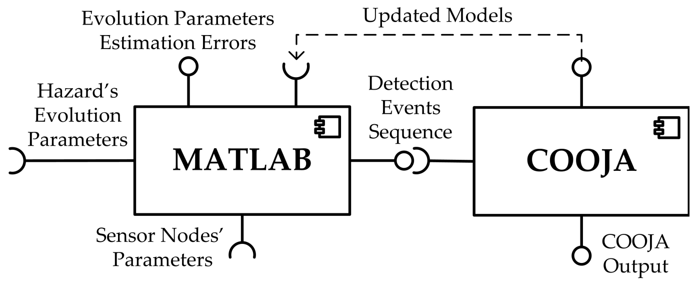

Fig. 3: UML component diagram of Matlab-COOJA based simulation workflow.

To update the direction of evolution parameter δ_i^*, node S_i^M derives the equation of the line $f_i^*(x)$ that is determined by points $K_1(x_1, y_1)$ and $K_2(x_2, y_2)$ (see Figure 2).

$$f_i^*(x) = \phi_i^* x + b_i^* \tag{10}$$

where $b_i^* = y_1 - \phi_i^* x_1$

Subsequently, node S_i^M substitutes its abscissa (x_i) in (10) and checks the $sgn(f_i^*(x_i))$. If $sgn(f_i^*(x_i)) > 0$ $(sgn(f_i^*(x_i) < 0)$ then Master node S_i^M infers that the new local front line evolves into the *negative (positive)* half plane and it updates the direction parameter $\delta_i^* = -1(1)$ accordingly.

All model parameters are updated using closed form expressions that can be realized easily by embedded microprocessors commonly used in WSN node architectures.

3.2 Evaluation of the Algorithm

For the evaluation we have developed a flexible simulation workflow which allows us to generate and execute realistic WSN simulation scenarios with different sensor node densities, deployment strategies, sensor node failure probabilities, communication (Rx and Tx) failure probabilities, and propagating hazard front properties (shape, speed and acceleration).

Simulation Workflow

The WSN simulation workflow includes two main components: i) The flexible WSN simulator COOJA (COntiki Os JAva) for the Contiki sensor node operating system, and ii) a Matlab-based component which prepares the COOJA input file and evaluates the estimation accuracy of the proposed in-network algorithm.

As shown in the UML component diagram of Figure 3, the Matlab component takes as input information about: a) the deployed sensor nodes (location, prior model parameters, etc.), and b) the propagating hazard's front properties, and determines the sequence in which the deployed sensor nodes detect the evolving hazard. After that, it generates a file (*Detection Events Sequence*) which contains for each sensor node the following information: {*ID, location, time of detection, prior model parameters*}. This file is passed as input to COOJA used to simulate the behavior of the proposed distributed algorithm, as if it was implemented by a WSN consisting of Atmel's AVR RAVEN nodes. Using COOJA we simulate the IEEE 802.15.4 MAC protocol's byte stream and we can evaluate the proposed algorithm's behavior under different Rx/Tx failure probabilities.

At the end of a simulation, a *COOJA Output* file is produced which contains: a) The updated model parameters, b) the number of Rx and Tx messages/Bytes exchanged in the WSN, and c) the energy consumed for communication (Rx and Tx). To evaluate the estimation accuracy of the proposed algorithm, the updated models information is passed back as input to the Matlab component which compares the corresponding models' orientation and speed with the ground truth values.

Results and Discussion

In the conducted experiments the diffusive phenomenon (continuous object) was simulated using either a Matlab program, that simulates multi-source diffusive hazards, or FLogA a wildfires behavior simulator [9] that allow us to simulate complex diffusive hazards with irregular shapes.

Extensive computer simulation results show that the proposed algorithm is able to estimate with accuracy the evolution parameters (speed, orientation and evolution direction) of the diffusive hazardous phenomena. Its accuracy seems be insensitive to changes in sensor nodes density, node failure probability, and Rx/Tx failure probability. This was also confirmed by comparing pairwise the means of the error densities using Student's t-test. For all cases the difference of the means was found to be insignificant at the 0.05 significance level. Moreover, the results indicate that the accuracy of the proposed algorithm slightly decreases when the sensing radius R_d increases. This can be explained if we consider that an increase of the sensing radius implies increasing the uncertainty associated with the front line's location at the time of the hazard's detection (see Section 2).

4 Assesing Requirements for Large Scale implementation using Simulation-Driven WSN Emulation

For all WSN schemes, computer simulations can be used to assess the expected WSN behavior as a function of its density. However simulations fail to provide: a) accurate energy consumption estimates and how they scale with the size of the network, and b) information about the processing and memory requirements of the distributed algorithm's implementation. Since having such estimates is very important before attempting to deploy a large-scale WSN for environmental monitoring application the real question becomes, how can we meet this requirement without having to deploy a large-scale WSN?

To address this question we introduce a simulation-driven WSN emulation workflow (see Figure 4) which allows us to emulate the operation of a large-scale WSN deployment for environmental applications by reutilizing only a small number of real sensor nodes. The key idea of the proposed method is to re-allocate

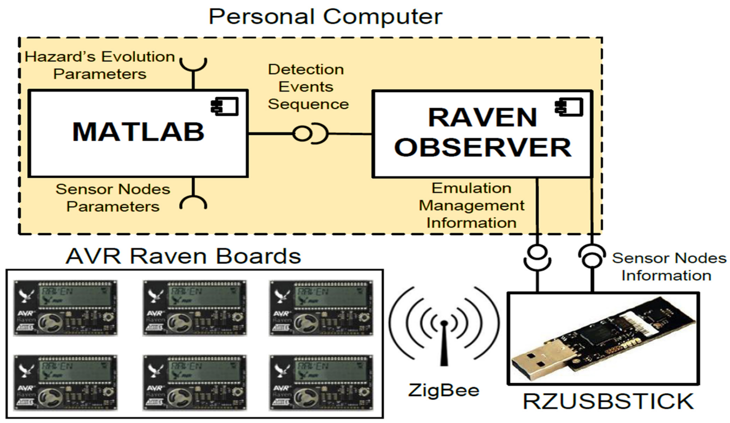

Fig. 4: Simulation driven emulation workflow.

(virtually reposition) the available sensor nodes so that they implement WSN nodes located close to the hazards front line as it evolves [10]. We demonstrate its capabilities using the distributed algorithm we introduced in Section 3 for estimating the spatiotemporal evolution parameters of diffusing environmental hazards. The WSN implementation of the proposed collaborative algorithm was based on the affordable Atmel Raven evaluation kit.The distributed WSN algorithm was coded in C on the IPv6 ready RTOS Contiki, an open source operating system for networked, memory-constrained systems with a particular focus on low-power wireless Internet of Things devices.

Emulation results clearly indicate that our algorithm is suitable for a large-scale WSN deployment, since it respects WSNs' communication, processing, memory and energy constraints. The proposed emulation approach can be followed to assess the practicality of large-scale WSN deployment of other in-network algorithms of similar nature for environmental monitoring applications.

5 Continuous Object Boundary Reconstruction Algorithm

In this Section we present a novel algorithm which reconstructs with accuracy the boundary of an evolving continuous object using a small number of local front estimates [11]. Each local front estimate describes locally the evolution characteristics (orientation angle, direction and speed) of the continuous object's boundary. When a sufficient number of local front estimates becomes available at a fusion center the algorithm combines their information and determines a "smooth" curve that approximates the object's boundary.

The key idea of the proposed boundary reconstruction algorithm is as follows: Let's assume that a monitoring system (e.g. based on WSN technology -

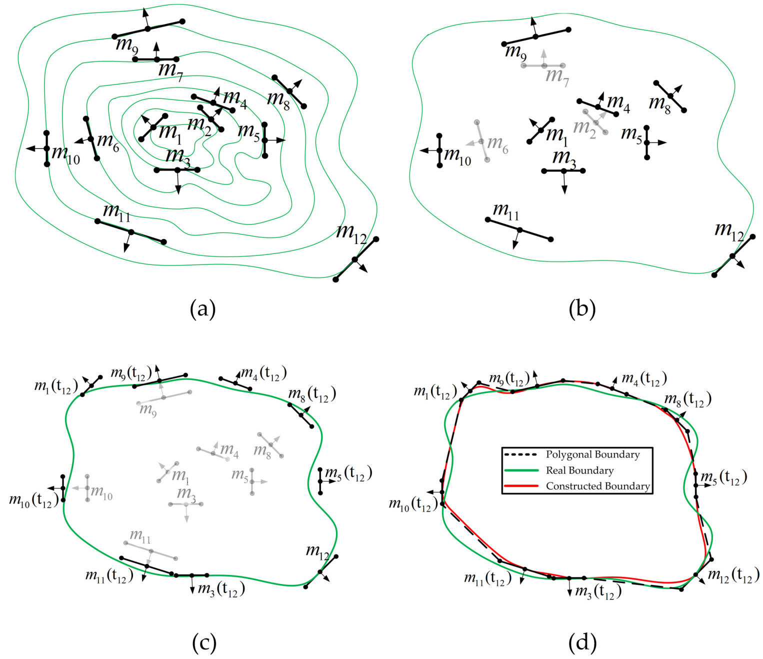

Fig. 5: a) Each green curve shows different instances of an evolving continuous object's boundary; each boundary corresponds to the time instance where a local front estimate (black segment) appears. to the diffusive continuous object's boundary at the times instance where the corresponding local front estimate (black segments) becomes available. b) The dark segments correspond to the subset local front estimates that will be used to determine the boundary at time $t = t_{12}$. c) The predicted locations of the selected local front segments at time $t = t_{12}$. d) The polygon (black dashed) and the smooth curve (red curve) that approximates the continuous object's boundary (green curve).

see Section 4) is able to estimate the evolution characteristics (orientation angle, direction and speed) of a continuous object at different locations and/or time instances (see black segment in Figure 5a). As soon as a sufficient number (application dependent) of local front estimates becomes available, the proposed algorithm combines their information and determines the set of local front estimates (black segments in Figure 5b) that will be used to reconstruct the boundary of the continuous object. In sequence, using their evolution characteristics it determines their locations at the time instance that we wish to reconstruct the continuous object's boundary (time t_{12} see Figure 5c). Using the "new" location coordinates and the evolution direction parameters of the local fronts, the proposed algorithm determines a polygon that approximates the continuous object's boundary (see black dashed polygon in Figure 5d). Subsequently, using uniform cubic B-splines the algorithm determines a "smooth" curve which is the reconstruction of the continuous object's boundary (see red curve in Figure 5d). Finally, based on the estimation uncertainties of local fronts' parameters, the algorithm computes a probability field, that indicates for each point, the probability to be reached by the continuous object at a given time.

Extensive simulation results demonstrate that the proposed algorithm is able to track accurately the boundary of different types of continuous objects (e.g. time-varying evolution rates and/or irregular boundary shapes), while using a small number of local fronts estimates which may be distorted with error.

6 Conclusions

We proposed a flexible probabilistic sensing modeling approach which in contrast with the existing works that assume a perfect sensing mechanism (see L4 in Section 1), can capture the detection distance uncertainty and the possibility for a sensor node to malfunction in a harsh environment created by an approaching hazard. This simple, yet realistic, sensing model allows us to formulate a local front models' parameters estimation problem in a Bayesian manner. We analytically solved this Bayesian problem and derived closed-form algebraic expression that can be easily implemented by microprocessors of the commodity sensor nodes.

To address limitations L1, L3, L4 and L5 (presented in Section 1) of the state of the art schemes, we developed an *asynchronous* collaborative algorithm that is able, using WSNs of *realistic* density, to estimate with accuracy the spatiotemporal evolution parameters (orientation, direction and speed) of a continuous object's boundary. The proposed parameters estimation procedure implemented in a collaborative fashion by dynamically formed clusters (triplets) of sensor nodes. The algorithm updates the local front model parameters and propagates them to sensor nodes situated in the direction of the hazard's propagation in a fully decentralized manner.

To realistically asses the requirements and behavior of the proposed algorithm (see L6 in Section 1), we developed a simulation-driven WSN emulation workflow which allows us to estimate, before attempting to deploy a large scale WSN, the energy, processing and memory requirements of collaborative algorithms as the WSN's size increases.

The state of the art are incapable to delineate automatically the boundary of an evolving continuous object (see L7 in Section 1). To address this limitation we developed an algorithm which combines dynamically the information of a small number of estimated local front models, as they become available to a fusion center, and determines a smooth curve that approximates the boundary of the continuous object at a specific time instance. By exploiting the estimation uncertainty of the local fronts evolution parameters, the proposed algorithm generates a probability field that indicate for each point of the considered area, the probability to be affected by the continuous object.

Acknowledgment

This research has been co-financed by the European Union (European Social Fund ESF) and Greek national funds through the Operational Program “Education and Lifelong Learning” of the National Strategic Reference Framework (NSRF) - Research Funding Program: Heracleitus II. Investing in knowledge society through the European Social Fund.

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