Human-Expert Data Aggregation for Situation-Based Automation of Regenerative Life Support Systems

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Regenerative life support systems (RLSS) introduce novel challenges for the development of automation systems given the emerging behaviors that result from incremental system closure. Switching control paradigms offer the ability to manage such uncertainty by allowing flexibility into the control path, enabling for autonomy modes that depend on the situation of the system. Previous research proposed a granular approach that combines sensor information to define operation conditions and act upon them. It makes use of fuzzy associative memories (FAM) to define the pairs (Situation, Controller) that assign control actions to each situation. The FAM are composed granules that represent situations in which the autonomous system may operate. One of the challenges of this approach is the combinatorial explosion that arises for large numbers of sensors. Human-system interaction offers a solution to this problem and, for such purpose, this paper elaborates on the aggregation of human-expert data to obtain the granular structure of the FAM. The aggregation process consists of an optimization process based on particle swarms. The result is a three dimensional array with parameters that define *n*-dimensional non-interactive granules. Two alternatives are presented in this paper: (1) a four-dimensional optimization algorithm to obtain normal fuzzy sets, and (2) a five-dimensional alternative that results in subnormal fuzzy sets. The results were obtained with simulations of an aquatic habitat that serves as a small-scale model of a RLSS. The discussion elaborates on which of the two alternatives may be better suited for applications in situation assessment and automation.

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 incremental system closure, new challenges arise from their operation. The closure of material cycles not only makes possible the interconnection of complex material networks, but also opens the possibility for unexpected events and emergent dynamic behaviors. Such behaviors are not susceptible to prediction and are discovered as *anomalies* during operation.[2] For closed-loop LSS, emergent behaviors may manifest by unexpected physico-chemical reactions and accumulation of undesired chemical compounds. Such is the case of the 2010 WRS anomaly caused by the accumulation of dimethylsilanediol (DMSD).[3] In addition, regenerative processes require energy and time to transform wastes and byproducts 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.

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The invention of methods to measure environmental variables by means of microsystems or optical devices tends to reduce the unit cost of novel sensor technology and opens opportunities for engineers to integrate evermore complex systems. Such innovations allow individual human operators to perform more complex tasks and to support their effort through automation. This paper proposes a multi-sensor fusion method that elaborates on a granular approach to these challenges.[4] It makes use of sensor data and expert assessments to generate a granular perception function in support of situation awareness. The method employs an agent architecture based on FAM[4] 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. However, the abundance of sensor information may result in a combinatorial explosion unsuited for the manual design of monitoring and automation systems; the difficulty of manually defining fuzzy sets for each individual condition makes such technique impractical. Therefore, the main contribution of this paper proposes to exploit the interaction of human experts with the system to collect situation-rich data useful to represent their situation knowledge base (SKB). The SKB is then used in the perception function of the FAM-based agents to generate the switching signals that combine control laws into its integrated control signal. Switching signals contain information about the situation of the system that may also be used in user-interfaces for human-automation coordination. This general contribution is composed of four more specific ones that include the following steps: (1) data collection, (2) aggregation algorithm, and (3) coherence operation. In particular, the method proposed in this paper makes use of particle swarm optimization[5] (PSO) to *compress* sensor data and a set of human-expert situation assessments into a granular representation of their SKB. 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.[6]

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.[7] 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:[7]

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 beliefs 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,[8] and evidential reasoning,[9–11] provide alternative approaches that help overcome these limitations.[7] 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-scale aquatic habitat and discusses results. Finally, Section V provides concluding remarks.

II. Granular Approach to the Automation and Assessment of LSS

The granular approach employed makes use of the FAM-based agent architecture.[4] The architecture is characterized by a (1) perception function, (2) a set of controllers, (3) and a correspondence function. The latter associates controllers to each situation that is detected by the perception function and combines them into a single integrated control signal. Each signal is intended to drive an actuator and, consequently, for each actuator a FAM-based agent may be defined. The FAM-based agent architecture implements a switched control paradigm[12] that assigns a control action to modes of operation in which the system may perform, *i.e.* in the form of (Situation, Controller). The switching nature of the agent introduces flexibility and modularity to the system and enables its incremental development. The challenge in this case is to develop the FAM with the intention to promote the coordination of multiple agents, including humans. Hence, the granular approach used is conceived as a situation-oriented and user-centered methodology, as will be presented in Section III. 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 and running examples have been shown in previous work.[4]

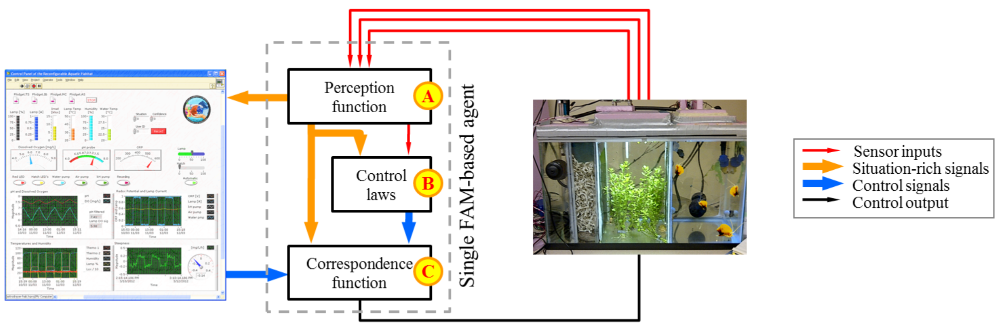

Figure 1. Diagram describing the FAM-based agent architecture and its components

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.[13] Such partitions are *coherent* when complying with the Ruspini condition:[14]

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

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[15] or a similar technique is required for controllers with integral control action (poles in zero). Considerations on switched control[12,16] 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 makes use of human-system interaction and of tools 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[4] and is not included in this paper.

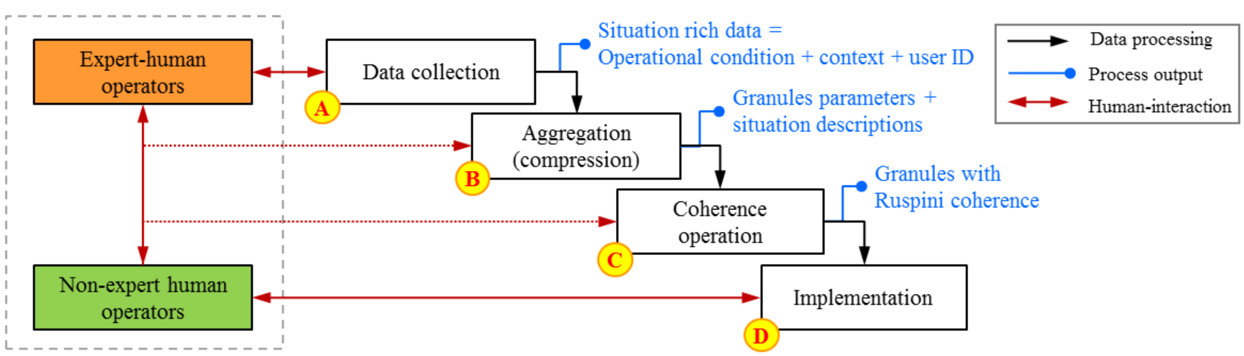

Figure 2. Human-system interaction and granular multi-sensor fusion method

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

The measurements from sensors x_i are denoted as x_{ij}, for $i = 1, 2, \ldots, n$. If a sensor measurement would not be electronically available, these values may also be manually introduced by the expert through a user interface. In addition to sensor measurements, the dataset includes assessments defining situation codes s_γ, for $\gamma = 1, 2, ..., G$. These values are accompanied by the 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 *levels of resolution* in the situation assessments;[17] *i.e.* a granule defined as "nominal" may be subdivided in subgranules, such as "nominal-high" and "nominal-low." This paper makes $G = l$, and does not address hierarchical granular structures. Finally, the user code h_j allows to identify the number of human experts contributing to the dataset, enabling for crowd-sourcing techniques.[18]

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 is shown in Figure 4, with parameters $P_4 = [a, b, c, d]$ for normal or $P_5 = [a, b, c, d, e]$ for subnormal fuzzy sets. Each membership function represents a single situation $\gamma = 1, ..., G$ for a single sensor x_i. The PSO process obtains the four or five parameters in each case, as described in the following Subsection.

2. *Particle swarm optimization*

A PSO[5] 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.

$$P^*_{4,5} = \arg\min_{x_i \in X_i} f(x_i) = \{x_i^* \in X_i : f(x_i^*) \leq f(x_i) \forall x_i \in X_i\} \tag{5}$$

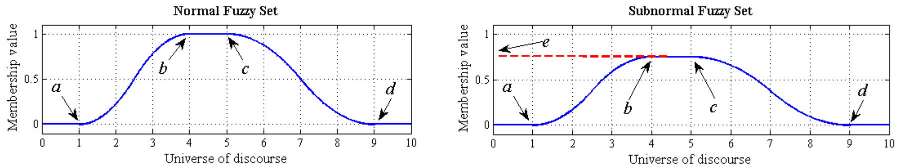

Figure 4. Plot of π-Membership functions with parameters P_4 and P_5.

	Constraints
1a:	$a \leq b \leq c \leq d$ for $P_{4,5}$, and 1b: $0 \leq e \leq 1$ for P_5
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 as the array of dimensions $G \times n \times 4$ shown in Figure 5. Although the PSO does not necessarily converges to the global optimum, 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.

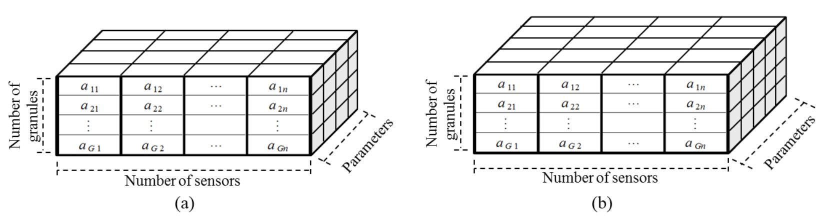

Figure 5. Three-dimensional array containing granular structure for (a) P_4 and (b) P_5.

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 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.

IV. Implementation in a Small-Scale Aquatic Habitat

A model of an aquatic habitat[19] was used to perform simulations of anomalies that exhibit operation condition transitions to enable data collection. It makes use of two sensors to allow visualization: dissolved oxygen (DO) and pH. Possible levels of pH are high, good, or low levels, while DO levels can be good or low, resulting in a combination of 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.

A. Results

Figure 6 shows six 3-D graphs comparing results obtained from human-expert data aggregation algorithm. Each situation is represented by a different color according to the legend. All graphs are meant to be compared with the prototype granular structure in the top left. Graph (A) (bottom left) provides a spatial distribution of the confidence values c_j. Graphs in the center column (B) are the result of the 4-D (top) and 5-D (bottom) aggregation variants. Outputs of step (B) are processed with a coherence operation based on similarity and proximity, resulting in the Graphs (C) of the third column (right-hand side).

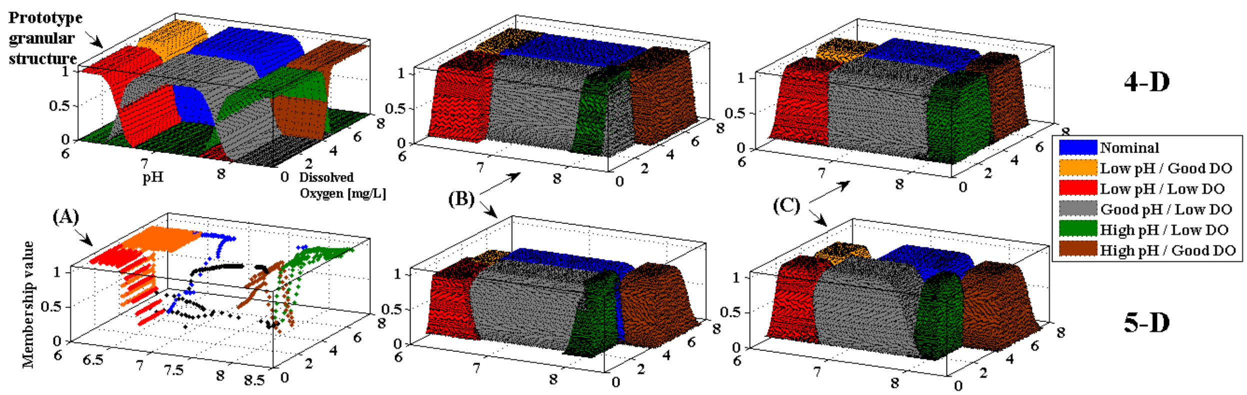

Figure 6. Comparison of the outputs of steps (A), (B), and (C) with prototype granular structure.

B. Discussion

From the granular structure obtained in (B) and (C), the four-dimensional algorithm with coherence operation (top-right) shows the best *regularity* in the distribution of granules and *similarity* to the prototype granular structure. The regularity refers to the positions of the situations, *e.g.* their location by color and lack of conflict with other situations (no intersections across). The greatest difference between these two is in their coverage of pH and DO values, *i.e.* their borders: for the prototype, the borders are "open," representing the SKB of the experts, while the other has "closed" borders. Because most points in the sensing space will be dominated by a single control action, regularity and coherence are best for automation applications. However, depending on the quality of the datasets, it may not be the best representation of the situation assessments made by experts. A faithful representation of the confidence values recorded by human experts could provide insights and useful information about unknown situations. Under such operation conditions, decision support tools may employ signals from subnormal granules to alert non-expert users about the need to call an expert to perform measurements and collect additional data points. Every time new data points are collected, the aggregation algorithm needs to be run to obtain an updated granular structure.

The situation-rich signals generated by the FAM-based agent take values between 0 and 1, and can be used as switching signals to activate or inhibit controllers driving each actuator in the system in each situation.[4] These signals are also useful to develop decision support tools and ecological user interfaces.[20] They are indeed an approach to data abstraction that may find applications in mission control consoles, astronaut decision aids, and anomaly detection. Future research aims to implement this approach in real-system settings, and to answer questions related to the quality of datasets, the performance of the aggregation algorithm, alternatives to the coherence operation, and techniques for the development of ecological user interfaces. Future theoretical advances will focus on how this approach may be further informed by tools in fuzzy logic and evidential reasoning toward the assessment and management of known and unknown situations in RLSS.

V. Conclusion

This paper elaborated on the aggregation of human-expert data to obtain a granular structure useful for applications in automation and situation assessment of closed-loop LSS. As regenerative LSS grow in complexity, so does the potential for emergent behaviors that result from incremental system closure. Switching control paradigms offer the ability to manage such uncertainty by adding flexibility and modularity to the control path of automation systems, enabling autonomy modes that depend on the situation of the system. This paper made use of the FAM-based agent architecture and focused on making use of human-system interaction to avoid the combinatorial explosion that results from abundant sensor information. The FAM are composed granules that represent situations in which the autonomous system may operate. The human-expert data aggregation process consists of an optimization algorithm based on particle swarms. Two alternatives were presented in this paper: (1) a four-dimensional PSO algorithm for π-membership functions to obtain normal fuzzy sets, and (2) a five-dimensional one that results in subnormal fuzzy sets. Future research will explore how these tools may be combined with principles in evidential reasoning to detect anomalies in the operation of closed-loop LSS, and to allow for operational margin and timely intervention.

Acknowledgments

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