

Application of artificial immune system in landslide forecasting

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Abstract: Current researches concluded that the stability of landslide is not only a problem of nonlinear system but also a very complex problem. The different stage of the deformation is, whereupon the type and target of the forecast are different and the corresponding method is diverse. So an accurate judgment of the stage of landslide deformation, especially identifying whether the deformation is in the stage of accelerated deformation, is a basic subject of landslide forecast. This paper made a studious attempt to apply the artificial immune algorithm to recognize the mutation point of deformation and very successful results are obtained in the concrete samples.

Résumé: Dans la recherche de la prévision et de la prédiction du glissement de terrain, la stabilité du glissement de terrain est le problème du système non-linéaire complexe. La période de sabotage de la déformation est différente. Il est différent pour le type et l'objet de la prévision. Il est aussi différent le moyen de la prévision. Car, déterminer précisément l'étape de l'évolution du clivus, notamment l'étape de la déformation accélérée qui est si à tel étape. Il est un des problèmes fondamentaux de la prévision de glissement de terrain. Le texte a essayé d'utiliser la méthode de calcul de l'immunisation artificielle pour déterminer la déformation du glissement de terrain. Le résultat pratique indique que cette utilisation est parfaite.

Keywords: Artificial immune system, clone selection, landslide, mutation point

INTRODUCTION

The categorization, destination, and the methodology of landslide forecast are all subject to the varying stages of the deformation of the slope (Li & Chen 1999). If the slope deforms, itself, at an even speed, signifying that the slope is in a state of limit equilibrium, the deformation may last for a period of time and finally reaches another stage of limit equilibrium. Accordingly, the forecast falls into the category on a fairly long-term or long-term basis, and the forecast goal is to determine the exact time when the slope begins to accelerate its deformation. If the deformation speeds up and loses its limit equilibrium, and the deformation velocity suddenly becomes great, the forecast will be an in-time one with a goal to foretell the time of loss of stabilization (Huang 2004). The accurate judgment of the evolutionary stage of the slope, especially the effective identification of whether the slope has evolved to a stage of accelerated deformation, therefore, becomes an essential problem in landslide research (Li *et al.* 1999).

Current researchers have concluded that the evolution stage can be macroscopically estimated in accordance with the monitoring curves or the rate of deformation. To put it in detail, the two methods are:

(1) The data from the observation of the deformations, macro-geological analysis, and the characteristics at each stage of the deformation are integrated so as to reach a conclusion. This method is mainly qualitative analysis and has been fully discussed in literature.

(2) Chronologically accumulated displacement data dealt with filters are utilized to quantitatively forecast the accelerated deformation. The undulatory property of the data being treated with filters, nevertheless, is tremendously reduced, and as a result, the diachronic curves become smooth. When the slope is at the stage of initiative deformation or even speed deformation, the rate of deformation gradually decreases or becomes close to a constant; when the slope is at a stage of accelerated deformation, the rate of deformation gradually increases. Consequently, the angle of contingency of the filter data of accumulated displacement, viz. gradient A of curve-fitting equation, is exploited to judge the stage of deformation.

The two methodologies, however, depend to a great extent on subjective judgments, thus causing suspicion of the accuracy of the predicted time of abrupt deformation, and even resulting in the challenge of the reliability of the forecast obtained from corresponding forecast model.

From the discussion above, we can safely conclude that it is becoming increasingly clear that the conventional approaches are to certain degree defective. In this paper the clone selection algorithm is applied to the forecast researches, and DanBa landslide and XinTan landslide are taken as two case studies.

ARTIFICIAL IMMUNE SYSTEM

BIS, Biological Immune System, is the complex system in the animal body that enables animals to resist diseases. This system, functioning in maintaining the balance of internal mechanism, has the capacity to adaptively recognize, eliminate antigenic foreign body, to learn, to memorize, and control self-adaptability.

Inspired by BIS, experts in AI have established AIS-Artificial Immune System. In 1970s, Jerne first put forward the idiotypic network theory (Jerne 1974), and Perelson (1989) developed the algorithm of AIS by setting forth the concept of dynamic feedback immune memory. The commonly adopted algorithms comprise negative selection algorithm, clone selection algorithm, immune learning algorithm etc. Up to now AIS has been applied to robot controlling, computer security, machine learning, and many other fields (Hunt & Cooke 1995, Ishida 1996, Ishiguro *et al.* 1997, Kim & Bentley 1998). The application of AIS to data analysis was first put forward by Hunt and Cooke who set up an algorithm to instruct machine learning in the classification of DNA. The results of their experiment showed that AIS is superior to ANN and other algorithms, except that it is short of model for general purposes, and the parameters are weak in the presentation of real-time adaptability. Timmis improved Hunt and Cooke's model and algorithm and put forward his conception of RLAIIS which defined the fundamental compositions of a net as ARB and established computational formula of the degree of stimulation between ARBs (Timmis & Neal 2000). The stability and robustness were all improved to a great extent, the system has developed the ability to proceed with its learning.

Clone selection algorithm

The mechanism of clone selection was first put forward by Jerne (1973) and later expounded in full by Burnet (1978). The brief content of clone selection is when lymphocytes have learnt to identify the antigens, viz. after the affinity between antibody and antigen is greater than a given value, B cell is activated and proliferates by cloning B cells which then mutate and turn into antibodies with specificity relating to antigens. The theory of clone selection has defined the properties to obtain immunological ability of sex, stating that only the immunological cells having identified the antigens will be reproduced, and the mutated immunological cells differentiates into effector cell (taken as antibody) and memory cell (Mo 2003, Li 2004, Xiao & Wang 2002).

The clone selection is mainly characteristic of the property that the immunological cells can reproduce themselves when stimulated by antigens, and subsequently mutate and differentiate into variety effector cell (e.g. antibodies) and memory cell. Clone selection parallels with a process of affinity mutation, namely a cell with low affinity toward the antigens, driven by mechanism of clone selection, improves its affinity and finally leads to affinity mutation via reproducing itself and mutating. The affinity mutation itself, therefore, is an essentially Darwinian process of evolution and mutation. The mechanism of clone selection works by means of inheritance operator (e.g. cross, mutation) and corresponding colony control.

Determining the stage of landslide deformation involves, in essence, defining the mutation point of the landslide. Thus, the filtered movement data can be regarded as antigens, the mutation point as an antibody when we make use of clone selection algorithm, and an antibody with high affinity mutation is selected from among the cloned and mutated. After the net finishes its learning once, all conceivable mutation points can be found, and more definite mutation point is then determined. (Note: Euclid distance is adopted to define the affinity between antigens and antibodies and the similarities between antibodies and antigens) The detailed algorithm (Zhu *et al.* 2004) is:

Step 1. The filtered data are treated as antigen (marked as Ag), random initialisation q antibody (marked as Ab), here, Ag and Ab are all data set;

Step 2. Operations of each antigen datum Ag_i ;

(1) Calculate the affinity a_{ij} between all the individuals in Ab and Ag_i ; thereinto, $a_{ij} = D(Ag_i, Ab_j)$, $i = 1, 2, \dots, N$ $j = 1, 2, \dots, q$

(2) Choose individuals n with high affinity a_{ij} , clone each antibody being chosen N_c times depending on the measurement of a_{ij} . If a_{ij} is greater, N_c is greater;

(3) The cloned antibodies undergo mutational operations in accordance with the formulae below to produce antibodies with even higher affinities: $Ab'_j = Ab_j - k(Ab_j - Ab_i)$ $j = 1, 2, \dots, N_c$ thereinto k refers to the mutation rate, and its value is determined by the random function and the affinity;

(4) Re-calculate the affinity a'_{ij} between each Ab'_j and Ag_i , and select the antibody with the highest affinity as element of memory set, marked as m_i ;

(5) Select the next generation of antigen data until every antigen datum has undergone the cloning, mutation, and restrain operation above, and finished one generation of net learning;

Step 3. Integrate all the memory element m_i and turn them into memory data set M ;

Step 4. Remove the individuals whose similarity s_{ij} is greater than the given value s_0 so as to realize the net restrain of different set, and $s_{ij} = D(Ab_i, Ab_j)$ $i = 1, 2, \dots, N$ $j = 1, 2, \dots, q$

Step 5. Randomly produced antibodies r take the place of the individuals with low affinity in the antibody aggregate to achieve self-organization of the immunological system;

Step 6. Return to step 2 and start the next generation net learning until the planned goal is reached and the learning algebra is obtained.

CASE STUDY

DanBa landslide

DanBa slide took place on the southern side of the Construction Road of DanBa County seat along the bottom section of the escarpment of Baixia Mountain on the right bank of Dajin River. The landslide, an oversize stack layer landslide, developed from a fossil landslide, the landslide surface taking the shape of a half ellipse (290m long, 0.08km² in area, thickness of 18-45.23m, average thickness 30m, volume 220 thousand m³).

The landslide deformation glided as a whole unit, and the gliding was powerful. The landslide deformation first pulled apart from the back edge and formed a split between the tail and the back edge, and around Feb. 15th 2005, and after, shearing cracks on both sides took shape and extended to further parts of the slope. The monitoring data showed that the main body of the landslide moved along the central axis at a fast speed, and the displacement rate of the rest is similar.

AIS applied, we worked on the accumulated displacement data obtained from three monitoring points of DanBa landslide and got the results below:

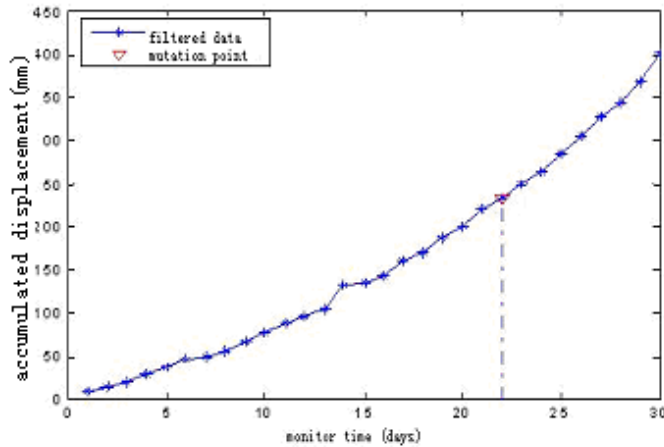


Figure 1. Monitoring point2 Accumulated displacement and mutation point (Mutation date: Feb. 14, 2005)

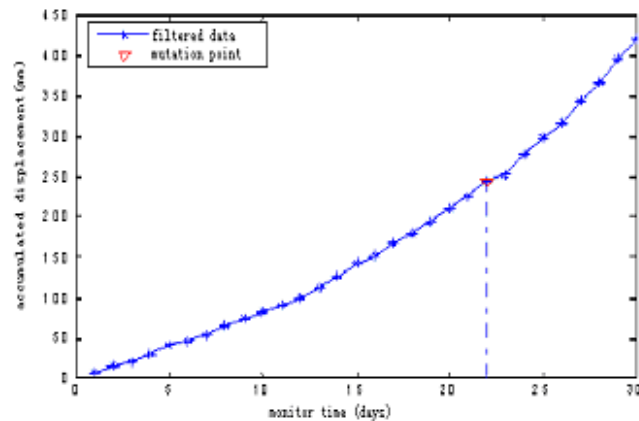


Figure 2. Monitoring point 6 Accumulated displacement and mutation point (Mutation date: Feb. 14, 2005)

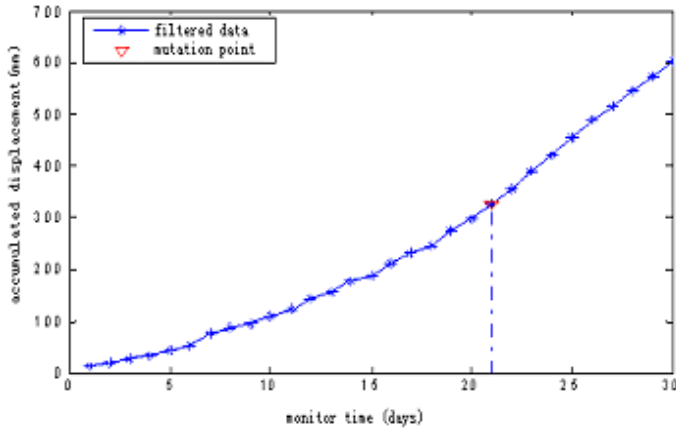


Figure 3. Monitoring point 9 Accumulated displacement and mutation point (Mutation date: Feb. 13, 2005)

The results we got meet well with the practical situation, which serves as well as a reliable model of the prevention of geo-disasters.

XinTan landslide

With the application of the same methodology as that of DanBa landslide to the research of XinTan landslide, which had already deviated from its normal position, we found that results of XinTan landslide matches well with the results obtained via other methods (Luo 1988). The treatment of the data from A3 Monitoring points is shown in Table 1.

Table 1. Displacement data from A3 Monitoring point of XinTan landslide

Monitoring Date	1979.4.1	1979.7.1	1979.10.1	1980.1.1	1980.4.1	1980.7.1	1980.10.1	1981.1.1
Accumulated Displacement (m)	0.077	0.092	0.615	0.650	0.690	0.738	0.846	0.962
Monitoring Date	1981.4.1	1981.7.1	1981.10.	1982.1.1	1982.4.1	1982.7.1	1982.10.1	1983.1.1
Accumulated Displacement (m)	1.000	1.030	1.061	1.077	1.100	1.230	2.460	2.754
Monitoring Date	1983.4.1	1983.7.1	1983.10.1	1984.1.1	1984.4.1	1984.7.1	1984.10.	1985.1.1
Accumulated Displacement (m)	2.830	2.920	3.460	4.000	4.230	4.380	4.615	5.770

With AIS applied, we get the following figure:

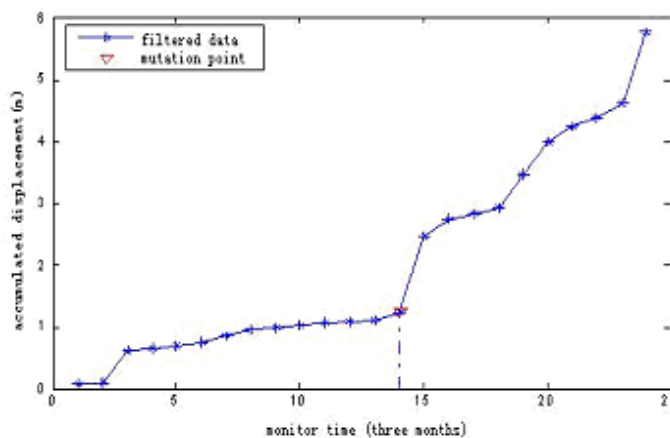


Figure 4. Monitoring point A3 Accumulated displacement and mutation point (Mutation date: Oct. 1, 1982)

In the book of *Landslide real-time tracking prediction* Prof. Li Tian-bing adopted fractal method and found the mutation point of XinTan landslide when the same data from A3 Monitoring points were analyzed (Figure 5).

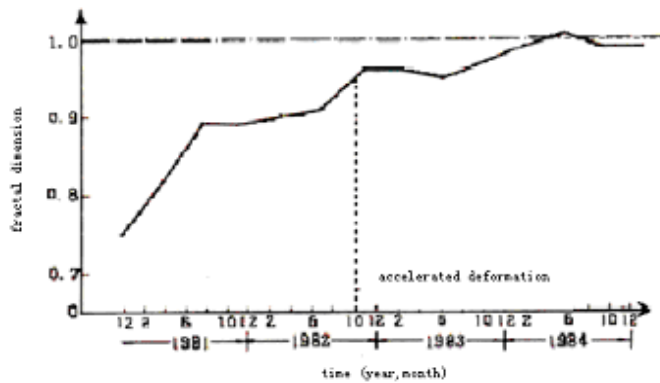


Figure 5. The dimensional dynamic variation curve in the process of deformation of XinTan landslide

Interestingly and excitingly, the comparison of Figure 4 and Figure 5 clearly shows that the mutation point obtained from AIS (October 1982) is in close agreement with the mutation point obtained via the fractal method. In research operations, the AIS saves the researchers from those complicated computation of fractal methods, and AIS only needs affinity and some given values. The study of the cases sheds light on the fact that AIS is effective and feasible in defining the mutation points of landslides.

CONCLUSIONS

After a brief introduction of AIS (especially the algorithm of clone selection), its development, and achievements, this paper applied AIS to the stage analysis of DanBa landslide and XinTan landslide, finding that the research results is in full agreement with factual situation, and thus denoting that AIS, with its own superiorities, is of bright perspective in its application to such fields as data mining, information retrieval, pattern recognize though it has a short history of development.

Acknowledgements: This work presented in this paper was carried out with funding from Special Fund of Scientific Research for Doctor Station of Higher Institution (China); grant number is 20040616005.

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