Methods and algorithms of the spelling control and correction on the basis of fuzzy qualifier with MIMO-structure

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The paper shows results of developing the conceptual principles and methods in construction of hyper semantic net for natural languages spelling control and correction on a basis of neural networks and methods of fuzzy logic at the expense of expert knowledge and account of uncertainty. The ways of formalization are offered for linguistic variable and parameters, represented quantitatively and qualitative, and for performance of fuzzy sets membership functions. The operability of net including various nodes of graph model is tested. The realization of net is carried out on the basis of model with MIMO-structure, combining in itself property of the neuro-fuzzy qualifier and fuzzy production system.

Keywords: Spelling control, hyper semantic net, neural network, fuzzy qualifier, production system.

Introduction

Use of intellectual technologies on a basis of neural networks and fuzzy logic models opens the large opportunities to detect and correct of spelling mistakes in the documents of automated paperwork systems, where the processing and control of reliability of large volumes textual information is required, by creation fundamentally new specific models, techniques and systems of data processing.

The decision of noted problem demands to create a conceptual approach to make logical-linguistic technology of hyper-semantic net, which is connected with realization of procedures of: textual information analysis and processing; search of dependences between final result of information processing and subjective factors representing probability process; definition of adequate model corresponding to a controllable image; creation of indistinctly given input and output data intercoupling models (Kravtsov et al., 2005; Agrawal et al., 1993). Besides, the spent researches require development of algorithms for: formations of membership functions and definition of fuzzy numbers key attributes such as normality, modality, convexity, continuity, parametricity; reception of a priory information about properties and specific attributes of checked object; reception of fuzzy numbers classes which necessary for information processing and analysis.

The present work is devoted to the models and algorithms in software construction of hyper-semantic net logical-linguistic technology on the basis of fuzzy qualifier with MIMO-structure which in the program system of Uzbek language spelling control and correction.

Formalization of linguistic variable of semantic hypernet

The first task of hyper-semantic net construction is to formalize the linguistic variable and parameters represented in quantitative or qualitative forms; and also to establish relations
between names of objects and subjects which reflect conformity of qualitative values to quantitative interpretation.

Linguistic variable is set as “fuzzy variable”, determined by a tuple \(<A, X, \tilde{A}>\), where \(A\) is an identifier of fuzzy variable; \(X = \{x\}\) is the domain of its definition; \(\tilde{A} = \bigcup \mu_x / x\) is the fuzzy set to \(X\), which sets restrictions on sets of numerical values of fuzzy variable \(\tilde{A}\).

Let's consider, that the result of linguistic variable processing is defined by a tuple \(<A, T, X, Q, W>\), where \(A\) is the name of linguistic variable; \(T\) is a set of terms (values) of linguistic variable, which are the name of fuzzy variables; \(X\) is the set, which is domain of definition for fuzzy variable; \(Q\) is the syntactic rule, which describes formation process of new values linguistic variable from set \(T\); \(W\) is the semantic procedure, which allows each new value, formed by procedure \(Q\), display to fuzzy variable.

The following stage of hyper-semantic net construction is to define the fuzzy sets membership functions statement ways.

**Establishment of relations between names of objects and subjects**

The natural text represents the formalizable with difficulty information with prevalence of the qualitative attitudes among proper nouns which have indistinct nonlinear character. According to that to reveal the relations among proper nouns in fuzzy semantic hypernet (FSHN) we use the approach to the target models of knowledge on the basis of construction the relation between names of objects and subjects. Thus, the setting of linguistic variable \(C\) is “syntactic construction” of fuzzy sets (e.g. De Baets, 2000).

For metatext processing in knowledge data (KD) of FSHN we set the following ensemble of values \(C := \{\text{word-combination, simple sentence, adjectival participle, adverbial participle, complex sentence, asyndetic sentence, sentence without the main members, transitive relation}\}\). The base set consists from sequence of integers from 0 up to 100 with a step 1: \(t^{\text{A}} = \{0,1,3,...,100\}\).

The definition of belonging of syntactic construction among proper nouns to term-set of linguistic variable \(C\) occurs on the basis of the morphological analysis, as a result of which to each morpheme - word or words combination of with any punctuation mark - in the normalized natural text the weight equivalent is given.

After the function of linguistics for each relation among proper nouns is defined as follow:

\[
f(R^{\text{A}}) = 100 - \sum_{i=1}^{E} w_i ,
\]

where \(E\) is the quantity of morphemes in relation \(R^{\text{A}}\); \(w_i\) is the weight equivalent of morpheme. By value of linguistics function we defined the belonging of relation between names \(R^{\text{A}}\) to term-set \(C_q, q = 1,9\) of linguistic variable.
On the basis of metatext model we defined the structure of linguistic processor which transforms the relation between proper nouns $R^{V-A}$ to the relations between objects $R^{\Sigma-\Lambda}$ on the basis of linguistic variable $C$.

The following task of hypernet building is the choice of representation ways for fuzzy sets membership functions.

**Representation ways for fuzzy sets membership functions**

We offer two ways of representation for fuzzy functions: trapezoid and quasiconcave membership functions (MF). On trapezoid MF use the fuzzy result represents the four numbers:

$$\tilde{x} = (m^-, d^-, m^+, m^+ + d^+)$$  \hspace{1cm} (1)

where $d^-$ is the left dispersion; $m^-$ is the left border of unit domain; $m^+$ is the right border of unit domain; $d^+$ is the right dispersion.

The statement of fuzzy number with quasiconcave MF is two numbers $(c, \sigma)$, where $c$ is the centre of bellformed figure, and $\sigma$ is the width of figure (e.g. Singpurwalla et al., 2004).

Let's note, that to rate the FSHN output it is necessary to take into account the factor of data incompleteness, which beside the indistinct includes also probability of event.

Then in new statement (1 *) the first element of pair is a fuzzy result, and second element is value $p_k$ of $k$-th output probability. Thus, the statement of one value of fuzzy casual size at trapezoid MF is five numbers

$$x^* = (m^-, d^-, m^+, m^+ + d^+, p_k)$$  \hspace{1cm} (1*)

and at quasiconcave MF is three numbers $x = (c, \sigma, p_k)$.

Thus, each of fuzzy size is characterized by several terms, and each fuzzy term-result is characterized by the given probability.

The modeling of MF is connected to tasks of: linguistic variable formation which in turn requires definitions of linguistic variable terms and them to be sorted; limiting values of linguistic variable; conducting of expert ratings on the basis of constructed MF for any of linguistic variable terms.

**Modeling of linguistic variable**

Let's note that the linguistic variable and appropriate terms are defined at a stage of FSHN description by qualitative or fuzzy notions. Thus, for terms the obligatory requirement is the resoluteness. $T_1 < T_2 < \ldots < T_n$, and the base terms of linguistic variable must meet to the following conditions:

- ordering of terms and precise designation of definition domain for linguistic variable $\mu_{T_1}(x_{\min}) = 1$, $\mu_{T_n}(x_{\max}) = 1$;
completeness and coordination of terms \( \forall i, i + 1 = 1, n : 0 < \max_{x \in X} \mu T_{i+1}^i (x) = 1; \)

- each notion in linguistic variable should have at least one standard or typical object \( \forall i = 1, n : \exists x \in X : x < \mu T_i (x) = 1; \)

- restriction of definition domain of \( X \) either by final set of points or by some piece or interval \( \forall i = 1, n : 0 < \int \mu T_i (x) dx < \infty, \) where \( n \) is quantity of base linguistic variable terms; \( x_{\min}, x_{\max} \) are borders of universal set \( X, \) on which is defined the linguistic variable. If \( X \subset R \Rightarrow X = [x_{\min}, x_{\max}]. \)

Further, we simulate procedures connected with specification of matrix \( H \) of relatedness between variable and terms and procedures to find the FSHN nodes, in which the MF minimum is reached. Let’s assume that each node of FSHN graph model is given by a vector of coordinates \( \{x_i, y_i, z_i\}. \) The decision of a task we start from a choice of initial coordinates \( x_j^0, y_j^0, z_j^0 \) for \( j \)-th node:

\[
\begin{align*}
x_j^0 &= \frac{1}{n_j} \sum_{i=1}^{n_j} x_i, \\
y_j^0 &= \frac{1}{n_j} \sum_{i=1}^{n_j} y_i, \\
z_j^0 &= \frac{1}{n_j} \sum_{i=1}^{n_j} z_i,
\end{align*}
\]

where \( n_j \) is quantity of graph model branches moved to \( j \)-th node; \( x_i, y_i, z_i \) are the coordinates of \( i \)-th node, which contacts to \( j \)-th node.

The important moments of FSHN construction is also to research into definition of initial coordinates “gravity centre” in conditions of uncertainty and change of target MF values \( F \) according to change of each coordinates values.

First, we consider process of a choice of coordinate \( x_j \) values change step size, which is reduced to consecutive change:

\[
x_j^{\eta+1} = x_j^\eta + \delta x_j,
\]

where the value \( \delta x_j \) is defined in a range of possible changes \( x_j \subset X. \)

Now on each \( (\eta + 1) \)-th step the value of target MF \( F_{\eta+1}(x_j) \) is counted up, and it is compared to value \( F_\eta(x_j), \) i.e. the follow condition is checked

\[
F_{\eta+1}(x_j) < F_\eta(x_j).
\]

If the condition is true, than the new value of variable \( x_j \) changes to the value \( x_j(\eta). \)
The procedure of divergences minimization for MF of \( (\eta) \) -th and \( (\eta + 1) \) -th step defines accuracy of received FSHN results by criterion

\[
|F_{\eta+1} - F_{\eta}| < \beta,
\]

where \( \beta \) - the given accuracy of receiving results.

Similar procedures are carried out for coordinates \( y_j \) and \( z_j \). The found values of \( x_j, y_j, z_j \) are used to stop the FSHN training.

Received theoretical and experimental results served as the precondition to construct the algorithms of Uzbek language metatext processing system. Thus, we defined the hierarchy classes and classes were made on the basis of the submitted contexts analysis and construction of FSHN treelike model with free quantity of branchings. We offer model with MIMO-structure (Multi Inputs Multi Outputs), combining in itself the property of neuro-fuzzy qualifier and fuzzy production system. Some of tasks of construction spelling control and correction system are stated in other paper of author (e.g. Akhatov and Jumanov, 2010). In the present work we state peculiarities of ways in which we use fuzzy logic methods and models with MIMO-structure (Medel et al., 2010).

**The way of fuzzy inference with use of MIMO-model**

Modeling the fuzzy inference process includes stages of creation the fuzzy MIMO-model, described by interdependence of target variable.

*Stage 1. Assigning of input and output parameters. Here we designated parameters of system status rating by three input \( P_{in1}, P_{in2}, P_{in3} \) and two output \( P_{out1}, P_{out2} \).*

*Stage 2. The scales of input and output logical-linguistic variable are formed and appropriate MF of fuzzy sets is defined. At this the various numbers of linguistic variable values for accepted input and output parameters are taken into account. Ratings of input and output variable are made on three terms {is least similar (unsatisfactory) - N, satisfactory similarity (contentious) - C, maximum similarity (best) - B}, i.e.:

\[
P_{in1} - N_{in1}, C_{in1}, B_{in1} ; \quad P_{in2} - N_{in2}, C_{in2}, B_{in2} ; \quad P_{in3} - N_{in3}, C_{in3}, B_{in3} ;
\]

\[
P_{out1} - N_{out1}, C_{out1}, B_{out1} ; \quad P_{out2} - N_{out2}, C_{out2}, B_{out2} .
\]

For assigning the term-sets of input and output parameters and to construction their logical-linguistic scales we proved the expediency of bellformed MF use. Then, for example the given function of output variable \( P_{out1} \) with value \( N_{out1} \) is set as following:

\[
\mu_{N_{out1}} (P_{out1}) = \exp \left[ -\frac{1}{2} \left( \frac{P_{out1} - a_{out1}}{b_{out1}} \right)^2 \right] , \quad (2)
\]
where $a_1, b_1$ are the parameters of bellformed MF.

Let's note, that the parameters $a_i, b_i$ of examined MF in researches are adapted in subsequent on results of concrete used model.

Stage 3. Correlation of output parameters value with the appropriate decisions and allocation of decisions groups for $P_{in1}, P_{in2}, P_{in3}$. It is necessary to note, that the changes of input parameters $P_{in1}, P_{in2}, P_{in3}$ result to complex change of output parameters $P_{out1}, P_{out2}$.

To optimize the conformity values of output parameters to accepted decisions we suggest new procedures of FSHN construction, in which classification definition of joint estimation for output parameters $P_{out1} \cup P_{out2}$ is done. Examples of these conformity establishments are given below.

<table>
<thead>
<tr>
<th>Value of $P_{out1}$</th>
<th>Value of $P_{out2}$</th>
<th>According Solution ($Sol_i$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{out1}$</td>
<td>$N_{out2}$</td>
<td>$+$</td>
</tr>
<tr>
<td>$N_{out1}$</td>
<td>$C_{out2}$</td>
<td>$+$</td>
</tr>
<tr>
<td>$N_{out1}$</td>
<td>$B_{out2}$</td>
<td>$+$</td>
</tr>
<tr>
<td>$C_{out1}$</td>
<td>$N_{out2}$</td>
<td>$+$</td>
</tr>
<tr>
<td>$C_{out1}$</td>
<td>$C_{out2}$</td>
<td>$+$</td>
</tr>
<tr>
<td>$C_{out1}$</td>
<td>$B_{out2}$</td>
<td>$+$</td>
</tr>
<tr>
<td>$B_{out1}$</td>
<td>$N_{out2}$</td>
<td>$+$</td>
</tr>
<tr>
<td>$B_{out1}$</td>
<td>$C_{out2}$</td>
<td>$+$</td>
</tr>
<tr>
<td>$B_{out1}$</td>
<td>$B_{out2}$</td>
<td>$+$</td>
</tr>
</tbody>
</table>

The offered classification model allows allocating the following groups of the decisions:

- **Group 1** - Sol$_1$; **Group 2** - Sol$_2$ & Sol$_3$; **Group 3** - Sol$_2$ & Sol$_5$; **Group 4** - Sol$_3$ & Sol$_5$; **Group 5** - Sol$_3$ & Sol$_7$; **Group 6** - Sol$_4$ & Sol$_5$; **Group 7** - Sol$_4$ & Sol$_7$.

Stage 4. The initial base formation of model's fuzzy rules of is based on the following fuzzy rules:

\[ R_1: \quad \text{IF } P_{in1} \text{ is } N_{in1} \text{ AND } P_{in2} \text{ is } N_{in2} \text{ AND } P_{in3} \text{ is } N_{in3}, \]
\[ \text{THEN } P_{out1} \text{ is } N_{out1} \text{ AND } P_{out2} \text{ is } N_{out2}, \quad (3) \]
In the Table 1 we illustrate the example of fuzzy rules initial base structure, generated on a basis of beforehand formulated classification definitions of qualitative estimations of output parameters.

**TABLE 1. STRUCTURE OF FUZZY RULES BASE**

<table>
<thead>
<tr>
<th>Rule number</th>
<th>Input variable</th>
<th>Output variable</th>
<th>Groups of decisions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P_{in1}$</td>
<td>$P_{in2}$</td>
<td>$P_{in3}$</td>
</tr>
<tr>
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<td>$N_{in1}$</td>
<td>$N_{in2}$</td>
<td>$N_{in3}$</td>
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<td>$R_4$</td>
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<td>$R_5$</td>
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<tr>
<td>$R_6$</td>
<td>$N_{in1}$</td>
<td>$C_{in2}$</td>
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<tr>
<td>$R_7$</td>
<td>$N_{in1}$</td>
<td>$B_{in2}$</td>
<td>$N_{in3}$</td>
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<tr>
<td>$R_8$</td>
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<td>$B_{in2}$</td>
<td>$C_{in3}$</td>
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<td>$R_9$</td>
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<td>$R_{18}$</td>
<td>$C_{in1}$</td>
<td>$B_{in2}$</td>
<td>$B_{in3}$</td>
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</table>
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<table>
<thead>
<tr>
<th>R&lt;sub&gt;19&lt;/sub&gt;</th>
<th>B&lt;sub&gt;in1&lt;/sub&gt;</th>
<th>N&lt;sub&gt;in2&lt;/sub&gt;</th>
<th>N&lt;sub&gt;in3&lt;/sub&gt;</th>
<th>C&lt;sub&gt;out1&lt;/sub&gt;</th>
<th>C&lt;sub&gt;out2&lt;/sub&gt;</th>
<th>Group 4</th>
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<tbody>
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<td>C&lt;sub&gt;in3&lt;/sub&gt;</td>
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<td>B&lt;sub&gt;out2&lt;/sub&gt;</td>
<td>Group 7</td>
</tr>
</tbody>
</table>

**Figure 1. Structure of neuro-fuzzy qualifier**
Stage 5. Formation of fuzzy rules subsets concerning the selected decisions groups. The analysis of data from Table 1 shows that one can include the groups 2 and 5 choosing the possible groups of leading decisions. All rules can be united the remained groups of decisions in the following subsets: Group 1 - (R1, R2, R4, R5); Group 3 - (R3, R7, R10); Group 4 - (R6, R8, R9, R11, R12, R13, R14, R15, R19, R20, R21); Group 6 - (R16, R17, R18, R22, R23, R25); Group 7 - (R24, R26, R27).

The received base of fuzzy rules is realized in FSHN by structure, illustrated in Figure 1, i.e. as neuro-fuzzy model (NFM).

**Structure of neuro-fuzzy model of FSHN**

The offered model combines in itself properties of the neuro-fuzzy qualifier for allocation of decisions group and fuzzy production system (e.g. Sun, 1993). The structure of NFM includes the neuro-fuzzy qualifier (layers 1-4) and set of fuzzy rules subsets appropriate to groups of the chosen decisions.

Neuro-fuzzy qualifier consists of the following layers.

*Layer 1.* On an output of this layer elements are formed degrees of belonging for input parameters.

*Layer 2.* Each element of this layer realizes operation of T-norm, for example, min.

*Layers 3-4.* The elements of these layers are intended for weighed accumulating of previous layer output elements values. The elements of layer 3 carry out operation of S-norm, for example, operation max.

Output elements of layer 4 are formed with use of sigmoid activation functions. These outputs are used for allocation of the appropriate group of decisions.

Let's note that the process of formation of fuzzy rules set is realized on the basis of Mamdani-algorithm. The result of use of production base of rules is estimated by a degree of expediency of choice of decisions from the appropriate group.

Now we shall present generalized algorithm of fuzzy inference, based on offered structure NFM.

**Construction of algorithm of fuzzy inference on the basis of neuro-fuzzy model**

The algorithm of fuzzy inference with use of the offered fuzzy model includes the following steps.

**Step 1.** Setting the parameter values $P_{in1}, P_{in2}, P_{in3}$. On the basis of these values, the validity degrees of input parameters are defined on layer 1 output of fuzzy qualifier.

**Step 2.** Aggregation of the appropriate input parameters validity degrees on the basis of T-norm operation in layer 2 of neuro-fuzzy qualifier.

**Step 3.** The output values activization for each allocated fuzzy rules subset on the basis of weighed accumulating of values with use of T-norm operation and sigmoid function in layers 3-4 of neuro-fuzzy qualifier.

The appropriate group of decisions is allocated by results of step 3.

**Step 4.** The realization of Mamdani’s fuzzy inference algorithm of fuzzy rules subset, appropriate to allocated group of decisions by results of neuro-fuzzy qualifier.

By this algorithm we choose the group of decisions and estimate the expediency degree of decision to choose from group.

The realized procedures authenticity in structure of FSHN is proved by results of experimental researches. To advance experiments the various types of hypothetical nets...
were investigated: “small net” including up to 50 nodes; “middle net” including from 50 up to 350 nodes; “large net” including from 350 up to 1000 nodes of FSHN graph model. After finding optimum nodes, the rating of accepted fuzzy decision is made according to MF. Let's note, that at realization of experiments the nodes intensity increase was made, that is at first one node with others, then second with others, third with others and so on.

In Figure 2 we illustrated the values of trapezoid and quasiconcave MF at reception of an expert qualifier decision rate for controllable element of text (letter, mark, word form) in the optimum node FSHN. The diagrams of MF ratings for various rules lay within the limits of the same decision groups, and it proves the developed qualifier efficiency.

**Conclusion**

The formulated approaches, developed models, algorithms and constructed hyper-semantic net on a basis of NN and fuzzy logic methods form a base of the intellectual natural language spelling control and corrections system, in which it is taken into account fuzzy statement of expert knowledge and uncertainty in checked text element recognition. We developed the formalization and modeling ways for linguistic variable and parameters represented in quantitative and qualitative view. Besides, we developed the ways of relation establish between names of objects and subjects, statement of fuzzy sets membership functions.

Testing the various types of hypothetical nets: “small”, “middle” and “large” allowed to establish the net productivity dependences on nodes number change intensity. The expert ratings are received for a controllable element of the text according to reference alternative images.

The tasks are solved for defining the hierarchy classes in intellectual Uzbek language spelling control and corrections system, constructed on a basis of hyper-semantic net and model with MIMO-structure, combining the property of neuro-fuzzy qualifier and fuzzy production system.
References


