Multi-level Computing With Words Model to Autonomous Systems Control

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Abstract. An autonomous system which must react to unforeseen situations is considered. The control task of such system is characterized by the processing of data from large number of sensors, uncertainty and dynamics. The traditional automation approaches cannot be used to create control system that satisfies these conditions. Fuzzy logic solves this problem due to ability to data generalize and take into account uncertainty, but only for simple applications presented by a small amount of data from sensors. L. Zadeh Computing with Words (CWW) approach overcome the problem of large dimensionality if the situation description is presented by a small number of words, but a high level of abstraction. However, the problem remains how numerical data from sensors to convert into the words representing the meaning of these data at a high level of abstraction. Three-phases CWW model is proposed to solve this problem. At the first phase, granular computing engine reveal the meaning of data from sensors and represents its by words of zero-level abstraction. Then abstracting with words engine maps its words into words of higher abstraction level representing the meaning of complex dynamic situations. And in the end, CWW engine obtain control decisions using as fuzzy inference inputs the meaning of the words of high levels abstraction. Such word-based processing of data from sensors is based on the proposed fuzzy models of the external and internal meanings of the word. An example of signal switching control of a smart traffic light is given.

Keywords: autonomous systems, computing with words, abstracting with words, data from sensors, fuzzy systems.

1 Introduction

Robotics, Internet of Things, smart machines, as automation applications, are designing based on Autonomous Systems (ASs) principles [1-3]. Since ASs leave ordered environments, for autonomous functioning in more complex, natural conditions, they have to react to unforeseen situations. In order to ensure autonomous, the AS Control System (CS) should be real-time decisions making based on the analysis of a complex situation, which is represented by a spatio-temporal set of data from sensors. Thus, the control task that AS solves is characterized by the processing of data from a large number of sensors, uncertainty and environment dynamics. The main restrictions of the traditional automation approaches are characterized by predefined abilities [4, 5]. The

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CS can only respond to expected situations and according to a pre-programmed action plan [6], which does not allow to fully realize autonomous behavior in the broad sense. Alternatively, AI can be used to control autonomous systems. This is one of the main tasks of the future AI, on the creation of which leading research teams are working today [7]. On this way, the problem of choosing an AI model that provides decisions making in the above AS conditions is arise.

The AI model, first of all, should satisfy the requirements for embedded real-time systems. Secondly, AI model should make decisions in the face of uncertainty (knowledge incompleteness and data ambiguity, fuzziness and aging) [8, 9]. Thirdly, the AI model should make decisions based on a large amount of data from sensors (dimension problem). Fourth, the AI model must scale solutions to adapt to dynamic changes in the situation (scalability problem) [8].

Models and approaches on the basis of which it is possible to develop AI that meets the formulated requirements can contingently be divided into two groups: 1) oriented to the data from sensors processing and 2) oriented to the knowledge processing.

The first group includes such approaches as intelligence analyzing, extracting knowledge from data streams, generation of informational patterns, aggregation of heterogeneous data from different sources in order to obtain, for example, the complex description of situation. All of them are directly addressed in works on information fusion processes [10, 11]. They are not suitable for automation of decision-making based on the analysis of complex sophisticated situations.

The knowledge-based AI approach belonging to the second group known as rules-based systems [12, 13] allow to implement the decision making tasks, taking into account the above features. Decision making in robotics, internet of things, smart machines domains carries out Rules Engine (RE) by searching among large number of situations and, possibly, involving heuristics [8, 13]. The RE widely used in embedded real-time systems [1, 2, 8, 14], however, the problem of the task dimensionality remains relevant. Thus, for crisp models the prototype of situation is associated with control decisions by the *if-then* rules. Since AS inputs are data from sensors, then situation prototype (condition in the *if* part of rule) should be built directly on a set of heterogeneous data from sensors. This require large number of rules to represent all possible situations in which AS must make decisions [15-18]. Using the Fuzzy Logic System (FLS) as an AI for autonomous systems is problematic for the following reasons, also. Firstly, among specialists in fuzzy systems there is a belief that it is possible to really configure or tune a fuzzy system for the not complicated tasks with the number of input variables not exceeding 5-7 [16, 19]. This circumstance limits using FLS in its “pure” form for such domains as modern robotics and the Internet of Things, in which data from sensors are used as input. Secondly, FLS does not have the property of scalability [8, 15]: adding new input numerical variables or changing the number or definition of linguistic variables terms requires changing the existing knowledge base (changing fuzzy rules).

Problems of dimensionality and uncertainty can be solving by words-based data processing approach thanks to ability of natural language words to generalize and abstract [17, 18]. However, the L. Zadeh Computing with Words (CWW) approach suggests that the words, and not the data from the sensors, come to the inputs of the CWW model. To use this approach, it is necessary to bridge the gap between the two “data from sensors” and “word” paradigms.

The purpose of this article is to propose an AI approach and model that solve this problem. AI model, by analogy with a human thinking, solves three tasks. First, in real time, AI maps the spatio-temporal stream of data from sensors into natural language words that reveal the meaning of this data. Second task is abstracting with words. Based on the words describing the local data sets, the AI should get a description of the meaning of the whole situation using words of a high level of abstraction. And, thirdly, according to CWW approach, control is making by fuzzy inference using the meaning of the words of high levels abstraction.

2 Background

The methodological basis of the AI model is Lotfi A. Zadeh restriction-centered theory of truth and meaning [20]. In accordance with the stated theory, in this paper we introduce External Meaning of the Word (EMW) and Internal Meaning of the Word (IMW) formal models. The decision-making process based on data from sensors is divided into three phases. In the first phase, the spatio-temporal segment of data from the sensors is transformed into a verbal description in the form of a set of IMWs. Data meaning presentation by the IMWs is proposed to be implemented based on the concept of information granule [19] and Granular Computing (GC) [22, 23]. Based on this concept a "bridge" between data from sensors and knowledge in an IMWs form is created. The second phase is the reasoning by abstraction and generalization method [12]. The Abstracting with Words (AW) Engine compute the IMWs, sequentially, starting from the IMWs received in the first phase, moving up to the words representing the situation at a high level of generalization. The AW Engine (AWE) inference based on knowledge in the form of EMW. In this work, we use the AWE model proposed in [8, 15, 24]. This model works with the IMW and EMW represented by fuzzy certainty factor. The third phase is obtaining IMWs of words which describes the control decision by logical inference according to the IF - THEN rules. The traditional Computing With Words (CWW) model [25] developed on the basis of Type-1 Fuzzy Sets (T1 FS) or Perceptual Computing [24] developed on the basis of interval Type-2 FS (T2 FS) [19, 27] is used in this phase. AWE and CWW Engine (CWWE) are consistent on inputs and outputs due to the fact, that CWW fuzzy sets are defined on the same universe (certainty factor) as an IMW. Fig. 1 shows three possible options for implementing computing with words methodology.

For the first option of the data processing based on the CWW approach the input and output are numerical data. Fig. 1 shows that initially a fuzzifier maps numerical (crisp) data into a FS which is used as input to the CWWE. Then, the CWWE performs fuzzy inference according to IF-THEN rules. The output of the CWWE is again the corresponding FS. And in the final phase of the computing, Defuzzifier maps the resulting FS into numerical data. The FSs at the input, output and belonging the rules represent the words of the lowest level of abstraction, which reflect the meaning of the directly data. Therefore, dimension problem (the number of input variables and rules in the knowledge base) is not completely solved. This circumstance limits using in "pure" form of this CWW technology in AS.

For the second option Fig. 1 shows that the inputs are natural language words for which Encoder matches either T1 FS or T2 FS [25, 26]. The output of the model is also the word. The CWWE performs fuzzy inference according to IF-THEN rules. The rules use words as inputs from a pre-prepared Word Vocabulary (WV), respectively, in the form of T1 FS or T2 FS. The output of the CWWE is again the corresponding FS. And in the final phase Decoder maps FS to words, words ranks, or words classes. In this case the FSs at the input, output and belonging the rules can represent the words of the different level of abstraction including high. The main reason that makes difficult to use this technology in AS is that data from sensors cannot be automatically converted to words (FS). A human implements the function of perceiving the environment and converting his perceptions into words, which are then the Encoder input.

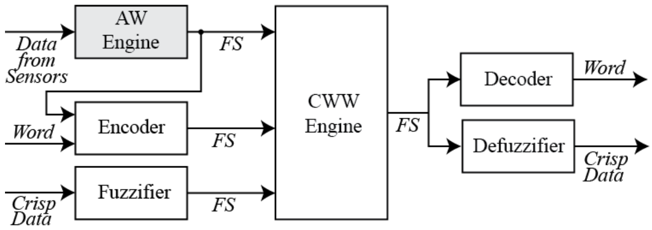

Fig. 1. Computing with words model options

In this article, we propose the third option, when the data processing from the sensors is carried out sequentially first by AWE, and then by CWWE. Fig. 1 shows that the AWE input is the data from sensors. The AWE in real time performs the first and second phases of data from sensors processing, automating such human function as sensation and perception [24]. The AWE maps the input data from sensors into IMW. The IMW is represented in the form of FS. The CWWE implements fuzzy reasoning with words that are the AWE output words (IMWs in the form of FS). Due to the fact that AWE creates a description of data from sensors in the form of words of a high level of abstraction, in CWWE decision-making is based on words that at a high level of generalization represent knowledge about solving a problem. It is significantly reduce the task dimension. Thus, the three-phases CWW model (GC → AW → CWW) satisfies the requirements for the AI model of AS. Call this model as expanded CWW (eCWW) model.

3 Abstracting With Words Model

3.1 Representation of the External Meaning of the Word

In semiotics, at the conceptual level, the word is represented by the triangle: firstly, the word is an element of the sign system; secondly, the word is a denotation of the sensation or perception of the real world essence, thirdly, the word has a designation giving the concept to the sign. Accordingly, three models of word are considered: sign model of the word, model of the internal meaning of the word and model of the external meaning of the word. To formalize AW, the last two of the three mentioned word models were used. A sign model in the form of a word representation in a natural language or a words combination or sentence or even a group of sentences is a component of the EMW model.

A graphic illustration of the word models is shown in Fig. 2. The Fig. 2 shows both models: EMW and IMW. The EMW model defines the meaning of a word N through the meaning of other words. Formally, this is a graph representing a semantic relationship: the vertex N of the graph is connected to the vertices M_i, which depict the corresponding words, through which the meaning of the word N is revealed [28]. The arcs of the graph indicate the parameters that determine the type of semantic relationship. The cloud around N, denoted by *knowledge about word*, depicts the representation in natural language of the word sign model. The WV is represented by set of knowledge portions in the form of Fig. 2. In WV the words are organized as a multilevel structure. Fig. 2 and Fig. 3 show that the meaning of the word N is an abstraction of a higher level compared to the meaning of the words $\{M_i, i=1, 2,...,k\}$, through which the EMW of the word N is revealed. In turn, the meaning of each of the words of the lower level, for example, M_i, is also represented through the words $\{W_{ij}, j=1, 2,...,p\}$ of a more lower levels. This EMW definition continues, going down the abstraction levels to words whose meaning is determined directly by the data from sensors. The WV lth level includes lth abstraction level words for which the EMW definition is given through the words l-1, l-2, ..., 0 abstraction levels.

As mentioned earlier, the EMW model is based on semantic relationships. In [8, 16] the choice of four semantic relationships "object-property" (*consist_of*); "whole-part" (*part_of*); "genus-species" (*is_a*); "action object-action-subject of action" (*before*) is founded. The first three relationships are used in knowledge representation model of traditional semantic network. The last relationship is introduced to represent knowledge about dynamical situations, processes passing in time including time events and actions.

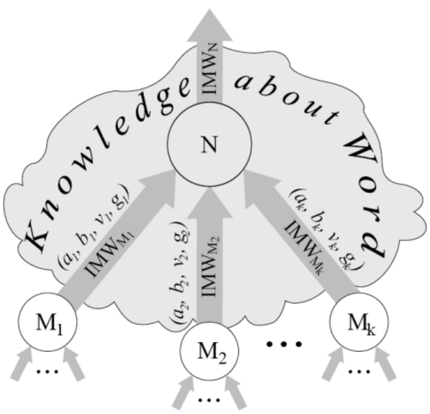

Fig. 2. Word meaning models

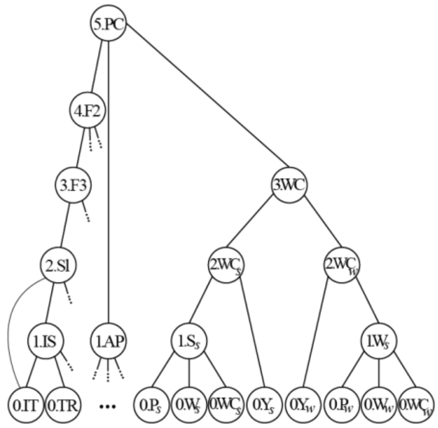

Fig. 3. Multilevel structure of the EMW

Relationships are parameterized. The following EMW model parameters are introduced. There are certainty (a), temporary delay (b), information aging rate (v) and information completeness (g). The EMW presentation base model is given below.

$$<N, know, \{<M_i, (a_i, b_i, v_i, g_i)>, M_i \in \Omega_N\}>, \quad (1)$$

where N is a word identifier; *know* is a signs word model; $\Omega_N = \{M_i\}_{i=1, 2,...,k}$ is a set of words of the lower levels of abstraction, which are used for the definition of the meaning of the word N; M_i is a low-level word identifier; (a_i, b_i, v_i, g_i) are the parameters.

The word N, according to Mendel's theory [18], has a different meaning (means different things) for different people. Therefore, the expert (group of experts) have different beliefs that the word M_i, can be used to explain the meaning of the word N. The quantitative assessment of certainty based on the Stanford theory of Certainty Factor (CF) [13]. In (1), the parameter $-1.0 \leq a \leq +1.0$ is the certainty. If it is necessary to indicate the presence or absence of a word M_i to determine meaning of the word N, then the certainty close to $a_i = +1.0$ or vice versa $a_i = -1.0$, respectively. The parameter b in (1) is a dynamic characteristic of the situation that the word N represents. The dynamic parameter $0 \leq b < \infty$ (time interval) is used to determine word that, in the sense, describe temporary event and process. For example, if in explaining the meaning of the word N it should be noted that the situation represented by the word M_i should appear later by τ time units than the situation whose meaning represents the word M_j, then in (1) $b_i = 0$, $b_j = \tau$. The information aging rate $0.0 \leq v_i \leq 1.0$ indicates how fast the relevance of information about situation presented by the word M_i have been lost. If the situation is a fast process, then the aging rate is close to $v_i = 1.0$. For static situation, the aging rate is $v_i = 0.0$. A parameter of the information completeness $0.0 \leq g_i \leq 1.0$ is characterization of the missing information to determine the meaning of the word N based on only the one M_i word. When the definition of the word N is given by enumeration of its representatives $\{M_i, i=1, 2,...,k\}$, then $g_i = 1.0$ for the each M_i. In the case when the word N definition needs a certain set of words, for example, $\{M_i, i=1,2,...,k\}$, then the parameters of information completeness for individual word M_i must satisfy the condition $g_1 + g_2 + \quad + g_k \geq 1.0$. Based on the model (1), it is possible to represent any of the *consist_of*, *part_of*, *is_a* or *before* relationships [24]. On the base of that relationships set, it is possible to represent external meaning of a word which on arbitrary level generalize the data from sensors. The following is an example of such a representation.

In this article, the eCWW model application is considered by the example of Smart Traffic-Light (STL). The EMW presentation in the form (1) is considered on the example of one of the criteria, namely, pedestrian comfortable conditions. In (2), an example of the EMW definition is given.

1. <***5.PC***, *pedestrian comfort*, {<***3.WC***, (0.95, *t*, 0.01, 0.4)>, <***1.AP***, (0.9, *t*, 0.5, 0.35)>, <***4.F2***, (1.0, *t*, 0.5, 0.25)>}>;
2. <***4.F2***, *factors of the 2nd degree of importance*, {<***0.Il***, (0.75, *t*, 0.01, 0.4)>, <***0.Ni***, (0.9, *t*, 0.5, 0.35)>, <***3.F3***, (1.0, *t*, 0.5, 0.25)>}>;
3. <***3.WC***, *weather comfort*, {<***2.WCs***, (0.95, *t*, 0.01, 1.0)>, <***2.WCw***, (0.95, *t*, 0.01, 1.0)>}>;
4. <***3.F3***, *factors of the 3rd degree of importance*, {<***2.Sl***, (−0.75, *t*, 0.15, 1.0)>, <***0.RR***, (−0.75, *t*, 0.15, 1.0)>}>;
5. <***2.WCs***, *weather comfort spring-summer season*, {<***1.Ss***, (0.75, *t*, 0.01, 1.0)>, <***0.Ys***, (0.75, *t*, 0.01, 1.0)>}>;
6. <***2.WCw***, *weather comfort fall-winter season*, {<***1.Ws***, (0.75, *t*, 0.01, 1.0)>, <***0.Yw***, (0.75, *t*, 0.01, 1.0)>}>;
7. <***2.Sl***, *sleet*, {<***0.Pd***, (0.75, *t*, 0.01, 0.4)>, <***0.IT***, (0.9, *t*, 0.5, 0.35)>, <***1.IS***, (0.75, *t*, 0.5, 0.25)>}>;
8. <***1.AP***, *air exhaust pollution*, {<***0.CH***, (0.9, *t*, 0.01, 0.3)>, <***0.CO***, (0.9, *t*, 0.01, 0.3)>, <***0.NO***, (0.9, *t*, 0.01, 0.4)>}>;
9. <***1.Ss***, *spring-summer season*, {<***0.Ps***, (0.75, *t*, 0.01, 0.3)>, <***0.Ws***, (0.75, *t*, 0.01, 0.3)>, <***0.WCs***, (0.75, *t*, 0.01, 0.4)>};
10. <***1.Ws***, *fall winter season*, {<***0.Pw***, (0.75, *t*, 0.1, 0.4)>, <***0.Ww***, (0.75, *t*, 0.1, 0.3)>, <***0.WCw***, (0.75, *t*, 0.1, 0.3)>}>;
11. <***1.IS***, *icing, snow sticking*, {<***0.Pd***, (0.75, t, 0.01, 0.45)>, <***0.TR***, (0.9, 10, 0.5, 0.25)>, <***0.IT***, (0.9, 0, 0.001, 0.5)>}>;
12. <***0.Ps***, *precipitation spring-summer*, {<*dry*, (1.0, *t*, 0.05, 1.0)>, <*drizzling rain*, (0.75, *t*, 0.05, 1.0)>}>;
13. <***0.Pw***, *precipitation fall-winter*, {<*dry*, (1.0, *t*, 0.05, 1.0)>}>;
14. <***0.Ws***, *wind spring-summer*, {<*calm*, (1.0, *t*, 0.1, 1.0)>, <*gentle*, (0.75, *t*, 0.1, 1.0)>, <*refreshing*, (0.35, *t*, 0.1, 1.0)>}>;

15.<***0.Ww***, *wind fall-winter*: {<*calm*, (1.0, *t*, 0.1, 1.0)>, <*gentle*, (0.55, *t*, 0.1, 1.0)>}>. (2)

In (2), the first digit of a word identifier indicates the WV abstraction level to which this word belongs. A full knowledge fragment is represented by 28 words, distributed across 5 levels (Fig. 3). At the top 5th level of abstraction, one word is ***5.PC*** (*pedestrian comfort*), EMW of which is given using the three words ***3.WC*** (*weather comfort*), ***1.AP*** (*air pollution*) and ***4.F2*** (*factors of the 2nd degree of importance*). EMW of the last word is also given with the help of three words of a lower level of abstraction. These are the words ***0.Ni*** (*noise*), ***0.Il*** (*illumination*) and ***3.F2*** (factors of the 3rd degree of importance). At the bottom zero WV level, pedestrian comfort is represented by 17 zero-level words that are defined on a set of IGs that represent input from precipitation, wind, temperature, air pollution, illumination, noises sensors and season data. The external meaning of 0-level words that are not included in the fragment (2) of the WV is explained below.These are such words: ***0.WCs*** (wind chill spring-summer), ***0.WCw*** (wind chill fall-winter), ***0.CH*** (air pollution CH), ***0.CO*** (air pollution CO), ***0.NO*** (air pollution NOy), ***0.Il*** (illumination), ***0.Ni*** (noises), ***0.RR*** (road repair work), ***0.Pd*** (precipitation fall-winter drizzling or more intense rain), ***0.IT*** (icing temperature), ***0.TR*** (temperature reduction), ***0.Ys*** (season of the year, spring-summer), ***0.Yw*** (season of the year, fall-winter). In their definition, there are references to IGs identifiers. For example, the definition of the word ***0.Pw*** in (2) is given using one IG *dry* with identifier *d*.

In fig. 3 arcs of the graph are bidirectional. This is explained by the following. In order to obtain EMW of the lth abstraction level, it is necessary to perform a downward l-step process of revealing the meaning through words of lower levels up to data from sensors. The converse is also true. In order to calculate IAM of the lth abstraction level, it is necessary to perform the l-step upward process of abstraction, starting with the data from the sensors.

3.2 Representation of the Internal Meaning of the Word

In Fig. 2, IMW is represented. This is depicted by shaded arrows inside which indicate IMW. This view emphasizes that the IMW is the computational meaning of the word. The IMW expresses the degree of conformity of EMW (1) with the situation represented by the spatio-temporal data set from the sensors. A numerical estimate of the IMW of the word *N* (Fig. 2) depends, firstly, on the parameters by which EMW was defined in (1), and, secondly, on the IMW of these words $\{M_i, \in \Omega_N\}$ calculated for the same spatio-temporal dataset. The [24], an estimate of the closeness of the meaning of data from sensors to their verbal description was introduced. We use this characteristic to formally define the IMW. The IMW is a fuzzy L-R number

$$\mathbf{X} : \{x \mid m_{\mathbf{X}}(x), \forall x \in [-1,+1]\} \tag{3}$$

with Gaussian L-R membership function

$$\begin{aligned} m_{\mathbf{X}}^{L}(x) &= \exp(-(x-\alpha)^2 / 2t_L^2, \forall x \in [-1,\alpha]; \\ m_{\mathbf{X}}^{R}(x) &= \exp(-(x-\alpha)^2 / 2t_R^2, \forall x \in [\alpha,+1]; \end{aligned} \tag{4}$$

the parameters of which are the certainty ($-1 \le \alpha \le +1$) and the dynamics $t=t_L+t_R$ ($0 \le t < \infty$), where t_L and t_R are the time intervals since the last data acquisition from the sensor and the data change, respectively.

Based on (3), (4), the certainty factor as an IMW crisp characteristic is calculated

$$cf = \alpha \cdot k_t , \tag{5}$$

where

$$k_t = 1 - v \cdot \frac{\sum\limits_{\forall x \in [-1, \alpha]} m_{\mathbf{X}}^L(x) + \sum\limits_{\forall x \in [\alpha, +1]} m_{\mathbf{X}}^R(x)}{Card([-1,+1])} .$$

3.3 The Internal Meaning of the Word: Computing Model

The inputs and output of the IMW computing model for the example of the word N are shown in Fig. 2. The IMW of the word N is calculated based on its EMW definition (1) and IMW_{M_1}, IMW_{M_2} ,…, IMW_{M_k} .

$$\mathbf{X}_N = f(\mathbf{X}_{M_1}, \mathbf{X}_{M_2}, ..., \mathbf{X}_{M_k}), \tag{6}$$

where $\mathbf{X}_{M_1}, \mathbf{X}_{M_2}, ..., \mathbf{X}_{M_k}$ are the IMWs of the words $M_1, M_2, \ldots, M_k$ in the form (3).

The IMW calculation are operations with fuzzy L-R numbers (3), (4). To calculate IMW in (6), the knowledge presented by the EMW model (1) is used. The essence of the calculations is the comparison of the EMW definition (1) with inputs IMWs. The computational procedure is divided into three steps: *matching* is pairwise comparison of the EMW parameters (a_i, b_i), presented in the EMW definition (1), with the IMW_{M_i} of the corresponding input variable; *aggregation* of similarity estimates obtained in the first step for all input variables; *actualization* the IMW_N parameters.

Matching is the operation of comparing two fuzzy L-R numbers: $\boldsymbol{X}_i = (a_i, 0, b_i)$, obtained from (1), and the $\mathbf{X}_i^{in} = (\alpha_i, t_{Li}, t_{Ri})$ which is the corresponding IMW_{M_i} input. The result of the comparison is the new L-R number $\boldsymbol{X}_i'$. It is a fuzzy certainty that the compared fuzzy numbers are close. Calculations on this and following phases are based on the generalization principle [16].

$$\mathbf{X}_i' = (\alpha_i', t_{Li}' = t_{Li}, t_{Ri}' = t_{Ri}) , \tag{7}$$

where

$$\alpha_i' = \alpha_i \cdot \exp(-v_i \cdot t_{Li}) \cdot MIN(\Delta_i^1, \Delta_i^2) , \tag{8}$$

$$\Delta_i^1 = \begin{cases} +1, \; if \;\; (-1 \le \alpha_i \le a_i \;\; or \;\; a_i \le \alpha_i \le +1), \; a_i > 0; \\ -1 + \dfrac{2(\alpha_i + 1)}{a_i + 1}, \; if \;\; -1 \le \alpha_i \le a_i, \; a_i > 0; \\ +1 + \dfrac{2(\alpha_i + a_i)}{a_i + 1}, if \;\; a_i \le \alpha_i \le +1, \; a_i < 0; \end{cases} \tag{9}$$

$$\Delta_i^2 = -1 + 2 \cdot \exp(-\nu_i \cdot | t_{Ri} - b_i |) \, . \qquad (10)$$

In (7)-(10), the parameters of the EMW definition a_i, b_i, v_i and input IMW parameters α_i, t_{Li}, t_{Ri}. are used. The α'_i in (7) is a closeness degree estimate of the input IMW_{M_i} parameters and the EMW definition parameters. With small differences, estimates (9), (10) are close to *+1*, with maximum differences, estimates tend to *–1*. If the estimate is obtained based on the actual data ($t_{Li} = 0$), then it is not adjusted. For aged input data, when the parameter $t_{Li} > 0$, the estimate (8) is corrected in proportion to the aging rate v_i so that $\alpha'_i \rightarrow 0$.

Aggregation of fuzzy closeness estimates obtained during the matching step for each input variable is carried out as an operation of adding *k* weighted fuzzy L-R numbers $\{\boldsymbol{X}_i'\}_{i=1,2,\ldots,k}$. The weighting coefficient is the information completeness parameter g_i from the EMW definition (1). The operation result is again a fuzzy L-R number.

$$\mathbf{X}'' = (\alpha'',\ t''_L = \sum_{i=1,2..k} t'_{Li},\ t''_R = \sum_{i=1,2..k} t'_{Ri}) \, , \qquad (11)$$

where

$$\alpha'' = \begin{cases} 2(\alpha''' - 0.5), & if \quad \alpha''' \le +1; \\ +1, & if \quad \alpha''' > +1; \end{cases}$$

$$\alpha''' = g_1 \cdot (\alpha'_1 + 1)/2 + \ldots + g_k \cdot (\alpha'_k + 1)/2 \, .$$

In the last expression (11), the rationing of components on the interval $0.0 \le (\alpha'_i+1)/2 \le +1.0$ is performed previously, and then the weighted sum of the normalized numbers is found. The inverse rationing operation is performed, so that $-1.0 \le \alpha'' \le +1.0$.

Actualization of IMW_N value at the output is the final phase of computing. The operation is as follows. First, on the basis of the found value $\boldsymbol{X}''$ of the fuzzy L-R number (11), the *cf* is calculated by the formula (5). Then this *cf* value is used to find the parameters of the L-R number $\mathbf{X}_N$, which is the final value of IMW_N.

$$\alpha_N = cf, \qquad (12)$$

$$t_{R_N} = \begin{cases} 0, & if \quad | cf - {}^{-}cf | \ge \varepsilon; \\ {}^{-}t_{R_N} + 1, & other\ wise; \end{cases} \qquad (13)$$

$$t_{L_N} = MAX\,(t_{L_1}, t_{L_2}, \ldots, t_{L_k}) \, , \qquad (14)$$

where ${}^{-}t_{R_N}, {}^{-}cf$ are the parameter values in the previous calculation step; $t_{L_1}, t_{L_2}, \ldots, t_{L_k}$ are the IMW parameters of input variables.

4 eCWW Model

As pointed earlier, the eCWW process consist of three phases: GC, AW and CWW.

In the first GC phase, the spatio-temporal segment of data from sensors is mapped into the IMWs. This is accomplished by Quantitative Abstraction (QA) and Definitive Abstraction (DA) [12]. The QA is restrictions on the numerical data from the sensors based on the requirements for the solution accuracy. The DA maps this quantitative restriction on the semantic representation in the form of IMW. The eCWW model is based on the hypothesis that data prototype (a spatio-temporal set of data from sensors) has the meaning that can be expressed by the natural language words. Due to the word model introduced in this article, the meaning of the data prototype can then be represented at different levels of abstraction in the form of IMW.

The QA result is the internal meaning of the data granule, which is not yet expressed in words. This is a “bridge” between the numerical data from the sensors and knowledge in the form of words. The QA granulation process is based on knowledge about the granules. This knowledge can be presented in the forms of the numerical interval with crisp boundaries, fuzzy intervals defined by T1 FS [16] or T2 FS [26]. In this work, the knowledge about the granules is presented by functional dependence of certainty $\alpha = f(p)$ on the data, for example, p as shown in Fig. 4.

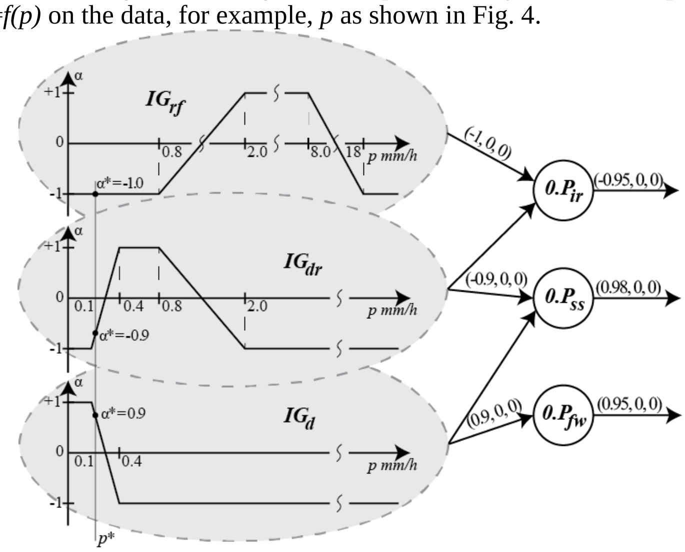

Fig. 4. IMW calculating at the first phase (quantitative and definitive abstraction)

The QA result is the IG fuzzy characteristic (internal meaning of the granule) in the form (3) $FC_{ig} = (\alpha_{ig}, t_{Lig}, t_{Rig})$. Fig. 4 shows an example of a QA for one rain precipitation sensor. The range of possible rainfall values p (universe) is represented by three granules *dry* (*d*), *drizzling rain* (*dr*), *heavy rainfal* (*rf*). The granules in the Fig.4 are shaded ovals and marked IG_d, IG_{dr}, IG_{rf}, accordingly. The definition of IG (restrictions) is given by certainty functions α_{ig} on an universe (the abscissa shows the universe of precipitation p in mm per hour). Certainty values ($-1 \leq \alpha \leq +1$) is along the ordinate axis. For the considered example, the α_{ig} are defined by trapezoidal piecewise linear functions with the parameters given in Table I. The computations of the internal meaning of the granules are carry out in real time for the input numerical value from sensor. For example, for the precipitation p^*: $FC_d = (\alpha_d(p^*), t_L, t_{Rd})$,

FC_{dr} = ($\alpha_{dr}(p^*)$, t_L, t_{Rdr}), FC_{rf} = ($\alpha_{rf}(p^*)$, t_L, t_{Rrf}). The values of t_{Rd}, t_{Rdr}, t_{Rrf} are found by formula (13). The value of t_L is found by formula (15).

$$t_L = \begin{cases} 0, & if \;\; m(p_i^*) \neq error; \\ {}^{-}t_{L_i} + 1, & if \;\; m(p_i^*) = error. \end{cases} \tag{15}$$

In (15), the time interval from the moment of the last control is set to zero when the correct data is received from the sensor.

TABLE I. IG DEFINITION

Input Data	**IG / *ig***	**IG definition α_{ig} (p_1, p_2, p_3, p_4)**
Precipitation	*Dry/d*	*0.0, 0.0, 0.1, 0.4*
	drizzling rain/dr	*0.1, 0.4, 0.8, 2.0*
	heavy rainfall/rf	*0.8, 2.0, 8.0, 18.0*

The QA computing is the real-time processing of data stream. The problem arising from stream processing is solved due to the introduction of the time delay b_i and aging rate v_i parameters into the EMW model (1). This allows to "blur" in time the time data segments, so that then fuzzy compare them with the prototypes. The transition from the processing of a sequence of data segments to one blurred in time prototype allowed us to move away from a regularly discrete time model to event time model.

The DA result is the IMWs of the all 0-level words. The 12-15 lines of the example (2), the EMW definitions of the zero level is given. It can be seen that the EMW definition is given in the form (1). The peculiarity is that the definition uses data granules, not words. In this regard, the DA computing is IMW calculations according to the computing model (6)-(14).

In the second AW phase, the IMWs of the first, second and so on abstraction levels are calculate. At each level, for each word belonging to this WV level, the AWE calculates IMW according to the model (6)-(14). Since words in WV are stratified by abstraction levels, the calculation process is performed from the bottom up rising sequentially by levels. As a result of the multi-step abstraction procedure, AWE computes IMWs for all WV words. These IMWs are available for CWWE in the next third processing phase (Fig. 1).

In the third phase, the CWWE performs inference T1 FS according to IF-THEN rules. Any of the known models (Mamdani, Takagi-Sugeno, Tsukamoto, Larsen) can be used here. The peculiarity of CWWE is that its rules use words from the WV of AWE. Namely, the use of α (IMW characteristic), obtained on the second phase, directly as T1 FS inputs imposes requirements on the IF-THEN rules presentation. Eny terms of Linguistic Variables (LV) in IF fields of the rules should be defined on the universe [−1, +1], on which the IMW crisp characteristic α is defined in (12). Since the meaning of the α characteristic is certainty, it is possible to use three or more linguistic assessments (terms), for example, HIGH, LOW and UNKNOWN. A hybrid version of the T1 FS is possible when part of LVs is defined on the [−1, +1] universe and another on the domain universe.

5 Smart Traffic-light Based on eCWW Model

The creation of urban traffic management systems as an AS is provided for in strategic plans for the development of smart cities. One of the components of such a system is Smart Traffic-Light (STL), which consists of a set of autonomous, intelligent, and wireless low-cost devices [29]. As an example, here we consider the possibility of using the eCWW model to control the STL installed at the pedestrian crossing. In STL a pedestrian button for changing a light signal is supposed. The STL model is developed and tested on the equipment of the IoT&SM training polygon [30].

The task of real-time control STL is set taking into account the following criterions: 1) Safety, 2) Local situation, 3) Pedestrian comfort, 4) Global transport situation, 5) Emergency cases. To control the STL based on the first four criteria, input from various sensors is used. For example, to describe safe situation is used data from ultrasonic, infrared, laser and video sensors: approaching / retreating vehicles, their distance, speed and acceleration [15, 30]. The EMW representation of the word *safe* in the form (1) is given in [15]. This article discusses an example of the EMW representation and the IMW calculation for STL control according to the one criterion of pedestrian comfort. Knowledge about granules and EMWs of 0-level WV of the first GC phase is fragmentarily presented in Fig. 4 and Table I. The EMWs presentation of the second AW phase is given in (2). The example of fuzzy rule of the third CWW phase is given below in (16). The example uses the CWWE of the T1 FS Mamdani model. The CWWE inputs are IMW coming directly from the upper abstraction levels of WV of an AWE, namely *safe*, *local situation*, *pedestrian comfort*, *global transport situation* and *emergency case* in the form of *cf*. In addition, two numerical variables are still used, coming directly from the sensors. This is *pedestrian waiting time* and *traffic light*. The CWWE outputs *switch light xxxx* is numerical certainty $-1 \leq \alpha \leq +1$. Fuzzy rules are built on the LVs whose names are the same as the names of words from WV of the AWE. Input and output LVs are defined on the universe $-1 \leq \alpha \leq +1$ and are not related to the domain scale. All LVs have three terms, each represented by trapezoidal membership functions. The membership functions parameters set are {LOW (*−1.0, −1.0, −0.5, 0.0*), UNKNOWN (*−0.5, −0.1, +0.1, +0.5*), HIGH (*+0.1, +0.5, +1.0, +1.0*)}.

IF *safe* is HIGH **and**
local situation is UNKNOWN **and**
pedestrian comfort is LOW **and**
global transport situation is HIGH **and**
emergency case is UNKNOWN **and**
pedestrian waiting time is MIDDLE **and**
traffic light is GREEN-CAR, RED-PEDESTRIAN
THEN *turn on the traffic light: yellow for car and red for pedestrian* is HIGH (16)

In conclusion, we give an example of eCWW computing for one time sample of processing data from sensors. A detailed description of the AWE computing algorithm can be found in [24]. Here we will focus on the integration of GC with AWE and CWWE computing. The computing operates in real time. The trigger event model for STL control is used. Events related to the fulfillment of condition (13) for any of the IGs activate AWE. After completion of the IMW calculations of all WV words, the CWWE is initiated. For the example below, it is assumed that changing the precipitation value led to the fulfillment condition (13). On the QA step, the GC calculated: FC_d = (*+0.95,0,0*), FC_{dr} = (−0.9,0,0), FC_{rf} = (*−1.0,0,0*). An example is considered for the *fall winter* season. On the DA step, AWE computed: $IMW_{0.Pw}$ = (*0.95,0,0*), $IMW_{0.Ps}$ = (*0.98,0,0*), $IMW_{0.Pr}$ = (*−0.95,0,0*). The results of these calculations can be seen in Fig. 4. The another IMWs are: $IMW_{0.Ww}$ = (*0.95,0,120*), $IMW_{0.WCw}$ = (*0.75,0,120*). Then, on AW step, on the basis of EMWs the AWE sequentially starting from the first level of the WV, then the second and so on calculated: $IMW_{1.Ws}$ = (*0.85,0,0*), $IMW_{1.Ss}$ = (*0.95,0,0*), $IMW_{2.WCss}$ = (*−0.75,0,0*), $IMW_{2.WCw}$ = (*0.85,0,0*), $IMW_{3.WC}$ = (*0.85,0,0*), $IMW_{5.PC}$ = (*0.8,0,0*). After completing the IMW computing of all WV levels, the CWWE wos activated. When processing the rules, for example, (16) the IMWs numerical characteristics $\alpha_{7.SF} = 0.9$, $\alpha_{6.LS} = -0.35$, $\alpha_{5.PC} = 0.8$, $\alpha_{3.GTS} = 0.6$, $\alpha_{5.EC} = 0.25$ found at the previous phase of the calculations, and the values from the sensors *t=42* sec, *TL=(0, 0, 1, 1, 0, 0)* as an inputs were used. After defuzzification of the inference results in CWWE, we obtained a rank of all control decisions by the certainty criterion, for example, $\alpha_{\text{turn on the traffic light: yellow for car and red for pedestrian}} = 0.65$.

6 Conclusion

The eCWW model expands the capabilities of the AS, which creates the conditions for its use in domains where it is required to make control decisions in unforeseen situations. Such opportunities appeared due to the transition from the concept of data from sensors processing to the concept of word processing in the form of a three-phase procedure. In the first, the spatio-temporal segment of data from sensors is mapped into the words. This allowed preliminary to generalize data from sensors into the words of higher abstraction levels and after that carry out fuzzy reasoning based on them. This became possible thanks to the introduction the models of the internal and external meaning of the word. Secondly, in AS control, the situation dynamic properties are taken into account and the effect of uncertainty associated with the incompleteness and aging of data, as well as the uncertainty of the experts in describing the AS behavior, is reduced. This opportunity appeared due to the presentation of the external meaning of the word by parametrized semantic relations and the internal meaning by the fuzzy characteristics of the word. Third, proposed model meets the requirements for real-time applications that use sophisticated dataset from sensors. The number of fuzzy rules has been significantly reduced due to the use words of high-level abstraction as CWW linguistics variables and inputs. Computing time is reduced due to this. Fourth, due to the WV openness property, the model adaptability and the possibility to evolving are supported. Therefore, predefined EMWs can subsequently be tuned using well-established methods for determining fuzzy sets, for example, Enhanced Interval Approach or an arsenal of evolutionary and bio-inspired methods.

In the future, it is planned to improve proposed eCWW model so that it has the ability to adapt and tune the parameters of the EMW in the operational mode.

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