19. J. A. Jensen, Field: A program for simulating ultrasound systems, Med. Biol. Eng. Comp., 10th Nordic-Baltic Conference on Biomedical Imaging, 1996,4, pp. 351-353.
20. O'Donnell and S. W. Flax, Phase-aberration correction using signals from point reflectors and diffuse scatterers: measurements," IEEE trans. Ultrasonics, Ferroelectrics, and Frequency Control, 1998,35,pp.768-774.

Brain CT Image Classification Based on Improving Harmony Search Algorithm Optimize LSSVM

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Abstract
In order to enhance the accuracy of brain CT image classification, this article proposes a brain CT image classification of improving harmony search algorithm to optimize LSSVM(HIS-LSSVM) aiming at the optimization problems of parameters of least squares support vector machine (LSSVM)in the classifier. This article first takes LSSVM parameters as a combination of tones from different musical instruments and then finds the optimal parameters through "tone tuning" of harmony search algorithm. It also introduces optimal position adjustment policy of particle swarm optimization to strengthen the algorithm's capability to jump out of local minimum. At last, this article establishes brain CT image classification model according to optimal parameters and implements simulation test to the performance of the model. It is shown from the simulation results that comparing with the contrast model, HIS-LSSVM not only enhances the accuracy of brain CT image classification, but also increases classification speed. It is more suitable for the real-time classification requirements of brain CT image.
Keywords: BRAIN CT IMAGE CLASSIFICATION, LEAST SQUARES SUPPORT VECTOR MACHINE, HARMONY SEARCH ALGORITHM, PARTICLE SWARM OPTIMIZATION

1. Introduction

In recent years, radiodiagnosis equipment is continuously renewed and perfected. Hospitals have collected a large amount of brain CT image data of patients. It becomes more and more important to dig information from these image data which can help doctors diagnose patients. The image classification is an important research content for brain CT image data digging. How to establish high accuracy and fast speed brain CT image classification model becomes a hot spot in computer-aided diagnosis research. Brain CT image classification is actually a model identification problem. The good or bad classification results are closely related to selection of classifier and optimization. At present, the brain CT image classifiers are mainly based on Bayesian Method, neural network and support vector machine (SVM) . The Bayesian Method and neural network are both based on "Large Sample"theorem. When satisfying the large sample conditions, they will have good classification results. But brain CT image is a kind of small sample and high-dimensional data which is easy to be caught in drawbacks such as local extremum and overfitting. It is difficult for the classification accuracy to satisfy brain CT image assisting diagnosis requirements. The LSSVM is a improved support vector machine which is based on minimum structure risk principles and better overcomes the drawbacks such as overfitting of neural network, slow speed of standard SVM and is widely used in brain CT image classification. The parameters of LSSVM have direct influences on brain CT image classification results. In order to solve this problem, scholars have proposed genetic algorithm, particle swarm algorithm, simulated annealing algorithm, ant colony algorithm and so on to optimize LSSVM parameters. But all of these algorithms have their own shortcomings and will influence the accuracy of brain CT image classification of LSSVM. Harmony search (HS)algorithm is a meta-heuristic search algorithm which simulates harmony theories in the band of musical performance and has a strongly parallel and global searching capability. It provides a new research instrument to LSSVM parameters optimization. In order to enhance the accuracy of brain CT image classification basing on LSSVM, improved HIS is introduced into LSSVM parameters optimization to establish a brain CT image classification model basing on HIS-LSSVM and also simulation test is implemented to examine the efficiency of the algorithm.

2. IHS Algorithm and LSSVM

2.1. Least Squares Support Vector Machine (LSSVM)

LSSVM is a kind of machine learning algorithm basing on statistical learning theory. It is a compromise between model complex rate and risk according to limited sample information to gain the best generalization ability. Given the training set is (x_i,y_i), i=1,2,…,n, n represents training sample number, $x_i \in R^m$ is sample input, yi∈{1,-1}is output, the linear function of LSSVM in high-dimensional space is:

$$f(x) = w^T \varphi(x) + b \tag{1}$$

In formula (1), ω is weight vector, b is offset.

According to minimum structure risk principle, after overall consideration of fitting error and complex rate of function, formula (1) is changed to:

$$\min_{w,b,e} J(w,e) = \frac{1}{2} W^T W + \frac{\gamma}{2} \sum_{i=1}^{n} e_i^2 \qquad s.t.\ \ y_i = w^T \varphi(x) + b + e_i, i = 1,2,\cdots,l \tag{2}$$

In formula (2), γ is regularization parameter, e_i is forecast error.

Convert formula (2)into non-restraint dual optimization problems through introducing Lagrange multiplier, that is

$$L(w,b,e,\alpha) = J(w,e) - \sum_{i=1}^{l} \alpha_i \left(w^T \varphi(x_i) + b + e_i - y_i \right) \tag{3}$$

In formula (3), a_i is Lagrange multiplier.

According to KKT conditions, it can get

$$\begin{bmatrix} 0 & e1^T \\ e1 & Q + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{4}$$

For non-linear classification problems, solve it through introducing kernel function to high-dimensional feature space. Comparing with other kernel functions, Radial Basis Function (RBF) has a few parameters and better performance. So it is selected as the kernel function of LSSVM. The definition of RBF is:

$$K(x_i, x_j) = \exp\left(-\left\| x_i - x_j \right\|^2 / 2\sigma^2 \right) \tag{5}$$

In formula (5), σ is the width parameter of RBF.

At last, the decision function of LSSVM classification is:

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{n} \alpha_i \exp\left(-\left\| x_i - x_j \right\|^2 / 2\sigma^2 \right) + b \right) \tag{6}$$

It is known from LSSVM classification theorem that the learning performance of LSSVM is related to parameters γ and σ. So if a good accuracy of brain CT image classification is to be obtained, the most reasonable γ, σ values must be selected.

2.2. Improved Harmony Search Algorithm

HS algorithm implements simulation to tone tuning of band and finally realizes perfect harmony. Solution for optimization problems according to this concept has been successfully applied to combination optimization problem. In HS algorithm, the "tone tuning" among the candidate solutions are independent from each other. There is no information sharing system, so it is easy to be caught in local minimum. In order to overcome this drawback, the optimal position renewal policy of particle swarm optimization is introduced. It refers to the "most beautiful harmony" in the harmony database to implement "tone tuning" which reserves tone tuning parameters and in the meantime prevents the "tone tuning" process from fading. The procedures of IHS algorithm are:

Step 1: Initialize the parameters such as harmony Memory Considering Rate (HMCR), Harmony Memory Size (HMS), Band Width (bw), Pitch Adjusting Rate (PAR), Iteration Number (NI) and so on.

Step 2: Given the solution of the problem is $X^k = \left\{x_1^k, x_2^k, \cdots, x_n^k\right\}$, the candidate solution is initialized to a random value within the value range of every dimension, that is $x_i^k = Rnd(L(x_i^k), U(x_i^k))$. And the $X^k \in R^n$, $k \in [1, HMs]$, $i \in [1, n]$. And calculate the fitness function of every initial solution.

Step 3: The r_1, r_2 are randomly generated. And randomly select a solution X^j in memory bank to generate a new solution $X' = \left| x_1', x_2', \cdots, x_n' \right|$ according to the following rules.

$$\begin{cases} x_i' = x_i' \quad , r_1 < HMCR \, , r_2 \geq PAR \\ x_i' = Rnd(x_i^{gBest} - bw, x_i^{gBest} + bw) \, , r_1 < HMCR \, , r_2 \geq PAR \\ x_i' = Rnd(L(x_i'), U(x_i')) \, , r_1 \geq HMCR \end{cases} \tag{7}$$

Among them, x_i^{gBest} is the optimal candidate solution which corresponds to the solution vector of No. i dimension in the harmony database.

By introducing optimal position renewal strategy of particle swarm optimization, it not only refers to the value of optimal candidate solution in the harmony database, but also reserves bw parameters and finally realizes the information sharing between optimal candidate solution and new solution.

Step 4: If the fitness value of new solution it(X') is superior to the candidate value in the harmony database, use X' to replace the solutions with worst fitness in the database.

Step 5: Check whether it satisfies the end conditions. If it is unsatisfied, then switch to Step 3 to continue iteration.

3. Brain CT Image Classification of IHS-LSSVM

3.1. Pre-estimation of LSSVM Parameters Range

During the LSSVM parameters optimization process, the parameters range needs to be pre-estimated. Because the kernel function can be understood as the sample covers samples in its surroundings, the kernel parameter σ can refer to the distance between samples. For the whole training samples, the range of σ is limited:

$$k_1 \, \mathrm{d}_{\min} = \sigma_l < \sigma < \sigma_u = k_2 \, \mathrm{d}_{\max} \tag{8}$$

In formula (8), d_{min} and d_{max} are the nearest and farthest distance in average of training set respectively.

(1)Lower Bound σl . When the radius of RBF kernel function is less than 0.003 (small probability event), then the current sample of LSSVM has extremely slight influence on neighboring samples. It is easy to have overfitting phenomenon. So, given k(xi,xj)=0.003, then σl =0.2935dmin .

(2)Upper Bound σu. The support vector has a greater influence on samples which are nearer than samples which are far away. So the greater the σ, the bigger the corresponding covering range. σu=12.29dmax.

According to the above analysis, approximately given k_1=0.3, k_2=13, the setting of σ parameter range is [0.001,1000].

It is difficult to determine the range of parameter γ. So it is set as [1,1000] according to experience.

3.2. Brain CT Image Classification of LSSVM Parameters Optimized by IHS

(1) Collect brain CT image data and implement pre-treatment with denoising and strengthening to enhance the quality of image.

(2) Extract image features. Adopt gray level co-occurrence matrix textural features as classification features which include gray value and angular second moment of pixel, inverse difference moment, entropy, relevant textural features in specific to determine training sample set and forecast sample set.

(3) The different dimensions of feature data cause the greater change of data range. In order to prevent the features of greater value weakening the properties of smaller value, implement normalization treatment to the features and scale them between [0,1]. The specific is shown below:

$$x_{ik}' = \frac{x_{ik} - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{9}$$

X_{ij} represents the value of No. j in the feature of No.i. $\min(x_i)$ and $\max(x_i)$ represent the minimum value and maximum value of feature of No.i. respectively.

(4) Set the range of γ, σ as well as relevant parameters of HS algorithm.

(5) Initialize harmony memory bank. There are m initial solutions. Every X corresponds to a group of parameters (γ,σ). And calculate the fitness value of every individual in memory bank (Accuracy of Brain CT Image Classification).

(6) Generate new individual X' according to formula (7) and calculate fitness value of the new individual. If this individual is better than the maximum fitness value in memory bank, adopt X' to replace the individual corresponding to maximum fitness value in HM.

(7) Iteration k=k+1. If k is bigger than maximum iteration NI, then the (γ,σ) corresponding to optimal individual should be taken as the optimal parameter of LSSVM. Otherwise switch to step (6) to continue iteration.

(8) Retrain LSSVM classifier according to optimal parameter combination(γ,σ)) to establish the optimal brain CT image classifier.

(9) Use the established optimal brain CT image classifier to classify test sample set.

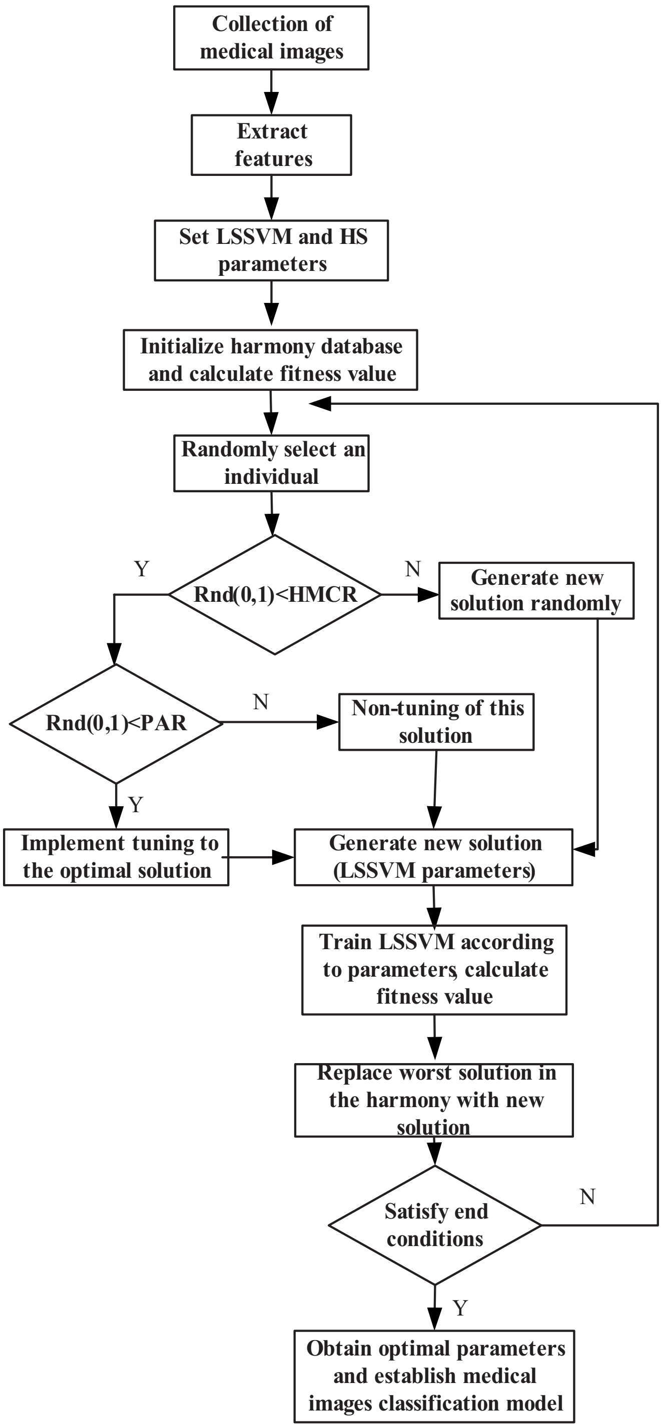
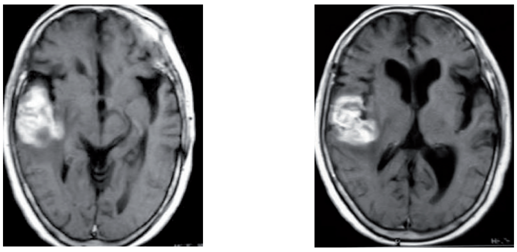


Diagram 1. Brain CT Image Modeling Classification Flow

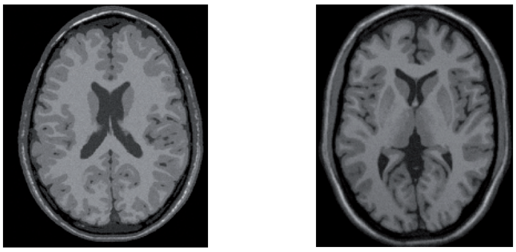
4. Simulation Experiment

4.1. Data Source

Adopt Matlab 2009a to realize algorithm on CPU:Intel Intel(R) Dual 2.3GHZ, RAM 3GB, Windows XP platform. The data comes from the online image library of McConnell Brain Image Center of McGill University, http://www.bic.mni.mcgill.ca/brainweb/). The images are divided into normal images and abnormal images. There are 500 images of training samples and 100 images of test samples. The abnormal and normal images are shown in Picture 1.



(b) Normal Images



(a) Abnormal Images

Figure 1. Brain CT Image

4.2. Method Comparison and Evaluation Index

In order to make the IHS-LSSVM classification results comparable, genetic algorithm is adopted to optimize LSSVM(GA-LSSVM). Particle swarm optimization algorithm is used to optimize LSSVM(PSO-LSSVM) which is taken as contrast model. The evaluation index of model performance are sensitivity and specificity. Their specific definitions are shown as follows:

$$sensitivity = \frac{t\_pos}{pos} \times 100\% \quad (11)$$

$$specificity = \frac{t\_neg}{neg} \times 100\% \quad (12)$$

t_pos T is the correctly identified normal brain CT image number, pos is normal brain CT image number. t_neg is correctly identified abnormal brain CT image number, neg is abnormal brain CT image number.

4.3. Results and Analysis

First, extract normal and abnormal brain CT image features respectively and implement normalization treatment. Then take these features as input vectors of LSSVM and category of image as output vectors. Input the training sample into LSSVM for learning. Use GA, PSO and IHS algorithms to optimize the LSSVM parameters (γ, σ) and obtain the optimal parameters. See Table 1.

Table 1. Optimal LSSVM Parameters Obtained from Different Algorithms

Optimization Algorithm of Parameters	γ	σ
GA	28.311	2.292
PSO	40.405	2.136
IHS	51.026	2.150

Adopt the optimal parameters in Table 1 to establish GA-LSSVM, PSO-LSSVM, IHS-LSSVM brain CT classifier. Classify the test samples set to obtain the results shown in Table 2. It is known from Table 2 that comparing with GA-LSSVM, PSO-LSSVM, IHS-LSSVM can obtain much better classification results which has a high accuracy for correct normal and abnormal brain CT image classification. In the meantime, the specificity value is much more close to 100% which explains that it has slim chance to misclassify abnormal brain CT images. This is what the medical experts expect. It is shown from the contrast results that HS can get much more optimal LSSVM parameters and is in favor of enhancing the accuracy of brain CT images classification.

Table 2. Comparison of Classification Algorithm

Algorithm	Sensitivity (%)	Specificity (%)
GA-LSSVM	90.04	90.28
PSO-LSSVM	91.32	91.80
IHS-LSSVM	92.18	92.09

In order to verify the efficiency of improved standard HS algorithm, this article adopts standard HS algorithm to implement contrast simulation experiments. There are altogether 5 experiments. The results are shown in Table 3. It is known from Table 3 that the classification performance of IHS-LSSVM is better than HS-LSSVM. And the training time is reduced obviously. The brain CT image classification speed is accelerated sharply. This is mainly because IHS-LSSVM discovers a more optimal LSSVM parameters which reduce support vector points number and sample storage volume and speed up rate of convergence. It is much more conform to the real-time and online requirements of modern brain CT images classification.

Conclusions

This article proposes a brain CT image classification of improving harmony search algorithm to optimize LSSVM(HIS-LSSVM) aiming at the optimization problems of parameters of LSSVM in brain CT classification modeling process. It is shown from the simulation results that IHS algorithm better solves the parameters optimization problems of LSSVM. It not only enhances the accuracy of brain CT classification, but also enhances classification efficiency. At the same time, the automatic classification of brain CT is also related to features selection. The combined optimization of features selection and LSSVM will be the next research contents.

References

1. Xiaoming Li, Zhihan Lv, Baoyun Zhang, Ling Yin, Weixi Wang, Shengzhong Feng, Jinxing Hu. “Traffic Management and Forecasting System Based on 3D GIS”. 2015 15th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGrid). IEEE, London,2015,pp.1296-1302.
2. Zhihan Lv. “Wearable Smartphone: Wearable Hybrid Framework for Hand and Foot Gesture Interaction on Smartphone”. IEEE International Workshop on Wearable Computer Vision Systems at International Conference on Computer Vision 2013 (ICCV 2013), Sydney, 2013,pp.986-988.
3. Dingde Jiang, Zhengzheng Xu, Peng Zhang, and Ting Zhu. “A transform domain-based anomaly detection approach to network-wide traffic.” Journal of Network and Computer Applications, 2014,40,pp.292-306.
4. Jie He, Yishuang Geng, Fei Liu, Cheng Xu, CC-KF: Enhanced TOA Performance in Multipath and NLOS Indoor Extreme Environment, IEEE Sensor Journal, 2014,11, pp.3766-3774.
5. Shuang Zhou, Liang Mi, Hao Chen, Yishuang Geng, Building detection in Digital surface model, 2013 IEEE International Conference on Imaging Systems and Techniques (IST), London, 2013,pp.568-561.
6. Jie He, Yishuang Geng, Kaveh Pahlavan, Toward Accurate Human Tracking: Modeling Time-of-Arrival for Wireless Wearable Sensors in Multipath Environment, IEEE Sensor Journal, 2014,11, pp.3996-4006.
7. Na Lu, Caiwu Lu, Zhen Yang, Yishuang Geng, Modeling Framework for Mining Lifecycle Management, Journal of Networks, 2014,9, pp.719-725.
8. Yishuang Geng, Kaveh Pahlavan, On the accuracy of rf and image processing based hybrid localization for wireless capsule endoscopy, IEEE Wireless Communications and Networking Conference (WCNC), New York,2015,pp.1299-1302.
9. Guanxiong Liu, Yishuang Geng, Kaveh Pahlavan, Effects of calibration RFID tags on performance of inertial navigation in indoor environment, 2015 International Conference on Computing, Networking and Communications (ICNC), Sydney,2015,pp.758-762.
10. Jie He, Yishuang Geng, Yadong Wan, Shen Li, Kaveh Pahlavan, A cyber physical test-bed for virtualization of RF access environment for body sensor network, IEEE Sensor Journal, 2013,10, pp.3826-3836.
11. Wenhua Huang, Yishuang Geng, Identification Method of Attack Path Based on Immune Intrusion Detection, Journal of Networks, 2014,9, pp.964-971.
12. Xiaoming Li, Zhihan Lv, Baoyun Zhang, Weixi Wang, Shengzhong Feng, Jinxing Hu. XEarth: A 3D GIS Platform for managing massive city information. 2015 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications(CIVEMSA 2015).Beijing, 2015, pp. 365-368.
13. Liguo Zhang, Binghang He, Jianguo Sun, Mingzhu Lai, Zhihan Lv. “Double Image Multi-Encryption Algorithm based on Fractional Chaotic Time Series”. Journal of Computational and Theoretical Nanoscience. 2015,3,pp.136-140.
14. Wei Luo, Zhiyong Wang, Zhihan LV. Method to Acquire a Complete Road Network in High-resolution Remote Sensing Image Based on Tensor Voting Algorithm. EXCLI JOURNAL, 2015,14,pp.456-458.
15. Song Zhang, and Huajiong Jing. “Fast log-Gabor-based nonlocal means image denoising methods.” 2014 IEEE International Conference on Image Processing (ICIP). London,2014,pp. 2724-2728.
16. Alex Tek, et al.. “Advances in Human-Protein Interaction-Interactive and Immersive Molecular Simulations.” Biochemistry, Genetics and Molecular Biology’’Protein-Protein Interactions-Computational and Experimental Tools.2012,12,pp.27-65.

17. Zhihan Lv, Alaa Halawani, Shengzhong Feng, Shafiq ur Rehman, Haibo Li. "Touch-less Interactive Augmented Reality Game on Vision Based Wearable Device". Personal and Ubiquitous Computing. 2015,5,pp.242-246.
18. Tianyun Su, et al.. "Rapid Delaunay Triangulation for Random Distributed Point Cloud Data Using Adaptive Hilbert Curve". Computers & Graphics ,2015,3,pp.124-125.
19. Xiaoming Li, et al.. "WebVRGIS Based Traffic Analysis and Visualization System". Advances in Engineering Software , 2015, 4, pp.36-39.

PSR-SVR Network Public Opinion Prediction Model

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Abstract
The accurate prediction of network public opinion trends has great significance to prevent the public safety threat of negative network public opinion, and in allusion to time-dependent nature and chaos characteristic, this paper has proposed network public opinion prediction model (PSR-SVR) combined with chaos theory and SVRM. Firstly, the chaotic characteristic of network of public opinion has been proved, and Takens theorem is used to determine time-series phase-space reconstruction delay time and embedding dimension of network public opinion using mutual information method and GP method. Finally, in the phase space, support vector regression (SVR) is used to establish network public opinion prediction models and prediction model and to conduct comparison experiments with other prediction models. The results show that compared to the comparative models, PSR-SVR has improved the prediction accuracy and reliability of network public opinion, and its forecasted results have some practical values.
Keywords: PHASE-SPACE RECONSTRUCTION, CHAOS THEORY, NETWORK PUBLIC OPINION, SUPPORT VECTOR MACHINE, PREDICTION MODEL

1. Introduction

Internet public opinion is an important part of social public opinion, and as opposed to the traditional news media, it's strongly interactive, and users are both receivers and message originators, so that dissemination of information on the network can be more timely and rapid. Negative Internet public opinion will pose a larger threat to public safety, thus