# A Fuzzy Based Architecture for Learning Relevant Embedded Agents Associations in Ambient Intelligent Environments

Hakan Duman, *Member, IEEE*, Hani Hagras, *Senior Member, IEEE* and Victor Callaghan

***Abstract*—This paper presents a novel fuzzy-based intelligent architecture that aims to find relevant associations between services provided by devices and embedded agents residing in Ambient Intelligent Environments (AIEs). The embedded agents perform two processes where the first process monitors the inhabitants of the AIE and learns their behaviors in an online, non-intrusive and life-long fashion. The second process then evaluates the relevance and significance of the associations to various services and eliminates the redundant associations in order to minimize the agent computational latency within the AIE. We will present real world experiments that were conducted in the Essex intelligent Dormitory (iDorm) to evaluate and validate the significance of the proposed architecture.**

## I. Introduction

The notion of Ambient Intelligence (AmI) has initially arisen through the efforts of the European Commission in identifying challenges for European research and development [1]. The main aim of AmI is to deliver digital services and applications for the occupants of every inhabitable environment and to support their every day activities in a non-intrusive manner [1]. AmI is a multi-disciplinary research field combining many areas including ubiquitous computing, pervasive communications and intelligent agents. The ubiquitous computing and pervasive communication technologies provide a scalable distribution and seamless integration of devices and their services into a heterogeneous environment. On the other hand, *intelligent agents* equip these devices with intelligent reasoning and learning capabilities.

In general, the AmI vision describes an environment of potentially hundreds of thousands of embedded and mobile devices interacting to support particularized user goals and activities. However the multitude of interconnected devices and services can result in major agent computational latency (accumulating from the processing and communication overheads) as well as creating inherent complexities in programming and configuring the Ambient Intelligent Environments (AIEs) (i.e. the environments that possess AmI). Hence, a major challenge in AmI involves finding the *most relevant* associations between devices and services that are suitable for the environment and the user's specific needs while eliminating unnecessary and redundant associations (thus dissolving unneeded communication links). This will lead to realization of AIEs with large number of devices as well as improving the efficiency and reliability of the overall network in an AIE. To date, different approaches have been proposed to address the relevancy of devices for a given problem and domain. One of the well-known approaches is the semantic web [2] where devices and their services are tagged with attributes and semantic descriptions so that they can exhibit the ability to autonomously search through the space for similar devices and services and form associations with them. Based on a given ontology the devices emerge to semantically-driven functional clusters and provide a reliable device as well as service discovery and aggregation. A significant body of work is also emerging within the multi-agent system community which studies the integration of agent technologies to intelligently learn and exploit relevancy between associations [3], [4]. The learning employed in [3], [4] was accomplished by task-specific predefined policies which enable the agents to specifically associate with available devices in the search space and allow some degree of adaptation e.g. to have policies for new devices joining the domain or a existing ones leaving, which is commonly the case for mobile devices. However, it cannot always be assumed that the devices and services present in an AIE are semantically described or predefined with operational policies. Hence, to allow the full realization of AIEs, the devices need to learn their associations and adapt their policies or rules during operation to changes and failures occurring within the environment.

This paper presents a novel fuzzy based intelligent method that is based on a function/semantic-independent exploration algorithm to find and learn the most relevant associations between various devices and services in an AIE. The proposed approach employs fuzzy-based embedded agents due to their robustness to the uncertainties, noise and imprecision attributed to real world systems as in AIEs. The embedded agents seek to reduce the number of associations to other devices to minimize both the communication and computational processing latencies generated by the redundantly interconnected devices while satisfying the AIE and the user's personalized needs. The proposed approach for the Fuzzy Intelligent Association System (F-IAS) based agents employs two processes. The first process uses a one-pass unsupervised online life-long learning technique to generate a fuzzy model of the user's particularized behavior and needs. The second process performs an online intelligent association exploration based on modified hebbian-learning to calculate the association weights (relevancy) between services and the F-IAS agents. The proposed approach has

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Hakan Duman, Hani Hagras and Victor Callaghan are with the Computer Science Department, University of Essex, Wivenhoe Park, Colchester, CO43SQ, UK (e-mail: hduman@essex.ac.uk).

been tested and verified in the Essex intelligent Dormitory (iDorm) which is a unique test bed for AIEs research.

Section II will introduce the Intelligent Association System Framework. Section III will present the fuzzy F-IAS agents. Section IV will present the experiments and results followed by the conclusions in section V.

## II. The Intelligent Association System Framework

The Intelligent Association System (IAS) defines the architectural framework for the intelligent association exploration method as depicted in figure 1 [5]. The IAS framework combines all devices and their services to a decentralized service-oriented overlay network architecture. The services provided by devices are combined into societies according to their relevancy and are associated with Fuzzy-IAS agents (F-IAS) which integrate intelligent association learning and exploration capabilities. It should be noted that F-IAS agents can be separate entity of the system (e.g. in form of software agents) however here these agents are embedded into actuation devices (e.g. lamp, heater, TV etc) thus becoming *intelligent embedded agents*. In contrast, the services are pure information providers where they can transmit sensory states, etc. The F-IAS agents aim to learn their particularized behavior by monitoring the user interacting with them in a non-intrusive and life-long manner. The agents simultaneously conduct a search through the IAS overlay network to find the most relevant services required for their tasks.

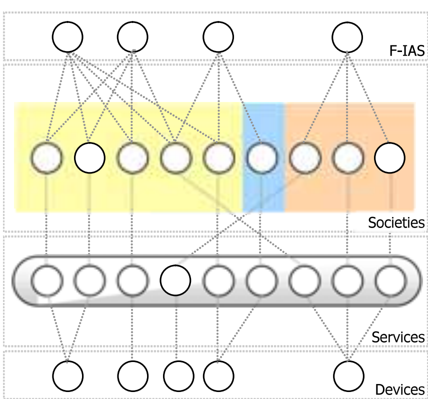


Fig. 1. The Intelligent Association System Framework.

## III. The Fuzzy-IAS Agents

### A. Fuzzy Cognitive Maps

A Fuzzy Cognitive Map (FCM) is a combination of fuzzy logic and neural networks; it combines the heuristic and common sense rules of fuzzy logic with the learning capabilities of neural networks [6]. They were introduced by Kosko [6], who used fuzzy reasoning to enhance the cognitive maps that had been previously used in the field of socio-economic and political sciences to analyze social decision making problems. Kosko considered fuzzy values in the variables of cognitive maps and utilized them in order to represent causal reasoning.

The F-IAS agents uses the structural notions and descriptions of Fuzzy Cognitive Maps (FCMs) [5] allowing causal evaluation among the associated services. The most significant characteristics of FCMs that comply with the F-IAS agents are:

- The FCMs structure allows the F-IAS agents to dynamically reorganize themselves, e.g. new services can be integrated or existing ones removed during operation in an ad-hoc fashion.
- The F-IAS agents or services can form the concepts/nodes of FCMs.
- The connections of the FCMs can illustrate the association and causality, e.g. an associated service causes the F-IAS agent to change its state.
- The association among the F-IAS agents and services is indicated with a weight value, which illustrates the strength of the causation and as a result represent the importance of the association.
- An unsupervised mechanism (mostly Hebbian learning [5]) for FCMs gradually learns the association strengths after correlating the changes of two associated entities.
- The overall system is event-driven and decentralized.

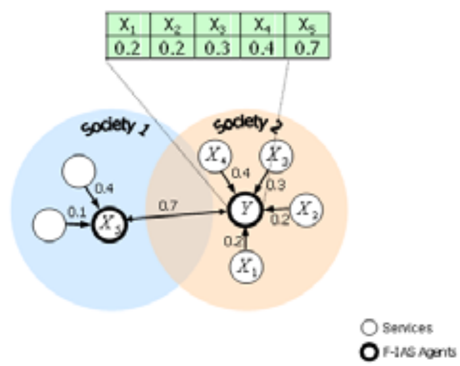


Fig. 2. The concept of Fuzzy Cognitive Maps for F-IAS Agents.

The above characteristics show that FCMs in general are well suited for determining the relevant associations among F-IAS agents and services. In addition, FCMs comply with the high-level concept and notions of the IAS architecture.

F-IAS agents and services are associated with each other to shape a society. The dynamic nature of FCMs allows the societies to become an ad-hoc and distributed environment, where new devices can join or existing ones leave in real time and without human intervention. Figure 2 illustrates how FCMs are employed for the IAS framework based on two societies.

Note that the services and F-IAS agents of each society are fully interconnected with each other at the physical layer of a network. However since the IAS framework resides at a higher level the services can demonstrate different associations between the F-IAS agents forming various structures of societies. Furthermore the F-IAS agents personify Embassador Agent capabilities [5] which can form a bridge between the societies so that information from a service based in society 1 can be transmitted via the F-IAS agent to society 2. The main advantage of employing Embassador capabilities to a F-IAS agent is to reduce the networking and processing overloads and enable them to learn the users behavior only based on the required and relevant services. Hence, instead of receiving information from every single service of the network, the F-IAS agents can communicate and request society related filtered information from each other [5].

### *B. The F-IAS Agent Controller*

The F-IAS agent perceives the environment through the sensory information provided by the associated services and it affects the environment through its actuator based on its learnt fuzzy logic controller that approximates and models the particularized preferences of the user. It is assumed that each F-IAS agent has a *N:1* relationship meaning that *N* possible services can be associated to *1* F-IAS agent's output. It should be noted that this assumption can easily be extended to a relationship associating multiple inputs to multiple outputs but for the sake of simplicity to describe the proposed approaches, it is considered that the F-IAS agent has only to control one output actuator. In addition, it should be emphasized that an F-IAS agent output can also be used as a service for another F-IAS agent, however in this paper it is assumed that sensory services are the sole inputs for the F-IAS agents.

For an AIE, after collecting the data set of $K$ input-output data pairs each vector datum $(\vec{x}^k, y^k)$ can be expressed as $(x_1^k, x_2^k, ..., x_N^k; y^k)$, where $k = 1,2,...,K$. The fuzzy system rule base comprises of a set of $L$ IF-THEN fuzzy rules where the $i^{th}$ rule has the following form:

$$R^i: \text{ IF } x_1 \text{ is } A_1^i \text{ AND } x_2 \text{ is } A_2^i \text{ AND ... AND } x_N \text{ is } A_N^i \text{ THEN } y \text{ is } B^{i*} \quad (1)$$

where $N$ is number of the services of the F-IAS Agent. The variable $y$ represents the output of the F-IAS Agent and is represented by a gaussian fuzzy set $B^{i*}$.

The F-IAS Agent controller uses singleton fuzzification, *max-product* inference method and height defuzzification, so the crisp output of this controller can be written as follows [5], [6]:

$$y = \frac{\sum_{i=1}^{L} w_i \overline{B}^{i*}}{\sum_{i=1}^{L} w_i} \quad (2)$$

where $\overline{B}^{i*}$ is the centre of the output fuzzy set of the $i^{th}$ rule and $w_i$ is the rule firing strength which is equal to the product of the membership values of the inputs for each rule.

The lifelong learning and adaptation capabilities of the F-IAS agent for AIEs requires to have an effective, fast and reliable learning method that can generate new rules as well as adapting, changing and removing the existing rules. The rule induction method of the F-IAS which operates in an online and lifelong learning mode is described next.

### *C. Extracting Fuzzy Rules*

The rule induction method adopted by the F-IAS agents is based on an enhanced version of the Wang-Mendel (WM) method, using a one-pass technique to extract fuzzy rules from a sampled data set [7]. The procedure involves the following steps and is used to obtain the initial model of the system which at the same time characterizes the user's behavior [5]:

- *Step I*: Establish associations to selected services. These services may have been selected by the user, randomly or intelligently [5].
- *Step II:* Monitor the user interaction with the associated services and in the event of a change, the information is saved in a local storage.
- *Step III:* Once enough data (based on events) have been collected, assign for each input of the Fuzzy Locig Controller (FLC) a set of fuzzy membership functions. A double-clustering approach combining fuzzy c-means and hierarchical clustering is applied for obtaining these fuzzy membership functions. More information regarding the clustering algorithm can be obtained from [8].
- *Step IV:* Expert rules are allowed but not necessary and may be combined with rules induced from the collected data set. This can be in form of accompanied rule (or fuzzy policies) provided by the manufacturer or freely added by the user (e.g. safety rules should not be overridden).
- *Step V:* Start reading events from the collected data set and for each data pair $(x^k, y^k)$, compute the membership values $\mu_{A_j^q}(x_j^k)$ for each fuzzy set $q = 1,...,V$, and input $j = 1,...,N$, find $q \in \{1,...,V\}$, such that $\mu_{A_j^q}(x_j^k)$ is maximum. The following is the rule generated by $(x^k, y^k)$.

$$\text{IF } x_1^k \text{ is } A_1^q \text{ AND ... AND } x_N^k \text{ is } A_N^q \text{ THEN } y \text{ is } y^k \quad (3)$$

- *Step VI:* Repeat *Step V* for all $k$ from $1,...,K$ to obtain $K$ data generated fuzzy rules in the form of equation 3. Divide the resulting rules into groups (*conflicting rule groups*) sharing the same IF part (antecedents) and having different consequents. Combine the group $l$ with $K_l$ rules into a single rule in the form of equation 1 where $B^{i^*}$ is a Gaussian fuzzy set. The antecedents and the consequent of the obtained rule becomes the following form

$$\text{IF } x_1^k \text{ is } A_1^q \text{ AND ... AND } x_N^k \text{ is } A_N^q \text{ THEN } y^{k(av^l, \sigma^l)} \quad (4)$$

with the *consequents' average* $av^l$ and *variance* $\sigma^l$ computed as follows:

$$av^l = \frac{\sum_{k=1}^{K_l} y_k^l w_k^l}{\sum_{k=1}^{K_l} w_k^l} \quad (5)$$

$$\sigma^l = \frac{\sum_{k=1}^{K_l} \left| y_k^l - av^l \right| w_k^l}{\sum_{k=1}^{K_l} w_k^l} \quad (6)$$

where $w_k^l$ is the rule weight of each conflicting rules within group $l$ and is computed as

$$w_k^l = \prod_{j=1}^{N} \mu_{A_j^q}(x_j^k) \quad (7)$$

- *Step VII:* Repeat this combination for all conflicting groups $l$ to obtain the final rule set which contains $L$ rules in the form of equation 1 and store it in F-IAS Agent's *Rule Base*.

The above procedure is employed online and in a life-long learning mode which allows the rule base to be adaptive so that new rules may be inserted or existing rules modified or deleted.

*D. Intelligent Association Exploration*

In the intelligent association exploration system, the weights are continuously computed and updated in the occurrence of an event. The weights increase when the state of both, the F-IAS agent and the corresponding services simultaneously change. In contrast, the weights decrease over time when the state change of a service cannot be correlated. The algorithm of the intelligent association exploration of a F-IAS is described as follows:

- *Step I:* Initiate a $FCM(Y)$ for the F-IAS Agent and establish associations to $N$ services ($X_j \rightarrow Y$), $j=1,\ldots,N$. The associations during the rule extraction process are used although different services may be selected.
- *Step II:* Set the association weights $\alpha_{X_j \rightarrow Y}$ of $FCM(Y)$ to zero, for all associated services so that the association matrix of F-IAS becomes $\Lambda_{X_j \rightarrow Y} = [X_1 = 0, X_2 = 0, X_3 = 0 \ldots X_N = 0]$.
- *Step III:* Set the learning rate $\delta$ = 0.1 and initialize the pre-associative flag to zero ($\xi_{X_j}$ = 0) and post-associative flag to zero ($\xi_Y$ = 0) for the agent pair $X_j \rightarrow Y$.
- *Step VI:* In the occasion of an event (service state change) do the following:
  a. For each event, update the pre-associative flag of the corresponding service $\xi_{X_j}$ to 1
  b. Calculate the resulting output of the event $x_j^k$ by applying equation 2 of the F-IAS Agent
  c. Update $\xi_Y$ to 1 *only* if the F-IAS Agent has adjusted its output state due to event $x_j^k$
  d. Calculate the new association weights $\alpha_{X_j \rightarrow Y}$ for each F-IAS Agent/Service pair $X_j \rightarrow Y$ at time $k$ by applying the following equation

$$(\alpha_{X_j \rightarrow Y})^k = (\alpha_{X_j \rightarrow Y})^{k-1}(1-\tau)\delta\xi_{X_j}\xi_Y \quad (8)$$

  where $(\alpha_{X_j \rightarrow Y})^{k-1}$ is the association weight before applying equation 8 and $\tau$ is the decay value which is set to 0.01.

  e. Reset $\xi_{X_j}$ and $\xi_Y$ to 0.
  f. Repeat *Step IV* continuously until a given time $k$. As our system is operating in a life long learning mode, it will keep receiving new events and updating the associations.

The reason for adding a decay value $\tau$ is to prevent the association values calculation to increase endlessly. An association which was important for the F-IAS at the beginning might become redundant over time and without a decrease in the association weights this would never be noticeable. The decay value 0.01 has been derived empirically.

Another major issue that needs to be addressed is the frequency of use of the services. It is obvious that the use of different services differs according to their functionality and purpose. Additionally different services provide different information. For example a chair pressure sensor only sends out an event if someone sits on it or stands up, whereby a temperature sensor constantly measures the temperature of the environment and regularly sends the updates. By using the algorithm above it is clear that the fewer events a service transmits, the less likely it will be regarded as a strong association. To overcome this situation, the following procedure aims to normalize the association weights according to their frequency of use, so that a better judgment of the importance between all associated agents can be performed.

- *Step I*: While running the above intelligent association weight exploration, count the total number of events $Count\left(x_j^k\right)$ for each service $X_j$.
- *Step II*: For each $X_j$, apply the following equation to obtain the normalization constant value

$$\gamma_{X_j} = \left(1 - \left(\frac{Count\left(x_j^k\right)}{K}\right)\right) \quad (9)$$

- *Step III*: Assign $\gamma_{X_j}$ to the following equation which forms a sigmoid function with a normalized constant value for each service

$$f_{sig}(\alpha_{X_j \rightarrow Y}) = \frac{1}{1 + e^{-\alpha_{X_j \rightarrow Y} \times \gamma_{X_j}}} \quad (10)$$

 

- *Step IV*: The above equation generates normalized association weights so that an equal and fair judgment on the importance of association between the services and the F-IAS can be performed
- *Step V*: Insert the obtained $\alpha_{X_j \to Y}$ into the association matrix $\Lambda$ of the F-IAS Agent

If $f(\alpha_{X_j \to Y}) \geq \Theta$ (where $\Theta$ is a predefined threshold e.g. 0.15) then the association is of great importance to the F-IAS Agent. On the other hand if the association weight of a F-IAS agent is smaller than the threshold $\Theta$ than this service may be considered as irrelevant or redundant and would become a candidate to be removed.

During the life-time of the F-IAS agents, the intelligent association exploration mechanism constantly seeks to reduce irrelevant associations to services and simultaneously evaluates new and potentially more relevant and significant services that will maintain the fuzzy model quality while decreasing the overall agents communication and computational processing loads.

## IV. Experiments and Results

### A. The iDorm – an AIE Test Bed

Several experiments were conducted within the iDorm at the University of Essex. The iDorm is a unique real world AIE fitted with a plethora of embedded sensors and actuators and different network platforms such as LonTalk, Tini 1-wire, IP and X10 all glued together by UPnP to form a heterogeneous network. The iDorm is ubiquitous because the user is surrounded by a multitude of interconnected devices and transparent since the devices are seamlessly integrated into the environment. The current iDorm is equipped with the following sensors: Internal Light Level (ILL), External Light Level (ELL), Internal Temperature (ITEMP), External Temperature (ETEMP), Chair Pressure (CHAIR), BED Pressure (BED), and a Clock (HOUR). The actuators and thus the F-IAS agents consist of the Desk Lamp (DESKLAMP), Bed Lamp (BEDLAMP), 4 Dimmable Ceiling Lamps (DIM1-4), Heater (HEATER) and a Cooler (COOLER). It should be noted that during the experiments, all the sensors were run on separate and independent hardware processing units whilst the UPnP stacks and intelligent agent mechanisms were run on a single PC as software multi-processes. The hardware processors used in this experiments were small (20MHz, 0.5MB RAM processors) that could not support complex agents and so we utilized the PC as a proxy for these agents (a common technique in distributed embedded-architectures). This approach provides a more flexible experimental structure.

### B. Results and Evaluation

Several experiments on the intelligent association exploration mechanism were conducted within the iDorm with different users. Due to the limited space, this paper will present a small subset of these experiments as described below. A detailed description of the experimental setup can be acquired from [5].

A user was asked to stay in the iDorm for 5 consecutive days. During this period the user interacted with the devices and performed his everyday normal activities, such as studying, watching DVDs and sleeping. During, the first 3 days the F-IAS agents (embedded in the actuating devices) monitored the user and collected the data based on events from the associated services (sensors). For this experiment, the F-IAS agents selected associations to all available services with the aim to eliminate the redundant services that are not required for the user's tasks.

For simplicity, the DESKLAMP F-IAS agent (hereafter only F-IAS agent) is used to explain the results. At the end of the third day the F-IAS agent extracted a total of 297 rules from 400 collected data sets. This formed the initial fuzzy rule base which resulted in a fuzzy model that approximated the user behavior with a Normalized Mean Squared Error (NMSE) of 0.0108. The processing time obtained for each F-IAS agent to go through a single control cycle for the 400 data sets was in average 4797ms. An agent computational latency criterion (ACLC) was introduced to measure the F-IAS agent's additional computational processing load based on communicating UPnP sensors and F-IAS agents. More specifically, the ACLC calculates the period between an UPnP event initiation and acknowledgement delivery. Initially, the ACLC for this experiment was 3220ms. After the F-IAS agent has generated the initial model and extracted the required rules for its controller, it changed its operation to the actuation mode and started to perform the intelligent association exploration. In this mode, the F-IAS agent continued with adaptation of rules and calculating the relevance of association whenever a state change of the services (events) took place. At every simultaneous change of the F-IAS agent and the services, the new association weight $\alpha_{X_j \to Y}$ was calculated. The calculated association weights of the F-IAS agent and different services during the last two days are depicted in figure 3. It becomes clear that the F-IAS agent in this experiment is strongly associated with the CHAIR. The resultant association weights for all services with the F-IAS Agent are as follows:

$$\Lambda_{X_j \to DESKLAMP} = [ILL = 0.15, ELL = 0.31, ETEMP = 0.04,$$
$$ITEMP = 0.03, CHAIR = 0.63, BED = 0.26, HOUR = 0.34]$$

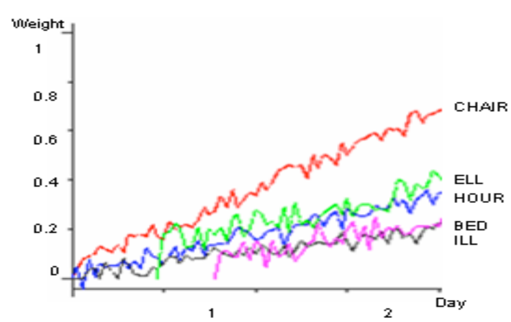


Fig. 3. The intelligent association exploration calculation process.

After applying the threshold $\Theta$ (0.15), (which can differ for each F-IAS agent depending on the limitations of resources in processing, network connections and memory) the most relevant associations were selected and irrelevant ones removed. With this, the F-IAS agent in this experiment defines its own society of services which included ILL, ELL, CHAIR, BED and HOUR. After eliminating ETEMP and ITEMP the number of rules reduced to 139, the NMSE increased slightly to 0.0518 (thus the model quality was not so much affected), the processing time for one control cycle reduced to 1203ms and finally the ACLC decreased to 924ms due to less message transmission in the overlay network. This demonstrates the efficiency of the F-IAS agent where it reduces the processing and communication latencies while maintaining the quality of the learnt model. The experiments were also conducted in a life learning modes in which the system managed to find the most relevant associations in various scenarios when services break down or new services are introduced.

Table 1 shows the association matrix for all remaining F-IAS agents that were used in this experiment, where x indicates a deleted association.

TABLE I
F-IAS AGENTS' ASSOCIATION MATRIX

| $\Lambda$ | X1 | X2 | X3 | X4 | X5 | X6 | X7 |
|---|---|---|---|---|---|---|---|
| DIM1 | 0.24 | 0.25 | x | x | 0.35 | 0.21 | 0.28 |
| DIM2 | 0.27 | 0.34 | x | x | 0.23 | 0.27 | 0.32 |
| DIM3 | 0.16 | x | x | x | 0.23 | x | x |
| DIM4 | 0.42 | 0.38 | x | x | 0.32 | 0.28 | 0.25 |
| BEDL | 0.23 | x | x | x | 0.16 | 0.56 | 0.34 |

Services: X1 = ILL, X2 = ELL, X3 = ETEMP, X4 = ITEMP, X5 = CHAIR, X6 = BED, X7 = HOUR

## V. CONCLUSIONS

This paper has presented the intelligent association exploration mechanism for F-IAS agents operating in an AIE environment which is a novel approach to learn the associative strength and thus the importance of associated services in an online fashion. The F-IAS agents employ a special type of FCMs which use a tailored Hebbian learning style procedure to calculate the association weights of their interconnections. The weights are continuously computed and updated in the occurrence of an event. The weights increase when the state of both, the F-IAS agents and the corresponding services simultaneously change. In contrast, the weights decrease over time when the state change of a service cannot be correlated.

As has been discovered through extensive sets of experiments conducted by various users, the proposed system can result in decreasing the F-IAS agents rule base by almost 53% which can lead to fewer memory requirements and faster processing for the F-IAS agents. Moreover, through elimination of irrelevant associations, the ACLC reduced from 3220ms to 924ms. This demonstrates the significance of the proposed method where it reduces the irrelevant and insignificant services, which leads to increasing the efficiency and reducing the computational and processing complexity of the AIE while not decreasing the quality of the produced fuzzy model.

For our future work, we are investigating the trial of the proposed system in a truly distributed AIE with a richer set of sensors, actuators and F-IAS agents based on multiple overlapping societies, e.g. in the form of multiple rooms (like the newly established Essex intelligent Flat, namely iDorm-2). We are also aiming to explore more the tradeoff between human intervention and accuracy and efficiency of F-IAS agents as well providing the agents with the ability to make good judgment on the priorities of their functionalities.

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