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ORIGINAL RESEARCH

Enhanced humanoid assisted human interaction model based on linear structural modeling for knowledge representation

S. Periyanayagi[1] · A. Azhagu Jaisudhan Pazhani[1] · V. Sumathy[2]

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Abstract
Certain rules and regulations are adapted to the linguistic production model to support the decision of human computer interaction using linguistic protection rule method. This paper proposes linear linguistic advanced structural modeling (LLASM) approach to develop weighted linguistic reasoning (WLR) algorithm for the purpose of reasoning and knowledge representation. In this article human computer interaction faces optimal flow and job Characteristics experience using individual computers in the workplace which helps to overcome the issues using LLASM in a variety of organizations with Robotic assistance for verbal and non-verbal sequence using humanoid robot. This model introduces global weight and local knowledge fuzzy rules to determine the optimal flow and job characterization problem faced in linguistic reasoning method. Here, The Weighted linguistic reasoning algorithm allows fuzzy rule-based expert systems with the help of the LLASM method to execute the intelligent and flexible knowledge reasoning model with robotic assistance. Finally, case studies are presented to show the effectiveness of the re-scheduling process which benefits the proposed method using the Linguistic reasoning model.

Keywords Robotic assistance · Humanoid · Linear linguistic advanced structural modeling (LLASM) · Weighted linguistic reasoning (WLR) · Human–computer interaction · Linguistic reasoning model

1 Preliminary significant studies

In recent years academic scholars have proved that the LLASM is an effective tool for constructing expert models. Here, the concept of weighted fuzzy reasoning algorithm is also used to represent the multiple fuzzy productions in a parallel way to execute the reasoning automatically (Chiachío et al. 2018). In addition, there are the same similarity measures in general weighted fuzzy output rules that can improve the evaluation of the multi-level fuzzy reasoning method (Yue et al. 2019). It is mainly applied to diagnose faults in the manufacturing systems in Human computer interface models. Adaptive dynamic network (Shen 2006) is formed to adjust the variations for the knowledge representation and reasoning rule based machine interface systems (Li and Lara-Rosano 2000).

The above Fig. 1. Represents the set of linguistic input values which are received by the translation devices to manipulate the received input sequence and finally it retranslates the structure and produces the set of linguistic output values. Even the same methodology process is involved to enhance the human interaction model based on probability analysis. In the real world in many situations, The major problem in user interface system is due to the imprecise and vague information which will un-successfully involve in the uncertainty framework (Cariñena et al. 2002). During this process numerical based mathematical modeling systems has certain representations of uncertain information's which are not always at an adequate level (Peng et al. 2013).

In the Fig. 2 in The human computer interaction model, human interacts more with the computers in multiple ways; the interface among people and PCs is better to encourage

S. Periyanayagi
periyanayagisphd@gmail.com

[1] Department of Electronics and Communication Engineering, Ramco Institute of Technology, Rajapalayam, Tamilnadu, India

[2] Department of Electronics and Communication Engineering, Government College of Engineering, Dharmapuri, Tamilnadu, India

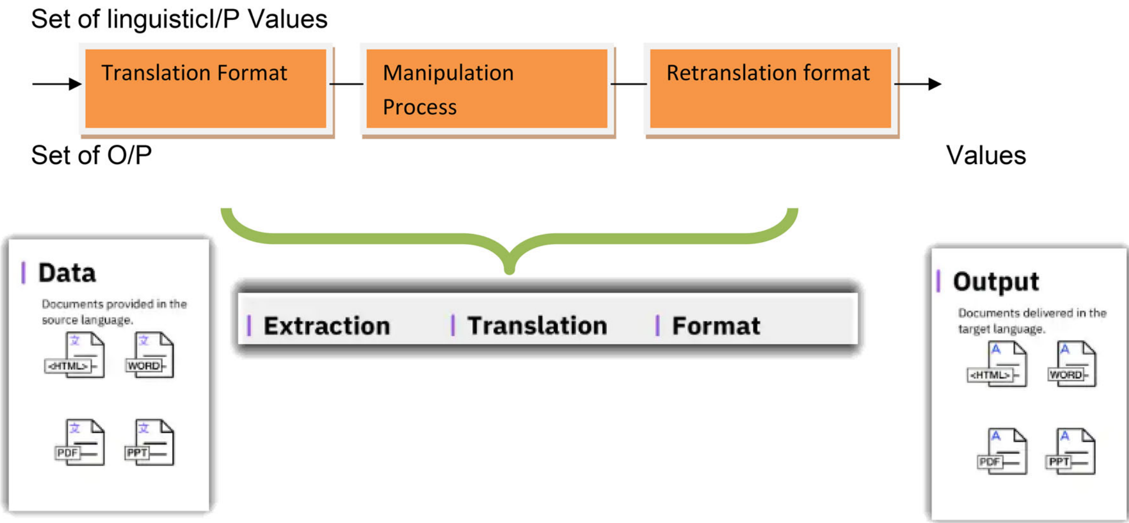

Fig. 1 Scheme for computing format representation of user interface system

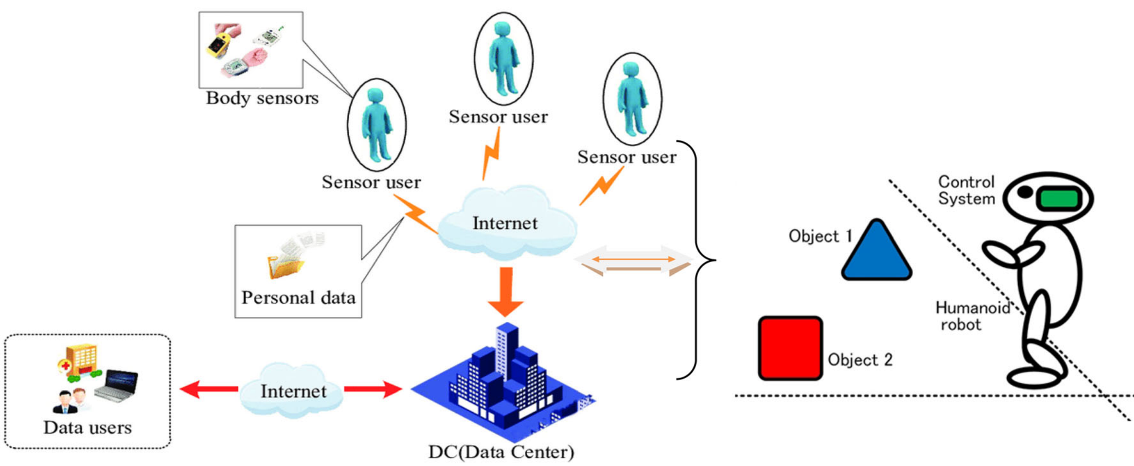

Fig. 2 Human–computer interaction model with humanoid robotic object control system

this connection through various body sensors (Ye et al. 2009). Work area applications, web programs, handheld PCs, and PC stands, utilize the common graphical user interface (UI) models at a data center via internet as on today. Voice UIs (VUI) are utilized for acknowledgment and integrating frameworks (Hamed et al. 2009; Chiang et al. 2000; Zhang et al. 2006), are used to develop multi-modular and Graphical UIs (GUI) which enable people to enhance non probabilistic uncertainty rules to produce successful results using LLASM model in user interface standards. The development in human–PC cooperation field with a humanoid robot control (Liu et al. 2013; Liu et al. 2015) has been in nature of communication, Rather than structuring ordinary interfaces, the distinctive research branches have had an alternate spotlight on the ideas of multimodality (Shih et al. 2007; Liu et al. 2017; Kamala and Justus 2016) instead of unimodality systems.

In this type of cases to handle the uncertainty probabilistic nature, brings numerical precise information which is difficult to understand by the user interface system, Hence the proposed LLASM model deals with non probabilistic uncertainty rules to produce successful results in every situation (Ye et al. 2009).

The correlation state of art enhanced human interaction model based on linear structural modeling for knowledge representation and existing methods has been discussed in Sects. 1 and 2 respectively. The mathematical model and algorithm discussed in Sect. 3 gives an overview about the global weight and local knowledge rules to determine the optimal flow and job characterization problem faced in linguistic reasoning method. Finally the experimental results and conclusion have been discussed in Sects. 4 and 5 correspondingly with future scope.

2 Background study

Ribarić et al. (2009) introduces a new type of dynamic adaptive fuzzy petri net (DAFPN) model to solve the issues which are faced with Fuzzy Petri Net systems that suffers from some type of deficiencies in the parameter threshold, here the certainty factor and weight are not accurately noted for the increasing knowledge based on the expert system to overcome the issues using dynamic adaptive fuzzy petri net (DAFPN) model introduced by the authors. In this method maximum algebra based reasoning algorithm was implemented automatically to represent the model and experts with experience can be implemented with the knowledge based reasoning method dynamically.

Yang et al. (2004) Introduces Modified Fuzzy Reasoning Algorithm (MFRA) model to enhance the capability of reasoning in the original algorithm. The expert knowledge faces issues to represent the knowledge representation method in exact type. On the other hand they cannot easily represent non fuzzy knowledge format that consists of linguistic variables. To enhance the computer interaction model a new modified fuzzy reasoning algorithm (MFRA) with robotic assistance was introduced to built adjacent places and reach ability sets. These types of algorithms are implemented to build a fuzzy based expert system that helps the students to choose their academic departments and colleges.

Lee et al. (2004) Introduces a knowledge representation scheme (KRS) to describe the intersection search for inference procedure based on the fuzzy Petri net. The procedure of knowledge representation was introduced to determine the dynamical properties of the relationship between the concepts of interest model which is obtained by the intersection algorithm. These algorithms are accompanied by the linguistic values expressing the assurance of relations with robotic assistance. To enhance the human interaction model the knowledge representation scheme is used to determine the set of linguistic variables under probabilistic condition.

Chiachío et al. (2018) Introduces a new model for Petri Net that combines the principles of Petri net to determine the information's when they are at uncertain knowledge representation condition. The new proposed model results plausible petri net (PPN) model for the main feature to determine the efficiency by considering the evaluation of discrete event systems to find with uncertain type of information using state representation. In this paper algebraic method format was considered to find the evaluation of uncertain state variables Petri net dynamics. To illustrate the real world challenges related to the uncertainty plausible petri net (PPN) is considered as one of the best expert system to demonstrate the monitoring data model effectiveness (Chen 2010).

Scarpelli et al. (1996) Introduces a new model to compromise the promising method for knowledge, reasoning and representation using fuzzy Petri net. Still some issues are faced due to fuzzy Petri Net model to overcome those difficulties by the author which introduces a new technique called Self-Learning Interval Type 2 Fuzzy Petri Net (SLIT2FPN) to determine the alternative optimal condition and to collect the expert of cognition using weighting factors. This network is used to identify the motion model for modular robots on the basis of experimental data, so as to obtain the non-linear cinematics robots model. Such form of neural network is therefore highly suited for the recognition and motion control of robot cinematics models (Chen 2019). The self learning method was introduced to improve the stability model according to the dynamic information. This process helps to improve the feasibility cognition and to attract the individual features with good performance. Hence, in this article human computer interaction faces optimal flow and job Characteristics experience using individual computers in the workplace which helps to overcome the issues using LLASM in a variety of organization (Konar 1999).

No research centered on how children communicate spontaneously and experience robotic virtual settings. Although thorough research is conducted into the experience of the full body and the innate handling of adult robots, there was no similar study with infants (Sun 2019). Here, authors proposes a movement anticipation review, which established children's favorite movements and body language communication for controlling ground robots. The findings of the elicitation analysis were used to evaluate the gestural vocabulary, which includes a good tolerance of 6–12 age groups in the different preferences of gestures according to age and gender.

Not only does it agree with the basic characteristics of biological neural networks, but it also has the benefits of simple algorithm, quick learning convergences and good linear and nonlinear structures detection precision (Pons and Jaen 2019).

This model introduces global weight and local knowledge fuzzy rules to determine the optimal flow and job characterization problem faced in linguistic reasoning method as discussed as follows,

3 Linear linguistic advanced structural modeling for purpose of reasoning and knowledge representation with robotic assistance

The proposed model refers to a linguistic variable value which is not expressed as numbers in linguistic terms, sentences or words where as it is denoted as artificial or natural language format. The definition of linguistic variables is useful to manage both complex situations and a variety of linguistic terms are expressed mathematically as denoted as W = {w_0, w_1, $w_{2,}$…, w_h} as odd cardinality. Further the parameter, h is the even number representation with w_j represents the linguistic variables of possible values. The linguistic set satisfies following conditions as listed as follows,

1. *Operator as negation : Neg* (w_j)= w_j *that is i = h-j.*
2. *Ordered set:* w_j> w_i, *if j > i.*
3. *Operator at max level: max*(w_j, w_i) = w_j *if* $w_j \geq w_i$.
4. *Operator at min level: min* (w_j, w_i) = w_j *if* $w_j \leq w_i$.

The linguistic 2-tuple approach has been suggested based on the concept of symbolic translation and adapted mainly in the form of 2-tuple (w_j, β) linguisticlabel which is represented as w_j, from the pre-defined linguistic set. Furthermore, w and β are the numerical value representation of the symbolic translation values. Here β modifies the corresponding numeric value to the linguistic term for the 2-tuple values which can be denoted little more, if β is positive and little less if β is negative to denote positive and negative values.

In the above Fig. 3, the image format are received to the linguistic processor with the help of sensors. And the image format is splitted into visual and auditory image in the storing device. Then the file is transferred to the memory processor in which long term memory and cognitive device images are correlated sensed with the help of the sensor unit. After processing it is transferred to linguistic 2 Tuple processor, for the purpose of reasoning and knowledge representation with appropriate memory storage. As inferred Few Definitions and its corresponding mathematical notations are expressed as follows to determine the habitual behavior of the system in connection with various objects used as controlled by the humanoid system as shown in the Fig. 4.

As inferred From the Fig. 4 various definitions are discussed as follows,

Definition 1 Let W = {w_0, w_1, w_2,…, w_h} be the linguistic set of functions h + 1 and $\alpha \in [0,1]$ it is the value represented as the result of symbolic aggregation process to identify the high and low pitch values. Here, the 2-tuple equivalent value of information is expressed as α and it is computed in the following equations

$$\nabla : [0,1] \rightarrow \mathrm{W}^{*}\left[-\frac{1}{2h},\frac{1}{2h}\right] \tag{1}$$

$$\nabla\alpha = \left(\mathrm{W}_{\mathrm{j}}\beta\right), \quad \text{with} \quad \left\{\begin{array}{l} w_{jj=round}\,\alpha.h \\ \beta = \alpha - \frac{1}{2h}, \beta \in \left[-\frac{1}{2h},\frac{1}{2h}\right] \end{array}\right\} \tag{2}$$

Usual rounding operation is denoted as round (.) and w_j has the closest label index to α, the symbolic representation is denoted as.

Definition 2 Let W = {w_0, w_1, w_2, …, w_h} be the linguistic set of terms and (w_j β) be the representation of 2-tuple. The existing function can be converted into ∇^{-1} that is the equivalent numerical value $\alpha \in [0,1]$. Thus the reverse function is expressed in the following Eqs. (3) and (4)

$$\nabla^{-1} : \mathrm{W}^{*}\left[-\frac{1}{2h},\frac{1}{2h}\right] \rightarrow [0,1] \tag{3}$$

$$\nabla^{-1}\left(\mathrm{W}_{\mathrm{j}}\beta\right) = \frac{j}{h} + \beta = \alpha \tag{4}$$

Here the linguistic term is converted into linguistic 2—tuple values consisting 0 and β.

Definition 3 Let (w_l, β_1) and (w_k, β_2) be the 2—tuple linguistic values that are defined in following Eqs. (5) and (6)

$$\text{If } 1 < \mathrm{K} \text{ then } (\mathrm{w}_l, \beta_1) \text{ is smaller than the } (\mathrm{w}_k, \beta_2). \tag{5}$$

If l = k then:

If β_1 = β_2, then (w_1,β_1) is equal to (w_k,β_2) = For Polite Representation.

If $\beta_1 < \beta_2$, then (w_l, β_1) is smaller than (w_k, β_2).

$$\begin{aligned} &\text{If } \beta_1 > \beta_2, \text{ then } (\mathrm{w}_l, \beta_1) \text{ is bigger than } (\mathrm{w}_k, \beta_2) \\ &\quad = \text{For imPolite Representation} \end{aligned} \tag{6}$$

Definition 4 Based upon 2- tuples (w_l, β_1) and (w_k,β_2), let ∇^{-1}(w_l,β_1) = α_1 and ∇^{-1} (w_k,β_2) = α_2 and $\mu \in [0,1]$. Therefore the linguistic 2-tuples basic operational laws are determined in the following equation as

$$(\mathrm{W}_l, \beta_1) + (\mathrm{w}_k, \beta_2) = \nabla[\alpha_1 + \alpha_2] \tag{7}$$

$$(\mathrm{W}_l, \beta_1) * (\mathrm{w}_k, \beta_2) = \nabla[\alpha_1.\alpha_2] \tag{8}$$

$$\mu(\mathrm{W}_l, \beta_1) = \nabla[\mu\alpha_1] \tag{9}$$

$$(w_l, \beta_1)^{\mu} = \nabla\alpha_1^{\mu} \tag{10}$$

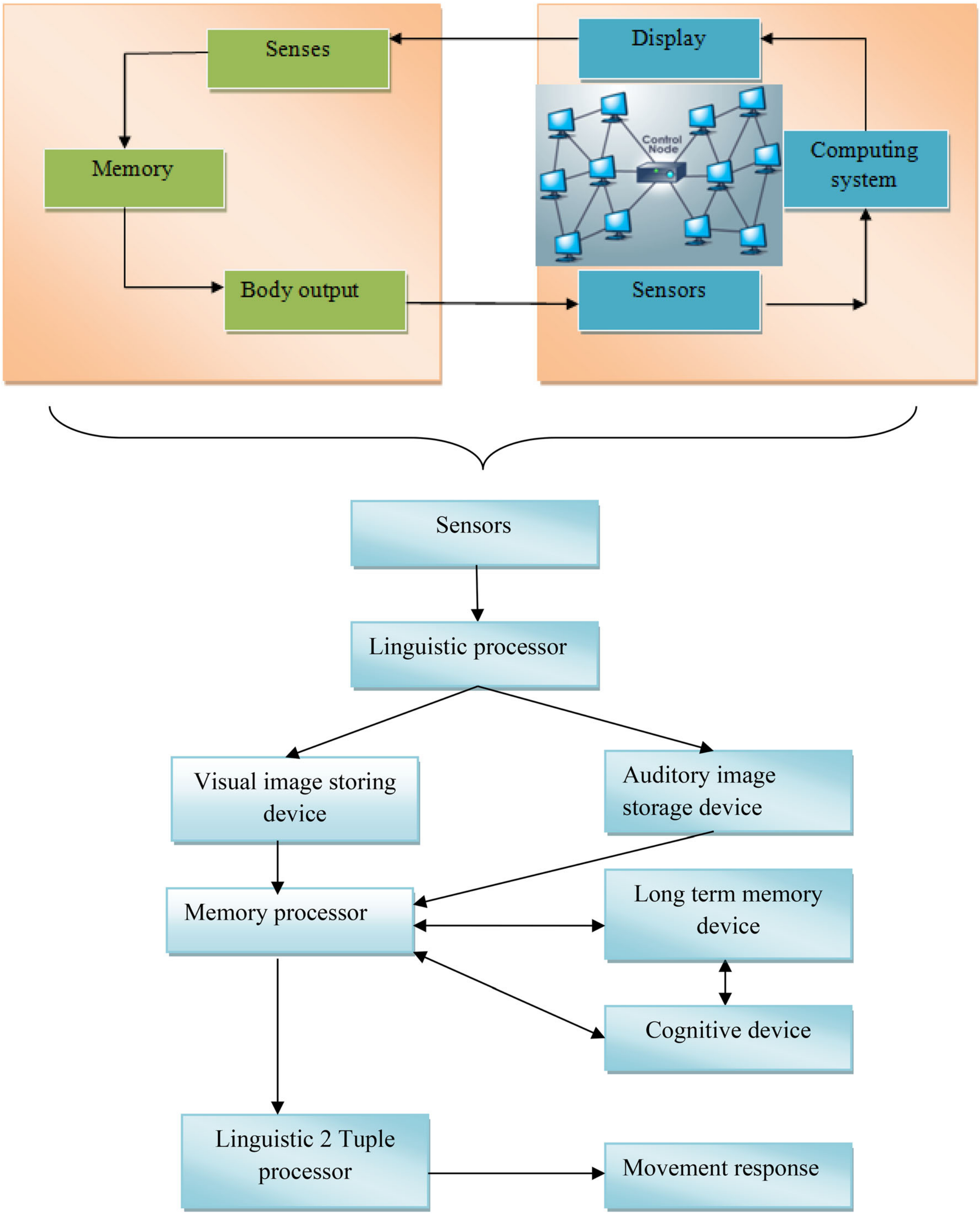

Fig. 3 Block diagram representation of linguistic processor

Definition 5 According to certain function θ formats, the fundamental operational laws of 2- tuple linguistics are based on normalized functions of x- and y with its corresponding speed has been analyzed, for instance, if $\theta(Y)$ =-log (y) then the algebraic functions are derived as

$$(\mathrm{W}_1, \beta_1) + (\mathrm{w}_k, \beta_2) = \nabla[\alpha_1 + \alpha_2 - \alpha_1\alpha_2] \tag{11}$$

$$(\mathrm{W}_1, \beta_1) * (\mathrm{w}_k, \beta_2) = \nabla[\alpha_1 \cdot \alpha_2] \tag{12}$$

$$\mu(\mathrm{W}_1, \beta_1) = \nabla[1 - (1 - \mu\alpha_1)\mu] \tag{13}$$

$$(w_l, \beta_1)^{\mu} = \nabla\alpha_1^{\mu} \tag{14}$$

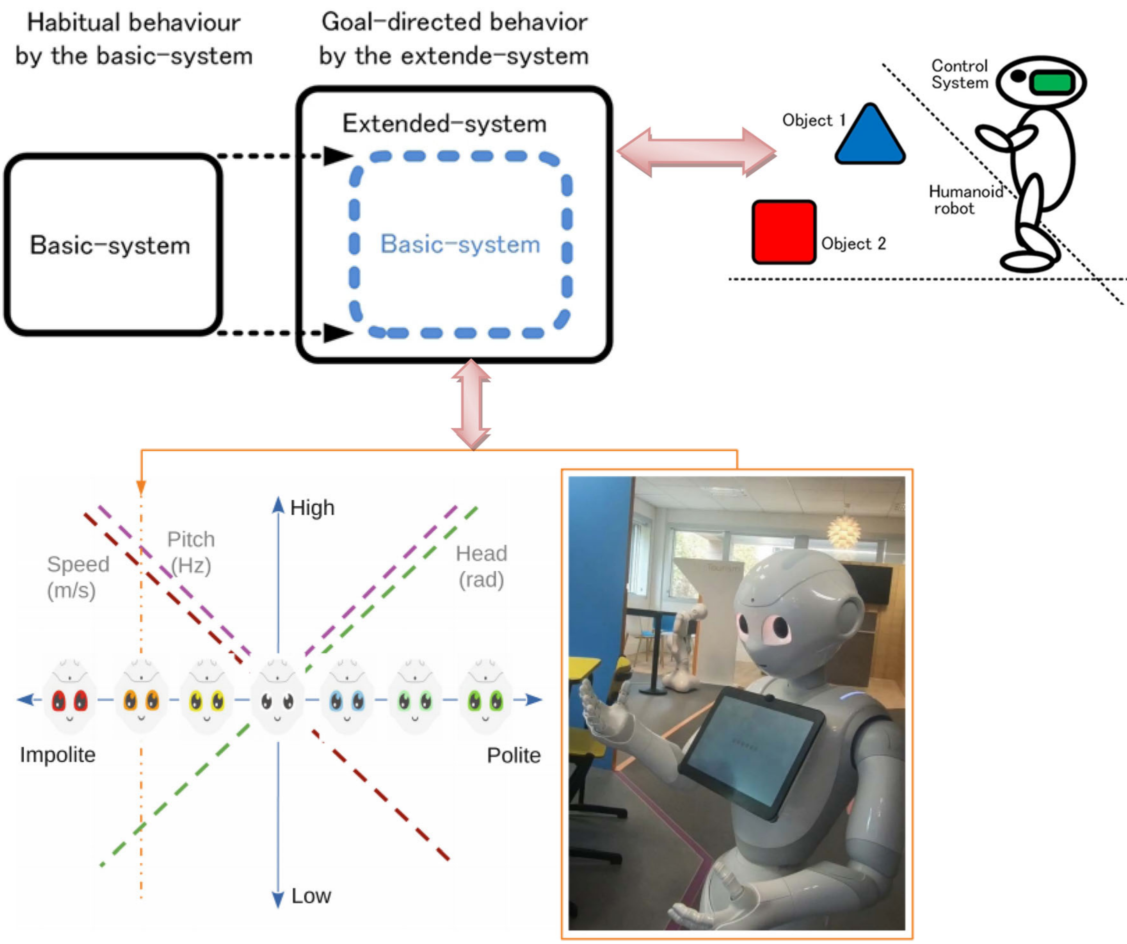

Fig. 4 Various verbal and non-verbal analysis with lingustic functions

In the above equations the selection of the perfect weighting factor is used to derive various types of 2-tuple linguistic operators. The minimum and maximum values of 2 tuples are found if $s_1 = 1$ and $s_i = 0$ for all $i \neq 1$, and if $s_n = 1$ and $s_i = 0$ for all $i \neq m$. In this proposed study, a number of methods for evaluating the weight average functions have been implemented.

3.1 Linguistic weighted order reasoning technique (LWORL)

In this section LWORL approach is analyzed for Fuzzy rule-based system expert and the analysis are explained for five types of linguistic production fuzzy rules based upon expert systems. The following techniques are explained in detail in following case studies.

3.2 Case 1: Linguistics simple protection fuzzy rule analysis

3.2.1 Solution

$$J: \text{ IF } x \text{ THEN } y\ (\check{\delta};\ ct; \check{\gamma};\ bt) \tag{15}$$

Here x and y are the propositions,$\check{\delta}$ and $\check{\gamma}$ are the linguistic 2-tuples that are $W = \{w_0, w_1, w_2, \ldots, w_h\}$ of functions. At the same time, the threshold value is determined under the specified rule J of the proposition x. The local weight (ct) and the global weight (bt) are respectively indicated. The real values of local and global weight range from 0 to 1. Assuming the linguistic value of true proposition x as denoted as $\check{x}_x$, where $\check{x}_x$ is the linguistic set W defined from linguistic 2-tuple functions. Therefore the linguistic value of true proportion y is computed in the following Eq. (16).

$$\check{x}_x = \nabla\left[\exp\left(-1.5 * \left(\nabla^{-1}(\check{\gamma}) * \nabla^{-1} - 1\right)^2\right)\right] \quad \text{when} \quad \check{x}_x \geq \check{\delta} \tag{16}$$

Exponential operation of linguistic 2-tuple is expressed as exp (.). In this paper the exponential function is computed based upon consequent linguistic true value. For this type of fuzzy rules only one proportion is applied consequently so here both the global weight and local weight are equal to 1.

3.3 Case 2: A linguistic composite conjunctive fuzzy rule is followed in antecedent

3.3.1 Solution

$$\begin{aligned} &J: \text{ IF } x_1 \text{AND } x_2 \text{ AND}\ldots\text{AND } x_n \text{THEN } y \\ &(\check{\delta}_1, \check{\delta}_2, \ldots, \check{\delta}_n;\ s_1,\ s_2, \ldots, s_n; \check{\gamma};\ bt) \end{aligned} \tag{17}$$

$\check{\delta}$ *and* $\check{\gamma}$ is the threshold value of the proposition factor x_j and the certainty factor is denoted as J respectively. Assuming the weight of the proportion as x_j and the rule weight J are determined as ct_j and bt respectively. The real values of local weight are noted between 0 and 1 and global weight is 1. Further, assuming the linguistic true values of proposition $x_1, x_2, \ldots, x_n$ are denoted as $\check{x}_{x1}, \check{x}_{x2}, \ldots, \check{x}_{xn}$. The true linguistic value of the proposition variable is as

$$\check{x}_y = \nabla[\exp(-1.5 * (\text{TOWA}(\check{x}_{x1}, \check{x}_{x2}, \ldots, \check{x}_{xn}) * \nabla^{-1}(\check{\gamma}) - 1)^2] \quad \text{when} \quad \check{x}_x \geq \check{\delta}_j \quad j = 1, 2, \ldots,\ n \tag{18}$$

Here from the above equation is noted to consider the wide range of Tuple Operated Weighted Factor (TOWA) operators to the 2-tuple maximum and minimum value.

3.4 Case 3: A linguistic certainty fuzzy rule factor is followed in antecedent

3.4.1 Solution

$$\begin{aligned} &J: \text{ IF x THEN } y_1 \text{AND } y_2 \text{AND } \ldots y_n \\ &(\check{\delta};\ ct; \check{\gamma}_1, \check{\gamma}_2, \ldots, \check{\gamma}_n;\ bt_1,\ bt_2, \ldots, bt_n) \end{aligned} \tag{19}$$

$\check{\delta}$ *and* $\check{\gamma}_j$ is the threshold value represented separately for the proposition factor x and the certainty rule J presenting the propositions y_j. Here, let us assume the weight of the proposition factor x is CT and the certainty fuzzy rule factor J includes the proposition y_j are bt_j, respectively, where ct = 1 and $bt_j = 1$. Thus if the linguistic true value of the proposition y_j is computed as in the following Eq. (20)

$$\check{x}_{yj} = \nabla[\exp(-1.5 * (\nabla^{-1}(\check{x}_x) * \nabla^{-1}(\check{\gamma}_j) - 1)^2] \quad \text{when} \quad \check{x}_x \geq \check{\delta}_j \quad j = 1, 2, \ldots,\ n \tag{20}$$

3.5 Case 4: A linguistic composite disjunctive fuzzy rule is followed in antecedent

3.5.1 Solution

$$J: \text{ IF } x_1 \text{OR } x_2 \text{OR}\ldots\text{OR } x_n \text{THEN } y \tag{21}$$

$\check{\delta}_j$ *and* $\check{\gamma}_j$ is the threshold value represented for the proposition factor x_j and the certainty sub-rule J_j from the proposition factor x_j to the proposition y, which are represented as the linguistic true value proposition that is computed in the following Eq. (22)

$$\check{x}_y = \text{TOWA}[\nabla\left[\exp\left(-1.5 * \left(\nabla^{-1}(\check{x}_{xj})\nabla^{-1}(\check{\gamma}_j) - 1\right)^2\right)\right] \quad \text{when} \quad \check{x}_{xj} \geq \check{\delta}_j \quad j = 1, 2, \ldots,\ n \tag{22}$$

3.6 Case 5: A linguistic composite disjunctive Fuzzy rule is followed in antecedent

3.6.1 Solution

$$\begin{aligned} &J: \text{ IF x THEN } y_1 \text{OR } y_2 \text{OR } \ldots .\ y_n \\ &(\check{\delta}_1, \check{\delta}_2, \ldots, \check{\delta}_n;\ ct_1,\ ct_2, \ldots, ct_n; \check{\gamma}_1, \check{\gamma}_2, \ldots, \check{\gamma}_n;\ bt_1,\ bt_2, \ldots, bt_n) \end{aligned} \tag{23}$$

$\check{\delta}_j$ *and* $\check{\gamma}_j$ is the threshold value for the proposition factor x with respect to x_j and the certainty sub-rule J_j presenting the propositions y_j. Here, let us assume the weight of the proposition factor x_j is ct_j and the weight of the jth rule is represented as bt_j, where $ct_j = 1$ and $bt_j = 1$. Thus the linguistic true values of the propositions $x_1, x_2, \ldots, x_n$ are $\check{x}_{x1}, \check{x}_{x2}, \ldots, \check{x}_{xn}$ therefore the linguistic true value proposition y_j is computed as in the following Eq. (24)

$$\check{x}_{yj} = \nabla[\exp(-1.5 * (\nabla^{-1}(\check{x}_x) * \nabla^{-1}(\check{\gamma}_j) - 1)^2] \quad \text{when} \quad \check{x}_x \geq \check{\delta}_j \quad j = 1, 2, \ldots,\ n \tag{24}$$

Basically, these fuzzy rules that have been followed in every case will not be applied in the knowledge-based technical model, as the linear linguistic reasoning model is modified into several rules as discussed below. Here the global and local weight of the linguistic production will be assumed to be crisp type of values which will be very easy to determine the knowledge representation parameters. As a result, in the evaluation of consequent linguistic true values for considering case 2 and 4 linguistic problems will be solved.

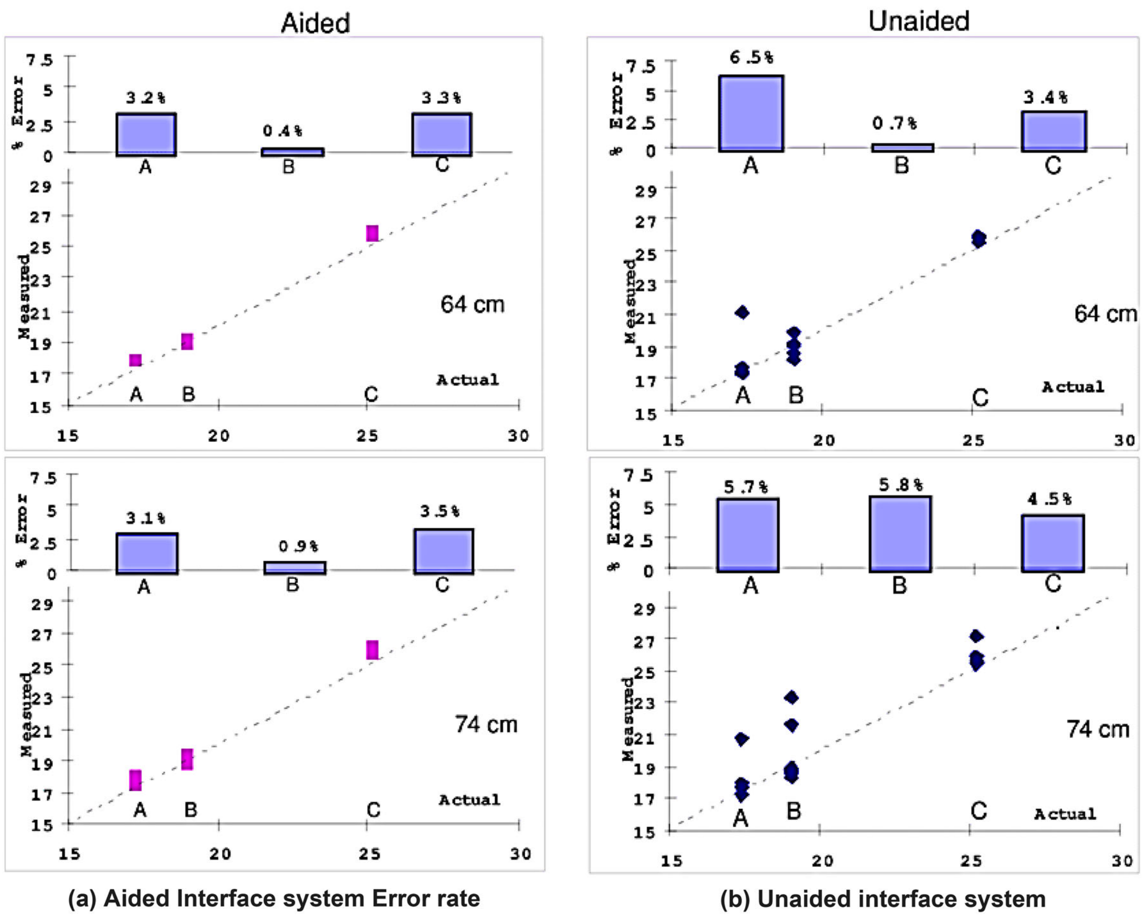

Fig. 5 Error rate evaluation for aided and unaided robotic system. **a–c** Image frame sequence error analysis rate

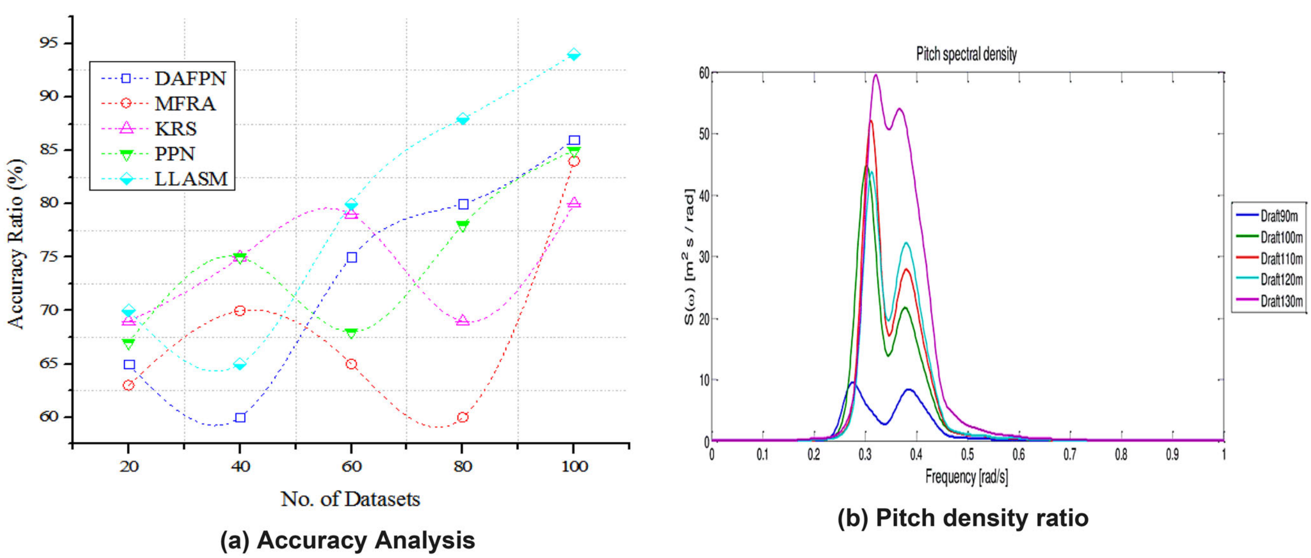

Fig. 6 Accuracy and pitch density ratio of LLASM method

Table 1 Local weight validation

No. of datasets	DAFPN	MFRA	KRS	PPN	LLASM
20	70.3	72.4	75.7	73.56	77.56
40	77.7	65.78	80.4	65.4	72.6
60	82.4	78.7	76.7	60.78	85.6
80	75.6	81.5	84.6	78.9	90.2

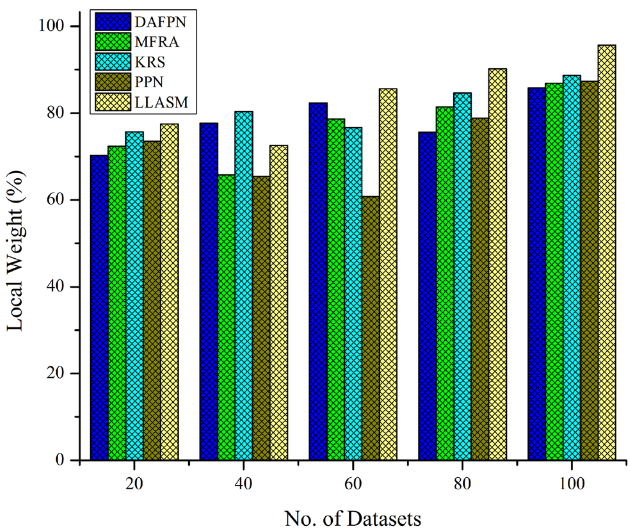

Fig. 7 Local weight validation of the method

Table 2 Global weight of LLASM method

No. of datasets	DAFPN	MFRA	KRS	PPN	LLASM
20	65.6	66.7	68.7	62.5	70.7
40	78.9	74.5	60.9	70.4	68.56
60	72.4	80.6	69.3	65.78	83.6
80	79.9	74.3	76.7	75.8	88.9
100	85.4	82.5	86.78	87.6	95.89

3.7 Linear linguistic reasoning model with humanoid assistance

3.7.1 Definition of LLASM

In this section the proposed LLASM model based upon knowledge based system expert considering set of 2-tuples set function as defined as in linguistic set W = $\{w_0, w_1, w_2, \ldots, w_h\}$. The following definition of LLASM structure is described below

LLASM = (A; B; C; D; E)

where, A = $\{a_1, a_2, \ldots, a_n\}$ represents the non-empty finite set of places. B = $\{b_1, b_2, \ldots, b_n\}$ Denotes non empty final set of transitions. C = A*B $\rightarrow \{0, 1\}$ n*m represents matrix in the form of input defining the direct arc places to the transitions. $C_{ji} = 1$ if it exists from the direct arc from the particular place a_j to the transition place b_i and $C_{ji} = 0$ if no direct arc from a_j to the place b_i, for j = 1, 2, …, n and i = 1, 2, …, m. D = $[B * A]^T \rightarrow \{0, 1\}$ n*m represents matrix in the form of output defining the direct arc places to the transitions. $D_{ji} = 1$ if it exists from the direct arc from the particular place b_i to the transition place a_j and $D_{ji} = 0$ if no direct arc from b_i to the place a_j, for j = 1, 2, …, n and i = 1, 2, …, m. E = $\{e_1, e_2 \ldots e_n\}$ that denotes the finite set of propositions $A \bigcap B \bigcap E = \theta \; A \neq E$.

Generally linguistic production rules are considered to set the goal proposition by describing the dynamics rule in the reasoning process with the humanoid assistance model which helps to improve optimal flow and job Characteristics experience. Hence The Weighted linguistic reasoning algorithm allows rule-based expert systems with the help of the LLASM method to execute the intelligent and flexible knowledge reasoning model has been experimentally analyzed which are discussed as follows.

4 Case analysis and discussion

The weighted average operator is used to measure the reasoning results in linguistic production rules in the above mentioned linguistic processing reasoning. Strong points are proposed in the LLASM model to compare the results with minimum and maximum exponent level. The linguistic true values are obtained to represent the values by applying the traditional minimum and maximum operation. In this proposed model the following parameters are analyzed such as Local Weight, Global Weight, Accuracy, Performance Ratio and Error Rate.

Error rate refers to frequency of errors that is occurring and it is used to determine the difference between the total numbers of error rate in images, frames and total number of units transmitted in a video format for the aided and unaided user interface module. The value of Error Rate is low in the proposed method since the weight factors and certainty value are placed efficiently in the processor region and the graphical representation has been shown in the Fig. 5 and explains the linguistic true values.

It is inferred that aided value (Fig. 5a) shows less error ratio than unaided (Fig. 5a) component as mentioned in the Fig. 5. Here the aided system has less error rate because the weight of the proposition factor x is CT and the certainty fuzzy rule factor J includes the proposition y_j are bt_j, respectively, where ct = 1 and $bt_j = 1$.

Accuracy refers to the nearest measurement specific value; mostly it differs from true values and the result [21].

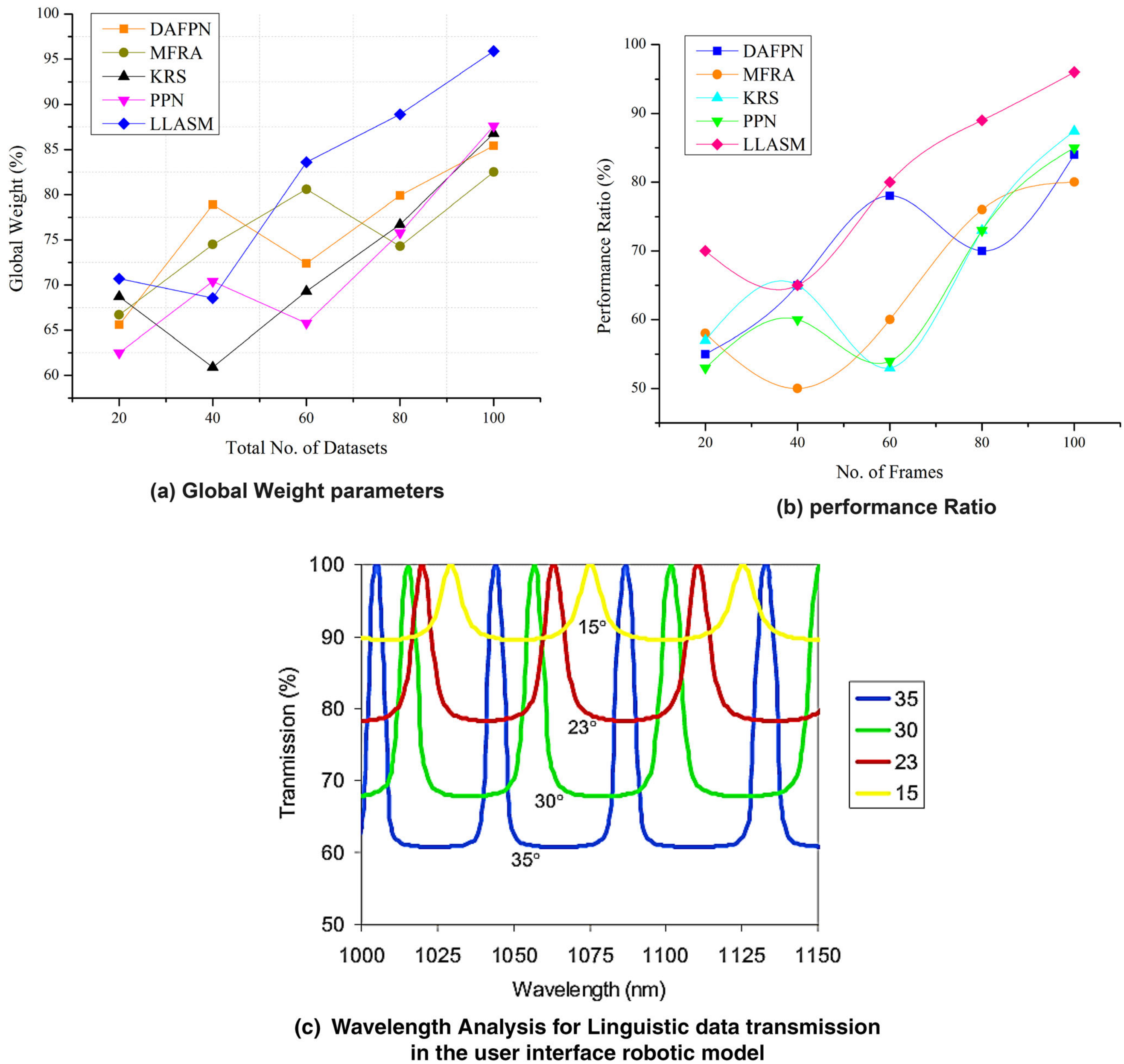

Fig. 8 Performance ratio analysis

In a same quantity of data points repeated measurement is taken to find the accurate value. In this proposed Linear Linguistic Advanced Structural Modeling (LLASM) method accuracy value is high when compared to existing algorithms such as DAFPN, MFRA, KRS and PPN. The value of Accuracy is high in the proposed method since the weight factors and the certainty value are placed equivalently to linguistic true values are shown in Fig. 6a.

As inferred From the Fig. 6. Certain function θ formats and its fundamental operational laws of 2- tuple linguistics is considered based on the normalized functions of x- and y with its corresponding pitch spectral density S(w) ratio has been analyzed in accordance various existing counterparts in Figs. 5 and 6b. The Proposed method shows less pitch scale density for smoother linguistic translates. The LWORL approach is analyzed for Fuzzy rule-based system expert and the analysis are explained for linguistic production fuzzy rules based upon expert systems. Here the local weight of the linguistic production will be assumed to be crisp type of values which will be very easy to determine the knowledge representation parameters. Table 1 shows the numerical values of local weight factors.

The Linguistic proposition values are divided into local weight and global weight respectively. The local weights in the human interaction model are denoted in the values between 0 and 1. The local weight (ct) determined using case study of linguistic composite disjunctive rule ct_1, ct_2,…, ct_n; Fig. 7 illustrate the local weight factors with linguistic true value shows prominent improvement in local weight factor.

The linguistic production rules are considered to set the goal proposition by describing the dynamics rule in a reasoning process model which helps to improve optimal flow and job Characteristics experience. Here the Table 2 shows the numerical values of global weight factor LLASM method for improving the significance of linguistic reasoning process.

The Linguistic proposition values are divided into local weight and global weight respectively bt and ct. The Global weights in the human interaction model are denoted in the values between 0 and 1. Global weight and local weight are examined as the relative significance to the linguistic reasoning process and evaluated using linguistic composite disjunctive rule bt_1, bt_2,…,bt_n. Helps to improve the ratio factor in an effective and efficient manner, as discussed in the Fig. 8a.

Performance ratio is used to measure the quality of the image and it describes the form of theoretical and actual image format. Here the performance ratio level is measured for all the weight and certainty factors of the frames of transmission in accordance to wavelength as shown in the Fig. 8c. The value of the Performance ratio is high in the proposed method since the certainty value and weight factors are placed equivalently to linguistic true values. Figure 8b explains the performance ratio of the proposed LLASM method in accordance with existing factor.

From the case analysis report. The weighted linguistic reasoning algorithm allows fuzzy rule-based expert systems with the help of the LLASM method to execute the intelligent and flexible knowledge reasoning model with robotic assistance shows more effectiveness of the rescheduling process which benefits the Linguistic reasoning model.

5 Conclusion

The linguistic production model decision making are finalized based on the certainty factor of linguistic rules and Weight factor of the proposition which is represented by 2-tuples linguistic. As an ordered weighted linguistic inference, the LWORL rule structure algorithm is performed for the true linguistic values of the whole proposition. The relative importance to the linguistic reasoning process are also seen by global weight and regional weight. Finally, the proposed inference method was tested successfully by an empirical analysis with humanoid assistance. Therefore LWORL rule can deal with some of the drawbacks raised in previous papers by the fuzzy reasoning methods. Further more studies can be implemented to perform linguistic reasoning algorithm in effective way and large scale data can be used efficiently. The second is the efficient improvement in LLASM model of parameters for information representation, such as accuracy, performance ratio and error rate, to efficiently represent the dynamic nature of knowledge uncertainty in real world applications. The paper is the main analysis based on the possibility of LWORL fuzzy knowledge inference rule operations. In future other type of aggregation operators will be introduced in LWORL rule approach and hybrid weighted averaging operators for developing further extension in LLASM model. In future this algorithm has been planned to incorporate in light weight cryptography and robotic arm.

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