Intelligent task planner for cloud robotics using level of attention empowered with fuzzy system

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Abstract

Cloud robotics is a field of robotics that endeavors to summon cloud advances, for instance, cloud computing, and other internet advances focused on the advantages of merged framework and shared administrations for robotics. In this research, an intelligent task planning mechanism is proposed to attain a certain level of attention for knowledge sharing among cloud-based robots using mamdani fuzzy inference system (MFIS). The proposed task planning mechanism using mamdani fuzzy inference system (TPM-MFIS), can classify the different stages of attention such as very high, high, medium, low, very low and none. In this recommended intelligent system, cloud robotics services are used to maintain the workload of each robot. Whereas, all fuzzification and decision-making policies handled on cloud to avoid the redundancy task planning consumption on individual level. This system has two input variables that are facial expression and motion rate. Input variables detect the output level of attention to be very high, high, medium, low, very low, and none. This paper presents an analysis of the result's accuracy using proposed TPM-MFIS to model the task planning process.

Keywords Task planning · Attention mechanism · Facial expression

1 Introduction

In the field of cognitive robotics, the level of attention is a crucial component of the task selection and task planning mechanism. Inappropriate environmental analysis often leads to an inadequate level of attention that leads to inept execution of a task. Robot working in a dynamic environment develops its sensory perception to infer environmental changes by sensing the stimuli unconsciously from the real world [1]. It is tricky, and execution intensive task for a robot to process all the stimuli it had perceived; as a result, the robot may get confused. Selective attention will assist robot to get rid of this situation by limiting the workload through selective filtering on perceived input [2]. The attention mechanism in the hierarchical

system will enable robots to regulate attention by gathering information from its surroundings by interacting with other robots of the same or different layers of the cloud computing [3, 4].

For the efficient execution of a task, the robot must decide when and where to pay attention. To resolve this decision making would be done by robots whether the perceived stimuli need processing to perform a specific task. A selective attention mechanism will assist the robot in decision making. Selective attention can be interrelated to how the bottleneck restricts fluid flow. The obstacle prevents the liquid from entering the bottle body immediately; instead, it allows the fluid to flow in a predetermined amount of flow until both come into the bottle body.

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For the practical demonstration of the attention mechanism in robots, an example of a supermarket is taken where robots perform the overall working from the accountant to keeping a record of products in a market. Heterogeneous robots like cognitive cameras, screens, and humanoid robots are distributed among various levels connected with each other via a cloud robotics proxy-based model [5] as shown in Fig. 1. Each robot is cognitive and capable of decision making independently via communication with other robots. In this networked robotic environment, one robot is connected with cloud and work like leader. Leader robot is responsible for task scheduling. Task scheduling includes task selection from cloud and assign to the most relevant featured robot for execution in dynamic environment.

When a person enters a market, the information regarding the person will be updated to knowledgebase and shared with other robots in a hierarchy. Selective attention mechanism will help robots that where to pay attention whether a person entered in a market is a regular customer or a volunteer. FE and emotions of customers are analyzed and decision making is done by robots that, how to priorities customers by paying the amount of attention required. Cognitive cameras share the gathered information with other robots, whether the customer is confused to find some product, want to get information regarding some product or is done with shopping. Smart screens will listen to the queries of customers and guide them about the market demand or a location of a particular product in a market. Smart screens are the part of the Internet of Things (IoT), which will allow the connectivity of various devices for the sake of communication among them.

According to literature, robots will be the next big advance in humans' domestic welfare, robots are able

to assist elderly people and disable persons. However, each user has his/her own preferences, needs, and abilities. Therefore, robotic assistants will need to adapt them, behaving accordingly. Towards this purpose an approach was proposed to adjust the behavior, by means of conceptual job planning to computer settings. A user model was developed with a flavory deduction system from the user's responses to questions and instead integrated into the design field. The adjustment approach based on user satisfaction and results are defined according to the penalties equally applied to the planner's rules. In a basic slide fitting example, demonstrate the implementation of the adjustment approach with experiments in simulated user environments. The results indicate a rapid behavior adaptation and reliability to the incorrect assumption of an original user model, even though the user personality changes. Finally, a range of insights is given into the non-simulated world of shoe fitting [6].

Fuzzy rules are designed for FE detection and motion recognition in combinations for the level of attention measurement which makes it easier to find the goal in the first hit [7]. Characteristics of FE are obtained from external stimuli and an emotional space mapped using Mamdani relational model [8]. FE are recognized using fuzzy logic where the fuzzy rule base (FRB) designed in such a way to infer the collective set of facial animation parameters as a particular FE [9]. Fuzzy logic-based expert system together with the neural network technique used to diagnose the level of disease (like abnormality of human liver on the basis of four liver tests as input). This automated system does not also increase the accuracy, however reduces the chances of human error while the diagnosis of organ disorder [10]. Fuzzy-neural network-based application introduced to simulate the learning of mobile agents to

Fig. 1 Work flow of cloud robotics proxy-based model

perform action planning learned from humans [11]. The fuzzy logic-based model can be used to select the appropriate action for the decided course of behavior [12].

Various problems to research were linked recently to authorized the latest incorporations of evolutionary algorithms [13, 14], Swarm intelligence [15, 16], the neural network, and Fuzzy systems [17–19]. This opened up for the researchers some space afterward.

Taking various cloud computing parameters like data center, virtual machine and the IoT as input of MFIS a system is proposed to decide the level of efficient load balancing of cloud as an output of the automated system [20]. Smart city concept aroused to assist people living in cities in various ways to make the living comfortable through keeping them up to date regarding their current environment. Taking this thing into consideration a system is proposed based on a MFIS to determine the traffic congestion condition in a city based on various road parameters served as the input of the system [21]. Multilayered MFIS scheme has been used in robotics applications, medical field and cloud infrastructure to identifying the critical findings. In the diagnosis of diseases like hepatitis, multilayered FIS can dictate the target state of infection with hepatitis, which can help in the analysis and then accurate results [22–24].

2 Proposed task planning in cloud robotics

Every robot tries to solve the task by itself in cognitive robotics (CR) according recommended algorithm [25, 26]. While these CR are working on the cloud, they need to resolve the task as cloud instructions. Whereas the cloud has managed the load balancing of various tasks and provide much space to process multiple tasks at the same time. The proposed research work explained the realistic mechanism of task planning for cloud robotics according to the attention level.

The key factor is choosing a task to resolve the attention. Furthermore, it is basically the priority setting with multiple tasks for proper scheduling. The proposed research based on the fundamental elements like FE of the person and his/her rate of body motion to find the level of attention. The combination of both elements manages the variety of solutions for task planning indirectly via attention level mechanism [27].

Figure 2 is showing an overview of task planning mechanism for robots via cloud infrastructure. All CRs are attached to the cloud for the efficiency and reliability of resources. Each CR has access to the cloud for a fuzzy system to compute the level of attention. A number of CRs are working according to the current situation and other cognitive robots can re-validate the fuzzy with each

other. Artificial intelligence is currently being used for the enhancement of cognitive abilities in the field of robotics [28–31]. The fuzzy inference system is a dominant system for analyzing complications and offer alternatives to them. FIS is helpful when there is a possibility of uncertainty. Applications of the fuzzy system are useful in every field of life like Cognitive Science, Robotics, Industry, Medical Field, Agriculture, Weather forecasting, etc. Fuzzy based simulation for attention mechanism in CR is performed to describe the level of attention required based on the type of motion and FE [32, 33]. In this research, attention depends upon the selected values of FE and motion. The simulated and calculated results are according to the dependence scheme. FE and emotions of customers are analyzed and decision making is done by robots that how to prioritize tasks by paying the amount of attention required.

2.1 Attention mechanism

The attention mechanism triggers the task planning module to priorities the vital task. The worth of the task depends on several parameters. This research uses two significant elements FE and the body motion of the person for attention selection. There is a different type of attention mechanisms already defined for CR. Bestowing to this research, selective attention mechanism has been used for better results of task planning. The level of attention is the output of this research, while FE and body motion rate are the input for rational processing.

2.1.1 Facial expressions

Researchers have found a total of twenty-one different human FE. These FE obviously depend on the human facial muscles [34]. According to the research, there is a total of forty-three muscles in the human face. The associative movement of these muscles generates meaningful FE to others. Essentially FE has four types “active”, “reactive”, “external”, and “internal” [35]. Consciously generated FE is named as active FE, unconsciously generated FE is named as reactive FE, external stimuli-based FE is named as external FE, and internal thoughts-based FE is named as internal FE. This research deals with the external FE that received stimuli from the external environment. Each FE exactly mapped with the muscles of the face which is simplified by researchers as facial action coding system (FACS) [36–39]. The following table represents the glance view of FACS according to this research [40, 41].

Table 1 is useful for FE detection. Computer vision-based applications trained for such FACS for further FE detection easily. In this application, the Human face mapped with multiple dots on the different positions of

Fig. 2 Proposed task planning mechanism on cloud for robots using fuzzy inference

Table 1 Facial action coding system for facial expressions [42]

Emotion	Action units	Facial action coding system (FACS) name
Happy	6, and 12	Cheek raiser, and Lip corner puller
Surprise	1, 2, 5B, and 26	Inner brow raiser, Outer brow raiser, Upper lid raiser (Slight), and Jaw drop
Fear	1, 2, 4, 5, 7, 20, and 26	Inner brow raiser, Outer brow raiser, Brow lowerer, Upper lid raiser, Lid tightener, Lip stretcher, and Jaw drop
Anger	4, 5, 7, 23	Brow lowerer, Upper lid raiser, Lid tightener, and Lip tightener
Disgust	9, 15, 16	Nose wrinkle, Lip corner depressor, and Lower lip depressor

the facial muscles and the orientation of this dotted position has been analyzed to grasp the exact pose of the face for the specific FE.

2.1.2 Body motion

The motion of the body has much information for others to convey a lot of messages; also known as body language. Such type of communication has a substantial impact in real environment as compared to the verbal language. This research deals with the visual aspects only and detects the motion of the human body and FE from the

real environment via camera. Motion and the FE associatively produce the preminent consequence for the level of attention.

2.2 Mechanical Turk and crowdsourcing

The best variation of the FRB is integrated in this section. This section will be enabled for crowdsourcing of human intelligence, if the automatic system fails rationally or algorithmically in the real environment. With the help of the Mechanical Turk module, the proposed solution will not consistently be going down. In a real-world scenario, every

human cognition is not perfect. They are not free from mistakes; they learn from mistakes and try to follow the path of successful persons. This situation is dealing with the outer boundary of human cognition in which a person can learn from the trained (experienced) person (that is refined knowledge). Mechanical Turk crowdsourcing would allow human intelligence to modify the proposed system's fuzzy rule and knowledge base in accordance with the scenario, complex environment, and sensitive issues.

3 Proposed fuzzy system for task planner cloud robots

The introduced algorithm for this research is comprised of two fuzzifier variables as input. Five-member functions (MFs) that are reasonably dispersed over a scale range of 0 to 100 for the motion and 0 to 100 for FE inputs. The six fuzzifier MFs for motion input are termed as Very-Slow 0 to 25, Slow 20 to 50, Normal 40 to 70, Fast 60 to 85 and Very-Fast 80 to 100. The five fuzzifier MFs for expression input is termed as Happy 0 to 25, Surprise 20 to 50, Fear 40 to 70, Anger 60 to 85 and Disgust 80 to 100. The six MFs of Attention levels none, very low, low, medium, high, and very high.

Fuzzy sets are vividly representing the MFs. The x-axis signifies the universe of discourse, i.e. input area, whereas the y-axis signifies the degrees of MFs in the $[0,1]$ interval. A MFs for a fuzzy set on the universe of discourse X (Expression and Motion) is defined as $\mu_X \rightarrow [0,1]$, where each element of X is mapped to a value between 0 and 1. This value, called membership value or degree of membership, quantifies the grade of membership of the element in X to the fuzzy set. Simple functions are used to build MFs.

3.1 Input variables

3.1.1 Motion

The movement of a person, with possible values: very slow, slow, normal, fast and very fast.

3.1.2 Expression

Expression of a person, with possible values: happy, surprised, fear, anger, and disgust (Table 2).

3.2 Output variables

3.2.1 Attention

The level of attention selected by the robot as a result of the motion and FE of a person. The levels are none, low, very low, high, and very high (Table 3).

Table 2 Input variables of proposed TPM-MFIS

Sr #	Input parameters	Ranges	Semantic sign
1.	Expression	B/W 0–25	Happy
		B/W 20–50	Surprised
		B/W 40–70	Fear
		B/W 60–85	Anger
		B/W 80–100	Disgust
2.	Motion	B/W 0–25	Very slow
		B/W 20–50	Slow
		B/W 40–70	Random
		B/W 60–85	Fast
		B/W 80–100	Very fast

Table 3 Input variables of proposed TPM-MFIS

Sr #	Output variable	Semantic sign
1.	Attention	None
		Very low
		Low
		Medium
		High
		Very high

3.3 Membership functions

The system's MFs shows curve values between zero to one and a mathematical function that provides statistical output variables using input variables. Graphical and mathematical representation of proposed TPM-MFIS MFs of input and output variables that are shown in Table 4.

3.4 Fuzzy prepositions

Here the function t-norm for a fuzzy layer is defined as:

$$t : [0, 1] \times [0, 1] \rightarrow [0, 1] \quad (1)$$

Equation (1) transforms the membership functions of fuzzy sets of Motion, and Expression for the proposed fuzzy inference system among membership function of the intersection of Motion, and Expression that is:

$$t[\mu_E(e), \mu_M(m)] = \min[\mu_E(e), \mu_M(m)] \quad (2)$$

In (Eq. 1), for the function t ; getting qualified as an intersection, following axioms must be satisfied and will be called as t-norm:

Axiom t1 $t(0, 0) = 0; t(\delta, 1) = t(1, \delta) = \delta$ (Bounded Condition)

Table 4 Membership functions used in proposed TPM-MFIS

Sr #.	Input variables	Membership function (MF)	Graphical representation of MF
1.	Facial expression = $E(\mu_E(e))$	$\mu_{E,H}(e) = \begin{cases} 1, & 0 \leq e \leq 20 \\ \frac{25-e}{5}, & 20 \leq e \leq 25 \\ 0, & 25 \leq e \end{cases}$ $\mu_{E,F}(e) = \begin{cases} 0, & e \leq 20 \\ \frac{e-20}{5}, & 20 \leq e \leq 25 \\ 1, & 25 \leq e \leq 40 \\ \frac{50-e}{10}, & 40 \leq e \leq 50 \\ 0, & 50 \leq e \end{cases}$ $\mu_{E,S}(e) = \begin{cases} 0, & e \leq 40 \\ \frac{e-40}{10}, & 40 \leq e \leq 50 \\ 1, & 50 \leq e \leq 60 \\ \frac{70-e}{10}, & 60 \leq e \leq 70 \\ 0, & 70 \leq e \end{cases}$ $\mu_{E,A}(e) = \begin{cases} 0, & e \leq 60 \\ \frac{e-60}{10}, & 60 \leq e \leq 70 \\ 1, & 70 \leq e \leq 80 \\ \frac{85-e}{5}, & 80 \leq e \leq 85 \\ 0, & 85 \leq e \end{cases}$ $\mu_{E,D}(e) = \begin{cases} 0, & e \leq 80 \\ \frac{e-80}{5}, & 80 \leq e \leq 85 \\ 1, & 85 \leq e \leq 100 \end{cases}$	
2.	Motion = $M(\mu_M(m))$	$\mu_{M,VS}(m) = \begin{cases} 1, & 0 \leq m \leq 20 \\ \frac{25-m}{5}, & 20 \leq m \leq 25 \\ 0, & 25 \leq m \end{cases}$ $\mu_{M,S}(m) = \begin{cases} 0, & m \leq 20 \\ \frac{m-20}{5}, & 20 \leq m \leq 25 \\ 1, & 25 \leq m \leq 40 \\ \frac{50-m}{10}, & 40 \leq m \leq 50 \\ 0, & 50 \leq m \end{cases}$ $\mu_{M,R}(m) = \begin{cases} 0, & m \leq 40 \\ \frac{m-40}{10}, & 40 \leq m \leq 50 \\ 1, & 50 \leq m \leq 60 \\ \frac{70-m}{10}, & 60 \leq m \leq 70 \\ 0, & 70 \leq m \end{cases}$ $\mu_{M,F}(m) = \begin{cases} 0, & m \leq 60 \\ \frac{m-60}{10}, & 60 \leq m \leq 70 \\ 1, & 70 \leq m \leq 80 \\ \frac{85-m}{5}, & 80 \leq m \leq 85 \\ 0, & 85 \leq m \end{cases}$ $\mu_{M,VF}(m) = \begin{cases} 0, & m \leq 80 \\ \frac{m-80}{5}, & 80 \leq m \leq 85 \\ 1, & 85 \leq m \leq 100 \end{cases}$	

Table 4 Continued

Sr #.	Input variables	Membership function (MF)	Graphical representation of MF
3.	Attention = A ($\mu_A(a)$)	$\mu_{A,N}(a) = \begin{cases} \frac{20-a}{20}, & 0 \leq a \leq 20 \\ 0, & 20 < a \leq 100 \end{cases}$ $\mu_{A,VL}(a) = \begin{cases} \frac{a}{40}, & 0 \leq a \leq 20 \\ \frac{40-a}{20}, & 20 \leq a \leq 40 \\ 0, & 40 < a \leq 100 \end{cases}$ $\mu_{A,L}(a) = \begin{cases} \frac{a-20}{20}, & 20 \leq a \leq 40 \\ \frac{60-a}{20}, & 40 \leq a \leq 60 \\ 0, & 60 < a \leq 100 \end{cases}$ $\mu_{A,M}(a) = \begin{cases} \frac{a-40}{20}, & 40 \leq a \leq 60 \\ \frac{80-a}{20}, & 60 \leq a \leq 80 \\ 0, & 80 < a \leq 100 \end{cases}$ $\mu_{A,H}(a) = \begin{cases} \frac{a-60}{20}, & 60 \leq a \leq 80 \\ \frac{100-a}{20}, & 80 \leq a \leq 100 \\ 0, & 0 \leq a < 60 \end{cases}$ $\mu_{A,VH}(a) = \begin{cases} \frac{a-80}{20}, & 80 \leq a \leq 100 \\ 0, & 0 \leq a < 80 \end{cases}$	

Axiom t2 $t(\delta, \zeta) = t(\zeta, \delta)$, (Commutativity)

Axiom t3 If $\delta \leq \delta' \wedge \zeta \leq \zeta'$, then $t(\delta, \zeta) \leq t(\delta', \zeta')$ (Nondecreasing)

Axiom t4 $t[t(\delta, \zeta), \xi] = t[\delta, t(\zeta, \xi)]$ (Associativity)
(Eq. 2) can be written in terms of t-norm as:

$$\mu_{E \cap M}(e, m) = t[\mu_E(e), \mu_M(m)] \quad (3)$$

From Eq. (2) and (3)

$$\mu_{E \cap M}(e, m) = \min[\mu_E(e), \mu_M(m)] \quad (4)$$

3.5 Fuzzy if–then rules

To formulate the conditional statements that embrace fuzzy logic, if–then statements are used. These statements explain the core grounds to construct a fuzzy rule base. In the current situation, few rules for the fuzzy inference system are provided as under.

IF (E is Happy and M is Slow) THEN A is Medium
 IF (E is Happy and M is Random) THEN A is Low
 ...
 IF (E is Disgust and M is Very Slow) THEN A is Very Low
 IF (E is Disgust and M is Very Fast) THEN A is High

The fuzzy IF–THEN rule in above Sect. 3.5 is interpreted as a fuzzy relation Q25 with the membership function for the membership function is written as

$$\mu_{Q25}(e, m) = \min[\mu_{PF1}(e), \mu_{PF2}(m)] \quad (5)$$

Then it can be computing product of fuzzy for Expression: Happy and Motion: Very Slow PF1 as under

$$\mu_{PF1}(\text{Happy, VerySlow}) = \mu_{\text{Expression}}(e) \mu_{\text{Motion}}(m) \quad (6)$$

$$\mu_{PF1}(\text{Happy, VerySlow}) = \begin{cases} 1, & 0 \leq e, m \leq 20 \\ \left(\frac{25-e}{5}\right)\left(\frac{25-m}{5}\right), & 20 \leq e, m \leq 25 \\ 0, & 25 \leq e, m \end{cases} \quad (7)$$

It can be written as

$$\mu_{PF1}(\text{Happy, VerySlow}) = \begin{cases} 1, & 0 \leq e, m \leq 20 \\ \frac{(25-e)(25-m)}{25}, & 20 \leq e, m \leq 25 \\ 0, & 25 \leq e, m \end{cases}$$

3.6 Fuzzy rule base

The expert system's efficiency relies on fuzzy rules. Fuzzy rule base includes rules that have all possible fuzzy relations between inputs and outputs according to the opinion of the experts. These rules are expressed in the IF–THEN format. The rules required by a cognitive agent to pay a certain level of attention are presented as fuzzy IF–THEN rules. Fuzzy IF–THEN rules are the constituents of the fuzzy rule base. The fuzzy rule base is the major component of the fuzzy system because all other components are used to implement these rules in a realistic and proficient way. Fuzzy rule base comprises the following fuzzy IF–THEN rules, where rules are denoted by Ru^w , where $1 \leq w \leq 25$:

$Ru^1 =$ IF Expression is Happy and Motion is Very Slow THEN, Attention is Medium
 $Ru^2 =$ IF Expression is Happy and Motion is Random THEN Attention is Low
 $Ru^3 =$ IF Expression is Happy and Motion is Fast THEN Attention is High
 $\vdots$
 $Ru^{25} =$ IF Expression is Disgust and Motion is Very Fast THEN Attention is High

3.7 Fuzzy inference engine (FIE)

The working of FIE is based on the fuzzy rule base in which fuzzy IF–THEN rules are used to construct the combinations of the fuzzy input variables to an output fuzzy set. This research proposed implications in section 2.5 that

$$\mu_{\varphi}(\text{Attention}) = \max_{1 \leq i \leq 25} \left[\sup_{f_{ij} \in (E, M)} \left(\prod_{k=1}^{25} \left(\mu_{M_k E_k}(m, e) \right) \right) \right]_{\mu_{\mathbb{Y}}(\mathbb{Y})} \quad (12)$$

specify the fuzzy combinations using fuzzy IF–THEN rule with the input variables (facial expression and motion rate) and output variable (level of attention). Entire rules in the fuzzy rule base are united into a single fuzzy relation that is based on composition inference. It lies under the inner product on input universes of discourse, which is then noticed as a single fuzzy IF–THEN rule. A reasonable operator for combining the rules is union [42–44]. In existing implementation, the union method has been used for a set of rules as independent conditional statements.

Let Ru^w be a fuzzy relation that represents any fuzzy IF–THEN rule in section 2.5 that is,

$$Ru^w = E^w \times M^w \rightarrow A^w \quad (8)$$

Then Eq. (11) hold as below.

$$\mu_{E \cap M}(e, m) = \mu_E(e) \cap \mu_M(m) \quad (9)$$

The rules in the method given in Sect. 2.6 are an interpreter As a single fuzzy relation Q_{25} are defined by

$$Q_{25} = \bigcup_{w=1}^{25} Ru^w \quad (10)$$

3.8 Product inference engine (PIE)

Let, φ be arbitrary fuzzy sets and be the output and input to the FIE correspondingly. Formerly, by showing Q_{25} , as a single fuzzy IF and THEN rule and using the comprehensive modus ponens, the obtained output of the FIE as

$$\mu_{None} \cap \text{VeryLow} \cap \text{Low} \cap \text{Low} \cap \text{Medium} \cap \text{High} \cap \text{Very High} (\varphi) = \sup_{f_{ij} \in (E, M)}$$

$$\sup_{f_{ij} \in (E, M)} t[\mu_{f_{ij}}(e, m), \mu_{Q_{25}}(e, m, A)] \quad (11)$$

Here

$$Y_1 = \mu_{\varphi}(\text{None}, \text{VeryLow}, \text{Low}, \text{Medium}, \text{High}, \text{VeryHigh})$$

The obtained product inference engine as

Here $\mathbb{Y}$ is the output universe of discourse. Given a fuzzy set f_{ij} , the product inference engine in Eq. (12) provides a fuzzy set φ as output.

3.9 De-fuzzifier

A fuzzy set φ is output for FIE, it is based on fuzzy set mapping for the de-fuzzifier. Theoretically, the duty of the de-fuzzifier is to specify a point in output universe of discourse that best represents the fuzzy set φ . This is related to the average value of a random variable conversely since φ is constructed in several choices in determining this representing point. The center of gravity de-fuzzifier specifies the o^* as the center of the area covered by the membership function of φ , that is,

$$o^* = \frac{\int \varphi \mu_{\varphi}(\varphi) d\varphi}{\int \mu_{\varphi}(\varphi) d\varphi} \quad (13)$$

De-fuzzifier is one of the crucial key parts of any Expert system. There are various kinds of de-fuzzifier that exist. In this paper, the centroid form of the de-fuzzifier has been used. Figure 2 represents the Rule surface of Proposed TPM-MFIS concerning Motion and Expression.

The above figure showed that if the expression is Happy and motion of the person is very slow then it doesn't achieve any cloud robotic attention. But if an expression is Happy and motion is fast or expression is fear and motion is slow/random then robot gives attention b/w very low to low. If Expression is Happy and Motion is very fast, or Expression is Fear/Anger and Motion is random/fast, then

the robot gives high attention. However if Expression is Fear/Anger/Disgust and motion is very fast then the cloud robot gives very high attention.

Figure 3 demonstrated the graphical representation of Proposed TPM-MFIS based on Motion and Expression. It shows that if the Expression value lies in between 30 and 100 and Motion lies in between 80 and 100 then the Attention will be Strong. If the Expression value lies in between 0 and 80 and Motion lies in between 50 and 100 then the Attention will be Satisfactory and if the Expression value lies in between 0 and 100 and Motion lies in between 0 and 50 then the Attention will be Weak.

Figure 4 demonstrated the graphical representation of Proposed TPM-MFIS based on Expression and Motion. It shows that if the Motion value lies in between 80 and 100 and Expression lies in between 40 and 70 then the Attention will be Strong. If the Motion value lies in between 40 and 80 and Expression lies in between 0 and 80 then the Attention will be Satisfactory and if the Motion value lies in between 0 and 40 and Expression lies in between 0 and 50 then the Attention will be Weak.

3.10 Simulation and results

MATLAB is used in modeling, simulation, creation of algorithms, prototyping, and many other areas. MATLAB is effective programming, information analysis, visualization, and computation tool. Figures 5 to 7 show the lookup diagram of proposed TPM-MFIS with various attention levels of cloud robot concerning different values of Expression and Motion.

Figure 5 shows that if FE is Happy and Motion rate of the person is Slow, then the Proposed TPM-MFIS based robot gives Low attention. Figure 6 shows the if FE is Surprise and Motion rate of the person is Very Slow, then the Proposed TPM-MFIS based robot gives None attention. Figure 7 shows the if FE is Disgust and Motion rate of the

person is Fast, then the Proposed TPM-MFIS based robot gives Very High attention.

In the evaluation phase of this research, an application has been designed to run the idea of software to produce real-time data for fuzzy sets. It is a component-based application developed on the .Net framework with the help of high-level libraries that can get live video streams and perform versatile functions like face detection, motion detection, and FE. Such type of data has been transformed into the fuzzy sets and generate live fuzzy on the spot for outcome of the level of attention, as shown in Fig. 2. Features and the results of software applications are described in Fig. 8.

In Fig. 8, testing data contains sets, each set having the face of a human. The face is detected from 34 points on a human face. This categorization helps to define attention. Each block clearly defines the functionality of every phase like five types of FE (Happy, Surprise, Fear, Anger, and Disgust) with a real motion rate. This is mapped with all the lookup tables that have been defined according to the fuzzy rules. These fuzzy rules have been managed in this application and generate the corresponding results according to Fig. 9. All the results are boldly described, although these streams captured in different environments.

In Fig. 9, the multiple faces of the humans detected and simulate to find the level of attention. Detection of faces is not limited to only one face rather the application can detect more than two faces. This shows the robustness of the application. The criteria for detecting face is that it can detect a face in live camera feed through 34 points on the face. Once multiple faces detected through live camera feed, the level of attention will decide to whom attention should be given according to the task. For instance, three faces detected through live camera feed, two faces have a normal combination of FE and motion rate while one face has a terrific assessment of happy FE and high motion

Fig. 3 Rule surface of proposed TPM-MFIS

Fig. 4 Rule surface of proposed TPM-MFIS

Fig. 5 Look up the diagram of proposed TPM-MFIS with none attention

Fig. 6 Look up the diagram of Proposed TPM-MFIS with None Attention

Fig. 7 Lookup a diagram of Proposed TPM-MFIS with Low Attention

Fig. 8 Single facial expressions and motion simulation results for proposed TPM-M

Fig. 9 Attention to specific person using proposed TPM-MFIS

rate of the body then the level of attention will make a red square around that face showing the sign of attention. As different persons have different FE, so this attention might be moved to another person if he/she will show the best combination of motion and FE.

4 Conclusion and future work

This research focuses primarily on designing a system to assist agents in deciding the level of attention required based on motion and FE of a person. The suggested system is obvious and simple to use for simulating the behavior of robots working in dynamic environments. A common understanding of the working of attention mechanisms could be achieved through this system. The agenda of this research is to assist cognitive agents in deciding the level of attention. In the future, the reliability of the suggested system can be enhanced using other methods such as computer intelligence like Neuro-fuzzy and multilayered fuzzy. It is possible to extend this study to other types of cognitive abilities in agents.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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