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개선된 공간 탐색 알고리즘을 이용한 정보입자 기반 퍼지모델 설계

Design of IG-based Fuzzy Models Using Improved Space Search Algorithm

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Abstract

This study is concerned with the identification of fuzzy models. To address the optimization of fuzzy model, we proposed an improved space search evolutionary algorithm (ISSA) which is realized with the combination of space search algorithm and Gaussian mutation. The proposed ISSA is exploited here as the optimization vehicle for the design of fuzzy models. Considering the design of fuzzy models, we developed a hybrid identification method using information granulation and the ISSA. Information granules are treated as collections of objects (e.g. data) brought together by the criteria of proximity, similarity, or functionality. The overall hybrid identification comes in the form of two optimization mechanisms: structure identification and parameter identification. The structure identification is supported by the ISSA and C-Means while the parameter estimation is realized via the ISSA and weighted least square error method. A suite of comparative studies show that the proposed model leads to better performance in comparison with some existing models.

Key Words:Improved space search algorithm (ISSA), Fuzzy inference systems (FIS), Information Granulation (IG)

1. Introduction

Fuzzy modeling may be considered as a system based on fuzzy logic with fuzzy predicates and it is widely used in many application fields. Lots of pioneering works such as Tong et. al [1], Xu et. al [2] and Pedrycz [3] have studied different problems for fuzzy modeling. When designing a fuzzy models, identifying "good" initial parameters of the fuzzy rules is an important problem. In [4] Oh presented that using genetic algorithm and a concept of Information granulation (IG) to develop fuzzy inference systems. In our previous study [5-8], we proposed a space search algorithm (SSA) and used it as a vehicle to finding the parameters of fuzzy rules. Here we present an improved space search algorithm (ISSA) by means of gaussian mutation [9]. A hybrid optimization of fuzzy inference systems based on the improved space search algorithm (ISSA) and information granulation (IG) is constructed. ISSA is exploited here to carry out the parameter estimation of the fuzzy models as well as to realize structural optimization. The identification process is comprised of two phases, namely a structural optimization and parametric optimization. The ISSA and the weighted least square method (WLSE) are used in each phase of this sequence. Information granulation is realized with the aid of HCM, ISSA and WLSE. Hard Clustering Method (HCM) is used to help determine the initial parameters of the fuzzy model such as the initial location of apexes of the membership functions and the prototypes of the polynomial functions being used in the premise and consequence parts of the fuzzy rules, while ISSA and WLSE are employed to adjust the initial values of the parameters. The evaluation of the performance of the proposed model is carried out by using two well-known data sets. To demonstrate the performance of ISSA, we compared it with some existing fuzzy models reported in the literature.

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2. Improved space search algorithm

The SSA is a heuristic algorithm whose search method comes with the analysis of the solution space. In essence, the solution space is the set of all feasible solutions for the optimization problem (or mathematical programming problem), which is stated as the problem of determining the best solution coming from the solution space. In SSA, the search method is based on the operator of space search, which generates two basic steps: generate a new subspace and search the new space. Search in the new space is realized by randomly generating a new solution located in this space. Regarding the generation of the new space, we consider two cases: (a) space search based on M selected solutions, and (b) space search based on one selected solution.

In Case I, the new subspace is generated by M selected solutions. For convenience, a solution X can be presented in another way $X=(x_1,x_2,\cdots,x_n)$, where n is the index of the dimension. Regarding the M solutions, we use the following representations: $X^k=(x_1^k,x_2^k,\cdots,x_n^k)$, $k=1,2,\cdots,M$. We generate the new space V_1 based on the following expression:

$$V_1=\left\{X^{new}|x_i^{new}=\sum_{k=1}^{M}a_i x_i^k \cup X^{new}\in S\right\} \quad (1)$$
$$where \sum_{k=1}^{M}a_i=1,\ -1\le a_i\le 2$$

In Case II, the space search operation is based on a given solution. In this case, the given solution is the best solution in the current solution set. Assume that we randomly select i is an integer of [1, n]. The new space V_2 is generated based on the following expression:

$$V_2=\left\{\begin{matrix}\left(x_1^{new},x_2^{new},\cdots,x_n^{new}\right)|x_j^{new}=x_j \\ (j\neq i)\cup x_i^{new}\in[l_i,u_i]\end{matrix}\right\} \quad (2)$$

In the ISSA, the operator of case I is the same as SSA. However, a new operator is employed in case II. The expression that generates a new solution is as follows:

$$X^{new}=\left\{\left(x_1,x_2,\cdots,x_{i-1},x_i^{new},x_{i+1},\cdots,x_n\right)\right\} \quad (3)$$
$$where\ \ x_i^{new}=x_i^{new}+\gamma N(0,1);$$

$$\gamma=\gamma\exp\left(\frac{1}{\sqrt{2n}}N(0,1)+\frac{1}{\sqrt{2\sqrt{n}}}N(0,1)\right); \quad (4)$$

where γ is a coefficient, $N(0,1)$ and $N(0,1)$ are random real numbers generated by the normal distribution, respectively. The initial value of γ is set as 3.0.

3. Design of the IG-based fuzzy models

Considering the identification of fuzzy models, we realized the structure identification as well as parameter identification. The structure identification is supported by the ISSA and C-means while the parameter estimation is realized via the ISSA and weighted least square error method. IG is aimed at transforming the problem at hand into several smaller and therefore more manageable tasks. In this study granulation of information is aimed at transforming the problem at hand into several smaller and therefore more manageable tasks. In this way, we partition the task into a series of well-defined subproblems (modules) of far lower computational complexity than the original one. The identification procedure for fuzzy models is split into the identification activities dealing with the development of the premise and the consequence part of rules. The identification completed at the premise level consists of two main steps. First, we select the input variables x1,x2,⋯, xk of the rules. Second, we form fuzzy partitions (by specifying fuzzy sets of well-defined semantics such as e.g., Low, High, etc.) of the spaces over which these individual variables are defined. In such a sense, this phase is all about information granulation as the elements of the fuzzy partitions we are interested in when developing any rule-based model. The number of the fuzzy sets constructed there implies directly the number of the rules of the model itself. In addition, one has to determine membership functions of the information granules.

The identification of the premise part is completed in the following manner.

Given is a set of data $U=\{x_1,x_2,\cdots,x_l;y\}$, where $X_k=[x_{1k},\cdots,x_{mk}]^T$, $Y=[y_1,\cdots,y_m]^T$, where l 1 is the number of variables and m is the number of data.

[Step 1] Arrange a set of data U into data set X_k composed of the corresponding input and output data.

$$X_k=[x_k;y] \quad (5)$$

[Step 2] Run the K-Means to determine the centers (prototypes) v_{kg} within the data set X_k.

[Step 2-1] Arrange data set X_k into c-clusters (in essence this is effectively the granulation of information)

[Step 2-2] Calculate the centers v_{kg} of each cluster.

$$v_{kg}=\{v_{k1},v_{k2},\cdots,v_{kx}\} \quad (6)$$

[Step 3] Partition the corresponding input space using the prototypes of the clusters v_{kg}. Associate each cluster with some meaning (semantics), say Small, Large, etc.

[Step 4] Set the initial apexes of the membership functions using the prototypes v_{kg}.

The identification of the conclusion parts of the rules deals with a selection of their structure (type 1, type 2, type 3 and type 4) that is followed by the determination of the respective parameters of the local functions occurring there. The conclusion part of the rule that is extended form of a typical fuzzy rule in the TSK (Takagi-Sugeno-Kang) fuzzy model has the form.

$$R^j: If\ x_i\ is\ A_{1c}\ \text{and} \cdots \text{and}\ x_k\ is\ A_{kc}\ then\ y_j - M_j = f_j(x_1, ..., x_k) \quad (7)$$

Type 1 (Simplified Inference):

$$f_j = a_{j0} \quad (8)$$

Type 2 (Linear Inference):

$$f_j = a_{j0} + a_{j1}(x_1 - V_{j1}) + \cdots + a_{jk}(x_k - V_{jk}) \quad (9)$$

Type 3 (Quadratic Inference):

$$\begin{aligned} f_j = & a_{j0} + a_{j1}(x_1 - V_{j1}) + \cdots + a_{jk}(x_k - V_{kj}) + a_{j(k+1)}(x_1 - V_{1j}) \\ & + a_{j(2k+1)}(x_1 - V_{1j})(x_2 - V_{2j}) + \cdots \\ & + a_{j((k+2)(k+1))/2)}(x_{k-1} - V_{(k-1)j}) \end{aligned} \quad (10)$$

Type 4 (Modified Quadratic Inference):

$$\begin{aligned} f_j = & a_{j0} + a_{j1}(x_1 - V_{j1}) + \cdots + a_{jk}(x_k - V_{kj}) \\ & + a_{j(k+1)}(x_1 - V_{1j})(x_2 - V_{2j}) + \cdots \\ & + a_{j(k(k+1)/2)}(x_{k-1} - V_{(k-1)j})(x_k - V_{kj}) \end{aligned} \quad (11)$$

The optimal coefficients of the model is estimated through the minimization of the objective function J_L

$$J_L = \sum_{i=1}^{n} \sum_{k=1}^{m} w_{ik} (y_k - f_i(\mathrm{x_k} - \mathrm{v_i}))^2 \quad (12)$$

Where w_{ik} is the normalized firing strength (activation level) of the i th rule.

The performance index J_L can be rearranged as

$$\begin{aligned} J_L &= \sum_{i=1}^{n} (Y - X_i a_i)^T W_i (Y - X_i a_i) \\ &= \sum_{i=1}^{n} (W_i^{1/2} Y - W_i^{1/2} X_i a_i)^T (W_i^{1/2} Y - W_i^{1/2} X_i a_i) \end{aligned} \quad (13)$$

Where a_i is the vector of coefficients of ith consequent polynomial (local model), Y is the vector of output data, W_i is the diagonal matrix (weighting factor matrix) which represents degree of activation of the individual information granules by the input data. X_i is a matrix which is formed with input data and information granules (centers of cluster). In case the consequent polynomial is Type 2 (linear or a first-order polynomial), X_i and a_i read as follows

$$W_i = \begin{bmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{im} \end{bmatrix} \in R^{m \times m} \quad (14)$$

$$X_i = \begin{bmatrix} 1 & (x_{11} - v_{i1}) & \cdots & (x_{l1} - v_{il}) \\ 1 & (x_{12} - v_{i1}) & \cdots & (x_{l1} - v_{il}) \\ 1 & \vdots & \ddots & \vdots \\ 1 & (x_{1m} - v_{i1}) & \cdots & (x_{lm} - v_{il}) \end{bmatrix} \quad (15)$$

$$a_i = [a_{i0}\, a_{i1} \cdots a_{il}] \quad (16)$$

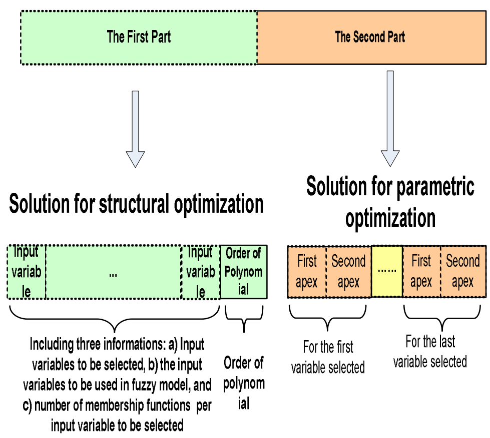
For the local learning algorithm, the objective function is defined as a linear combination of the squared error, which is a difference between output data and the result produced each fuzzy rule when considering the weighting factor matrix W_i. This matrix captures the activation levels of input data with respect to ith sub-space. In this sense we can consider the weighting factor matrix as a discrete version of the fuzzy (linguistic) representation for the corresponding sub-space.

The optimal coefficients of the consequent polynomial of the ith fuzzy rule can be determined in a usual manner that is

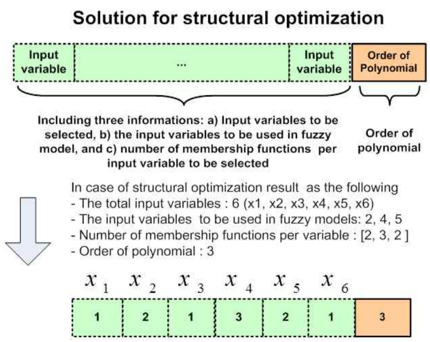
$$a_i = (X_i^T W_i X_i)^{-1} X_i W_i Y \quad (17)$$

Notice that the coefficients of the consequent polynomial of each fuzzy rule have been computed independently using a subset of training data. These computations can be implemented in parallel and in this case the overall computing load becomes unaffected by the total number of the rules.

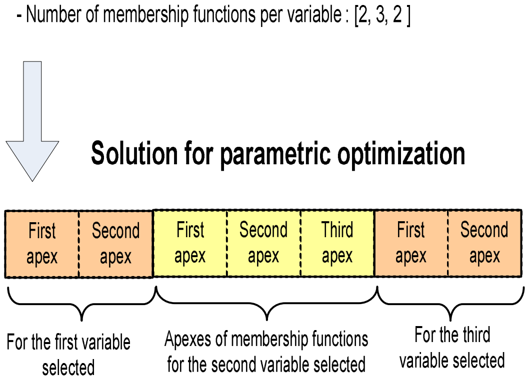
The proposed ISSA is exploited here to optimize the fuzzy models. Figure 1 depicts the arrangement of chromosomes. Genes for structural optimization are linked up with genes used for parametric optimization. The size of the chromosomes for structural optimization of the IG-based fuzzy model is determined according to the number of all input variables of the system. The size of the chromosomes for parametric optimization depends on structurally optimized fuzzy inference system. When constructing fuzzy models, we simultaneously realize the structural as well as parametric optimization of the model.



(a) Arrangement of solutions



(b) An example of the first part (for structural optimization)



(c) An example of the second part (for parametric optimization).

Fig. 1. Arrangement of the chromosome in ISSA

Fig. 1 depicts the arrangement of solutions in the SSA-based sequential tuning method. The first part for structural optimization is separated from the second part used for parametric optimization. The size of the solutions for structural optimization of the IG-based fuzzy model is determined according to the number of all input variables of the system. The size of the solutions for parametric optimization depends on structurally optimized fuzzy inference system. In a nutshell, from the viewpoint of structure identification, only one fixed parameter set, which is the assigned apexes of membership functions obtained by C-Means clustering, is considered to carry out the overall structural optimization of fuzzy model. From the viewpoint of parameter identification, only one structurally optimized model that is obtained during the structure identification is considered to be involved in the overall parametric optimization. We simultaneously realize the structural as well as parametric optimization of the model. The second part for parametric identification is linked up with the first part for structure identification within a solution (an individual). The size and arrangement of the first part for structure identification is the same as those in the sequential tuning method, while the size of the second part for parameter identification is determined by considering both the number of the system's input variables and the number of the membership functions being used in their representation. A stochastic variable (a variant identification ratio) used within a modified simple search space operator in the ISSA is used support an efficient successive tuning embracing both the structural as well as parametric optimization of the model. During the initial generations of the ISSA, the space search operator is assigned with higher probability to the solution region involving the first part responsible for structural optimization. This probability becomes lower when dealing with a region of the solution involving the second part responsible for parametric optimization. In this manner, the optimization becomes mostly focused on the structural optimization. Over the course of the space search optimization (for higher generations), the probability that the first part can be generated (assigned) within the second part responsible for parameter optimization gradually increases. In this sense, the optimization of the IG-based fuzzy set model becomes predominantly focused on the parametric optimization. The second part related to the parameter optimization of model is serially connected with the first part related to the structural optimization of model. Therefore the "simultaneous topology/parameter search" is carried out for optimization, and the successive tuning method enables us to consider much more extensive topology/parameter search space for optimization.

The space search operator in the ISSA for the successive tuning method being realized with the aid of a variant identification ratio is implemented. Their essential parameters such as gen, maxgen, and l are given. Here, gen is an index of the current generation, maxgen stands for the maximal number of generations being used in the algorithm, and l serves as some adjustment coefficient whose values can determine a variant identification ratio (p) for both structural and parametric optimization. The detailed space search operator in the SSA algorithm is presented as follows:

While { the termination conditions are not met }
Select M solutions (parent individuals) from the current solution set, where M is a given number.
Generate random variable (r1).
Calculate a variant identification ratio (p) which is a generation-based stochastic variable of the form

$$p = \frac{r_1 + (1 - \geq n/\max gan)}{\lambda} \quad (18)$$

IF {p > 0.5}
Search solution space within the first part of solutions for structural optimization.
Else
Search solution space within the second part of solutions for parametric optimization.
End IF
Complete the space search operation.
End while

The objective function (performance index) is regarded as a basic mechanism guiding the evolutionary search carried out in the solution space of potential solutions. The objective function involves both the training and testing data and comes as a convex combination of these two components

$$f(PI, E\_PI) = \theta \times PI + (1-\theta) \times E\_PI \quad (19)$$

Here, PI and E_PI denote the performance index for the training data and testing (validation) data, respectively. θ is a weighting factor that allows us to form a sound balance between the performance of the model for the training and testing data. Depending upon the values of the weighting factor, several specific cases of the objective function are worth distinguishing.

(i) If $\theta = 1$ then the model is optimized based on the training data. No testing data is taken into consideration.

(ii) If $\theta = 0.5$ then both the training and testing data are taken into account. Moreover it is assumed that they exhibit the same impact on the performance of the model.

(iii) The case $\theta = \alpha$ where $\alpha \in [0,1]$ embraces both the cases stated above. The choice of α establishes a certain tradeoff between the approximation and generalization aspects of the fuzzy model.

Here we use performance index of the standard root mean squared error (RMSE) and mean squared error (MSE)

$$PI(\text{or } E\_PI) = \begin{cases} \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - y_i^*)^2} & (RMSE) \\ \frac{1}{m}\sum_{i=1}^{m}(y_i - y_i^*)^2 & (MSE) \end{cases} \quad (20)$$

4. Experimental studies

This section reports on comprehensive numeric studies illustrating the design of the fuzzy model. We use two well-known data sets. Each data set is divided into two parts of the same size. PI denotes the performance index for the training data and E_PI stands for the testing data. In all considerations, the weighting factor θ was set to 0.5.

4.1 NOx emission process data

NOx emission process of a GE gas turbine power plant located in Virginia, USA, is chosen in this experiment. The input variables include AT (ambient temperature a site), CS (compressor speed), LPTS (low pressure turbine speed), CDP (compressor discharge pressure), and TET (turbine exhaust temperature). The output variable is NOx. We consider 260 pairs of the original input-output data. 130 out of 260 pairs of input-output data are used as the learning set; the remaining part serves as a testing set. The identification error of the proposed model is compared with the performance of some other models; refer to Table 1. It is clear that the proposed model outperforms several previous fuzzy models known in the literature.

Table 1. Comparative analysis of selected models (NOx)

Model		PI	E_PI	No. of rules
Regression model		17.68	19.23	
Hybrid FS-FNNs [10]		2.806	5.164	
Hybrid FR-FNNs [11]		0.080	0.190	
Multi-FNN[12]		0.720	2.205	
Hybrid rule-based FNNs[13]		3.725	5.291	
SOFPNN [14]		0.012	0.094	
Choi's model [10]		0.012	0.067	18
Our model	GA	0.019	0.132	16
	SSA[5]	0.004	0.019	16
	ISSA	0.003	0.003	16

4.2 Automobile Miles Per Gallon (MPG) Data

The first dataset is an automobile MPG data (ftp://ics.uci.edu/pub/machine-learning-databased/auto-mpg) with the output being the automobile's fuel consumption expressed in miles per gallon. The data set includes 392 input-output pairs (after removing incomplete instances) where the input space involves 8 input variables. To come up with a quantitative evaluation of the fuzzy model, we use the standard RMSE performance index.

The automobile MPG data is partitioned into two separate parts. The first 235 data pairs are used as the training data set for IG-based FIS while the remaining 157 pairs are the testing data set for assessing the predictive performance. The identification error of the proposed model is compared with the performance of some other model; refer to Table 7. The selected values of the performance indexes of the IG-FIS are marked in Table 5 and Table 6, respectively. It is easy to see that the performance of the proposed model is better in the sense of its approximation and prediction abilities.

Table 2. Comparative analysis of selected models (MPG)

Model		PI (RMSE)	E_PI (RMSE)	No. of rules
RBFNN [15]		3.24	3.62	36
Linguistic model [16]		2.86	3.24	36
Functional RBFNN[25]		2.41	2.82	33
Our model	GA	2.97	2.89	8
	SSA[5]	2.74	2.88	8
	ISSA	2.67	2.31	8

5. Conclusions

This paper introduced a hybrid identification of fuzzy models by means of an ISSA and IG. Experimental results show that ISSA-based model lead to better performance than some other fuzzy models reported in the literature.

참 고 문 헌

[1] R.M. Tong, “The evaluation of fuzzy models derived from experimental data” J. Fuzzy Sets Syst. Vol. 13, pp 1-12, 1980.

[2] C.W. Xu, Y. Zailu, “Fuzzy model identification self learning for dynamic system” J. IEEE Trans. on System, Man, and Cybernetics. Vol. 17(4), pp, 683-689, 1987.

[3] S.K. Oh., W. Pedrycz, “Identification of Fuzzy Systems by means of an Auto-Tuning Algorithm and Its Application to Nonlinear Systems” J. Fuzzy Sets and Syst. Vol 115(2), pp, 205-230, 2000.

[4] S.K. Oh, W. Pedrycz, K.J Park, “Identification of fuzzy systems by means of genetic optimization and data granulation”, Journal of Intelligent & Fuzzy Systems, Vol 18, pp. 31-41, 2007.

[5] W. Huang, L. Ding, S.K. Oh, C.W. Jeong, and S.C. Joo. 2010. Identification of fuzzy inference system based on information granulation. KSII Trans. Internet and Information systems. 4(4), 575-594.

[6] R. Hinterding. Gaussian mutation and self-adaption for numeric genetic algorithms. 1995. IEEE international conference on evolutionary computation. 384-389.

[7] W. Pedrycz, “An identification algorithm in fuzzy relational system”. J. Fuzzy Sets Syst. Vol 13, pp, 153-167, 1984.

[8] M. Sugeno, T. Yasukawa, “Linguistic modeling based on numerical data” In: IFSA’91 Brussels, Computer, Management & System Science. pp, 264-267. 1991.

[9] B. J. Park., W. Pedrycz., S. K. Oh, “Identification of Fuzzy Models with the Aid of Evolutionary Data Granulation”. IEE Proc.-Control Theory and Applications, Vol. 148, pp, 406-418, 2001.

[10] J.N. Choi, S.K. Oh, and W. Pedrycz, “Structural and parametric design of fuzzy inference systems using hierarchical fair competition-based parallel genetic algorithms and information granulation”, International Journal of Approximate Reasoning, Vol 49, pp, 631-648, 2008.

[11] Oh, S.K., Pedrycz, W., and Prak, H.S. 2003. Hybrid identification in fuzzy-neural networks. Fuzzy Set System. 138 (Sep. 2003), 399-426.

[12] Park, H.S., and Oh, S.K. 2003. Fuzzy relation-based fuzzy neural-networks using a hybrid identification algorithm. Int. J. Cont., Autom., Syst. 1 (Sep. 2003), 289-300.
Park, H.S., and Oh, S.K. 2003. Multi-FNN identification based on HCM clustering and evolutionary fuzzy granulation. Int. J. Cont., Autom., Syst. 1 (Jun. 2003), 194-202.

[13] Oh, S.K., Pedrycz, W., and Prak, H.S. 2002. Implicit rule-based fuzzy-neural networks using the identification algorithm of hybrid scheme based on information granulation. Adv. Eng.Inform.16(Oct.2002),247-263.

[14] Oh, S.K., and Pedrycz, W. 2004. A new approach to self-organizing multi-layer fuzzy polynomial neural networks based on genetic optimization. Adv. Eng.Inform.18(Jan.2004),29-39.

[15] Pedrycz, W., and Kwak, K.C. “Linguistic models as a framework of user-centric system modeling,” IEEE Trans. Syst., man cybern. - PART A: Systems and humans, vol. 36, no. 4, pp. 727 - 745, 2006.

[16] Pedrycz, W., Park, H.S., and S.K. Oh, “A granular-oriented development of functional radial basis function neural networks,” Neurocomputing, vol. 72, pp. 420 - 435, 2008.

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