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SWeFS: Sensor Web Fire Shield for forest fire detection and monitoring

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Abstract

Fires are a common, disastrous phenomenon (hazard) that constitutes a serious threat for many years. Due to their speed of propagation and intensity they often lead to property damages, personal injuries and loss of human lives. The probability of forest fire eruption in the Wildland-Urban Interface (WUI) is steadily increasing due to the climate change and human activities. WUI refers to all types of areas where forests, water bodies, and rural lands interface with homes, other buildings and infrastructures, including first and secondary home areas, industrial areas and tourist developments.

The Sensor Web Fire Shield (SWeFS) research project designs, develops and demonstrates an integrated system of sensors, networking and computing infrastructure aimed to detecting, monitoring, predicting and assisting in natural hazards such as forest fires at the WUI zones. Its goal is to deliver: (i) a methodology for developing a novel Sensor Web platform for dynamic data-driven assimilation (DDDAS) for securing the WUI zones against environmental risks, and, (ii) a prototype DDDAS system specifically optimized/tuned for addressing the serious threat of forest fires in Greece. SWeFS pushes the state-of-the-art by combining and using technologies derived from multidisciplinary research in the areas of sensor networks, distributed vision systems, remote sensing, geographical information systems (GIS), data stream fusion, space-time predictive modeling and control systems.

***Keywords**: fire detection and monitoring, active sensing, wireless sensor networks, dynamic data driven assimilation, data fusion, space-time predictive modelling, closed-loop architecture*

1. Introduction

Countries in the Mediterranean basin suffer from 50.000 fires annually with damaged land that covers 600.000 hectares. The cost of fire prevention and fire fighting in the Southern European countries scales up to 1 billion USD. The cost of the destructive fires of 2007 in Greece has been estimated to 1 billion euros. The land impacted by fires annually in the same region is equivalent to the surface of Crete or Corsica while the fires in Spain, Portugal, France, Italy and Greece have quadrupled since the 1960's. The rapid development of WUI areas is the outcome of pollution and overpopulation of city centers that grew in the ‘70s. Settlements were built without efficient road networks while homes and other buildings were developed in or near areas that form the flood plain of water catchments.

To minimize the aforementioned damages, early detection of environmental hazards like forest fires is critical. It is also very important to have early and accurate information about the exact origin(s) of the fire and its course as it spreads. Great technological effort has been invested on the design of systems for fire detection and monitoring. From an engineering perspective, machineries can be designed and used to help with detection or prediction of the disastrous events. One technology that enables (near) real-time detection of such events is the so-called Wireless Sensor Networks (WSNs). WSNs typically consist of a large number of small, low-cost sensor nodes distributed over a large area. The sensor nodes are integrated with sensing, processing and wireless communication capabilities. A simple WSN could be based only on a network of multi-sensor field devices that are able to detect increases in the temperature and/or decreases in the humidity percentage. However, the most promising approach for the early forest fire detection in WUI zones is the combination of various heterogeneous sensors. Typical temperature and humidity sensors can be combined with video-capable wireless sensors, optimally placed in an area of interest, to better observe the outbreaks of various hazardous phenomena. The prediction accuracy of such an approach could be enhanced through the exploitation of remote sensing products such as satellite monitoring (another source of information interfaced to the systems). Of course, one of the requirements that have to be addressed is the optimal placement of the available sensor infrastructure in order to maximize the coverage of the monitored area. WSN systems can reach, at a reasonable cost, the density of physical parameter measurements needed for an accurate and timely fire detection, localization and progress monitoring.

During the past years, a lot of research has been conducted in the area of forest fire detection. The study from Elmas et. al. (2011) discusses a Forest Fire Decision Support System (FOFDESS) model, which is a multi-agent Decision Support System for Forest Fire. Depending on the existing meteorological state and environmental observations, FOFDESS does the fire danger rating by predicting the forest fire and it can also approximate fire spread speed and quickly detect a started fire. The considered model adopts data fusion algorithms such as Artificial Neural Network (ANN), Naive Bayes Classifier (NBC), Fuzzy Switching (FS) and image processing. The SFEDONA project (co-funded by ESA) deals with a complete end-to-end fire detection and alerting application which makes use of state-of-the-art fire detection technologies based on terrestrial optical cameras and sensors, data fusion, satellite and wireless communications as well as modern IT technologies. The SFEDONA project adopts a terrestrial wireless network for the interconnection of various components installed on-field such as optical and panoramic PTZ cameras, weather monitoring stations and wireless environmental sensors, as well as of a SatCom (satellite) network for the interconnection of the end user’s premises with local field. The SatCom connection is used for delivering alarms on fire events to the core control center. The model presented by Li et. al. (2005) discusses a hybrid contextual fire detection algorithm for airborne and satellite thermal images. This model essentially treats fire pixels as anomalies in images and can be considered a special case of the more general clutter or background suppression problem. The system from Lloret et. al. (2009) deploys wireless IP multi-sensors able to sense fire by infrared radiation and smoke. The system sends an alarm to the control system if the combination of physical sensors reports a fire event. When a fire is detected, the sensor alarm is sent through the wireless network to the control center. The center selects the closest wireless IP cameras to the sensor and sends them a signal in order to receive real-time images from the affected zone. Regarding the cases where the fire detection algorithms use satellite remote sensing capabilities, most of them are based on a single sensor approach and are using basic signal processing techniques. Specifically for MSG/SEVIRI data, the different approaches rely on variations of EUMETSAT's (the international organization managing the Meteosat series of geostationary meteorological satellites) proposed classification methodology. Sifakis et. al. (2011) from ISARS/NOA and Carvalheiro et. al. (2010), among others, have adopted a similar approach for identifying hotspots. It should be noted that the method presented by Calle et. al. (2006) was applied in the framework of SAFER (EC/GMES) project with noticeable omission errors for Greece, mainly attributed to insufficient customization for the geographic area's special characteristics in terms of vegetation species and underlying land cover. Finally, in the context of the EU project SCIER (Sensor and Computing Infrastructure for Environmental Risks management) as described from Sekkas et. al. (2010), a scalable system architecture that integrates private and public sensor and camera networks in a hierarchy has been developed and tested. The system was designed to protect WUI areas by adopting a scalable and modular approach for early detection and effective fire management. In addition to the sensory system (WSNs), SCIER provided the capability of performing parallel simulation (using Grid computing) of multiple fire scenarios corresponding to different environmental conditions (e.g. wind direction and speed). This unique capability was an innovation offered for the first time by SCIER. However, SCIER and the rest of the aforementioned approaches did not attempt to integrate WSN sensing and predictive modeling with remote sensing and GIS into a *closed-loop active sensing system* and implement a DDDAS scheme for fire detection and management. This unique innovative approach is pursued in

SWeFS. Moreover, SWeFS deals with multiple parameters and trade-offs, hence, considers and aims both for energy-efficiency and early-detection. The Sensor Web Fire Shield (SWeFS) research project aims at delivering: (i) a methodology for developing a novel Sensor Web platform as a Dynamic Data-Driven Assimilation System (DDDAS) for securing the WUI zones against environmental risks, and, (ii) a prototype DDDAS specifically optimized/tuned for addressing the serious threat of forest fires at national and international level.

2. SWeFS High Level Architecture

SWeFS adopts a combination of heterogeneous sensors including remote sensing and predictive risk propagation models in a *single closed loop active sensing system*. The first step towards the completion of SWeFS architecture (Figure 1) is the *efficient collection and processing of data streams* that is provided from the various subsystems of the Input Block (IB) (i.e., network of sensors, cameras, remote sensing and unmanned air vehicles).

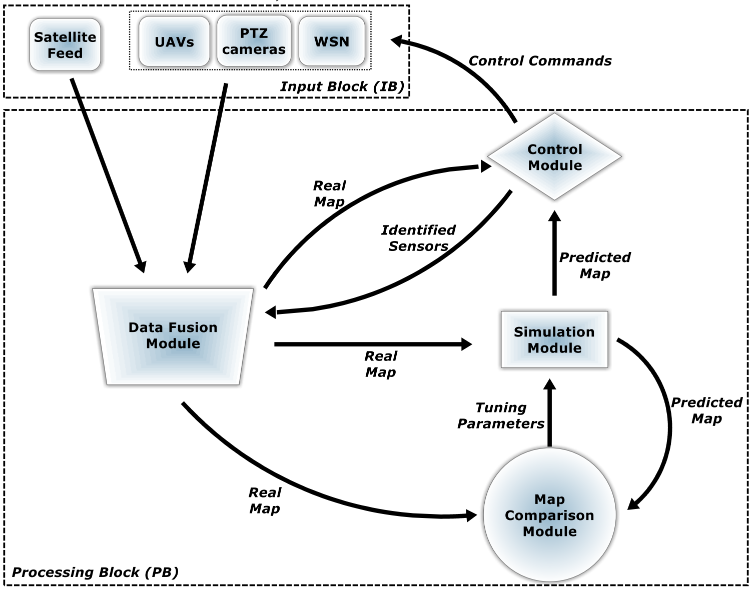

Figure 1- Interconnection of SWeFS components

The remote sensing methodologies employed in SWeFS greatly facilitate the early detection and monitoring of wildfires while the active sensing techniques give an identification mechanism for the type and combination of sensors that provide the most useful measurements from the field. In addition, the ability provided by SWeFS to simulate multiple scenarios in parallel is important from a management point of view since it enables "what if" type queries and worst case scenario identification in real-time. Of course, the prediction mechanism is equally important for the encapsulation of the DDDAS scheme in SWeFS. The processing of the streaming data derived from the IB is operated by the components of the Processing Block (PB), in a closed loop approach, in order to provide accurate information regarding the exact origin(s) of the fire and its course as it spreads. The outcome is the visualization of hazard maps for the monitored phenomenon on a map based graphical user interface (GUI). To the best of our knowledge, SWeFS is pioneer to its domain with respect to the adoption of a closed loop approach in order to detect and monitor the evolution of a hazardous phenomenon such as forest fires at the WUI zones.
Another important element of innovation in SWeFS is the simultaneous implementation of both asynchronous and synchronous communication, which is defined according to the type of functionalities and the information handled: in the former case (asynchronous), new information or information updates are either published from the components of the IB or consumed from the components of the PB as soon as they become available, while in the latter one (synchronous), access

to the needed data (i.e., spatial data for available sensors, fuel data, etc.) and functionalities (i.e., control of the sensory infrastructure) happen “on request”. This architecture is achieved through the utilization of a Message Oriented Middleware (MOM) to act as the communication infrastructure for the interconnection of the SWeFS structural components. Publisher and Subscriber entities are present in the various modules belonging either in the IB or the PB to respectively publish and consume information of interest through the MOM.

2.1. **Input Block**

The Input Block (IB) of SWeFS consists of a heterogeneous infrastructure of sensors that provides the means for the optimal collection of measurements related to a fire incident in the monitored area. Currently, the following categories of sensors are integrated:

- In-field sensors able to measure temperature, humidity and gas concentrations,
- Weather stations that provide additional information about rain rate, wind speed and wind direction
- Out-of-field sensors like:
    - Pan-Tilt-Zoom (PTZ) and Fixed Cameras
    - Unmanned Air Vehicles (UAVs) equipped with cameras
- Remote sensing and processing facilities

Figure 2-SWeFS Sensory Infrastructure

Raw data stemming from in-field sensors provide on-the-run information about the actual progress of the phenomenon to experts. On the other hand, the data coming from the satellite feed and the available camera network constitute pre-processed streams that provide an estimation (i.e., probability values) regarding the occurrence of a fire incident in the area that falls in their supervision. The processing stage of such feeds is based on widely accepted image processing techniques from the research community. These operations are either performed locally on the nodes, through the exploitation of Field-Programmable Gate Arrays (FPGAs) (i.e., camera feed processing) or centrally on the back-end infrastructure of the system (i.e., process satellite feed).

Due to the heterogeneity of the sensor sources, the description of the sensed information must be homogenized. Since the main idea in SWeFS is to take advantage and reuse open standards that secure the inbound interoperability, we have adopted the Open Geospatial Consortium (OGC) Sensor Observation Service (SOS) in order to provide access to sensor descriptions and observations. The SOS specification leverages the Observations and Measurements (O&M) specification to encode observations and the Sensor Model Language (SensorML) specification to encode sensor descriptions. Both of these formats are based on the Extensible Markup Language (XML). The SOS standard defines a Web-based interface (Web service) that allows querying observations, sensor metadata or representations of observed features. Further, this standard provides means to register new sensors or remove existing ones. It also defines operations to insert new sensor observations. The SOS operations follow the general pattern of other OGC Web Services and inherit or re-use, when needed, elements defined previously. For every available sensor category we developed the corresponding proxies that ensure the robust communication of the sensory infrastructure with the rest architecture. The role of each proxy is twofold since the sensors supporting SWeFS, apart from providing their sensing capabilities, can be also externally controlled in order to optimize the capabilities of the system. This broader meaning assigned to the sensing devices is illustrated in Figure 3.

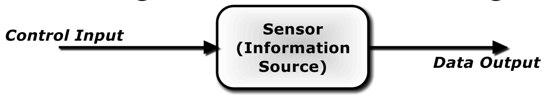

Figure 3. Sensor Entity of SWeFS

A proxy that lies upon a sensing element, on the one hand transforms/encapsulates the sensed values in SOS compliant messages which are subsequently forwarded to the MOM. On the other hand, these proxies act as controllers that translate and forward the consumed control commands and inform the rest system for the result. However, a fundamental issue is the way to process and combine the collected data streams and subsequently control the identified sensors of interest in order to reach to a meaningful decision related to the fire phenomenon. In SWeFS, the components of the PB undertake this task.

2.2. **Processing Block**

The building components of the PB are interconnected in a way to achieve the smart closed loop integration approach. The designed workflow is triggered by information derived from the elements of the IB. The processing task of the collected sensor data streams is assigned to the Data Fusion Module (DFM) while the Control Module (CM), the Map Comparison Module (MCM) and the Simulation Module (SM) enhance the active sensing capabilities and the DDDAS nature of SWeFS. As depicted inFigure Figure 1, an inner/smaller closed loop is shaped between these components. The DFM is the entry point for the sensor measurements in this circle while the CM is the component that broadcasts the result of the processing chain to the sensory infrastructure in the form of control commands. A description regarding each one of these modules follows.

Data Fusion Module (DFM): The DFM facilitates the integration and interpretation of different types of sensor data. In addition to the statistical advantage gained by combining same-source data (e.g., obtaining an improved estimate of a physical phenomenon via redundant observations), the use of multiple types of sensors increases the accuracy with which a quantity can be observed, interpreted and used for an event recognition in the context of SWeFS. The most fundamental mechanism of the DFM involves (i) the detection of pre-defined events, (ii) the decision or inference regarding the characteristics of an observed entity and (iii) an interpretation of the observed entity in the context of a surrounding environment and relationships to other entities.
The SWeFS sensor infrastructure provides an indication of the spatiotemporal evolution of the fire front. Such input can be highly localized (e.g., an alarm originating at a certain ground sensor) or of broader spatial scope (e.g., a sizeable ground segment of the observed terrain). The DFM processes data streams received from the available infrastructure in order to detect possible changes in their typical (no-event) distribution. Both types of input (coarse- and fine-grained) are taken into account for establishing the actual fire front (i.e., a time-invariant polygon that is approximated by the real feed; ground sensors, visual and satellite observations).
DFM architecture is partially based on the contextor’s theory presented by Coutaz et. al. (2002) and leverages the SOS standard for the interoperable integration of sensor data. A typical contextor is a software abstraction that models a relation between variables of an Observed System Context which is the composition of situations as observed by the system. A contextor does not exist as an isolated entity but rather as a part of a connected directional graph, produced by connecting Data-In channels with compliant Data-Out. The core principle of the DFM design is that each contextor encapsulates the functionality provided by a specific algorithm (e.g. Bayesian Network, Cumulative Sum, Linear

Opinion Pool, etc.) or operator (e.g., minimum, maximum, average, threshold, etc.). The DFM provides the necessary middleware services which will allow contextors to acquire data, execute the encapsulated algorithms, exchange information with each other, and finally produce the desired output. From an operational perspective, the DFM can be characterized as an event based system, which can run specific fusion applications. A fusion application comprises from a directional acyclic graph (DAG) of contextors with defined external inputs and defined outputs. Each input is a data flow coming from the network (i.e., sensory infrastructure), while each output is another data flow dispatched in specific format using a specific protocol adapter. What accounts as an event is a new value produced by an input data flow, both in macroscopic and microscopic level. So, in macroscopic level, this means that a new value coming from the network (e.g., a sensor) will trigger the engine by forcing the specific contextor which receives the corresponding data flow in its Data-In channel to execute. But, also, microscopically seen, inside the DFM, each output produced by a specific contextor, flows through its Data-out channel, to its connected contextor's Data-In channel, producing a corresponding event. This sequence of events results to the output of the DFM application which can be delivered in various formats using a variety of transport protocols such as http, email, etc. Both formatters and protocol adapters are pluggable modules which means that new implementations of both can be added at any time to the engine. DFM applications are modeled using a specific xml-based language, the Application Description Language (ADL). An XML parsing subcomponent inside the DMF is responsible to simply transform the static information of a script to Fusion Engine directives, used to build the application context inside the DFM.

The definition of the detected events depends upon the specific application under consideration. In a very simple scenario, the event detection mechanism in DFM could be based on certain pre-defined thresholds for evaluating the occurrence of an event. However, the combination of multiple sensor data sources and the implementation of advanced detection and fusion algorithms could achieve satisfactory detection levels in a variety of operating conditions. The output of the DFM can be an improved estimate on an event occurrence. The aforementioned capitalize on the dual nature of the DFM in the SWeFS context. On the one hand, through the exploitation of a simple fusion application script based on thresholding operators over the available sensor streams, the DFM can operate in a *detection mode*. In this case, the localization of the incident in the monitored area is pursued. On the other hand, by taking advantage of the detection mode's outcomes and the active sensing approach adopted in SWeFS, the DFM can also operate in a *monitoring mode*. The results of this mode are continuously improved through the periodic deployment of more sophisticated and near-to-real application scripts with respect to the selected data sources that participate in the process. These scripts are created dynamically in compliance with the outcomes of the active sensing process. Through the DDDAS approach and the active sensing scheme, the information of the sensor sources that should participate in each round is constantly refined and consequently, the fusion scripts are refined as well. This results in more accurate estimations regarding the current state of the monitored fire front. The output of the DFM in SWeFS is provided in the form of ASCII Raster files that describe the estimated probability maps (probabilistic and binary) for the monitored area.

Simulation Module (SM): Due to the dynamic nature of the wind, which is the most influential fire simulation parameter, the SM was developed around the notion of *Multiple Simulation Scenarios* (MSS). Multiple wind direction and speed scenarios are generated as perturbations around an expected average scenario and executed in parallel. When combined, the MSS simulation results give rise to a map of burn probabilities that can be visualized as a fire hazard map. The capability to simulate multiple scenarios in parallel is also important from a management stand point since it allows the Tactical Commanders to pose "what if" type queries in the field and identify worst case scenarios faster than real-time. Furthermore, it greatly facilitates dynamic sensor selection (active sensing) and accurate fire course predictive modeling.

The SM is based on *fireLib* by Bevins (1996), and it stems from a previous work on the Fire Logic Animator (*FLogA)* interactive wildfire simulator by Bogdos et. al. (2013). However, instead of using

fireLib's default fire propagation algorithm (which exploits only 8 possible fire propagation directions) the SM utilizes a more flexible 16-neighbors scheme. Consequently, the fire front's propagation is less biased and the resulting propagation distortion is not noticeable under spatially heterogeneous conditions. Furthermore, the SM is designed to take advantage of CPUs with multiple processor cores in order to take advantage of parallelism and reduce execution time, i.e. the different simulation scenarios are executed in parallel by adopting a Master-Workers processing pattern.
As suggested by the interaction of the various SWeFS modules depicted in Figure , the SM is triggered each time the DFM produces estimations for the current state of an ongoing fire. Just before generating and executing the MSS, the SM consumes the up-to-date weather data from the MOM and uses the current wind parameter values to define the mean of the sampling ranges to be used for the MSS generation. Moreover, the relative air moisture value is used to calculate the 10hr dead fuel moisture content value reduction (10-H timelag) as in Vasilakos *et al*. (2007).

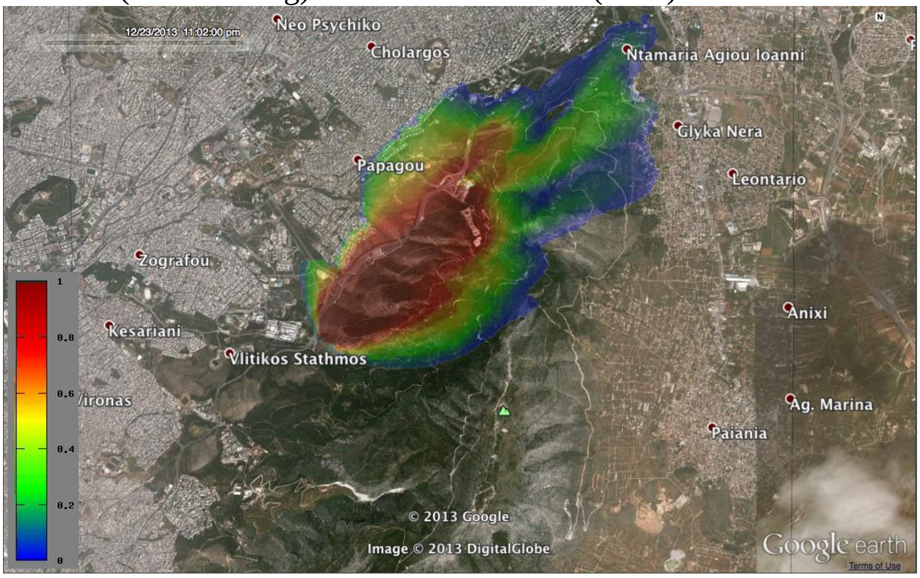

Figure 4: Visualization of a fire hazard map considering an MSS with 64 scenarios and equidistant (deterministic) parameters sampling around the expected wind direction and speed values.

The SM generates an MSS by performing deterministic or random sampling in a configurable wind speed and direction parameters range. Subsequently, the SM simulates the generated multiple scenarios as a combinatorial experiment, which means that it executes a wildfire simulation for each possible parameter values combination. The results are combined to produce KML visualization files using ground overlay images produced automatically by Gnuplot (2014) for the flame length of each scenario as well as the combined hazard map of the whole MSS. Figure 4 provides an example of a fire hazard map visualization based on a 8x8=64 scenarios MSS ignited at the northern end of the NKUA campus, in Athens. The prediction window was 2 hours while the ranges of the wind speed and direction parameters were 5m/s - 7m/s and 200º - 250º respectively (remaining constant throughout the simulation time). Moreover, equidistant (deterministic) parameters sampling was used.

Map Comparison Module (MCM): The DFM and the SM provide an estimation for the real map that describes the current state of the monitored fire front and a prediction for the phenomenon's possible evolution respectively. One of the objectives of the DDDAS approach is the continuous recalibration of the various components of a system in order to produce results as close as possible to the real situation. Hence, the actual fire front can be compared against the estimated (predicted) one derived through simulations in order to establish model accuracy metrics by taking into account the uncertainty in parts of the forest where data is not confirmatory of the real fire status. Such metrics (e.g., percent overlap between the estimated and the observed fire front) can be used for deciding on the recalibration of the model (simulator). A refined simulation outcome will result in a refined product from the CM's procedures as well, thus, the overall quality of the produced results is improved. This important task for the realization of the DDDAS approach in SWeFS is undertaken by the MCM.

The MCM receives at each *processing round* of the closed-loop the estimated real map from the DFM along with the prediction of the SM for the phenomenon's evolution. The input from the SM is multidimensional since parallel processing is performed and several simulation scenarios are produced in every simulation step from the engine. The MCM, by taking into account the spatial characteristics of the affected area, compares every received estimated map with the real one from the DFM. To eliminate possible map alignment issues the same coordinate system is utilized for the produced probability maps from DFM and SM. The metrics provided for the calculation of the overlap percent among the maps are the Jensen-Shannon Divergence, the Pearson Correlation Coefficient, the Kullback-Leibler Divergence and the Similarity Score. From these metrics, although the simplest one, the Similarity Score seems to outperform the other ones for map comparisons with respect to calculation accuracy and processing time in SWeFS.

Through the processing circle of the MCM an evaluation of the simulation results is performed by ranking the multiple simulation results (that refer to the same time horizon) based on the achieved score. This ranking is subsequently forwarded to the SM which in turn evaluates it and recalibrates, if need be, the appropriate internal tuning parameters. Should the MCM outcomes indicate that the simulation presents large deviation from the actual evolution of the phenomenon (i.e., quite low scores in terms of coverage percent), the SM restarts the simulation procedure by considering as ignition area the currently estimated real map from the DFM.

Control Module (CM): Through the existence of the CM, the active sensing aspect is implemented. Active sensing techniques are capable of identifying the type and combination of sensors that provide the most useful measurements (e.g., because they are placed close to the observed phenomenon). The CM receives the products of the DFM and SM, i.e., actual and predicted probability maps respectively, correlates them with the deployed sensor infrastructure and the spatial characteristics of the monitored region (e.g., elevation, slope, etc.) and identifies the sensor nodes that should be controlled. The algorithm that is used as the core of this internal procedure is based on the so called Cognitive-based Adaptive Optimization (CAO) approach presented by Kosmatopoulos et. al. (2009). CAO transforms the energy efficiency and the coverage problem into an optimization one where in every processing round the goal is to optimize the sensing capabilities of the available sensor resources so to meet the objective of the monitored area's optimal coverage with respect to energy efficiency. For instance, the CM can alter the sampling frequency and/or the strength of the transmitted signal for the in-field sensors, steer the available PTZ cameras by providing a new triplet of pan, tilt and zoom control directives and transmit a new waypoint for the available UAVs. This dynamic management of the infrastructure has a positive impact on the optimal monitoring of the affected area and the energy consumption of the nodes.

The CM outcomes are equally important for the recalibration of the results derived from the fusion processing. Since forest fires is a rapidly growing phenomenon as time evolves and the output of the DFM is highly correlated with the quality of the accounted data streams, is of paramount importance to know, at each iteration of SWeFS closed-loop processing, the combination of sensor sources that can monitor the phenomenon's evolution optimally. The CM is able to identify with accuracy these sensors. This information is forwarded via the MOM to the DFM in order to recalibrate its operation by dynamically configuring and deploying timely and accurate fusion application scripts. Through this procedure is assured that the produced result of the DFM is aligned with the evolution of the fire front and one aspect of the DDDAS nature of SWeFS is materialized.

3. DDDAS Approach

Unsurprisingly, a lot of praise has been given to the Dynamic Data-Driven Assimilation Systems (DDDAS) concept following its introduction from Darema (2004). In the classic simulation approach the applications are using a static input dataset. An inherent disadvantage of such applications is that they are not able to adjust the model parameters in case of significant simulation drift. Conversely, the DDDAS paradigm entails the ability to receive and respond to online data and measurements, thus recalibrating the simulation and allowing for more accurate predictions. The benefits of adopting a sound DDDAS strategy are indisputable for numerous environmental applications. For example Douglas (2005) mentions that before DDDAS it was more probable for meteorologists to fail in predicting the path and the scale of storms while the Forest Services were more likely to ignite controlled burns that would eventually become proper wildfires.

SWeFS aims to not only assimilate online measurements but also utilize them to improve the quality of the monitoring process (active sensing). To do this effectively, the SM needs to provide an accurate fire evolution prediction, so as to offer valuable data for the CM to steer the sensory infrastructure effectively based on the near future fire evolution predictions. This is why it is crucial for the SM to also conform to the DDDAS principles in order to provide as accurate predictions to the CM as possible.

One important point in taking a decision to calibrate the SM is to be able to discover how much the simulation has drifted from reality, by effectively comparing the simulation predictions and the field measurements. We approached the problem of comparing the predicted and real fire maps by borrowing some ideas from the image-processing field. Specifically, we observed that a fire hazard map in the form of a burn probability distribution shares many properties with a saliency map. We experimented extensively with various map comparison metrics reported in the literature and found that the simplistic Similarity Score by Judd et. al. (2012) is the most advantageous. Specifically, when comparing two burn probability maps (in the MCM) generated by two different MSSs, this comparison metric has the following desirable attributes:

1. The returned similarity scores reflect consistently the difference in the weather parameter values between the two MSS
2. The similarity scores remain unaffected by the size of the fire fronts
3. The calculation performance for the metric meets our real time constraints

Each time the SM is triggered by the DFM, it utilizes the comparison results from the MCM to obtain the Total Similarity Value (TSV) for the simulated MSS against the estimation of the real fire map (DFM outcome) and the Scenario Similarity Value (SSV), which is an indication for the accuracy of each scenario. Our DDDAS approach for the next step is to use two predefined threshold values thresh1 and thresh2, with thresh1 > thresh2, as follows:

1. If the *TSV* > *thresh1* then the simulation drift is considered *insignificant* and the SM continues with the same/previous settings.
2. If thresh2 < TSV < thresh1 then the simulation drift is considered *moderate* and the SM uses the SSV of each scenario to modify its weight coefficient used to compute the burn probability distribution of the MSS. More specifically, the weight of each scenario is modified as: $\mathrm{w_i} = \frac{\mathrm{SSV_i}}{\sum_1^n \mathrm{SSV_i}}$, where n is the number of simulation scenarios in the MSS. In this case the results of the individual scenarios do not change, as the MSS parameters remain unaltered. What changes is how these individual results are combined to produce the burn probability distribution of the MSS.
3. If TSV < thresh2 the simulation drift is considered *significant* and the SM adopts the wind speed and direction values of the best scenario (highest SSV) as the posterior mean wind speed and wind direction values to be used for the MSS redefinition at the next time step.

The CM consumes the updated prediction of the burn probability distribution raster file instantly and the latest fire hazard maps are updated automatically in the provided GUI.

4. Conclusions

In this paper we have discussed the SWeFS approach that delivers an integrated solution able to detect, monitor, predict and assist in the management of natural hazards at WUI areas. SWeFS enables several desired features of monitoring and surveillance systems, such as fusion of sensor data streams, remote sensing, forest fire simulation and closed-loop integration. The paper presents the overall system architecture describing the design approaches followed during the development phase as well as certain implementation details.

Through the flow of information within the SWeFS architecture, data assimilation is also accomplished to better observe a detected phenomenon. Consequently, SWeFS can be characterized as a DDDAS which constitutes a unique innovative approach in forest fire monitoring.

The presented sensor web based closed loop fire shielding system provides:

1. *Real-time data stream processing* for the estimation of parameters that affect the fire spreading models.
2. *Fast simulation of multiple fire scenarios* for predicting fire evolution and provisioning of dynamic (time varying) probabilistic hazard maps for a given area.
3. *Intelligent closed-loop control mechanism* acting on the basis of available measurements and estimating the most important sensors for optimized active sensing.

Future work includes the improvement of the existing sensor data fusion mechanism by implementing and integrating new data aggregation algorithms. Finally, we are planning to develop optical detection algorithms that can be deployed in the cameras located in the available UAVs targeting at the localization of a forest fire front. The latter will take into consideration data related to the current position, height and angle of the UAV.

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