An Integrated Inductive-Deductive Framework for Data Mapping in Wireless Sensor Networks

Mohammad Hammoudeh, Robert Newman, Sarah Mount, Christopher Dennett
School of Computing and IT
University of Wolverhampton
Wolverhampton, UK
Email: {m.h.h, r.newman, s.mount, c. dennett}@wlv.ac.uk

***Abstract*—Wireless sensor networks (WSNs) have an intrinsic interdependency with the environments in which they operate. The part of the world with which an application is concerned is defined as that application's domain. This paper advocates that an application domain of a WSN can serve as a supplement to analysis, interpretation, and visualisation methods and tools. We believe it is critical to elevate the capabilities of the data mapping services proposed in [1] to make use of the special characteristics of an application domain. In this paper, we propose an adaptive Multi-Dimensional Application Domain-driven (M-DAD) mapping framework that is suitable for mapping an arbitrary number of sense modalities and is capable of utilising the relations between different modalities as well as other parameters of the application domain to improve the mapping performance. M-DAD starts with an initial user defined model that is maintained and updated throughout the network lifetime. The experimental results demonstrate that M-DAD mapping framework performs as well or better than mapping services without its extended capabilities.**

I. Introduction

WSNs are being deployed for an increasingly diverse set of applications each with different characteristics and environmental constraints. As a consequence, scientists from different research fields have begun to realise the importance of identifying and understanding the characteristics and special deployment needs of different application domains. In many WSN deployments, the network owners have some knowledge about the monitored environment characteristics in which the target system operates. For example, in forest fire applications [2], [3], information about the forest topography can be obtained from GIS systems or satellites maps.

A domain model carries knowledge of an application domain. It is a conceptual model of a system which describes the various real world entities involved in that system and relationships between them. The domain model provides a structural view of the system which we suggest using to complement the information gained from analysing data gathered by a WSN. The logical integration of a domain model and sensory data from multiple heterogeneous sensory sources can be effectively used to explain past observations as well as to predict future observations. It exploits the local semantics from the environment of each sensor. It also takes advantage of human guidance and information from other available sources, e.g. satellites. Furthermore, it maintains the overall coherence of reasoning about the gathered data and helps to estimate the degree of confidence using probabilistic domain models. The use of knowledge made available by the domain model can also be a key to meeting the energy and channel capacity constraints of a WSN system. The energy efficiency of the system can be improved by utilising a domain model in the process of converting data into increasingly distilled and high-level representations. Finally, domain models help early detection and reduction of the amount of ineffective data forwarding across the network, rather than sustaining the energy expense of transmitting ineffective messages further along the path to the destination.

II. Related Work

WSN applications that incorporate the special characteristics of the environment in which they operate are starting to appear on the horizon. The authors of the BBQ [4] focus on using probabilistic models of the real-world to provide approximate answers efficiently. In contrast to our work, efforts such as BBQ [4] have adopted an approach that assumes that intelligence is placed at the edge of the network, such as a sink, which is assumed to be less resource constrained than the sensor nodes. An interrogation-based approach can not guarantee that all anomalies will always be detected. Finally, this approach was found to be effective with stable network topologies. In highly dynamic network topologies the cost of checking whether the estimation is accurate becomes excessively high. Such a model will require collecting values of all attributes at one location at each time step, and the cost of doing so will most likely reduce any savings in source-sink communication that might result.

Motivated by BBQ, Ken [5] exploits the fact that physical environments frequently exhibit predictable stable and strong attribute correlations to improve compression of the data communicated to the sink node. This approach is subject to failure as basic suppression. It does not have any mechanism to distinguish between node failure and the case that the data is always within the error bound. They propose periodic updates to ensure models can not be incorrect indefinitely. This approach is not suitable for raw value reconstruction; for any time-step where the model has suffered from failures and is incorrect, the corresponding raw value samples will be wrong. Finally, as the approach presented in [4], Ken can only handle static network topologies and does not make use of redundancy.

The authors of [1] propose a distributed data mapping service where groups of network nodes cooperate to produce local maps which are cached and merged at a sink node, producing a map of the global network. The sink node receives periodic map updates from each cluster head used to refine an up-to-date global map. The distributed mapping service is made of four modules: Application (contains the user defined applications, e.g. isopleth maps), Interpolation (a building block to generate maps), In-network Processing (process raw data received from various cluster heads) and Routing (responsible for data communication). This approach does not incorporate the characteristics of the application domain.

III. M-DAD Mapping Framework Details

The proposed mapping framework, M-DAD, utilises a blend of both inductive and deductive models to establish a successful mapping between sense data and universal physical principles. Deductive methods rely on a precise application environment and the explicit knowledge, called structural knowledge, of the underlying domain using first principles to create a model of the problem typically yielding governing equations [6]. On the other hand, inductive methods utilises experimental data as the only source of available knowledge [6]. Some applications can only be treated using experimental data knowledge due to the lack of other application domain knowledge. Nevertheless, the use of inductive information helps in the generation of data consistency checks based on the structural knowledge abstractions given in the domain model. Finally, applications have been observed to perform significantly better if they use a combination of the two methods [7]. Figure 1 shows how the inductive and deductive methods can be merged to capture the advantages of both methods. After the structural knowledge is fed to the system model (deductive process), the sense data is used to refine and complement the basic structural model of the application domain. This refinement procedure can be done continuously throughout the network life to keep consistent mapping between the physical model and the sense data.

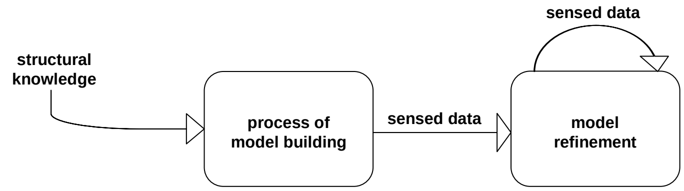

Figure 1. Merging of inductive and deductive methods

M-DAD makes use of knowledge given by the domain model in the map generation process. Knowledge from domain models provides guidance for map generation from high dimensional data set and has the potential to significantly speed up the map generation process and deliver more accurate maps. To the best of our knowledge, only few previous studies have considered the domain model. For instance, Hofierka et al. [8] incorporate the topographic characteristics to give better daily and annual mean precipitation predictions. The general lack of an appropriate data mapping framework for exploiting these rich sense data resources motivates this work.

Moreover, M-DAD mapping framework performs mapping from related multiple types of the sense data to overcome the limitations of generating a map from a single sense modality. A single sense modality map typically reveals only a small number of aspects of the monitored phenomena and is unable to infer the correct relations among other types in multi-modal sensing applications. In addition, high-throughput data sets also often contain errors and noise arising from imperfections of the sensing devices. Maps generated from a combination of different types of data are likely to lead to a more coherent map by consolidating information on various aspects of the monitored phenomena. Additionally, the effects of data noise on generated maps will be dramatically reduced, assuming that sensing errors across different data sets are largely independent and the probability an error is supported by more than one type of data is small. A natural approach is to make use of the relation between the multiple types of sense data to generate a map is to combine the maps generated from different types of data. We may combine the maps in different ways such as accepting a value at an observation point only when it is commensurate with all maps as defined in the given model. More interestingly, and allegedly with guarantees of delivering better maps, multiple types of data can be analysed concurrently under an integrated relational model. The latter method is novel in the sense that most existing n-dimensional interpolation schemes are defined by applying one-dimensional interpolation in each separate coordinate dimension without taking advantage of the known relations between diverse dimensions [9].

A. Multivariate Spatial Interpolation in M-DAD

Most spatial data interpolation methods are based on the distance between the interpolation location P and the given set of data points. M-DAD defines a new metric for distance, suitable for higher dimensions, in which the concept of closeness is described in terms of relationships between sets rather than in terms of the Euclidean distance between points. Using this distance metric, a new generalised interpolation function f that is suitable for an arbitrary number of variables is defined.

In multivariate interpolation every set S_i corresponds to an input variable i.e. a sense modality, called i, and referred to as a dimension. In M-DAD, the distance functions do not need to satisfy the formal mathematical requirements for the Euclidean distance definition. The power of such a generalisation can be seen when we include the time variable as one dimension. The spatial data interpolation problem can be stated as follows:
Given a set of randomly distributed data points

$$x_i \in \Omega,\ i \in [1, n]\,,\ \Omega \subset \mathbb{R}^n \tag{1}$$

with function values $y_i \in \mathbb{R}$, and $i \in [1, N]$ we require a continuous function $f : \Omega \longrightarrow \mathbb{R}$ to interpolate unknown intermediate points such that

$$f(x_i) = y_i \text{ where } i \in [1, N]\,. \tag{2}$$

We refer to x_i as the observation points. The integer n is the number of dimensions and Ω is a suitable domain containing the observation points. When rewriting this definition in terms of relationships between sets we get the following:
Given N ordered pairs of *separated* sets $S_i \subset \Omega$ with continuous functions

$$f_i : S_i \longrightarrow \mathbb{R},\ i \in [1, N] \tag{3}$$

we require a multivariate continuous function $f : \Omega \longrightarrow \mathbb{R}$, defined in the domain $\Omega = S_1 \cup S_2 \cup ... \cup S_{n-1} \cup S_n$ of the n-dimensional Euclidean space where

$$f(x_i) = f_i(x_i)\, \forall x_i \in S_i \text{ where } i \in [1, N] \tag{4}$$

The proof is omitted for brevity.

Using the point to set distance generalisation, the function f can be determined as a natural generalisation of methods developed for approximating univariate functions. Well-known univariate interpolation formulas are extended to the multivariate case by using *Geometric Algebra* (GA) in a special way while using a point to set distance metric. Burley et al. [10] discuss the usefulness of GA for adapting univariate numerical methods to multivariate data using no additional mathematical derivation. Their work was motivated by the fact that it is possible to define GAs over an arbitrary number of geometric dimensions and that it is therefore theoretically possible to work with any number of dimensions. This is done simply by replacing the algebra of the real numbers by that of the GA. We apply the ideas in [10] to find a multivariate analogues of univariate interpolation functions.

B. Scale-based Local Distance Metric

In this section we modify the distance metric defined in Section III-A to include the knowledge given by the domain model. The domain model helps to significantly reduce the size of the support nodes set. The difference in the size of the support nodes set can be several orders of magnitude with increasing problem dimension. The increase in the support size can lead to an increase in the computation and processing times of the interpolation algorithm and lead to the same drawbacks of global interpolation methods. Therefore, the proposed metric attempts to balance the size of the support sets with the interpolation algorithm complexity as well as interpolation accuracy.

We define the term *scale* for determining the weight of every given dimension with respect to P based on a combined Euclidean distance criteria and the information already known about the application domain a prior network deployment. While the term *weight* is reserved for the relevance of a data site by calculating the Euclidean distance from that location to P. A special case is when f_i is identical for all S_i which means that all sets have the same scale.

For the purposes of M-DAD we define a new scale-based weighting metric, m_P, which uses the information given by domain model to alter the distance weighting function to improve the interpolation results when applied to an arbitrary number of dimensions. In M-DAD, the support set, C_i, for P is calculated using m_P. Symbolically, C_i is calculated as

$$C_i = L\left(d\left(P, E_j\right), \delta\left(S_i\right)\right) \quad \forall E_j \in S_i \tag{5}$$

where S_i is a set of observation points, $i \in [1, N]$, L is a local model that selects the support set for calculating P, d is an Euclidean distance function, E_j is an observation point in the dimension S_i, and $\delta(S_i)$ a set of parameters for dimension S_i. Each dimension can have different set of parameters. These parameters are usually a set of relationships between different dimensions or other application domain characteristics such as obstacles. When predicting the value of a point in dimension S_i we refer to that dimension as S_P.

Uni-dimensional distance weighting functions can be extended to multi-dimensional distance weighting systems as follows

$$\omega = K\left(P, S_i\right), \quad i \in [0, n] \tag{6}$$

where $K\left(P, S_i\right)$ is the distance from the interpolation position P to data set S_i and n is the number of dimensions in the system. Equation 6 can now be extended to include the domain model parameters of arbitrary dimensional system. Then the dimension-based scaling metric can be defined as

$$m_P = \sum_i L\left(K(P, S_i), \delta\left(S_i\right)\right) \quad i \in [0, n] \tag{7}$$

where $S_i \neq C_P$ and C_P is the dimension containing P.

IV. Distributed Self-Adaptation in Mapping Services

A. Benefits of Self-Adaptation

In this section we extend the capabilities of M-DAD to overcome challenges imposed by the described external system changes, e.g. topographical changes, through applying self-adaptation intelligence to continuously adapt to erratic changes in the application domain conditions. At run time, M-DAD integrates the sensory data with contextual information to update the initial application domain model provided by network owners to maintain a coherent logical picture of the world over time. Self-adaptation is particularly useful in long-term WSNs deployments where the environmental conditions changes significantly over time which necessitate updating the domain model to reflect the changes in the contextual knowledge provided by the physical constraints imposed by the local environmental conditions where sensors are located. This allows mapping services to evolve at run-time with less intervention of the user and leads to near-optimal and flexible design that is simple and inexpensive to deploy and maintain. This adaptation procedure will recover, over time, the effects of user domain modelling inaccuracies.

We realise that self-adaptation is a challenging problem and considerable work is being done by the research community in that area. However, in this work we aim to deal with a small set of adaptivity issues that have a significant effect on the mapping services.

B. Adaptability Implementation in M-DAD

To implement adaptability in M-DAD we exploit the interpolation capability of the network to perform local training of the map generation service. Each node uses the readings of its surrounding nodes to predict its own reading value (y') using m_P (eq. 7). Then, y' is compared to the node measured value, y. It is desirable that the estimate of y'minimises the standard deviation (σ). Nodes modify the size of the support set to include the minimum number of nodes needed to predict y with a certain level of accuracy. Furthermore, in multi-dimensional applications, nodes will change the weight of each dimension to improve the prediction accuracy of y'. In fact, nodes will alter the relationships between different dimensions initially given in the domain model in order to recover the effect of inaccuracies in the given domain model or to adapt to emerging environmental changes. In that, these model updates influence the estimation results because y' is calculated using m_p. Finally, a prediction accuracy criterion, Δ, is defined as the average σ_j where $\sigma_j = \sum_i \sqrt{(y_i - y_i')^2} \quad j \in [1, n]$ and $i \in [1, N]$ where n is the number of dimensions and N is the number of readings in dimension j. Then Δ is written as $\Delta = \frac{\sum \sigma_j}{n} \quad j \in [1, n]$. Δ must always be minimised to achieve the best mapping results.

However, when individual nodes alter their programmed domain model independently from the network, the mapping service may become unstable because of the inconsistency in the domain model defined on various nodes. Such inconsistencies may lead to inconsistent system states and conflicting differences in calculating mapping values. To ensure mapping stability we propose a *Virtual Congress Algorithm* to manage global model updates locally.

The Virtual Congress Algorithm (VCA) provides a high-level collaboration environment in which the system can achieve globally efficient behaviour under dynamic environmental conditions. The network is viewed as a virtual congress where nodes are *senators* who vote for *legislating* changes to the domain model in response to locally detected environmental conditions. This algorithm is an attractive solution as senators collaboratively decide upon their local knowledge on the behaviour and correctness of the system. Logically related nodes, *chambers*, are granted some power to impute the local changes, *federal laws*, that is not detected by all nodes in the network. A senator may introduce a proposal in the chamber as a *bill*. To prevent overloading the chamber with proposals, each senator must monitor the changes over time using equation **??** before putting them into a bill. Senators send their voting results to the proposing senator. The proposing senator, upon receiving the required number of votes v disseminate the bill to the chamber and all nodes implement the new changes that have been agreed on. The value of v was empirically estimated to be over 50% of chamber population because it helps to avoid false positives. Once a bill is approved by one chamber, it is sent to other chamber heads who may accept or reject it. In order for the bill to become a *state law*, all chamber heads must agree to identical version of the bill. When the bill is submitted to the *president*, the sink node, he may choose to sign the bill, thereby making it *a state law*.

V. Experimental Evaluation

Experiment 1: Incorporation of the Domain Model in the Mapping Services

Aim: The aim of this experiment is to study the effect of integrating the knowledge given by the domain model into the mapping services.

Procedure: In this experiment the effective thermal diffusivity in a cargo ship is studied. Some aspects of a cargo ship fire were modelled, particularly, heat diffusion in the metal body of the ship. The model was restricted to a small area of the ship deck which has two big doors. The chosen part of the ship deck is modelled by a brass sheet which contains a hole segment excavation to model an opened door. A simple domain model was defined to carry information about doors that when opened they impact the heat diffusion in the ship body. The hole segment that represents an opened door was excavated in the brass sheet with $10mm$ width and $2cm$ length. A FLIR ThermaCAM P65 Infrared (IR) camera [11] was used to take sharp thermal images and produce an accurate temperature analysis and results. The IR camera delivers 320×240 IR resolution (640×480 pixels, full colour) at $0.08C$ thermal sensitivity. Finally, a 1371^oC blue flame was placed on the middle of one edge of the brass sheet as a heat source. Brass (an alloy of copper and zinc) was chosen for this experiment because it is a good thermal conductor.

The first experiment was ran using the brass sheet before the hole segment excavation. After applying heat, thermal measurements from the Toradex Oak sensors were recorded in addition to a thermal image taken by the IR camera. The mapping services were ran over a subset of the data collected from this experiment to observe how the heat will diffuse in the brass sheet in the absence

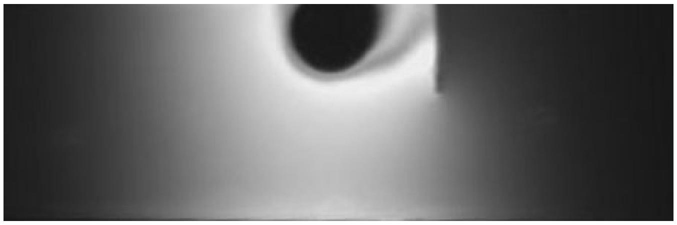

Figure 2. Heat diffusion map taken by ThermaCAM P65 Infrared (IR) camera.

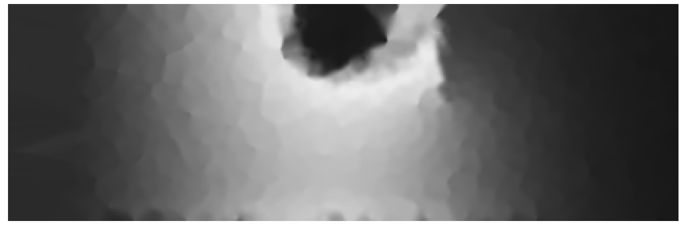

Figure 3. Heat map generated by the standard mapping service defined in [1].

of any obstacles. The same experiment was repeated on the sheet with the segment hole excavation and sensor thermal measurements as well as a IR camera image were taken after applying heat on the brass sheet. The mapping service were ran using the same size of the thermal data-set used in the previous experiment. Three experimental runs were performed: (1) Run the mapping services without any domain model knowledge. Particularly, the presence of the obstacle and its characteristics. (2) Run the mapping service which integrates *some* of the domain model knowledge. Particularly, the presence of the obstacle, its position, and length. (3) Run the mapping service which integrates all the knowledge given by the domain model. Particularly, the presence of the obstacle, its position, length, and strength.

Results and discussion: Figure 2 shows the heat diffusion map generated by the IR camera. Given that the heat is applied at the middle of the top edge of the brass sheet and the location of the obstacle, by comparing the left side and right side areas around the heat source, this figure shows that the existence of the obstacle has an effect on heat diffusion through the brass sheet. It its observed that the obstacle strongly reduced the temperature rise in the area on its right side. This map has been randomly downsampled to 1000 points, that is 1.5% of the total 455×147 to be used by the mapping service to generate the total heat map.

Figure 3 shows the map generated by the distributed mapping service described in [1]. Compared with Figure 2, the obtained map conserves perfectly the global appearance and many of the details of the original map with 98.5% less data. However, the area containing the obstacle has not been correctly reconstructed and caused hard edges around the location of heat source. This is due to attenuation between adjacent points and the fact that some interpolation areas contain many sensor readings with almost the same elevation. That asserts that modifications to map generation services are sometimes needed in order to interactively correct the mapping parameters.

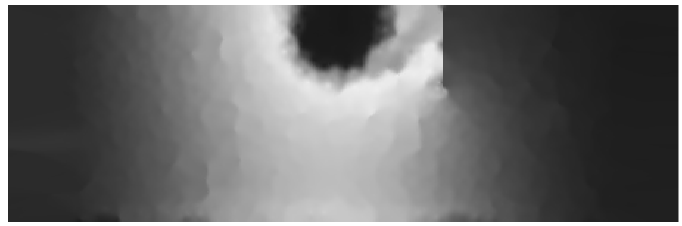

Figure 4. Interpolated heat map generated by M-DAD given obstacle location and length.

Figure 4 shows the map generated by the M-DAD mapping framework. M-DAD was given some information about the application domain including the existence of the obstacle, its location and length. We observe that the map obtained by M-DAD conserves perfectly the global appearance as the distributed mapping service (Figure 2). However, using the given local semantics, M-DAD reduced the prediction error and visually it accurately captured the effect of the heat obstacle on heat diffusion through the brass sheet. The M-DAD generated map is smoother than that rendered with the distributed mapping services, only in some sub-regions containing the obstacle and around the heat source location.

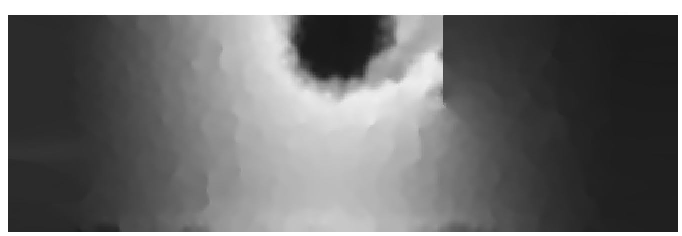

Figure 5. Interpolated heat map generated by M-DAD given obstacle location, width and length.

Figure 5 shows the map generated by M-DAD with a more complex domain model than the previous M-DAD version (Figure 4). In this version we give M-DAD the obstacle width. We notice a better approximation to the real surface near the obstacle. The new details included in the domain model removed two artifacts from both ends of the obstacle. This is due to the inclusion of the obstacle width in weighting sensor readings when calculating P which further reduces the effect of geographically nearby sensors that are disconnected from P by an obstacle.

Conclusion: This experiment proves that the incorporation of the domain model in the mapping service significantly improves the performance of the distributed mapping services.

Experiment 2: Mapping from Related Multiple Dimensions

Aim: The aim of this experiment is to study if mapping from related multiple types of the sense data can lead to an improved mapping performance by overcoming some of the limitations of generating a map from a single sense modality.

Procedure: 10 Toradex Sensors equipped with humidity and temperature sensors were placed over the brass sheet. Cold water was sprayed onto the brass sheet to increase the humidity in order to make relationships between the temperature and humidity more visible. Then, a blue flame was placed on the middle of the top edge of the brass sheet. Finally, the following steps were performed: (1) one temperature reading was removed from the collected data set; (2) the distributed mapping service was used to calculate the removed temperature reading using the rest of the data set; (3) M-DAD was used to calculated the removed temperature reading using the rest of the data set; (3) the standard deviation was calculated for the temperature value resulted from 2 and 3; (4) steps 1 to 4 were repeated for each of the 10 sensors temperature readings

Results and discussion: The relationship between the humidity and temperature was used to create a temperature map using the humidity map. Figure 6 shows the standard deviation of the calculated temperature values by M-DAD and the distributed mapping services. It is observed that M-DAD reduced the standard deviation by between 0.17% to 12% compared to the standard mapping service. This is done by constructing the support set from

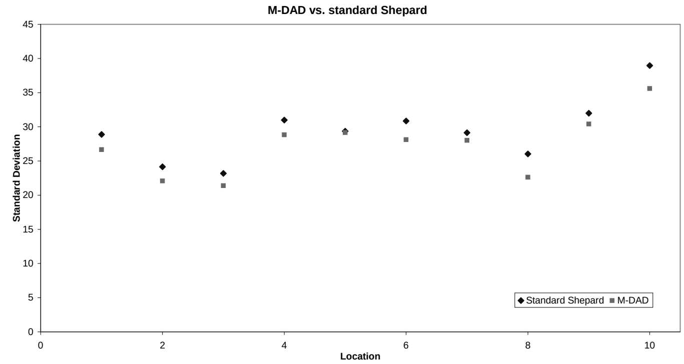

Figure 6. The standard deviation of temperature values at 10 locations calculated by M-DAD using the humidity map.

nodes which are more related to P, for example, nodes that have close humidity reading to that of P.

Conclusion: This experiment proves that mapping from related multiple dimensions can improve the generated map quality. This observation is confirmed by the data shown in Figure 6. The results from this experiment and Experiment 1 confirms the general theory of M-DAD defined in Section III.

Experiment 3: Adaptations to Changes in the Domain Model

Aim: The aim of this experiment is the study the effectiveness of the proposed VCA in modifying the domain model to better fit the current state of the application domain.

Procedure: The same experimental setup described in Experiment 1 is used here. The obstacle length was increased from $2cm$ to $3.6cm$. Then, the bill which contains the best detected obstacle length value, the federal laws, and the state laws were examined. Wireless communications breaks caused by an obstacle attenuation are hard to predict, but can be estimated using published metrics such that in [12]. It was assumed that the obstacle is continuous and the existence of this obstacle between two directly communicating nodes will break the wireless links between them. The local semantics of the application domain were defined to interpret the break of direct wireless links between two nodes while being able to communicate through an intermediate node(s) as *there exists an obstacle between the two communicating nodes.*

Results and discussion: Table I shows three M-DAD mapping runs each with different node distributions. We test three different randomly distributed nodes topologies because obstacle detection according to the model

Table I
THE OBSTACLE LENGTH (IN PIXELS) IN THE BEST PROPOSED BILL AND THE FEDERAL LAWS IN THREE M-DAD MAPPING RUNS AT 1000 NODES DENSITY.

Run	Num of bills	Best bill	Federal law
1	17	59.57	52.0
2	19	60.0	57.74
3	14	60.0	52.0

described here is highly dependent on the nodes location and density around the obstacle. Table I shows the number of proposed bills, the best proposed bill and the agreed bill for each mapping run. We notice that the obstacle length was always detected accurately and that the best proposed bill was not always agreed locally. This is partially due to the cluster formation process which is able to deal with obstacles (see [13]). Nonetheless, the average VCA agreed bills in the three mapping runs was 53.91 pixels which is close to the actual obstacle length (60 pixels). Adapting to the new obstacle length improves the produced map quality. Quantitatively, the RMS difference between the maps generated with 30 and 60 pixels obstacle length increased by 1.0.

We notice that in the three mapping runs, zero bills became federal laws. This is because all the changes in the application domain were local to part of the network and the majority of the clusters did not sense these changes. This illustrates the mutual benefit of localising the VCA and distributing it over two levels: the local/cluster level; and the global/network level.

Conclusion: This experiment shows that VCA helps to adapt to some changes in the domain model in a distributed manner. This experiment is an instance of the general case studied in Experiment 2, particularly, we are using the nearest neighbour triangulation RF connectivity map as one dimension to predict the heat map. Therefore, the improved mapping performance proved in this experiment confirms the results found in Experiment 2.

VI. Conclusion

In this paper we propose a new mapping framework called M-DAD. M-DAD is capable of dealing with an arbitrary number of sense modalities, performs distributed self-adaptation, exploits the application domain model, and generates maps using relationships between different sense modalities. M-DAD spontaneously responses to system changes. It starts with an initial model then it adapts and updates itself to give more precise image about the real world through a training procedure. Experimental results shows that M-DAD improves the mapping quality in terms of maps predictive error and smoothness.

References

[1] M. Hammoudeh, J. Shuttleworth, R. Newman, and S. Mount, "Experimental applications of hierarchical mapping services in wireless sensor networks," in *SENSORCOMM '08: Proceedings of the 2008 Second International Conference on Sensor Technologies and Applications*, 2008, pp. 36–43.

[2] M. Hefeeda and M. Bagheri, "Wireless sensor networks for early detection of forest fires," in *International Workshop on Mobile Ad hoc and Sensor Systems for Global and Homeland Security (MASS-GHS 07)*, Italy, October 2007.

[3] C. Hartung, R. Han, C. Seielstad, and S. Holbrook, "Firewxnet: a multi-tiered portable wireless system for monitoring weather conditions in wildland fire environments," in *MobiSys '06: Proceedings of the 4th international conference on Mobile systems, applications and services*, 2006, pp. 28–41.

[4] A. Deshpande, C. Guestrin, S. Madden, J. Hellerstein, and W. Hong, "Model-driven data acquisition in sensor networks," in *VLDB '04: Proceedings of the Thirtieth international conference on Very large data bases.* VLDB Endowment, 2004, pp. 588–599.

[5] D. Chu, A. Deshpande, J. Hellerstein, and W. Hong, "Approximate data collection in sensor networks using probabilistic models," in *ICDE '06: Proceedings of the 22nd International Conference on Data Engineering*, 2006, p. 48.

[6] P. Hertkorn and S. Rudolph, "From data to models: Synergies of a joint data mining and similarity theory approach," in *SPIE Aerosense 1999 Conference On Data Mining and Knowledge Discovery*, 1999.

[7] ——, "Dimensional analysis in case-based reasoning," in *International Workshop on Similarity Methods*, S. I. fr Statik und Dynarnik der Loft-und Raumfahrtkonstruktionen, Ed., 1998, pp. 163–178.

[8] J. Hofierka, J. Parajka, H. Mitasova, and L. Mitas, "Multivariate interpolation of precipitation using regularized spline with tension," *Transactions in GIS*, vol. 6, pp. 135–150, 2002.

[9] K. C. Johnson, *Multidimensional Interpolation Methods*, KJ Innovation, 2006, http://software.kjinnovation.com/InterpMethods.pdf.

[10] M. Burley, K. Bechkoum, and G. Pearce, "A formative survey of geometric algebra for multivariate modelling," in *UK Society for Modelling and Simulation*, 2006, pp. 37–40.

[11] F. Systems, "Thermacam p65," http://www.flir.com.hk/p65_print.htm, 2008, [Online; accessed 6-November-2008].

[12] Extricom, *Application Note - Wired and Wireless LAN Security*, Juniper Networks, November 2007.

[13] M. Hammoudeh, A. Kurtz, and E. Gaura, "MuMHR: multi-path, multi-hop, hierarchical routing," in *International Conference on Sensor Technologies and Applications (SENSORCOMM2007)*, 2007.