A Granular Multi-Sensor Data Fusion Method for Situation Observability in Life Support Systems

Gregorio E. Drayer* and Ayanna M. Howard†

Georgia Institute of Technology, Atlanta, Georgia, USA

Slow-changing characteristics of controlled environmental systems and the increasing availability of data from sensors and measurements offer opportunities for the development of computational methods to enhance situation observability, decrease human workload, and support real-time decision making. Multi-sensor data fusion, which combines observations and measurements from different sources to provide a complete description of a system and its environment, can be used in user-centered interfaces in support situation awareness and observability. Situation observability enables humans to perceive and comprehend the state of the system at a given instant, and helps human operators to decide what actions to take at any given time that may affect the projection of such state into the near future. This paper presents a multi-sensor data fusion method that collects discrete human-inputs and measurements to generate a granular perception function that supports situation observability. These human-inputs are situation-rich, meaning they combine measurements defining the operational condition of the system with a subjective assessment of its situation. As a result, the perception function produces situation-rich signals that may be employed in user-interfaces or in adaptive automation. The perception function is a fuzzy associative memory (FAM) composed of a number of granules equal to the number of situations that may be detected by human-experts; its development is based on their interaction with the system. The human-input data sets are transformed into a granular structure by an adaptive method based on particle swarms. The paper proposed describes the multi-sensor data fusion method and its application to a ground-based aquatic habitat working as a small-scale environmental system.

Nomenclature

x	Measured Variable	X	Universe of Discourse for x	X^{α}	Subset α in X
$\mu(x)$	Membership Function in x	$\tilde{A}$	Granular Structure	P^{*}	Parameter Solution

I. Introduction

One of the challenges of long-duration spaceflight is the capability of habitation systems to regenerate life support consumables, such as oxygen and water.[1] *Regenerative* life support systems (LSS) offer various options to recycle metabolic byproducts, such as urine, and to achieve an incremental closure of gaseous and liquid material cycles. Such *material closure* increases the autonomy of space habitats and helps reduce the frequency of resupply missions and their overall cost. An example of current regenerative LSS is the Water Recovery System (WRS) commissioned in the U.S. segment of the International Space Station (ISS), which recycles waste liquids back into potable (drinking) water. But as researchers continue efforts to integrate regenerative technologies and to achieve system closure, new challenges arise from unintended interactions between chemical species in the closed-loop system. Material loop closure not only makes possible the interconnection of complex material networks, but also promotes unintended interactions between

*Doctoral student, School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA 30332-0250, Fulbright S&T Fellow, and AIAA Member. E-mail: drayer@ieee.org

†Associate Professor, School of Electrical and Computer Engineering, Chair of the Robotics Ph.D. Program, Georgia Institute of Technology, Atlanta, GA 30332-0250, USA. E-mail: ayanna.howard@ece.gatech.edu

chemical species within the habitat. Such interactions may lead to the accumulation of unexpected chemical compounds that could affect individual life-support processes or crew health, or to the depletion of life support consumables. An example is the 2010 WRS anomaly caused by the accumulation of dimethylsilanediol (DMSD).[2] In addition, regenerative processes require energy and time to transform wastes and by-products into consumables. Consequently, their monitoring and operation impose considerable workload on human operators. All these challenges, in addition to their slow dynamic response, create vulnerabilities that, if unattended, may translate into human errors, performance deterioration, and failures.

The availability of novel chemical and biological sensors, together with evermore pervasive computational resources, enable the development of monitoring and automation systems to detect anomalies, alleviate human workload, avoid human error, and increase the overall reliability of LSS. This paper proposes a multi-sensor fusion method that elaborates on a granular approach to these challenges.[3] The approach employs an agent architecture based on FAM in an effort to allow for *situation observability*, *i.e.* the capability of non-expert human operators to probe for information about the situation of the system. Such attribute may also provide users with operational margin[2] to detect and respond to anomalies in a timely manner. However, the abundance of sensor information may result in a combinatorial explosion unsuited for the manual design of monitoring and automation systems. The core of this method consists of taking advantage of the interaction of human-experts with the LSS to generate and collect data useful for the development of the FAM that constitutes the perception function. In particular, the method proposed in this paper makes use of particle swarm optimization[4] (PSO) to *compress* sensor data and a set of human-expert situation assessments into a granular representation of their situation knowledge base (SKB). Such representation enables the transformation of sensor data into situation-rich signals useful for monitoring and automation purposes. Situation-rich signals may be used for adjustable autonomy mechanisms and for the design of ecological human interfaces in support of human-automation coordination and real-time decision making. In such a way, the purpose of this work is to make use of computational intelligence tools, consistent with control theory and principles in cognitive engineering, to contribute to the methodological development of situation-oriented and user-centered design approaches.[5]

A. Background

Multi-sensor data fusion consists of combining observations and measurements from a number of different sensors to provide a complete description of a system and its environment.[6] The main multi-sensor fusion methods are probabilistic in nature and derive from the application of tools in statistics, estimation, and control theory. These are: (1) the Bayes' rule, (2) probabilistic grids, (3) the Kalman filter, and (4) sequential Monte Carlo methods. However, shortcomings to probabilistic methods are found in their apparent inability to address unknown situations, which grows in importance for anomaly detection and management of emergent phenomena. There are four main limitations for probabilistic methods in multi-sensor data fusion:[6]

1. *Complexity*: This limitation in found in the large number of probabilities required to correctly apply probabilistic reasoning.
2. *Inconsistency*: It refers to the difficulty in obtaining consistent deductions about the state of a system from sets of belief that are not necessarily consistent.
3. *Precision of models*: This refers to the difficulty to obtain system representations, primarily caused by the inability to describe probabilities of quantities for which there is not enough available information.
4. *Uncertainty about uncertainty*: It is difficult to assign probabilities in the presence of unknown unknowns and uncertainty about sources of information.

Less traditional methods, such as interval calculus, fuzzy logic,[7] and evidential reasoning,[8–10] provide alternative approaches that help overcome these limitations.[6] Such approaches will support current research efforts in managing large-scale/ubiquitous sensor systems and anomaly detection applications. This paper represents a step toward a multi-sensor data fusion method for the development of monitoring and automation systems for LSS that may especially address unknown situations.

B. Organization

The paper is divided in four additional Sections. Section II introduces the FAM-based agent architecture on which the multi-sensor data fusion method proposed is developed. Section III presents the fusion method. Section IV illustrates the method with an application to the model of a small-scall aquatic habitat and discusses results. Finally, Section V provides concluding remarks.

II. Granular Approach to the Automation and Assessment of LSS

The FAM-based agent architecture has found motivation in the monitoring and automation of LSS[3] and implements a switched control approach[11] that assigns a control action to each situation in which the system may operate in the form of (Situation, Controller). The switching capability introduces flexibility in the behavior of the system and enables its development in a modular and incremental fashion. The architecture is characterized by a perception function, a set of controllers, and a correspondence function. The latter associates a controller to each situation defined in the perception function and combines them into an integrated control signal. Figure 1 shows a diagram of a single FAM-based agent with a user interface manipulating a single variable in a small-scale aquatic habitat. The diagram describes the components of the FAM-based agent consistent with Subsections A, B, and C. Some advantages of this approach have been shown in previous work.[3]

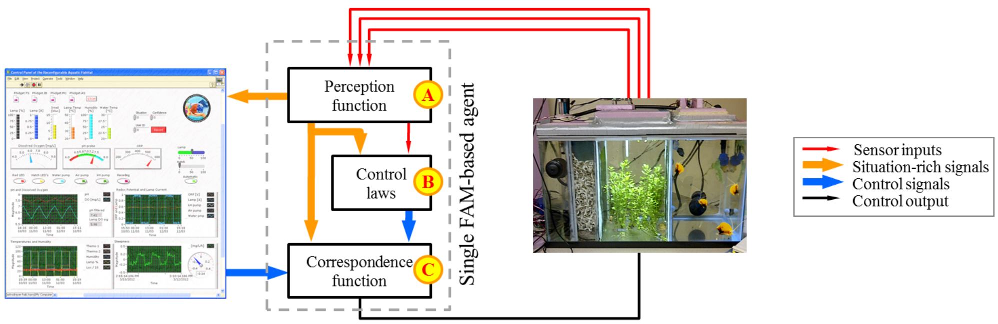

Figure 1. Diagram describing the FAM-based agent architecture and its components

A. Perception function and granular structure

Assuming the availability of n measurable variables x_i for $i = 1, 2, \ldots, n$ from sensors and their universes of discourse X_i so that $x_i \in X_i \subseteq \Re$, the variables being non-redundant and non-interactive: $X_i \neq X_j$; $j = 1, 2, \ldots, n$; $i \neq j$. Each universe X_i is partitioned in k_i subsets, each of which is denoted as $X_i^\alpha \subset X_i$, $\alpha = 1, 2, \ldots, k_i$. Continuous membership functions describe each one of the subsets as $\mu_{X_i^\alpha}(x_i)$, which are normal and convex.[12] Such partitions are *coherent* when complying with the Ruspini condition:[13]

$$\sum_{\alpha=1}^{k_i} \mu_{X_i^\alpha}(x_i) = 1 \qquad \forall i = 1, 2, \ldots, n \tag{1}$$

As a result, a number of l possible situations or operating conditions are defined as non-interactive fuzzy sets $\tilde{A}_j$, for $j = 1, 2, \ldots, l$. The l situations are the Cartesian product of the combination of the subsets X_i^α in X_i. The Cartesian product is implemented with the *minimum* operator as in Eq. 2, for $l = \prod_{i=1}^{n} = k_i = k_1 \cdot k_2 \cdot \cdots \cdot k_n$.

$$\tilde{A}_j\left(x_1, \ldots, x_n\right) = \min_{\substack{i=1,\ldots,n \\ \alpha=1,2,\ldots,k_i}} \left(\mu_{X_i^\alpha}\left(x_i\right)\right) \tag{2}$$

The set $\tilde{A} = \{\tilde{A}_j\}$ represents the granular structure in which each granule $\tilde{A}_j$ describes a different situation and a percept of the FAM-based agent.

B. Control signals

In the same fashion, the set of control signals $U = \{u_j\}$ are obtained from up to l different control laws. Controllers generate signals u_j that correspond to each condition $\tilde{A}_j$. These signals may be treated modularly to form the set $U = \{u_1, u_2, \ldots, u_l\}$, with the maximum number of different control signals limited by l. The control signals can be generated by model-based methods or techniques in soft-computing and computational intelligence. The error modulation solution[14] or a similar technique is required for controllers with integral control action (poles in zero). Considerations on switched control[11,15] should be included in this component of the FAM-based agent and in the correspondence function Ω described in the next Subsection.

C. Correspondence function and integrated control signal

With the sets $\tilde{A}$ and U defined, the Correspondence Function Ω can be expressed as a rule-base or in pairs (Situation, Control Signal) as in Eq. 3.

$$\begin{aligned}&\Omega : \tilde{A} \rightarrow U\\ &\Omega = \{\Omega_j\} = \left\{ \left(\tilde{A}_j\left(x_1, \ldots, x_n\right), u_j(t) \right) \right\}\end{aligned} \tag{3}$$

The resulting FAM is defuzzified with the weighted average technique to obtain an integrated control signal u_I. This signal drives a single actuator in the system. Thus, each actuator and its controller in a physical system may be conceived as an agent, constituting a FAM-based multi-agent system. The weights used in Eq. 4 are the membership values of each corresponding situation, and the weighted arguments are their corresponding control signals.

$$u_I\left(x_1, \ldots, x_n, t\right) = \frac{\sum_{i=1}^{l} \mu_{\tilde{A}_i}\left(x_1, \ldots, x_n\right) \cdot u_i(t)}{\sum_{i=1}^{l} \mu_{\tilde{A}_i}\left(x_1, \ldots, x_n\right)} \tag{4}$$

III. Granular Multi-Sensor Data Fusion Method

An advantage of the FAM-based agent architecture is the possibility to combine a large number of sensors. A disadvantage of this approach is the combinatorial explosion that makes intractable to manually define membership functions $\mu_{X_i^\alpha}(x_i)$ for situations α detected by each sensor $i = 1, 2, \ldots, n$. Therefore, this paper proposes the use of human-system interaction and the application of methods in computational intelligence to overcome this challenge. Figure 2 shows a diagram of the methodology proposed. The diagram describes the steps used, consistent with Subsections A, B, C. Step D has been addressed in previous work[3] and is not included in this paper.

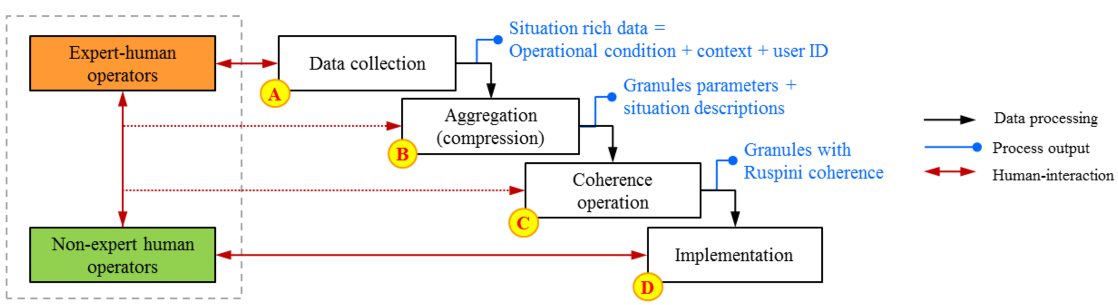

Figure 2. Human-system interaction and granular multi-sensor fusion method

The method collects situation assessments from expert human operators, i.e. system snapshots, to obtain situation-rich datasets that may be useful to generate a representation of the SKB of experts. Datasets containing a number of N snapshots are aggregated (compressed) into a parametric representation. The aggregation consists in a particle swarm optimization process that adapts π-membership functions to the data contained in the dataset for each sensor and each situation. The result is a granular structure useful for decision support tools and, when coherent, susceptible for adoption as the perception function of the FAM-based agent architecture. The following Subsections describe each one of these steps.

A. Data Collection

As Figure 2 shows, data collection consists of taking advantage of the interaction between expert human operators and the system to obtain situation rich datasets. These datasets include measurements of the *operating condition* of the system (internal state), its *context* (external state), and an *identifier* of the expert. Datasets contain N snapshots of the system at times t_j for $j = 1, 2, \ldots, N$ as shown in Figure 3.

	Measurements					Expert Input		
	Time	x_1	x_2	$\cdots$	x_n	Situation	Confidence	User Code
Dataset	t_1	x_{11}	x_{21}	$\cdots$	x_{n1}	s_1	c_1	h_1
	t_2	x_{12}	x_{22}	$\cdots$	x_{n2}	s_2	c_2	h_2
	$\vdots$	$\vdots$	$\vdots$		$\vdots$	$\vdots$	$\vdots$	$\vdots$
	t_N	x_{1N}	x_{2N}	$\cdots$	x_{nN}	s_G	c_N	h_N

Figure 3. Illustration of a data set resulting from the data collection process

Measurements of the system state, both internal and external, include values x_{ij} recorded by sensors x_i for $i = 1, 2, \ldots, n$. If sensors are not available, values may be systematically obtained and introduced by the expert through a user interface, depending on the nature of the measurement. In addition to measurements, the dataset includes *expert input* that defines to which situation s_γ the snapshots belong in each case, for $\gamma = 1, 2, ..., G$, and with what degree of confidence $c_j \in [0, 1]$. If $c_j = 1$, the expert is fully confident that the system snapshot taken at t_j belongs to situation s_γ. The number $G \geq l$ depends on the presence of hierarchical structures in the situation assessments according to the notion of *levels of resolution* in granular computing;[16] *i.e.* a situation assessed as "nominal" may be subdivided in more specific situations, such as "nominal-high" and "nominal-low." This paper does not address hierarchical granular structures, making $G = l$. Finally, the user code h_j allows the data collection process to identify the expert that contributed with each snapshot to the dataset, enabling for approaches in crowd-sourcing.[17,18] The intention with the following steps is to compress the dataset into a more compact and meaninful representation.

B. Aggregation or data compression

The aggregation algorithm transforms (compresses) situation-rich datasets into granular structures described by an array of parameters that define membership functions $\mu_{X_i^\alpha}$ for each situation γ susceptible for detection by sensors i. The following Subsections describe how situation knowledge is represented, how it is obtained from datasets, and suggests an approach to achieve coherence.

1. Knowledge representation

Given the need to allow for flexible adaptation of a membership function $\mu_{X_i^\alpha}$ to collections of snapshots found in the datasets, the aggregation algorithm makes use of a piece-wise differentiable function defined by four parameters and known as a π-membership function, defined in Table 1.

$\mu_{X_i^\alpha}$	0	$2\left(\frac{x_i-a}{b-a}\right)^2$	$1-2\left(\frac{x_i-b}{b-a}\right)^2$	1	$1-2\left(\frac{x_i-c}{d-c}\right)^2$	$2\left(\frac{x_i-d}{d-c}\right)^2$	0
Domain	$x_i \leq a$	$a < x_i \leq \frac{a+b}{2}$	$\frac{a+b}{2} < x_i \leq b$	$b < x_i \leq c$	$c < x_i \leq \frac{c+d}{2}$	$\frac{c+d}{2} < x_i \leq d$	$x_i \geq d$

Table 1. Piece-wise definition of $\mu_{X_i^\alpha}(x_i; a, b, c, d)$

The π-membership function results in the curve shown in Figure 4, with parameters $P = [a, b, c, d]$ defining the "feet" and "shoulders" of the curve. Each membership function in the aggregation process represents a single situation $\gamma = 1, ..., G$ for a single sensor x_i. The PSO process obtains the four parameters in each case, as described in the following Subsection.

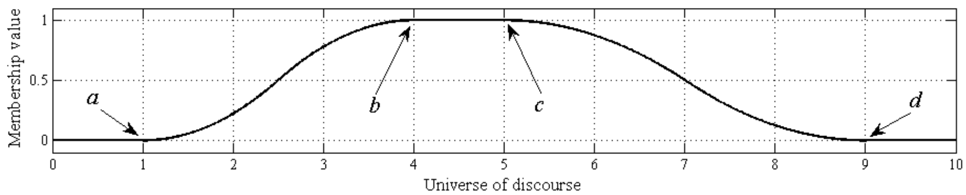

Figure 4. π-Membership function with parameters $P = [a, b, c, d] = [1, 4, 5, 9]$.

2. Particle swarm optimization

PSO[4] is the process that transforms the datasets in a granular structure. For each situation γ and sensor i, find $P^* \in X_i$ such that the condition in Eq. 5 is found, where $f(x_i) = \sum \left(\mu_{X_i^\alpha}(x_{ij}) - c_j\right)^2$ for $j = 1, 2, \ldots, N$ and in each case subject to the initial constraints shown in Table 2.

$$P^* = \arg\min_{x_i \in X_i} f(x_i) = \{x_i^* \in X_i : f(x_i^*) \leq f(x_i) \forall x_i \in X_i\} \tag{5}$$

	Constraints
1:	$a \leq b \leq c \leq d$
2:	$\min x_{ij} - 0.25 \lvert \max x_{ij} - \min x_{ij} \rvert \leq a \leq \min x_{ij}$
3:	$\min x_{ij} \leq b \leq \max x_{ij}$; $\min x_{ij} \leq c \leq \max x_{ij}$
4:	$\max x_{ij} \leq d \leq \max x_{ij} + 0.25 \lvert \max x_{ij} - \min x_{ij} \rvert$

Table 2. Initial constraints of the particle swarm optimization.

The swarm is subject to random variables $\zeta_1 \in [0, 1]$ and $\zeta_2 = 1 - \zeta_1$, to parameters $W = 0.99$, $\varphi = 0.02$, and follows the steps enumerated in Table 3 with p representing an agent (particle) in the population.

Step	Description
1.	Randomly distribute particle swarm (or swarm of agents) in the search space.
2.	Evaluate the performance of each particle according to $f(x_i)$.
3.	If the current position is better than previous ones, then update with the best.
4.	Determine the best particle so far according to their previous and present positions.
5.	Update velocities with $v_p^{t+1} = W \cdot v_p^t + \varphi \left[\zeta_1 \left(x_{lp}^t - x_p^t\right) + \zeta_2 \left(x_g^t - x_p^t\right)\right] \leq \frac{\lvert \max x_{ij} - \min x_{ij} \rvert}{100}$.
6.	Update positions of particles according to $x_p^{t+1} = x_p^t + v_p^{t+1}$.
7.	Repeat from (2) until $f(x_i^*) < \frac{\lvert \max x_{ij} - \min x_{ij} \rvert}{500}$ or iterations = 2000.

Table 3. Particle swarm optimization algorithm

The process results in a granular structure described by an array of dimensions $G \times n \times 4$ as shown in Figure 5. Although the PSO may converge to a "best" result, the irregularities introduced by the data collection step make necessary to employ a coherence operation to obtain granular structures that comply with the Ruspini condition in Eq. 1. The advantage of using PSO is the flexibility it provides to vary the computer power invested in the aggregation process.

C. Coherence operation

The coherence operation adjusts parameters P of each fuzzy set $\mu_{X_i^\alpha}$ by determining their similarity or proximity, and performing operations on $P = [a, b, c, d]$ in each case. For example, the similarity between two fuzzy sets with parameters P' and P'' can be determined by $\min(P'') < \bar{P}' < \max(P'')$, where $\bar{P}'$ is the average of the parameters of P'. Future research will elaborate on granular computing solutions to this operation. Section IV presents results from a numerical example that support such effort.

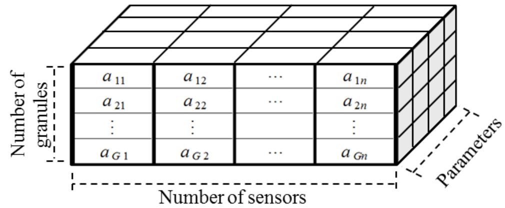

Figure 5. Three dimensional array containing granular structure

IV. Implementation in a Small-Scale Aquatic Habitat

A model of an aquatic habitat[19] was used to perform simulations of anomalies that exhibit transitions between various operation conditions. The purpose was to operate under all possible situations so that data could be collected. This example makes use of two sensors: dissolved oxygen(DO) and pH. Possible levels of pH are high, good, or low levels, while DO levels are good or low, resulting in six possible situations. Expert human operators were modeled as a prototype granular structure to collect data for confidence values greater than 0.1. They read a different situation every 5 minutes throughout 21 days, allowing for each situation to be monitored every 30 minutes. The data obtained is processed with steps (A), (B), and (C) of Section III.

A. Results

Figure 6 shows four 3-D graphs comparing results obtained from the sensor fusion algorithm with the prototype granular structure. Each situation is defined by a different color. Figure 6(A) provides a spatial distribution of the confidence values c_j. The number of data points collected in each situation is not uniform. The algorithm obtains granules independently of the number of data points. Figure 6(B) shows the resulting granules. The output of step (B) is processed with a coherence operation based on similarity and proximity, resulting in Figure 6(C).

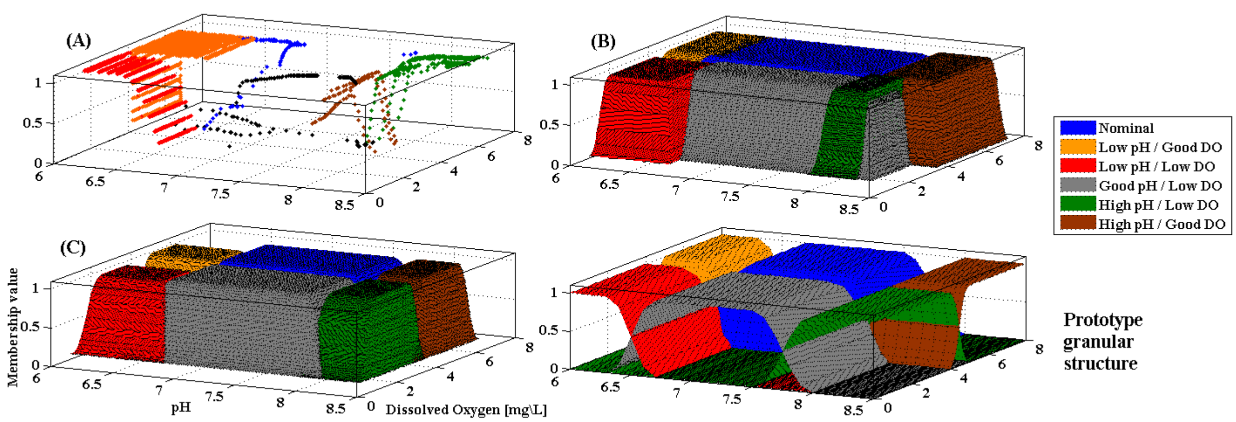

Figure 6. Comparison of the outputs of steps (A), (B), and (C) with prototype granular structure.

B. Discussion

The lack of uniformity in the distribution of data points collected by expert human operators poses a challenge to the application of tools in computational intelligence for the development of decision aids and automation systems. Special attention should be given to how experts collect data and on the number of data points needed to guarantee coherence of granular structures. With better datasets, the particle swarm optimization should arrive at solutions without excessive overlaps or holes, as those shown in Figure 6(B). However, the result also exhibits regularity in the distribution of the granules, even if some situations register a few number of data inputs. This regularity can be observed when comparing Figure 6(B) to the prototype granular structure used to model the SKB of expert human operators. Another question related to quality of datasets is how parameters of the particle swarm may compensate for the lack of human inputs. One advantage of making use of PSO is the flexibility it provides to increase computing power to arrive at solutions to the optimization problem. This supports and suggests the need for research that may help to characterize the performance of the particle swarm aggregation algorithm working under different search parameters, particle population sizes, and sizes of datasets. A final observation can be made on the borders of the output granular structures as compared to the prototype. Because the granules obtained are product of the datasets used, they are not able to define situations beyond those values. In other words, those areas not covered by the granules represent *unknown* situations. This implies that under such conditions a non-expert human operator should request assistance from experts, either to record new assessments in datasets or to evaluate the need for intervention.

V. Conclusions

This paper presented a granular multi-sensor data fusion method that collects assessments from expert human operators to generate a granular structure suitable for decision support tools and automation systems. The methodology presented in this paper offers an approach to overcome the combinatorial explosion of merging information from a large number of sensors. It makes use of human-system interaction to generate datasets that are processed with tools in computational intelligence. Expert assessments define the operational condition of the system with a subjective assessment of its situation. An algorithm based on particle swarm optimization obtains a representation of the SKB of human experts. This representation is useful to design ecological user-interfaces and for detecting unknown situations by non-expert users. Future research will explore how these tools may be combined with principles in evidential reasoning to detect anomalies in the operation of LSS, and to allow for operational margin and timely intervention.

Acknowledgments

This work was supported by the International Fulbright Science and Technology Program of the Bureau of Educational and Cultural Affairs of the U.S. Department of State and by the Human-Automation Systems Lab of the School of Electrical and Computer Engineering of the Georgia Institute of Technology.

References

[1] Eckart, P., *Spaceflight Life Support and Biospherics*, Springer, USA, 2nd ed., 2010.

[2] McCoy, T., Flint, S., Straub, J., Gazda, D., and Schultz, J., "The Story Behind the Numbers: Lessons Learned from the Integration of Monitoring Resources in Addressing an ISS Water Quality Anomaly," *41st ICES*, 2011.

[3] Drayer, G. and Howard, A., "A Granular Approach to the Automation of Bioregenerative Life Support Systems that Enhances Situation Awareness," *2nd IEEE CogSIMA*, 2012.

[4] Eberhart, R. C., Kennedy, J., and Shi, Y., *Swarm Intelligence*, Morgan Kaufmann, 2001.

[5] Endsley, M. and Jones, D. G., *Designing for situation awareness*, Taylor & Francis Group, 2nd ed., 2012.

[6] Durrant-Whyte, H. and Henderson, T. C., *Springer Handbook of Robotics*, chap. 25, Springer, 2008, pp. 585–614.

[7] Ross, T., *Fuzzy Logic with Engineering Applications*, John Wiley & Sons, 3rd ed., 2010.

[8] Shafer, G., *A Mathematical Theory of Evidence*, Princeton University Press, 1976.

[9] Kohlas, J. and Monney, P.-A., *A Mathematical Theory of Hints*, Springer-Verlag Berlin Heidelberg, 1995.

[10] Yager, R. R. and Liu, L., editors, *Classic Works of the Dempster-Shafer Theory of Belief Functions*, Springer, 2008.

[11] Hespanha, J. P., Liberzon, D., and Morse, A. S., "Overcoming the limitations of adaptive control by means of logic-based switching," *Systems & Control Letters*, Vol. 49, No. 1, 2003, pp. 49 – 65, Adaptive Control.

[12] Zadeh, L., "Fuzzy sets," *Information and Control*, Vol. 8, No. 3, 1965, pp. 338 – 353.

[13] Ruspini, E. H., "A new approach to clustering," *Information and Control*, Vol. 15, No. 1, 1969, pp. 22 – 32.

[14] Drayer, G. and Strefezza, M., "Integral Control with Error Modulation in a FAM-based Agent for a Furuta Inverted Pendulum," *2008 IEEE World Congress on Computational Intelligence*, Hong Kong, June 01-06 2008, pp. 1590–1597.

[15] Liberzon, D., *Switching in Systems and Control*, Birkhäuser, 2003.

[16] Yao, Y., "Perspectives of Granular Computing," *2005 IEEE Int'l Conf. on Granular Computing*, Vol. 1, 2005, pp. 85–90.

[17] Doan, A., Ramakrishnan, R., and Halevy, A. Y., "Crowdsourcing systems on the World-Wide Web," *Commun. ACM*, Vol. 54, April 2011, pp. 86–96.

[18] Prestopnik, N. R. and Crowston, K., "Gaming for (Citizen) Science: Exploring Motivation and Data Quality in the Context of Crowdsourced Science through the Design and Evaluation of a Social-Computational System," *e-Science Workshops, IEEE International Conference on*, Vol. 0, 2011, pp. 28–33.

[19] Drayer, G. and Howard, A., "Design, Modeling and Simulation of a Reconfigurable Aquatic Habitat for Life Support Control Research," *41st International Conference on Environmental Systems*, AIAA, Portland, Oregon, July 2011.