Acta Technica 62 (2017), No. 7A, 601–612

Hybrid intelligent translation mechanism based on multi source fuzzy information

Li Zhang[1]

Abstract. To improve performance of hybrid intelligent translation system, a hybrid intelligent translation mechanism based on multi-source fuzzy message is presented. Objective function is built in training with word-level semantic error, monolingual phrase/semantic error of rule, and bilingual phrase/semantic error of rule. Besides, a consideration is given to aligning message in a way that guides training of feature fusion of layered, multi-source and fuzzy message. During decoding, semantic vectors of some translation results are generated so as to finally obtain semantic relation between sentences. In this way, semantic message can be added into grammatical structure and a lack of semantic message about original layered model is overcome. Experimental result of such model shows effectiveness of layered machine translation model for feature fusion of multi-source fuzzy message.

Key words. Multi-source message, Feature fusion, Machine translation, Layered model.

1. Introduction

Modeling for difference between word orders of source language and target language is a main issue of statistical machine translation study. In statistical machine translation model based on phrase, phrase pair serves as a basic translation unit and phenomena of local hybrid intelligent translation mechanism are recorded automatically. However, there is a lack of effective description of phenomena of long-distance hybrid intelligent translation mechanism. To address problems of long-distance hybrid intelligent translation mechanism, researchers have made many trials and presented different methods. For example, Xiong et al presented lexicalized hybrid intelligent translation mechanism model based on maximum entropy and better described word order by means of lexical message. Chiang et al considered modeling for hybrid intelligent translation mechanism by means of layered structure of language.

[1]Sias University , Xinzheng Zhengzhou Henan, 451150, China

Between language pairs with a significant difference in word order, for example, English of S-V-O structure and Japanese of S-O-V structure, problems of long-distance hybrid intelligent translation mechanism are more prominent and hard to be addressed in translation system based on phrase. In grammatical system based on syntax, for example, Liu et al directly put message about syntax tree of source language in translation model, which is able to describe long-distance hybrid intelligent translation mechanism to a certain extent. However, problems, such as an enormous number of translations rules and long time of translation and decoding, are brought to translation model. Another method is called pre-hybrid intelligent translation mechanism, where sentences input in source language are adjusted, with message about vocabulary or syntax in source language section, to be in word order close to target language before translation and decoding and then a standard machine translation system based on phrase is used to translate sentences after hybrid intelligent translation mechanism. By this method of pre-hybrid intelligent translation mechanism, message about vocabulary or syntax in source language can be effectively used to help address problems of hybrid intelligent translation mechanism on the one hand; conciseness of translation system based on phrases is kept on the other hand. Such methods has better effects in practice. Main work based on pre-hybrid intelligent translation mechanism includes Tromble, Eisner and etc.

On the basis of the study orientation pre-hybrid intelligent translation mechanism, a pre-hybrid intelligent translation mechanism model for statistical machine translation based on multi-source fuzzy message is presented in this paper. A method of multi-source fuzzy message language model is used to abstractly represent learning vocabulary in unlabeled text; then this vocabulary representation is combined with other features by a multi-layer multi-source fuzzy message and integrated into a linear sequence model. We obtain training sample required for word order model from bilingual parallel corpus aligned automatically or aligned with manual annotation and differentiate training by random gradient descent. To verify effectiveness of this method, we have performed a test in machine translation task from Chinese to English and from Japanese to English. The test result show, in comparison with baseline system, pre-hybrid intelligent translation mechanism model, based on multi-source fuzzy message and presented in this paper, is able to improve performance of machine translation system remarkably in test data set.

2. Machine translation model for multi-source fuzzy message

2.1. System framework

This translation model is established in an idea of modularization, of which the advantage is that role of each module played in translation can be better measured. And joint training is performed during training so as to reflect importance of each module. Numerous symbolic representations are involved in this paper: bold standardized form stands for vector and matrix; (F, E) stands for sentences in training corpus; (f, e) stands for phrase/rule extracted from training corpus. To differentiate phrases and words in rule part, phrases are presented in capital letters with subscript and words are presented in phrases of small standardized form. For example, F_i stands for the phrase in ith location and F_i stands for the word in ith location.

Data preprocessing in Fig.1 includes monolingual preprocessing and bilingual preprocessing. Phrases and rules are extracted. Word vectors generated from trained, circulating and multi-source fuzzy message are input into algorithm in this paper for training. Number of layers of multi-source fuzzy message training part is the same as height of derivation tree generated from sentences (medium layers are replaced with ellipsis). Training part mainly includes two parts: auto-encoder based on phrase and rule.

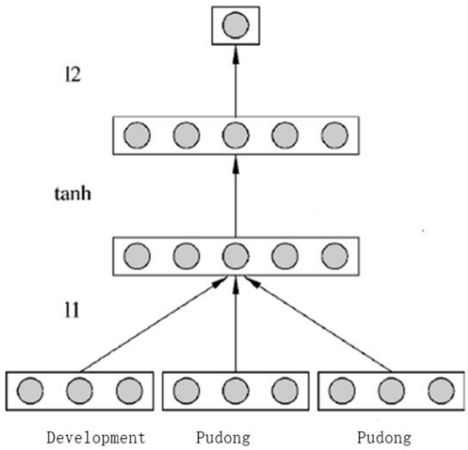

Fig. 1. Translation framework of multi-source fuzzy message system

Description of overall system training framework is to firstly extract phrases/rules of each sentence pair by preprocessing, obtain initial vector representation of monolingual words by the preprocessing stage, then put vector representation (namely overlapped part between two multi-source fuzzy messages) of these monolingual words in layered recursive multi-source fuzzy message in a way that obtains final semantic vector representation z_f, z_e, and measure similarity between phrase and rule by means of inner product $\langle z_f, z_e \rangle$.

In this model, modeling for bilingual sentence in training corpus is divided into two parts in general: obtaining word vector by the preprocessing stage and putting obtained word vector in algorithm model in this paper. In algorithm model in this paper, auto-encoders are divided into two types, based on phrase and based on rule. In each auto-encoder, monolingual auto-encoder and bilingual auto-encoder are included. In the process of training, firstly, layer-by-layer pre-training is conducted for each monolingual auto-encoder by adopted method; next, training is conducted for bilingual auto-encoder; in the end, joint training is conducted so as to balance importance of each part.

2.2. Semantic vector

(1) Auto-encoder based on phrase. Three encoders of feature fusion of multi-source fuzzy information are used and they are respectively auto-encoder of source language and target language and auto-encoder with source language as input and target language as output. Alignment relation between phrases is described in lower part of Fig. 2 and different projection/transformation matrix and semantic vector are explained in Section 3.3; recursive encoder of different structure of target/source language is generated according to alignment result of words in the phrase and semantic vector recovered from auto-encoding part of f_1 is denoted as f_1' and the others are similar to it. Empty words are sent to multi-source fuzzy information together with neighboring words for training. These nodes are added to deduction trees to obtain layered information; it will not affect deduction result and it only increases layers of deduction tree on the side of source/target language. Different vector forms are indicated with different gray degrees; layers with gray degree will not be added in training part without supervision and the layers need to be added in parts with supervision because these layers are layered structure of modeling translation.

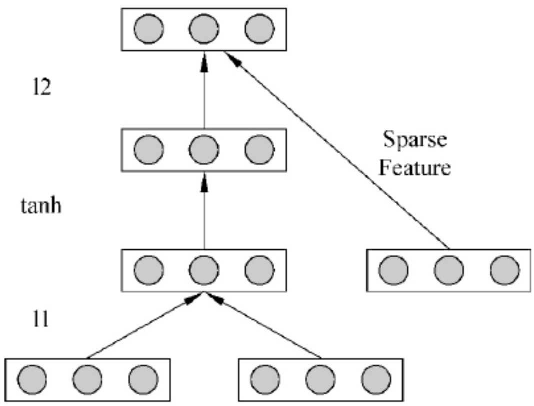

Fig. 2. model structure diagram in the model of pre mixed intelligent translation mechanism

(2) Auto-encoder based on rules. Rule pair is obtained based on extracting phrase pair in double sentence pair and rule pair with alignment information is sent to auto-encoder based on rules to calculate its similarity degree; similarity degree will be trained as a part of training target function so as to regulate parameter matrix in rule pair. Word embeddings obtained in training in pretreatment phase and phrase embeddings generated by auto-encoder based on phrases are embedded as input and output rules. Fig. 3 is used to better understand auto-encoding process of overall sentences.

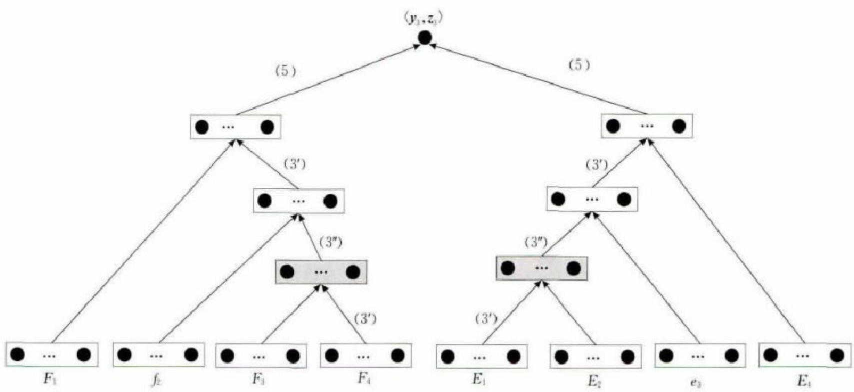

Fig. 3. Alignment relation of auto-encoder of rule grade

3. Message fusion for same features of different machine translation languages

3.1. Fusion function

Suppose there are N mechanical translation languages and m features are extracted from data measured in each mechanical translation language; there are k types of word and subordinating degree function of different mechanical translation languages of a certain feature belonging to all word types can be indicated in the following matrix form:

$$\mu = \begin{bmatrix} \mu_{11}(x_1) & \mu_{12}(x_1) & \cdots & \mu_{1K}(x_1) \\ \mu_{21}(x_1) & \mu_{22}(x_1) & \cdots & \mu_{2K}(x_1) \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{N1}(x_1) & \mu_{N2}(x_1) & \cdots & \mu_{NK}(x_1) \end{bmatrix}. \tag{1}$$

$\mu_{NK}(x_N)$ Indicates subordinating degree function that certain feature of Nth mechanical translation language belong to the kth type of words. Subordinating degree that a certain feature belongs to different words in the same word mode for the ith mechanical translation language and the jth mechanical translation language reflects the degree it belongs to certain kind of words; if the two mechanical translation languages mutually support each other, then difference between subordinating degree is surely very small. So, deviation size among subordinating degrees can be used to measure the degree for all mechanical translation languages to support each other. Euclidean distance is introduced to define the distance between two mechanical translation languages.

$$d_{ij} = \sqrt{(\mu_i - \mu_j)(\mu_i - \mu_j)^T}\,. \tag{2}$$

μ_i, μ_j Are line vectors composed by the ith line and the jth line of subordinating matrix and they are vectors composed by subordinating degrees that a certain feature of the ith mechanical translation language and the jth mechanical translation language belongs to all words; it is obtained that upon substitution:

$$d_{ij} = \sqrt{\sum_{k=1}^{K} (\mu_{ik}(x_i) - \mu_{jk}(x_j))^2}\,. \tag{3}$$

Where, $\mu_{ik}(x_i)$ refers to the membership degree to which a entropy value of machine-translated language i belongs to the word k, $\mu_{jk}(x_j)$ is the membership degree to which a entropy value of machine-translated language j belongs to the word k, d_{ij} means the confidence distance measure, indicating the differences in the characteristics of machine-translated languages, and $0 \le d_{ij} \le 1$. The greater the d_{ij} is, the lower the degree to which the i^{th} machine-translated language is supported by the j^{th} machine-translated language will be, otherwise, the support degree will be higher. The fusion function of two machine-translated languages is defined as follows:

$$r_{ij} = 1 - d_{ij}\,. \tag{4}$$

So the degree to which the i^{th} machine-translated language is supported by the j^{th} machine-translated language can be expressed as the fusion function, and many machine-translated languages can form the fusion matrix:

$$r = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1N} \\ r_{21} & r_{22} & \cdots & r_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ r_{N1} & r_{N2} & \cdots & r_{NN} \end{bmatrix}. \tag{5}$$

Given that $s = [s_1, s_2, \cdots, s_N]^T$ is the fusion vector of machine-translated language recognized by all other machine-translated languages, we can select the minimum value of fusion determination of fusion between other machine-translated languages and the i^{th} machine-translated language to ensure the maximum reliability, namely:

$$s_i = \min(r_{i1}, r_{i2}, \cdots, r_{iN})\,. \tag{6}$$

Where, s_i is degree to which the i^{th} machine-translated language is integrated by all other machine-translated languages, and the following result can be obtained after substituting formula (4) and (5):

$$s_i = \min(1 - \sqrt{\sum_{k=1}^{K} (\mu_{ik}(x_i) - \mu_{jk}(x_j))^2}), \quad j = 1, 2, \ldots, N\,. \tag{7}$$

3.2. Information fusion between different machine-translated languages

During the fusion of the same features of different machine-translated languages, we can assume that the weight coefficient vector is as follows to reflect the different proportion of different machine-translated languages in the fusion:

$$q = [q_1, q_2, \cdots, q_N]^T \ . \tag{8}$$

In formula (7), greater s_i indicates the higher degree to which the i^{th} machine-translated language recognized by other machine-translated languages and its large weigh in the process of fusion, otherwise, the weight will be small. Therefore, we assume that weight coefficient of the i^{th} machine-translated language can be determined by the proportion of s_i in the total fusion, namely:

$$q_i = s_i / \sum_{i=1}^{N} s_i \ . \tag{9}$$

In this way, the membership vector of the different machine-translated languages fused is as follows:

$$\beta = \eta^T . q = [\beta_1, \beta_2, \cdots, \beta_K] \tag{10}$$

Wherein, β_K is the membership degree to which this feature belongs to the K-type of words after fusion, of which value is:

$$\beta_K = \sum_{i=1}^{N} (\mu_{ik}(x_i).q_i) \ . \tag{11}$$

Fusion of a feature of different machine-translated languages is completed with the above methods. Similarly, other features can be fused to obtain the fusion results of other features of different machine-translated languages.

3.3. Evidence theory

Evidence theory is based on a nonempty set Θ, and this set is known as a recognition framework. It consists of a number of mutually exclusive and exhaustive elements, including all the current objects to be identified, which is marked as $\Theta = \{\theta_1, \theta_2, \theta_3, ..., \theta_n\}$. Each subset A of Θ belongs to the power set 2^Θ, and a value can be assigned to be called the basic trust distribution.

Definition: the basic trust distribution function (*mass* function) m is a map from the set 2^Θ to $[0, 1]$, A denotes any a subset of recognition framework Θ, marked as $A \subseteq \Theta$ and meeting $m(\phi) = 0$, $\sum\limits_{A \subset \Theta} m(A) = 1$. Then $m(A)$ is called the basic trust distribution function of event A.

The basic trust distribution function represents the degree to which evidence supports the occurrence of event A but does not support any proper subset of A; If $m(A) > 0$, then A is called the focal element of evidence, and the set of all focal elements is called the kernel.

Assume that BEL1 and BEL2 are two trust functions on the same recognition frame U, m_1 and m_2 are their corresponding basic trust distribution functions respectively. The focal elements are $A_1, \cdots, A_k$ and $B_1, \cdots, B_r$, and assume:

$$L = \sum_{A_i \cap B_j = \phi} m_1(A_i) m_2(B_j) < 1\,.$$

Then BPAF is after evidence fusion:

$$m(C) = \begin{cases} \dfrac{\sum\limits_{A_i \cap B_j = C} m_1(A_i) m_2(B_j)}{1 - L} & \forall C \subset U \quad C \neq \phi \\ 0 & C \neq \phi \end{cases} \tag{12}$$

Wherein, L is the conflict factor, reflecting the degree of evidence conflict, $1/(L\text{t}1)$ is called the normalization factor and its role is to avoid assignment of non-zero trust into the empty set during the integration. This combination rule is equivalent to distributing an empty set (conflict) to each set in the same proportion in a combination. For a combination of multiple evidences, this combination rule can be used to fuse evidences in pairs.

3.4. Identification of word types with evidence theory

For machine translation, the corresponding basic trust distribution functions are m_1, m_2, ... , m_M since M-type features are extracted, and each type of feature corresponds to the same K-type words. Therefore, so is the focal element of the basic trust distribution function which is set as $A_1, \cdots, A_k$. Then the conflict factor L can be turned into:

$$L = \sum_{i \neq j} m_1(A_i) m_2(A_j) < 1\,.$$

Then BPAF is after evidence fusion:

$$m(A_i) = \frac{\sum m_1(A_i) m_2(A_i)}{1 - L} \qquad i = 1, 2, ..., K\,. \tag{13}$$

The value of the basic trust distribution function can be obtained by transforming the fused membership value, which can be determined by the following formula for meeting $\sum m(A_i) = 1$.

$$m_r(A_i) = \beta_i^{(r)} / \sum_{i=1}^{K} \beta_i^{(r)}\,. \tag{14}$$

Where, $m_r(A_i)$ is the basic trust distribution function to which feature r belongs to word type i, $r = 1, 2, \ldots, M$, $i = 1, 2, \ldots, K$. $\beta_i^{(r)}$ is the membership value to which feature r belongs to word type i, which is obtained with the method mentioned in the first section. Because there are many types of features, the combination rules can be used to fuse the features in pairs, resulting in a trust distribution function $m(A_i)$ finally belonging to each word type. If $m(A_k) = \max m(A_i)$, the word type will be determined to be the k^{th} type.

4. Experimental analysis

4.1. Experimental data set

In this experiment, English translation task is completed in NIST, and the training corpuses LDC2000T50, LDC2002L27, LDC2002E18, LDC2003E4, LDC2005T10, LDC2005T83, LDC 2006E85 and LDC2007T09 are used. Bilingual corpus contains 0.99M sentence pairs, 31.3M Chinese words and 32.4M English words. The language mode is trained with the target languages of Uigaword corpus and bilingual training corpus, and bilingual corpus is filtered by feature decay algorithm. NIST02 is used in the development set and NIST05, NIST06 and NIST08 are used in the test set.

The preprocessing of bilingual corpus includes Chinese word segmentation using the maximum entropy model and English word segmentation using tokenizes.perl (http://www. statmt. org). In this paper, Berkeley LM tool is used to train a 5-meta language model, and the bilingual alignment is performed using GIZA + and then many-to-many word alignment is complted using Urow-Diag-Final-And heuristic rule. The case-insensitive 5-meta BLEU is used to evaluate the quality of the generated translation results, statistical significance test is performed on the translation results by re-sampling. The open-source system Thrax based on Hadoop technology is used for phrase extraction, and decoder adopts the decoding part of Joshua 5.0, a hierarchical translation model open-source system.

4.2. Result analysis

(1) Influence of semantic characteristics: to compare influence of semantic vector on translation performance and effectiveness of hierarchical multi-source fuzzy information, two baseline systems in the part are adopted: baseline 1 without adding any semantic characteristics and baseline 2 without adopting hierarchical modeling. Realization process of baseline 2 is basically the same with algorithm in the Paper and alignment is not taken into consideration during training to guide hierarchicalization of phrase/rule of source language and target language side; phrase/rule semantic vectors are established by adopting source language and target language from left to right; at the same time, baseline 2 also includes similarity characteristics of bilingual semantics. To verify effectiveness of characteristics, we add bilingual characteristics: similarity characteristics of bilingual semantics (bssm) and sensibility characteristics of bilingual semantics (bssn); add monolingual characteristics: monolingual semantic similarity characteristics (mssm) and monolingual semantic sensibility characteristics (mssn). Bold characters mean that it is superior to baseline system under verification index (pG0.05).

Corresponding experiment results have been provided in Table 1 and ALL shows that all test language materials are put together; it is found out that performance of baseline 2 is basically the same with baseline 1 and semantic information is not obtained basically to strengthen translation result. Result of algorithm in the Paper has improved 1.31, 0.9, 0. 85 and 1.56 BLEU scores respectively on 3 test sets and ALL compared with baseline 2, which has shown importance of alignment information in model establishment process. It is also found that bilingual semantic characteristics and bilingual sensibility degree characteristics have exerted influence during translation and bilingual semantic characteristics are more important, while bilingual semantic characteristics and bilingual sensibility characteristics fail to exert influence on translation performance of monolingual semantic similarity characteristics (mssm) and monolingual semantic sensibility characteristics (mssn); therefore, it also shows that algorithm model in the Paper adding bilingual semantic characteristics and bilingual sensibility characteristics are complementary with hierarchical phrase translation, which has embodied importance of semantic characteristics.

Table 1. Influence of different semantic characteristics

Methods	NIST05	NIST06	NISTO8	ALL
baseline1	35.98	33.88	30.17	35.12
baseline2	36.02	34.22	30.17	35.27
(bssm) Algorithm in the Paper (bssm)	36.82	35.83	30.80	36.22
(bssm+bssn) Algorithm in the Paper (bssm+bssn)	37.22	35.09	31.02	36.82
(bssm+bssn+mssm+mssn) Algorithm in the Paper (bssm+bssn+mssm+mssn)	37.33	35.12	31.02	36.83

To explore influence of semantic vector dimension on translation performance, experiment has been designed for taking different values for semantic vectors dimension $n = 50$, 100, 200. $n = 50$ is result in algorithm in the Paper (bssm+ bssn+ mssm+ mssn), which has been shown in Table 1 and will not be listed again. In Table 2, it is seen that result performance of the algorithm model adding bilingual and monolingual semantic characteristics is superior to baseline 1 and baseline 2 no matter what value n is taken; at the same time, when $n = 100$, it has reaches best performance, 0.22, 0.54, 0.64 and 0.28BLEU scores have been improved respectively on 3 test sets, that is to say, $n = 100$ can better distinguish good and bad translation results.

Table 2. Influence of semantic vector dimension on translation performance

Method	n	NIST05	NIST06	NISTO8	ALL
Algorithm of the Paper	100	37.55	35.64	31.66	37.11
	200	37.52	35.52	34.64	37.08

(2) Influence of monolingual/ bilingual automatic coders on phrase reconstruction. To compare mono-lingual phrase embedding (Mono-lingual Phrase Embedding) and bilingual phrase embedding (Bilingual Phrase Embedding), phrases are respectively written into MPE and BPE in the following experiments. Basic method of mono-lingual phrase embedding is to implement no supervision training to bilin-

gual semantic vector calculation; for inner product calculation similarity of generated mono-lingual phrase embedding, Table 3 has provided analysis on English phrase that causes performance difference; top three numerical values of mono-lingual similarity has been listed and it is found out that meaning of phrases generated by MPE are closer to surface meaning, while phrases generated by BPE have profound meaning, which shows that BRE can better master phrase meaning by source language.

Table 3. Difference and similarity of bilingual phrase embedding and mono-lingual phrase embedding

Phrase	MPE	HPE
work for the government	1.do for the office 2.work in the government 3.do and work in the office	1.work for the official 2.do something for the government 3.do things in the government
an office worker	1.an official worker 2.an office employer 3.a government worker	1.staff in the office 2.employer working for office 3.office staff
the same time	1.the same thing 2.in the meantime 3.same meantime	1.simultaneously 2.concurrently 3.meantime

5. Conclusion

The Paper has explored hierarchical translation model of multi-source fuzzy information fusion. The model more conforms to translation process and source language and target language generated by taking alignment as guidance have multi-source fuzzy information. Not only word vector with total information has been taken into consideration in the model and bilingual alignment information has been taken into consideration in multi-source fuzzy information. 3 training modules have been adopted in training; different target functions have been used for different modules, which can better balance influence of each module and hierarchical pre-training, has been adopted in no supervision part, so that each lay can train target function more quickly. Training data have adopted typical bilingual training language materials and have been filtered and test data have also adopted multiple-set data to reflect effectiveness of the method. It is found out that scores of the method have exceeded almost 1.84 BLEU scores compared with classic baseline system by experiment and significance test has been implemented to prove statistics meaning of the method.

References

[1] W. S. Pan, S. Z. Chen, Z. Y. Feng: *Investigating the Collaborative Intention and Semantic Structure among Co-occurring Tags using Graph Theory.* 2012 International Enterprise Distributed Object Computing Conference, IEEE, Beijing, (2012), 190–195.

[2] J. W. Chan, Y. Y. Zhang, and K. E. Uhrich: *Amphiphilic Macromolecule Self-Assembled Monolayers Suppress Smooth Muscle Cell Proliferation*, Bioconjugate Chemistry, *26* (2015), No. 7, 1359–1369.

[3] Y. Y. Zhang, E. Mintzer, and K. E. Uhrich: *Synthesis and Characterization of PEGylated Bolaamphiphiles with Enhanced Retention in Liposomes*, Journal of Colloid and Interface Science, *482* (2016), 19–26.

[4] J. J. Faig, A. Moretti, L. B. Joseph, Y. Y. Zhang, M. J. Nova, K. Smith, and K. E. Uhrich: *Biodegradable Kojic Acid-Based Polymers: Controlled Delivery of Bioactives for Melanogenesis Inhibition*, Biomacromolecules, *18* (2017), No. 2, 363–373.

[5] Z. Lv, A. Halawani, S. Feng, H. Li, & S. U. Réhman: *Multimodal hand and foot gesture interaction for handheld devices.* ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), *11* (2014), No. 1s, 10.

[6] D. Beauregard, V. Bhatnagar: *Synchronous and asynchronous brokering of IVR sessions for offline interaction and response: US*, US8155276[P] (2012).

[7] Shi Y. Computational science - ICCS 2007 : 7th International Conference, Beijing, China, May 27-30, 2007: proceedings[J]. None, 2007, 4490.

[8] G. Lin, J. Liang, Y. Qian Y., et al.: *A fuzzy multigranulation decision-theoretic approach to multi-source fuzzy information systems*[J]. Knowledge-Based Systems, *91* (2016), No. C, 102–113.

[9] B. F. Wu, C. C. Kao, J. H. Juang, et al.: A New Approach to Video-Based Traffic Surveillance Using Fuzzy Hybrid Information Inference Mechanism[J]. IEEE Transactions on Intelligent Transportation Systems, *14* (2013), No. 1, 485–491.

[10] H. R. H. Al-Absi, A. Abdullah, M. I. Hassan, et al.: *Hybrid Intelligent System for Disease Diagnosis Based on Artificial Neural Networks, Fuzzy Logic, and Genetic Algorithms*[M]// Informatics Engineering and Information Science. Springer Berlin Heidelberg, (2011), 128–139.

[11] A. Quirin: *On the Use of Bagging, Mutual Information-Based Feature Selection and Multicriteria Genetic Algorithms to Design Fuzzy Rule-Based Classification Ensembles*[C]// Eighth International Conference on Hybrid Intelligent Systems. IEEE, (2008), 549–554.

[12] H. R. H. Alabsi, A. Abdullah, M. I. Hassan, et al.: *Hybrid Intelligent System for Disease Diagnosis Based on Artificial Neural Networks, Fuzzy Logic, and Genetic Algorithms*[J]. Communications in Computer & Information Science, *252* (2011), 128–139.

Received May 7, 2017