Crowd Density Estimation Based on ELM Learning Algorithm

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***Abstract*—Crowd density estimation in public areas with people gathering and waiting is the important content of intelligent crowd surveillance. A real-time and high accuracy algorithm is necessary to be inputted in the classification and regression of crowd density estimation to improve the speed and increase the efficiency. Extreme Learning Machine (ELM) is a neural network architecture in which hidden layer weights are randomly chosen and output layer weights determined analytically. In this paper, we propose a new method which is based on Haralick's texture vectors, Gray-level Co-occurrence Matrix and ELM. The datasets are based on PETS2009 and UCSD. The performances are compared among SVM, BP and ELM. The experimental results suggest that the ELM learning algorithm has a good performance of accuracy and a very fast speed than other methods.**

***Index Terms*—ELM, crowd density estimation, SVM, BP**

I. Introduction

With the improvement of computer vision techniques, several applications in this area, like video surveillance, human behavior understanding, or measurements of athletic performance, have been tracked using automated or semi-automated techniques[1,2]. Among them crowd density estimation is one of the most important applications in visual surveillance, and it plays an essential role in crowd monitoring and management. Due to its importance, much work has been done on crowd density estimation in visual surveillance scenes.

In the classification and regression parts of crowd density estimation, most people use follow methods :

1) Support vector machine(SVM) [3-6], of which, Xinyu Wu et al[3] use texture analysis vectors which are extracted from a series of multi-resolution image cells and support vector machine(SVM) method to solve the problem of calculating the crowd density; Hang Suet al[4] estimate the crowd density by effective region feature extracting and using support vector machine;Li Xiaohua et al[5] also use a classifier based on a support vector machine to classify the extracted density character vectors into different density levels; Zi Ye et al[6] learn SVM classifiers with GLCM and statistical features. The SVM has a small rate of error, but it has a great disadvantage that it has large amount of calculation,and has too many parameters to adjust.

2) Neural network based methods [7-11], among them, Tang et al[7] classify the degree of crowd density of the scene into several grades and use BP neural network to conduct the classification model and obtain the estimation of crowd density; Cho, S.Y. et al[8] carry out the estimation by extracting a set of significant features from sequences of images and the feature indexes are modeled by a neural network to estimate the crowd density. The learning phase is based on hybrid of the least-squares and global search algorithms which are capable of providing the global search characteristic; Li et al[9] use a self-organizing map neral network to classify different crowds, though the accuracy is improved, the rate of true classification is just 86.3%; D. Huang et al[10] proposed an effective and flexible system for the purpose of performing on-line people counting, and a RBF neural network is employed for performing the classification task; Y.Cho et al[11] present a neural learning-based crowd estimation system for surveillance in complex scenes at the platform of underground stations. The neural network based methods has a strong robustness and good fault tolerance, but the training speed is not so quick and is hard to choose the appropriate parameters.

3) AdaBoost based methods[12-14], the algorithm proposed in [12] is based on multi-class Adaboost using texture features which represent a global texture pattern, the similar algorithm is used in [13], in this paper, the authors choose the GLDM texture features and generate a weak classifier by modifying a weight update equation of general Adaboost algorithm; S. Ghidoni et al[14] use the

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Real AdaBoost variant of the algorithm that provides a lower error rate by allowing weak classifiers to vote by their individual degree of certainty instead of making simple binary decision.There are also other methods to classify the levels of crowd density. A. N. Marana et al[15] use three types of classifiers: neural(implemented according to the Kohonen model), Bayesian, and an approach based on fitting functions to complete the experiment.

As we can see from above that a good crowd density estimation algorithm should be real-time, robust and effective. Since the ELM(Extreme Learning Machine) algorithm was proposed by Huang et al.[16-18], it has been applied into many areas. In paper [19], a thorough experimental study was done to show the superiority of the generalization capability of the Extreme Learning Machine (ELM) that is presented and compared with support vector machine (SVM) approach in the automatic classification of ECG beats. And the sensitivity of the ELM classifier is tested and compared with SVM combined with two classifiers, and they are the k-nearst Neighbor Classifier and the radial basis function neural network classifier, the obtained results clearly confirm the superiority of the ELM approach.

In paper [20], the ELM algorithm is applied into the classification of metagenomic taxonomic and shows an improved classification results. In paper [21], the ELM based classification approach is used for land cover classification, and the performance of ELM was compared with a back propagation neural network,, the results suggest that ELM works equally well to back propagation neural network in term of classification accuracy and involves in using a smaller computational cost. Zhili Zhao et al[22] use the ELM to classify the images from two datasets. There are kinds of images from the datasets, such as animals, people with various gestures, forms, cartoons and so on. The performance is compared with SVM and the results show that the ELM is not stable as the SVM, but ELM is faster and more effective than SVM. Paper [23] is the face recognition based on ELM, the results show that the Extreme Learning Machine are accurate and fast-learning innovative classification methods based on the random generation of the input-to-hidden-units weights followed by the resolution of the linear equations to obtain the hidden-to-output weights. From those papers we can see that Extreme Learning Machines are accurate and fast-learning innovative classification methods based on the random generation of the input-to-hidden-units weights. In paper[34], the ELM algorithm was applied to Social network service(SNS), SNS is a new emerging Web application. In order to solve the above problem, this paper proposed an ELM ensemble algorithm based on Bagging combined with semi-supervised Seeds set clustering for privacy preserving. The ensemble ELM is used to label the unlabeled data to enlarge the scale of Seeds set. Experimental results show that the method can improve the usability of the released data while preserving privacy.

There are also many papers[18,25-26,29,30] have done the comparison between ELM and SVM or BP. The paper [29] performs a comparative analysis of the basic ELMs and support vector machines (SVMs) from two viewpoints, one is the Vapnik－Chervonenkis (VC) dimension, and the other is their performance under different training sample sizes. The result obtained show that ELMs have weaker generalization ability than SVMs for small sample but can generalize as well as SVMs for large sample. Remarkably, great superiority in computational speed especially for large-scale sample problems is found in ELMs. Huang et al said in paper [30] that ELM provides a unified learning platform with a widespread type of feature mappings and can be applied in regression and multi-class classification applications directly; and in theory, compared to ELM, LS-SVM and PSVM achieve suboptimal solutions and require higher computational complexity; and ELM can approximate any target continuous function and classify any disjoint regions. As verified by the simulation results by Huang et al, ELM tends to have better scalability and achieve similar(for regression and binary class cases) or much better(for multi-class cases) generalization performance at much faster learning speed(up to thousands times) than traditional SVM.

The results show that ELM can be used easily and can complete learning phase at very fast computational speed and provide more compact network. So, in this paper we use ELM algorithm to do the regression and classification of crowd density estimation.

Ⅱ. PROPOSED METHOD

Crowd density estimation classification proposed in this paper comprises of two steps. In the first step, the feature vectors of crowd are extracted from the sequences of images. Then the feature vectors are sent into the classification and regression algorithm to estimate the levels of the crowd density. In this section, the ELM algorithm is briefly introduced in Section A. The database and experiments are introduced in Section B.

A. ELM Algorithm

Extreme Learning Machine (ELM) is an emerging learning paradigm for multi-class classification and regression problems[16-18]. The highlight of ELM compared to the other state of the art methodologies like neural networks, support vector machines is that the training speed of ELM is extremely fast. The key enabler for ELM’ s training speed is the random assignment of input layer parameters which do not require adaptation to the data. In such a setup, the output layer parameters can be determined analytically using least squares.

The ELM algorithm is summarized as follows:

For N arbitrary distinct samples (x_i, t_i) , where $x_i = [x_{i1}, x_{i2}, \cdots, x_{in}]^{\mathrm{T}} \in R^n$ and $t_i = [t_{i1}, t_{i2}, \cdots, t_{im}]^{\mathrm{T}} \in R^m$,standard SLFNs with $\tilde{N}$ hidden neurons with activation function $g(x)$.

step 1: Randomly assign the hidden nodes parameters w_i and b_i, where $w_i = [w_{i1}, w_{i2}, \cdots, w_{in}]^T$ is the weight vector connecting the i th hidden neuron and the input neurons, b_i is the threshold of the i th hidden neuron, $i = 1, \cdots, \tilde{N}$.

step 2 Calculate the hidden layer output matrix H.

step 3 Estimate the output weight β: $\hat{\beta} = \mathrm{H}'\mathrm{T}$.

The structure of ELM network is shown in Figure 1. ELM contains an input layer, hidden layer and an output layer.

Some of the attractive features of ELM are listed below:

1) ELM is an universal approximator

2) ELM results in the smallest training error without getting trapped in local minima (better accuracy)

3) ELM does not require iterative training (low computational demand)

4) ELM solution has the smallest norm of weights (better generalization)

5) The minimum norm least square solution by ELM is Unique.

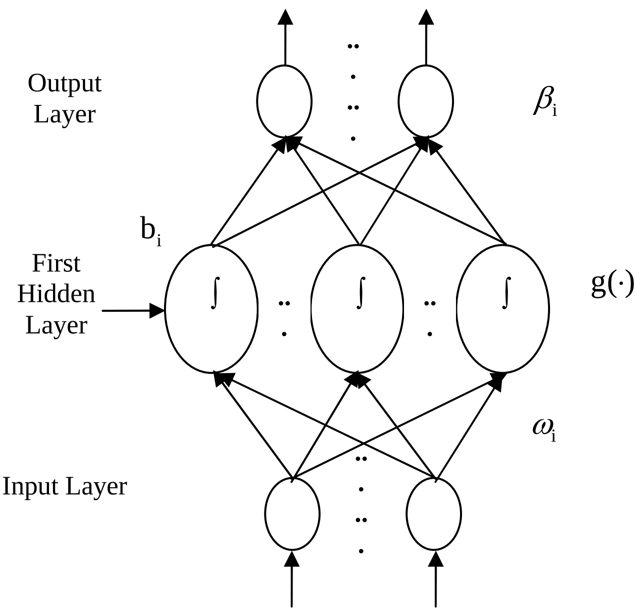


Figure 1. Structure of ELM network

B. Dataset and Experiments

1) Database

In this paper, we use the PETS(Performance Evaluation of Tracking Systems) 2009[20] datasets and UCSD pedestrian databases[24]. The sample images are showed in Fig. 2 and Fig. 3 respectively. The PETS 2009 datasets are multisensor sequences containing different crowd activities. There are five main datasets, and we choose the first three subsets to do the experiments. Each subset contains several sequences and each sequence contains different views(4 up to 8),we choose the pictures of view 1. The UCSD pedestrian database is provided by the Statistical Visual Computing Lab, University of California, San Diego. The database has several "sparse traffic" and "heavy traffic" scenes [31]. The UCSD pedestrian database contains video of pedestrians on UCSD walkways, taken from a stationary camera.All videos are 8-bit gray-scale, with dimensions 238×158 at 10 fps.

Figure 2. The sample image for experiments from PETS database

(a)

(b)

(c)

(d)

Figure 3. The sample image for experiments from UCSD database. The different levels of the crowd density.

As can be seen from Figure 2 and Figure 3 that, the back ground of the images is complex and the road sign, the grasses, the trees and so on have a great influence on the features extracting, so we do the preprocessing and extract the region of interest to obtain the features which can better present the character of the crowd. Figure 4 shows the interested of the crowd image from UCSD. The features extracted from the crowd are on the basis of the characters of the different crowds[28].

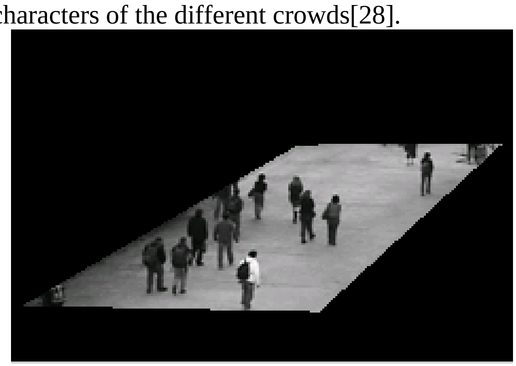
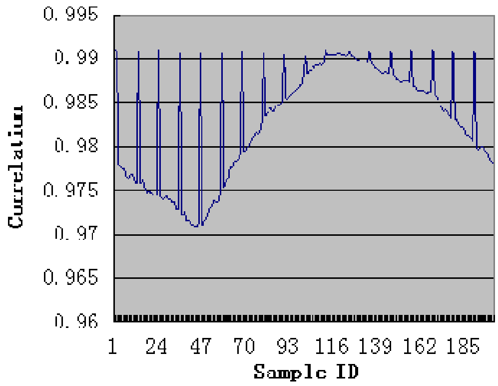
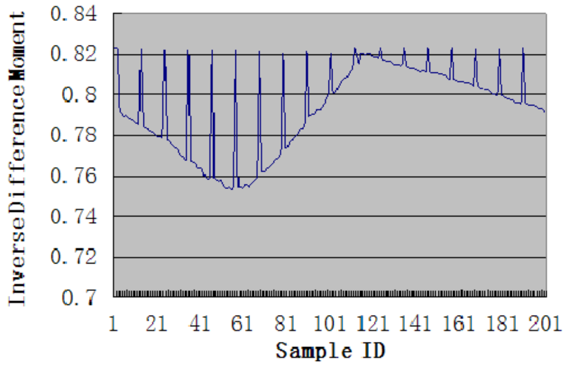


Figure 4. The region of interest extracted from the crowd image.

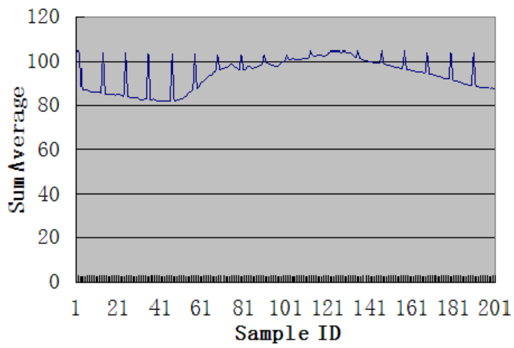
As to database PETS we extract the follow 13 texture features: Energy, Correlation, Inertia, Entropy, Inverse Difference Moment, Sum Average, Sum Variance, Sum Entropy, Difference Average, Difference Variance, Difference Entropy, Information measure of correlation 1, Information measure of correlation 2. The 13 Haralick's texture generates from Spatial Level Dependence Matrix(SGLD) of gray scale images[32]. And the database UCSD we extract the follow 17 features: the Energy, Entropy, Correlation, Contrast of four directions 0,45,90,135, and the foreground pixels. For the data we obtained are not unified specification, so we normalize the feature vectors before classification. Figure 5 shows the texture features extracted by Haralick's method. It reflect not only the gray level statistics of the image, but also reflect the spatial distribution information of image and structure information.



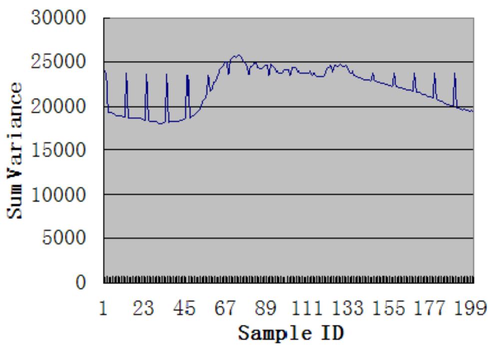
(a)



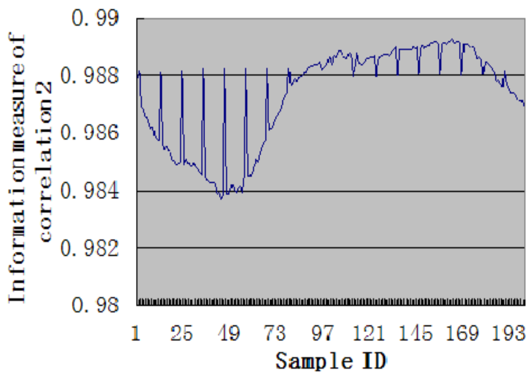
(b)



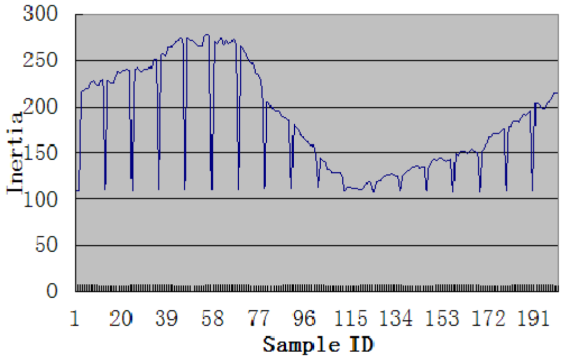
(c)



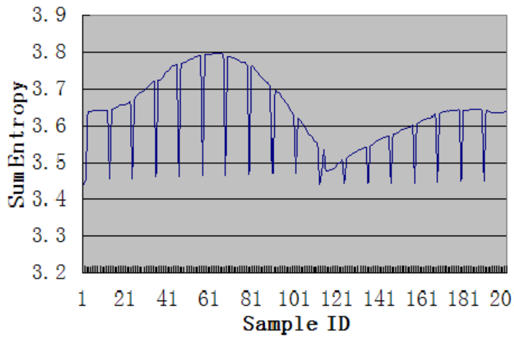
(d)



(e)



(f)



(g)

Figure 5. The texture features extracted from the PETS database. (a)Correlation, (b)Inverse Difference Moment, (c)Sum Average, (d)Sum Variance, (e)Information measure of correlation 2, (f)Inertia, (g)Sum Entropy

The flow chart of the crowd density estimation experiment is as Figure 6.

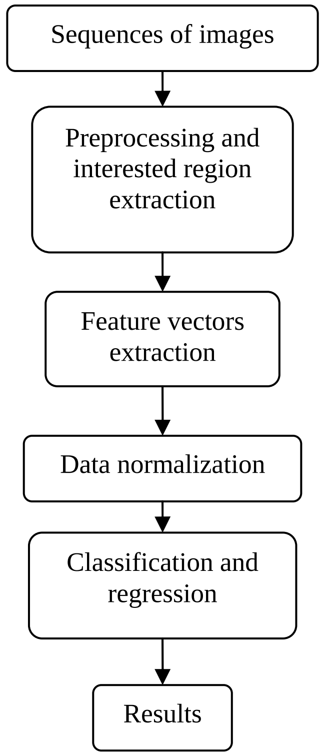


Figure 6. The flow chart of the crowd density estimation

2) Training and Testing

In determining crowd densities, we followed the following rules: less than 5 people are categorized as Very Low density, from 5 to 10 people as Low density,between 10 and 15 as Moderate density, and finally 15 or higher as High density. In this paper, as to the databases we classify the crowds as the above 4 classes to estimate the density.

During training session the system learns how to estimate the density of people within the input frame according to its feature vectors. Initially the input frames are processed by basic operations and the outputs are 13 dimensions (PETS) and 17 dimensions (UCSD) feature vectors. Then the feature vectors the category labels are set as inputs into the regression and classification. In this part we randomly select 200 frames (150 for training and 50 for testing) from PETS database and 1417 frames(1000 for training and 417 for testing) from UCSD database, as can be shown in Table I.

TABLE I.
SPECIFICATION OF MULTICLASS CLASSIFICATION AND REGRESSION PROBLEMS

Datasets	Train	Test	Features	Classes	Random Permutation
PETS	150	50	13	4	Yes
UCSD	1000	417	17	4	Yes

III. RESULTS

During the experiments, we found that the neural node is a very important factor for the efficiency of ELM, and we found that neither the numbers of node too low nor too high can get a good performance. So we do a series of experiments to get the best node number. As can be seen from the Figure 7 that when the node number of the ELM network is 30, we obtain the best accuracy 89.75%.

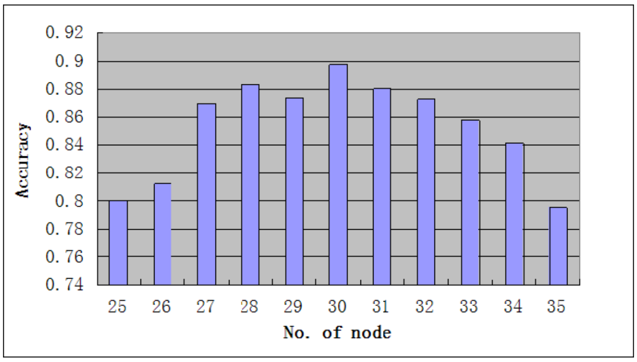


Figure 7. The relation between the accuracy of ELM and the number of ELM node

In this paper, MSE is the mean squared error, MSE measures the average of the squares of the "error". In regression, the smaller the value of MSE, the better performance of the model. R^2 is the coefficient of determination, it is most often seen as a number between 0 and 1.0, used to describe how well a regression line fits a set of data. An R^2 near 1.0 indicates that a regression line fits the data well, while an R^2 closer to 0 indicates a regression line does not fit the data very well.

The Figure 8 shows the testing regression result of the ELM approach based on UCSD database. We can see that the mse is 0.029962 and the R^2 is 0.9716.

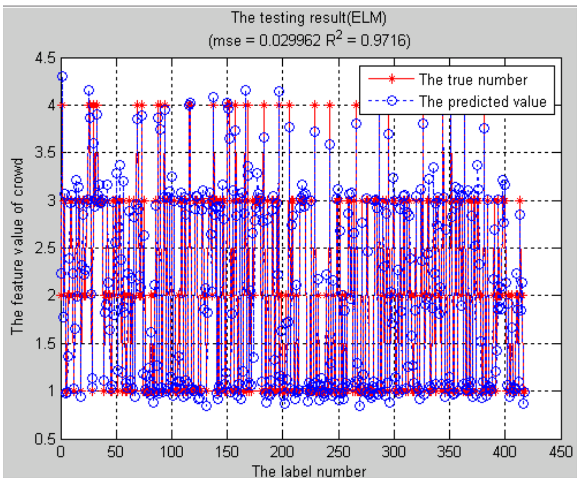


Figure 8. The testing result of ELM regression

In order to verify the robustness and efficiency of our method, the performance of the ELM learning algorithm is compared with the popular Support Vector Machines (SVMs) and Back Propagation(BP) on regression and classification areas.

In the experiments, the method of SVM we use, is the libsvm software package which developed by Chih-Chung Chang and Chih-Jen Lin [33]. LIBSVM is an integrated software for support vector classification, (C-SVC, nu-SVC), regression (epsilon-SVR, nu-SVR) and distribution estimation (one-class SVM). It supports multi-class classification. The neural network we used is the BP neural network comes from the MATLAB. It is a supervised learning method, and is a generalization of the delta rule. It requires a dataset of the desired output for many inputs, making up the training set. It is most useful for feed-forward networks (networks that have no feedback, or simply, that have no connections that loop). Back propagation requires that the activation function used by the artificial neurons (or "nodes") be differentiable.

TABLE II showed the performance comparison of regression between ELM approach, SVM and BP. As we can see that as to PETS database, the minimum value of MSE is the ELM method, the maximum value of R^2 is the ELM method; as to UCSD database, the minimum value of MSE is the BP algorithm, the maximum value of R^2 is the ELM approach. It suggests that the ELM's average of the squares of the "error" is small than SVM, sometimes small than BP; and it also shows that the ELM approach is suitable for crowd density estimation for it has a good regression line. All of the data are the average value of experiments more than ten times.

TABLE II.
PERFORMANCE COMPARISON OF THE SVM,BP AND ELM LEARNING ALGORITHMS(A)

Datasets	**SVM**		**BP**		**ELM**	
	MSE	R^2	***MSE***	R^2	***MSE***	R^2
PETS	0.07156	0.84569	0.06504	0.84242	0.06194	0.86639
UCSD	0.04250	0.97033	0.01198	0.95309	0.02996	0.97160

As can be seen from TABLE III, in PETS database, the minimum value of training time is obtained from the ELM algorithm, it is 0.0317s; the minimum value of testing time is also obtained from ELM approach, is 0.0136s. As to UCSD database, the minimum values of training and testing time are both required from ELM method. The results show that no matter in training or testing, ELM learning algorithm has the fastest learning speed (up to thousands of times) than the other two algorithm.

TABLE III.
PERFORMANCE COMPARISON OF THE SVM,BP AND ELM LEARNING ALGORITHMS(B)

Datasets	SVM		BP		ELM	
	Training Time(s)	***Testing Time(s)***	***Training Time(s)***	***Testing Time(s)***	***Training Time(s)***	***Testing Time(s)***
PETS	5.5663	0.0282	2.4078	0.0712	0.0317	0.0136
UCSD	7.9000	0.0890	3.0926	0.0587	0.0359	0.0182

As verified by the simulation results, compared to SVM and BP, ELM achieves similar or better generalization performance for regression and classification cases. Also ELM has better scalability and runs at much faster learning speed (up to thousands of times) than traditional SVM and BP. This paper also has shown that the ELM can be well applied into crowed density estimation and achieved a good performance.

Ⅳ. CONCULSIONS

In summary, we have presented an approach of using the Extreme Learning Machine algorithm for crowd density estimation in the sequences images from two databases.

In the initial stage, the input images are reprocessed and the interested region is extracted. Then the Haralick texture features generated from the GLDM is extracted for the region of interest. After that, the category labels are marked and the feature vectors are fed into the training system to solving the nonlinear regression problem. Besides this, the three algorithm: ELM, SVM and BP are respectively used for the regression and classification in PETS and UCSD databases.The low computational complexity enables our approach possible for real-time monitoring. Experimental results demonstrate the effectiveness and real-time of our method in real scenes.

Nevertheless, there is a lot of scope for improvement in our approach. In our future work we would like to reduce the false estimations, incorporate additional methods to reason out occlusions in a crowded scene and make the ELM approach more stable.

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REFERENCES

[1] Junior, J.C.S.J., Musse, S.R. and Jung, C.R., “Crowd analysis using computer vision techniques: a survey”. IEEE Signal Process. Mag. v27 i5. 66-77,2010

[2] J.D. Sime, "Crowd psychology and engineering", Safety Science, vol. 21, pp. 1-14, 1995.

[3] Xinyu Wu, Guoyuan Liang, Ka Keung Lee, Yangsheng Xu, "Crowd Density Estimation Using Texture Analysis and Learning",Bulletin of advanced technology research, Vol.3,No.5/May 2009

[4] Hua Yang, Hang Su , Shibao Zheng ,Sha Wei ,Yawen Fan,"The large-scale crowd density estimation based on sparse spatiotemporal local binary pattern", Multimedia and Expo (ICME), 2011 IEEE International Conference on, 11-15 July 2011

[5] Li Xiaohua, Shen Lansun, and Li Huanqin, “Estimation of Crowd Density Based on Wavelet and Support Vector Machine”, Transactions of the Institute of Measurement and Control August 28: 299-308, 2006.

[6] Zi Ye,Jinqiao Wang,Zhenchong Wang,Hanqing Lu, "Multiple features fusion for crowd density estimation ", ICIMCS '12 Proceedings of the 4th International Conference on Internet Multimedia Computing and Service,ACM New York, NY, USA ©2012

[7] Tang Fei Liu ,SunDong ,Guo Sen, “A novel method of crowd estimation in public locations " ,BioMedical Information Engineering, 2009. FBIE 2009. International Conference on Future,13-14 Dec. 2009

[8] Cho, S.Y., Chow, T.W.S., Leung, C.T.: A Neural-Based Crowd Estimation by Hybrid Global Learning Algorithm. IEEE Trans. on System, Man, and Cybernetics 29(4) (August 1999)

[9] Li, W.: Crowd Density Estimation: An Improved Approach. In: 2010 IEEE 10th International Conference on Signal Processing, pp. 1213–1216 (2010)

[10] D. Huang, T.W.S. Chow, and W.N. Chau. Neural network based system for counting people, IEEE Trans on Systems, Man, and Cybernetics, Part B, Vol. 31, no. 4, 2002, pp. 2197-2200.

[11] Y.Cho, and T.W.S. Chow. A fast neural learning vision system for crowd estimation at underground stations platform, Neural processing letters, Vol. 10, no. 2, pp. 111-120, 1999.

[12] Kim,Daehum;Lee,Younghyun;Ku,Bonhwa;Ko,Hanseok; “Crowd Density Estimation Using Multi-class Adaboost”,Advanced Video and Signal-Based Surveillance (AVSS) 2012 IEEE Ninth International Conference on;447- 451,2012

[13] Kim, Dae-Hun ; Lee, Young-Hyun ; Ku, Bon-Hwa ; Ko, Han-Seok ;”Crowd Density Estimation with Multi-class Adaboost in elevator”Journal of the Korea Society of Computer and Information, pp.45-52,2012

[14] S. Ghidoni, G. Cielniak and E. Menegatti. "Texture-based Crowd Detection and Localisation". Proceedings of the International Conference on Autonomous Intelligent Systems (IAS-12). 2012.

[15] A. N. Marana, L. F. Costa, R. A. Lotufo, and S. A. Velastin, On the efficacy of texture analysis for crowd monitoring, in Proc. Computer Graphics, Image Processing, and Vision, Rio de Janeiro, Brazil, pp. 354–361, 1998.

[16] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme learning machine: A new learning scheme of feed forward neural networks", in Proceedings of International Joint Conference on Neural Net-works (IJCNN2004), (Budapest, Hungary), 25-29 July, 2004.

[17] G.-B. Huang and C.-K. Siew, "Extreme learning ma-chine: RBF network case", in Proceedings of the Eighth International Conference on Control, Automation, Robotics and Vision (ICARCV 2004), (Kunming, China), 6-9 Dec, 2004.
[18] [G.-B. Huang and C.-K. Siew, "Extreme learning ma-chine with randomly assigned RBF kernels", Inter-national Journal of Information Technology, vol. 11,no. 1, 2005.
[19] Karpagachelvi, S.; Arthanari, M.; Sivakumar, M. , "Classification of electrocardiogram signals with support vector machines and extreme learning machine ",Neural Computing & Applications. Sep2012, Vol. 21 Issue 6, p1331-1339. 9p. 3 Charts, 3 Graphs. DOI: 10.1007/s00521-011-0572-z.
[20] RASHEED,ZEEHASHAM;RANGWALA,HUZEFA."Metagenomic Taxonomic Classification Using Extreme Learning Machines", Journal of Bioinformatics & Computational Biology. Oct2012, Vol. 10 Issue 5, p-1. 19p. 1 Diagram, 11 Charts. DOI: 10.1142/S0219720012 500151.
[21] Mahesh Pal , "Extreme Learning Machine for land cover classification ",Department of Civil Engineering N. I. T. Kurukshetra, Harayana, 136119, 2008,INDIA
[22] Cao, Feilong; Liu, Bo; Sun Park, Dong. “Image classification based on effective extreme learning machine",Neurocomputing.Feb2012,Vol.102,p90-97.8p.DOI: 10.1016/j.neucom.2012.02. 042.
[23] Marques, Ion; Graña, Manuel. "Face recognition with lattice independent component analysis and extreme learning machines ", Soft Computing - A Fusion of Foundations, Methodologies & Applications. Sep2012, Vol. 16 Issue 9, p1525-1537. 13p. DOI: 10.1007/s00500-012-0826-4.
[24] http://www.svcl.ucsd.edu/projects/motiondytex/
[25] V. N. Vapnik, “The nature of statistical learning theory,” New York: Springer-Verlag, 1995.
[26] V. N. Vapnik, “Statistical learning theory,” New York: Wiley, 1998.
[27] C. Cortes and V. N. Vapnik, “Support vector networks,” Machine Learning,vol. 20, pp. 273—297, 1995.
[28] Sen, G., Wei, L., Ping, Y.H.: “Counting people in crowd open scene based on gray level dependence matrix”. In: International Conference on Information and Automation, pp. 228-231 (2009).
[29] Liu, Xueyi,Gao, Chuanhou,”A comparative analysis of support vector machines and extreme learning machines”, Neural Networks, Sep2012, Vol. 33, p58-66, 9p
[30] G.-B. Huang, H. Zhou, X. Ding and R. Zhang,”Extreme Learning Machine for Regression and Multi-Class Classification”, submitted to IEEE Transactions on Pattern Analysis and Machine Intelligence, October 2010
[31] A. B. Chan and N. Vasconcelos, “Modeling, Clustering, and Segmenting Video with Mixtures of Dynamic Textures,” IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 30(5), pp. 909-926, May 2008
[32] Robert M. Haralick, “Statistical and structural approaches to texture,” Proc. IEEE, vol. 67, no. 5, pp. 786-804, 1979.
[33] http://www.csie.ntu.edu.tw/~cjlin/libsvm/
[34] Kunlun Li, Zhe Wang, Chao Ma, Song Song, “SNS Privacy Protection based on the ELM Integration and Semi-supervised Clustering”, Journal of Software, Vol 8, No 1 (2013), 160-167, Jan 2013 doi:10.4304/jsw.8.1.160-167

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