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An improved method on rough set theory and application in prediction of pest attack

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ABSTRACT

In order to improve the forecasting accuracy of the occurrence period of insect pests, this paper puts forward a kind of improved method of attribute reduction on rough set theory based on discernibility matrix. And, the forecasting model of insect pests is established by using improved rough set and BP network. The test results show that improved algorithm can reduce the complexity of computing, the number of conditional attribute reduction and the number of condition attributes after reduction than the original algorithm has obvious advantages. the average accuracy of the forecasting model reached to 90%.

KEYWORDS

Insect pests;
Forecasting method;
Rough set theory;
Particle swarm optimization;
BP neural network.

INTRODUCTION

The Euphrates poplar forests of the tarim river basin is the main body of maintaining the ecological system, but many euphrates poplar die of insect pests every spring. Predicting the occurrence period of forest pests is the precondition to take effective prevention and control measures[1]. So the timely and reliable forecasting method is very important to the prevention and accurate control of the Euphrates poplar forests.

The forecasting method of the occurrence period of insect pests mainly includes development progress method, forecast by emergence interval and effective accumulated temperature method and phonological method. Although these method is accurate and easy for basic forecasters, the traditional forecasting methods are time-consuming, arduous, poor timeliness[2].In recent years, mathematical statistics, fuzzy mathematics and pattern recognition technology are more and more widely used in the prediction of forest pests along with the development of the ecological mathematics and computer technology rapidly[3]. The main methods include a regression analysis, multiple regression analysis, factor comprehensive correlation method, step statistics, cycle analysis, Markov chain, fuzzy priority ratio method, topology method, neural network, support vector machine, etc[4-6], Due to the application of these methods, the forecasting quality and standards have been improved significantly. However, There are many factors to affect forecasting accuracy, if these impact factors are not preferred the problem of high data dimension, weak stability and low precision of recognition of the classifier will appear. In addition, the BP neural network has the problem that weights and thresholds are not easy to be determined. So, the forecasting accuracy of the occurrence period of pests is a bit low[7].

The article takes the most serious pest (spring inchworm) in Tarim river basin as the object of study, using attribute reduction algorithm of rough set theory to screen condition attribute set (temperature, humidity, rainfall, etc) and to establish minimum decision table, and using the BP neural network to establish forecast model. The method can not only reduce the data dimension and the complexity of computing, but also increase the forecasting precision.

ROUGH SET THEORY

The imperfection and uncertainty of prediction of pest attack has always been a difficult problem for researchers. rough set theory is a mathematical tool that can describe imperfection and uncertainty, can effectively analysis and deal with imprecise, inconsistent, incomplete information, and find the implicit knowledge, reveal the law of potential. so, rough set theory is more suitable for prediction of forest pests in comparing many methods processing uncertain knowledge. the basic concepts of rough set theory is introduced as follows[8-10]:

Lower approximation and upper approximationt of rough set

$K=(U,S)$ is a given knowledge base, U represents a domain of discourse, S represents equivalence relation cluster in the U,then $\forall X\subseteq U$ and a equivalence relation of the domain of discourse is $R\in \mathrm{IND}(K)$ ÿwe define the lower approximation and upper approximation of the subset (X) are as follows:

$$\begin{aligned}\underline{R}(X)&=\{x\mid(\forall x\in U)\wedge([x]_R\subseteq X)\}\\&=\bigcup\{Y\mid(\forall Y\in U/R)\wedge(Y\subseteq X)\}\end{aligned}\qquad(1)$$

$$\begin{aligned}\overline{R}(X)&=\{x\mid(\forall x\in U)\wedge([x]_R\cap X\neq\varnothing)\}\\&=\bigcup\{Y\mid(Y\in U/R)\wedge(Y\cap X\neq\varnothing)\}\end{aligned}\qquad(2)$$

Lower approximation named $\underline{R}(X)$ and upper approximation named $\overline{R}(X)$ of the set have the following properties:

(1) $\underline{R}(X)\subseteq X\subseteq\overline{R}(X)$

(2) $\underline{R}(\varnothing)=\overline{R}(\varnothing)=\varnothing,\underline{R}(U)=\overline{R}(U)=U$

(3) $\overline{R}(X\cup Y)=\overline{R}(X)\cup\overline{R}(Y)$

(4) $\overline{R}(X\cup Y)=\overline{R}(X)\cup\overline{R}(Y)$

(5) $X\subseteq Y\Rightarrow\underline{R}(X)\subseteq\underline{R}(Y)$

(6) $X\subseteq Y\Rightarrow\overline{R}(X)\subseteq\overline{R}(Y)$

(7) $\overline{R}(X\cap Y)\subseteq\overline{R}(X)\cap\overline{R}(Y)$

(8) $\underline{R}(X\cup Y)\supseteq\underline{R}(X)\cup\underline{R}(Y)$

(9) $\underline{R}(\sim X)=\sim\overline{R}(X)$

(10) $\overline{R}(\sim X)=\sim\underline{R}(X)$

(11) $\underline{R}(\underline{R}(X))=\overline{R}(\underline{R}(X))=\underline{R}(X)$

(12) $\overline{R}(\overline{R}(X))=\underline{R}(\overline{R}(X))=\overline{R}(X)$

(13) $\underline{R}(X)=\sim\overline{R}(\sim X)$

(14) $\overline{R}(X)=\sim\underline{R}(\sim X)$

(15) $X\subseteq\underline{R}(\overline{R}(X))$

(16) $\overline{R}(\underline{R}(X))\subseteq X$

The relation between approximation and member

The concept of member relationship is put forward by approximate set. Only when $x\in\overline{R}(X)$, then x is called R member relationship of the X. Inaccuracy of the set is due to the presence of edge boundaries, its edge boundaries are the bigger, the accuracy is the lower. The concept of approximate precision and roughness of the set are introduced in order to more accurately express it.

A domain of discourse named U and an equivalence relation named R in the U are given, $\forall X\subseteq U$,then the approximation accuracy and roughness of the X that equivalence relation named R defined are as follows:

$$\alpha(x)=\frac{|\underline{R}(X)|}{|\overline{R}(X)|}\qquad(3)$$

$$\beta(x)=1-\alpha(x)\qquad(4)$$

Where $|R(X)|$ is the number of members of the set X. A division named $\pi(U)$ of U is given, when $\pi(U)=\{X_1,X_2,...,X_n\}\in\prod(U)$, even this division is independent of R, among them, the subset named $X_i(i=1,2,...,n)$ is the equivalence class of . The lower approximation and upper approximation of R of are as follows:

$$\underline{R}(\pi(U))=\underline{R}(X_1)\cup\underline{R}(X_2)\cup...\underline{R}(X_n)=\bigcup_{i=1}^{n}\underline{R}(X_i)\qquad(5)$$

$$\overline{R}(\pi(U)) = \overline{R}(X_1) \cup \overline{R}(X_2) \cup ... \overline{R}(X_n) = \bigcup_{i=1}^{n} \overline{R}(X_i) \quad (6)$$

According to the above formula, the approximate classification accuracy and quality of R of are as follows:

$$\alpha(\pi(U)) = \frac{\sum_{i=1}^{n} |\underline{R}(X_i)|}{\sum_{i=1}^{n} |\overline{R}(X_i)|} = \frac{card(\underline{R}(\pi(U)))}{card(\overline{R}(\pi(U)))} = \frac{|\underline{R}(\pi(U))|}{|\overline{R}(\pi(U))|} \quad (7)$$

$$\gamma(\pi(U)) = \frac{\sum_{i=1}^{n} |\underline{R}(X_i)|}{|U|} = \frac{card(\underline{R}(\pi(U)))}{card(U)} = \frac{|\underline{R}(\pi(U))|}{|U|} \quad (8)$$

When the classification number is equal to one, approximate classification accuracy is equal to approximate accuracy of the set

The reduction of condition attribute set

Reduction of knowledge is the kernel of the rough set theory. Usually the important degree of knowledge in knowledge base has great difference, even some of the knowledge is unnecessary. The purpose of reduction of knowledge is to delete the unnecessary knowledge in keeping the same classification ability[11].

Real-time monitor of the impact factors is a continuous process in forecasting insect pests of the euphrates poplar forests, so the information becomes more and more. So the reduction of the impact factors of pests is very important. The main task of the reduction is to delete the unnecessary knowledge in keeping the same classification ability, that is n dimension information space $\{x_1, x_2, ..., x_n\}$ reduce to m dimension $\{x_1, x_2, ..., x_m\}$ (m < n).

The purpose of reducing condition attribute set is that find a number of condition attributes in no losing any information in decision table. Reduction algorithm of attribute set mainly includes blind delete attribute reduction algorithm, attribute reduction algorithm based on Pawlak attribute importance, attribute reduction algorithm based on discernibility matrix, attribute reduction algorithm based on difference function, etc.

This paper puts forward an improved attribute reduction algorithm based on discernibility matrix. The original attribute reduction algorithm based on discernibility matrix is as follows[12,13]:

$K = \{U, C \cup D, V, f\}$ is a given decision table, among them $U = \{x_1, x_2, ..., x_n\}$, is domain of discourse $|U| = n$ and the discernibility matrix of decision table is as follows:

$$M_{n\times n} = (c_{ij})_{n\times n} = \begin{bmatrix} c_{11} & c_{12} & ... & c_{1n} \\ c_{21} & c_{22} & ... & c_{2n} \\ ... & ... & ... & ... \\ c_{n1} & c_{n2} & ... & c_{nn} \end{bmatrix} = \begin{bmatrix} c_{11} & * & ... & * \\ c_{21} & c_{22} & ... & * \\ ... & ... & ... & ... \\ c_{n1} & c_{n2} & ... & c_{nn} \end{bmatrix} \quad (9)$$

Where i,j=1,2,…n.

$$c_{ij} = \begin{cases} \{\alpha \mid (\alpha \in C) \wedge (f_\alpha(x_i) \neq f_\alpha(x_j))\},\ f_D(x_i) \neq f_D(x_j) \\ \varnothing,\ f_D(x_i) \neq f_D(x_j) \wedge f_C(x_i) = f_C(x_j) \\ -,\ f_D(x_i) = f_D(x_j) \end{cases} \quad (10)$$

The process of attribute reduction algorithm based on discernibility matrix about as follows:

(1).Input: $K = \{U, C \cup D, V, f\}$;

(2).Write the lower triangular matrix of the $M_{n\times n}(K) = (c_{ij})_{n\times n}$ according to the definition of discernibility matrix, where i,j=1,2,…,n.

$$c_{ij} = \begin{cases} \{\alpha \mid (\alpha \in C) \wedge (f_\alpha(x_i) \neq f_\alpha(x_j))\},\ f_D(x_i) \neq f_D(x_j) \\ \varnothing,\ f_D(x_i) \neq f_D(x_j) \wedge f_C(x_i) = f_C(x_j) \\ -,\ f_D(x_i) = f_D(x_j) \end{cases}$$

(3).Search discernibility matrix. If the value of all elements are not equal to $\varnothing$, turn to (4) steps, otherwise quit.

(4).Search discernibility matrix, and all single attribute element value assigned to $CORE_C(D)$, output: $CORE_C(D) = \{\alpha \mid (\alpha \in C) \wedge (\exists c_{ij}, ((c_{ij} \in M_{n\times n}(K)) \wedge (c_{ij} = \{\alpha\})))\}$

(5).Find out all possible attribute combination containing relative kernel of D, judge whether they meet the following two requirements:

The first condition: $\forall c_{ij} \in M_{n\times n}(K)$, while $c_{ij} \neq \varnothing$, there is $B \cap c_{ij} \neq \varnothing$;

The second condition: B is independent.

If they meet the two conditions, then their value are assigned to $RED_C(D)$, and all attributes combination of including relative kernel of D are traversed;

(6).Output $RED_C(D)$, end.

The process of attribute reduction algorithm based on improved discernibility matrix is shown as follows:

(1).Input: $K = \{U, C \cup D, V, f\}$;

(2).Calculate the dependency named $\gamma_\alpha(D)(\alpha \in C)$ of the condition attributes named α ,while $\gamma_\alpha(D)$ =0,

$C = C - \{\alpha\}$;

(3).Write a lower triangular matrix $M_{n\times n}(K) = (c_{ij})_{n\times n}$ according to the condition attribute set of $\gamma_{\alpha}(D) \neq 0$, there,: i,j=1,2,…n.

$$c_{ij} = \begin{cases} \{\alpha \mid (\alpha \in C) \wedge (f_{\alpha}(x_i) \neq f_{\alpha}(x_j))\},\ f_D(x_i) \neq f_D(x_j) \\ \varnothing,\ f_D(x_i) \neq f_D(x_j) \wedge f_C(x_i) = f_C(x_j) \\ -,\ f_D(x_i) = f_D(x_j) \end{cases}$$

(4).Search discernibility matrix. If the value of all elements are not equal to $\varnothing$, turn to (5) step, otherwise quit.

(5).Search discernibility matrix, and all single attribute element value assigned to $CORE_C(D)$, output: $CORE_C(D) = \{\alpha \mid (\alpha \in C) \wedge (\exists c_{ij}, ((c_{ij} \in M_{n\times n}(K)) \wedge (c_{ij} = \{\alpha\})))\}$

(6).Find out all possible attribute combination containing relative kernel of D, judge whether they meet the following two requirements:

The first condition: $\forall c_{ij} \in M_{n\times n}(K)$, while $c_{ij} \neq \varnothing$, there is $B \cap c_{ij} \neq \varnothing$;

The second condition: B is independent.

If meet the two conditions, then their value are assigned to $RED_C(D)$, and traverse all attributes combination of including relative kernel of D;

(7).Output $RED_C(D)$, calculate the importance of attributes $\sigma_{CD}(\alpha) = \gamma_C(D) - \gamma_{C-\{\alpha\}}(D)$, there, $\alpha \in C$, while $\sigma_{CD}(\alpha)$ >0.9,then $RED_C(D) \Leftarrow RED_C(D) \cup \alpha$, traverse all attribute combination of the $RED_C(D)$, calculate credibility of the $RED_C(D)$

(8).Output $RED_C(D)$, end.

The comparison of the improved attribute reduction algorithm with previously known algorithm is as shown in TABLE 1 based on the rough set analysis software – Rosetta.

And thus, at the same time of meet the requirements, the improved algorithm of attribute reduction based on discernibility matrix reduce the complexity of computing, the number of conditional attribute reduction and the number of condition attributes after reduction than the original algorithm has obvious advantages. Experiments show that it is an effective method of attribute reduction

TABLE 1 : The comparative result between the two algorithms

Comparison of the project	Original algorithm	Improved algorithm
Subtract the number	12	8
The number of reduction attributes	6	3
Whether meet the requirements	YES	YES

VALIDATION OF IMPROVED ALGORITHM

Matlab r2009a, Windows XP were selected as the software platform of the forecasting model; PC machine, INTER dual-core processor, 2G memory were selected as the hardware platform. The simulation test content included two parts, the first part was the feature reduction based on rough set theory; the second part was test for accuracy of the forecasting model.

Feature reduction based on rough set theory

The main factors that pests (Spring inchworm) happen include temperature, humidity, rainfall, etcÿfor example, winter temperature, temperature and humidity data of the March, April and may each year. Among them, the domain of discourse U={1998,1999,2000,2001,2002, 2003,2004,2005,2006,2007,2008,2009,2010,2011},the condition attribute set { $x_1 \sim x_{16}$ } consists of precipitation, average temperature, average humidity, accumulated temperature, etc. Decision attributes is divided into four levels {1, 2, 3, 4} according to the initiation period respectively. The decision table are established as shown in TABLE 2.

Rough set requires that attribute value of the sample is discrete, so continuous condition attribute value of the decision table need to be transformed into discrete. Methods of discretization mainly include equidistance method, equifrequent method, maximum line method, greedy algorithm, discretization method based on genetic algorithm, candidate breakpoint set algorithm and MD heuristic algorithm, etc[21], The equidistance discrete method is simple, practical and effective, therefore this paper adopted a method of equidistance to turn training sample set into discrete[22]. U{1,2,3,4,…,14} instead of year. The rainfall is divided into four grades, that is {0,1,2,3}, the attribute value of monthly rainfall between 0 and 1 is expressed as 0;the attribute value of monthly rainfall between 1 and 2 is expressed as 1; the attribute value of monthly rainfall between 2 and 3 is expressed as 2; the attribute value of monthly rainfall between 3 and ∞ is expressed as 3.Similarly,attribute value of total precipitation, effective accumulated temperature, average humidity and average temperature are divided into four levels. The decision table of discretization are established as shown in TABLE 3.

TABLE 2 : Decision table of forecasting model of pests

sample	Condition attribute																Decision attribute
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	
1998	75	3.5	2.8	9.2	6.8	14.7	19.2	82	78	68	3870	3550	3300	933	699	445	1
1999	80	2.8	1.6	8.9	6.9	14.5	19.3	80	76	67	3745	3487	3078	945	785	467	2
2000	65	4.2	2.5	10.2	7.1	14.9	19.1	83	79	69	3924	3815	3152	938	712	411	1
2001	72	1.5	1.9	8.7	6.7	15.0	19.6	82	76	65	3601	3574	3067	971	724	435	3
2002	77	3.6	3.6	10.3	7.2	14.5	18.8	84	79	68	3651	3589	2956	980	703	415	3
2003	82	2.6	2.3	7.5	6.8	15.3	19.6	81	78	68	3646	3561	2914	912	687	460	2
2004	98	3.8	1.8	8.6	7.1	14.6	19.5	83	79	69	3735	3600	3058	945	680	452	2
2005	79	4.3	2.8	9.5	6.9	14.9	19.4	85	80	71	3617	3568	3018	925	705	476	3
2006	81	2.8	2.6	8.6	7.6	14.7	19.6	84	78	68	3685	3630	2875	901	692	437	4
2007	86	1.8	3.5	7.9	7.9	15.0	18.9	82	79	67	3726	3658	3281	887	683	418	3
2008	90	1.5	1.9	8.9	7.0	14.8	20.2	81	78	69	3685	3587	3158	904	710	438	4
2009	98	3.2	2.6	11.5	7.3	14.9	19.7	83	80	70	3557	3500	3398	998	725	468	4
2010	120	4.5	5.8	13.6	7.5	15.1	19.8	84	82	71	4001	3825	3679	875	645	402	1
2011	110	3.6	4.9	12.5	7.8	15.2	20.1	85	81	70	4156	4015	3855	867	635	397	1

Note x_1 : total rainfall; x_2 - x_4 :rainfall of March, April and May, x_5 - x_7 : Average temperature of March, April and May, x_8 - x_{10} Average humidity of March, April and May, x_{11} - x_{13} : accumulated temperature greater than 0 !, 5 !, 10 !, x_{14} - x_{16} :accumulated temperature less than - 10°c, -15°c, -20°c.

TABLE 3 : The decision table of discretization

SAMPLE	CONDITION ATTRIBUTE																DECISION ATTRIBUTE
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	
U1	0	2	1	2	0	1	1	1	1	1	2	1	3	2	1	2	1
U2	1	1	0	1	1	0	1	0	0	0	1	0	1	2	3	3	2
U3	0	3	1	2	2	2	0	2	2	2	2	3	2	2	2	1	1
U4	0	0	0	1	0	3	2	1	0	0	0	1	1	3	3	2	3
U5	1	2	2	2	2	0	0	3	2	1	0	1	0	3	2	1	3
U6	1	1	1	0	0	3	2	1	1	1	0	1	0	1	1	3	2
U7	2	2	0	1	2	0	2	2	2	2	1	2	1	2	1	3	2
U8	1	3	1	2	1	2	1	3	3	3	0	1	1	1	2	3	3
U9	1	1	1	1	3	1	2	3	1	1	0	2	0	1	1	2	4
U10	2	0	2	0	3	3	0	1	2	0	1	2	2	0	1	1	3
U11	2	0	0	1	2	1	3	1	1	2	0	1	2	1	2	2	4
U12	2	2	1	3	2	2	2	2	3	3	0	0	3	3	3	3	4
U13	3	3	3	3	3	3	3	3	3	3	3	3	3	0	0	0	1
U14	3	2	3	3	3	3	3	3	3	3	3	3	3	0	0	0	1

Using the improved attribute reduction algorithm based on discernibility matrix deal with decision table of discretization. first of all, data of the decision table was preliminary dealed with according to the dependency of decision attribute, secondly, the nuclear of decision table was quickly calculated by using the advantages of discernibility matrix; finally, reasonable rules were obtained according to values of attribute importance and reduction credibility. the improved algorithm can also obtain the minimum reduction of decision table whether the difference matrix contains single attribute elements. the minimum decision table of reduction is shown in TABLE 4. condition attributes were reduced from 16 to 8 after the rough set simplified the condition attributes.

TABLE 4 : The minimum decision table of reduction

SAMPLE	CONDITION ATTRIBUTE								DECISION ATTRIBUTE
	x_1	x_5	x_6	x_8	x_9	x_{13}	x_{15}	x_{16}	
U1	0	0	1	1	1	3	1	2	1
U2	1	1	0	0	0	1	3	3	2
U3	0	2	2	2	2	2	2	1	1
U4	0	0	3	1	0	1	3	2	3
U5	1	2	0	3	2	0	2	1	3
U6	1	0	3	1	1	0	1	3	2
U7	2	2	0	2	2	1	1	3	2
U8	1	1	2	3	3	1	2	3	3
U9	1	3	1	3	1	0	1	2	4
U10	2	3	3	1	2	2	1	1	3
U11	2	2	1	1	1	2	2	2	4
U12	2	2	2	2	3	3	3	3	4
U13	3	3	3	3	3	3	0	0	1
U14	3	3	3	3	3	3	0	0	1

Test and analysis of the model

BP neural network of three layer was established, set a input layer of six neurons, hidden layer of 19 neurons, output layer of five neurons, learning rate of 0.5,inertia coefficient of 0.8, target error of 0.01, the iterative number of 200 times. Weights and threshold of BP neural network were optimized by the improved particle swarm optimization (PSO) algorithm[14,15].

Forecasting model were established by not simplified data and standard BP neural network, and not simplified data and PSO-BP neural network, simplified data and BP network, simplified data and the PSO-BP neural network. The compared results were shown in TABLE 5.

TABLE 5 : The comparison of several kinds of prediction model

Whether reduction?	Whether improved BP?	The accuracy of model (%)	Training time (S)
NO	BP	80.3	156.26
NO	PSO-BP	83.6	126.32
YES	BP	87.8	108.96
YES	PSO-BP	90	85.76

The above table showed that attribute reduction method of rough set can eliminate the redundant attributes and simplify the structure of BP neural network. The combination of the rough set theory and the PSO not only can optimize the BP neural network, and shorten the training time, but also improve the accuracy of prediction model. So, the method which rough set combines with neural network was reasonable and effective.

CONCLUSION

Accurate prediction of forest pest is the precondition of effective prevention and control. In this paper, we used reduction algorithm of rough set to preprocess condition attributes, which combined with the PSO-BP neural network to establish prediction model, and improved the accuracy of the prediction model. The conclusions are summed up as follows:

(1) At the same time to meet the requirement of the application, the improved attribute reduction algorithm based on discernibility matrix reduces the computational complexity and the number of attributes than the original method. Reduction algorithm of rough set is a kind of efficient attribute reduction method. However, the environment which insect pests happen is changeable, the amount of data is huge. More sophisticated methods screening data and efficient technologies mining data need to be further researched.

(2) Rough set theory has strong ability to process imprecise information, PSO algorithm has strong ability to search and optimize weights and thresholds of BP network, BP neural network is fit for dealing with nonlinear problems especially for its good ability for nonlinear mapping. This paper combined the three technology to put forward a kind of forecasting method of forest pests, average recognition accuracy reaches 90%, it can provide some reference for the prediction of all kinds of plant diseases and insect pests.

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