Journal of Theoretical and Applied Information Technology
20th March 2013. Vol. 49 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A RESEARCH OF FACE SUPER-RESOLUTION TECHNOLOGY IN LOW-QUALITY ENVIRONMENT

[1]YONGJUN PENG [1]JIAN HE [1]JUN SUN
[1] Academy of National Defense Information, HuBei Wuhan
E-mail: [1]pyj1976@163.com

ABSTRACT

In recent years, with the extensive application of video surveillance system in police's criminal investigation, video investigation technology is playing a more and more important role in detection of cases. Key characters in case spots, such as criminal suspects and witnesses are often targets that attract most attentions. Therefore, face image become the key clue of a case. While in actual surveillance, due to distance and limitation of equipment, definition of most face images is of low-quality. Face super-resolution technology can make use of information in face sample database to restore high definition face image, which can effectively enhance definition of face images in surveillance video and restore detail information of face features. This technology is extremely important to improve the clarity of face image, increase accuracy of face recognition, and thus increasing the police's ratio of solving cases. In this thesis, the author introduces shape semantics model and posterior image information into the frontier global face and partial face super-resolution approach, and put forward the corresponding algorithm, which can not only increase the robustness of single mode face super-resolution algorithm, but also can be used for reference for other image processing technology that research robustness. Simultaneously, this thesis extend the approach based on shape semantics model and posterior image information to multi mode face super-resolution, which increases the robustness of multi mode face super-resolution, and provides train of thought for applications of the approach put forward.

Keywords: *Face Super-Resolution, Shape Model, Multi-Mode, Video Surveillance*

1. INTRODUCTION

In recent three years, over 20 billion RMB has been invested to national peaceful cities construction. In 2006, the total number of cameras set around the whole country was over 1 million. These existing video surveillance systems have been widely applied in police's criminal investigation [1]. Image investigation technology has grown into a new growth point for case solving. Image operation has developed most quickly in police industry. In criminal investigation, key characters in case spots, such as criminal suspects and witnesses are often targets that attract most attentions [2]. And face images in surveillance video are the most direct and key clue for identifying crucial character in crimes. But in actual application of surveillance, on one hand, there is a distance between the camera and criminals' faces, on the other hand, due to the limited bandwidth and storage resource, low definition of video, most face images in surveillance video are of low definition and thus it's hard to provide detail information of face features [3]. Therefore, it's needed as a core technology to provide identifiable face image of high-quality on the basis of original face image of low definition. Face super-resolution technology can make use of face sample images to restore face image of high definition which is the most similar to the original face image of low definition. This approach can effectively enhance definition of face images in surveillance video and restore detail information of face features [4]. This technology is extremely important to improve the clarity of face image, increase accuracy of face recognition, and thus increase the police's ratio of solving cases.

Traditional face super-resolution approach doesn't consider the influences caused by noise in actual surveillance environment, and only use the difference of image pixel value as principle for face similarity. While in actual surveillance, many factors will cause strong noise disturbance to the image pixel value, and thus cause pixel to become dark, distorted and aliasing. This phenomenon may lower the accuracy of principle for face similarity, and also the similarity and identifiably of face image restored by traditional approach, which can hardly satisfy the need of actual video investigation application.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2. RELATED WORK

2.1 Blur Image Processing and Face Super-Resolution

There are many reasons for image degradation, and different forms of deteriorate image are caused. According to specific circumstances, there are mainly three forms of image degradation: distortion, noise and blur [5]. The main reasons for distortion are the following ones: 1. aberration, deformation and limited bandwidth of imaging system; 2. solar radiation and atmospheric turbulence's influences on remote pictures; 3. digital pictures' process of sampling, quantification and AD conversion. Noise disturbance is a common problem in image degradation, which can often be divided into additive noise and multiplicative noise. As to images of motion blur, if the direction and scale causing the blur can be known, point spread function can be got and then the original image can be restored by using the method of inverse filtering. In the beginning, use bilinear interpolation and 3×3 direction differential operator, and then process high precise identification after deciding the rough range of motion blur direction [6]. After that, get the blur scale by using pixel relevance, and finally get the restored image by using inverse filtering with the parameter acquired [7].

Blurred image restoration technology is an important branch in digital image processing, which can play an indispensable role in certain application scenes (e.g. camera dithering, lens defocus, atmospheric sensing interference, etc.) [8]. At present, there is no general way of blur processing. In actual surveillance scenes, images are often open to the influence of many degraded factors. Effect of approaches that analyze one certain degraded factor and process is rather limited [9]. And the restoration problem of the blur caused by complicated influential factors can not be solved by simply subsequently process each factor. The current research is just primary. For instance, in 2010, considering that image in actual environment are often influenced by many blur degradation process, Peng Silon put forward an image degradation model and corresponding restoration algorithm. Different from traditional serial way, this algorithm assumes that blur kernel function is a weighted sum form of defocus blur and motion blur [10]. Under this assumption, this method uses Laplace distribution in broad sense as the statistical model of motion blur, and estimate blur kernel function under the algorithm framework of expectation maximization [11]. Finally, the image is restored by using the estimated blur kernel function. This method provides a train of thought for mixed degradation restoration algorithm. But the two assumptions mentioned are very limited, and in real practice, it's hard to make sure that there are only defocus and motion blur. What else, the assumption given by defocus blur is also hard to satisfy.

Super-resolution approach can be thought as an extension of traditional restoration approach, which uses the methods of statistics and signal processing to enhance image's definition and provide a new train of thought for solving the problem of restoration of blur images [12]. Single frame image super-resolution is to use information of the image itself to enhance definition. Interpolation amplification is the most original approach. Scholars also put forward other different algorithms of single frame super-resolution. For instance, in 2005, Peng silong and some others in Institute of Automation of Academia Sinica put forward the idea of using partial structure similarity to restrict the problem of super-resolution, based on the similarity of images' partial structure and similarity preserving on different definition scale. That means to find out similar area in images according to similarity judgment rule, and generate many similar images in terms of similarity degree, sequentially use the algorithm of image sequence super-resolution for solution [13].

In the same year, they brought forward the idea of introducing multi-core backward projecting operator with parameters under the framework of traditional super-resolution algorithm based on iterative backward projecting (back projection iteration), and acquiring the operator parameter through the method of training estimation. But image information used by single super-resolution technology is rather limited and the effect is average. Traditional video multi-frame sequence super-resolution approach mainly enhances images' definition by integrating complementary information of neighboring frames, which has the effect of deblurring. This approach succeeds in the field of global registration image sequence. But because the problem of accurate local registration of surveillance video is hard to solve, application of this approach in actual surveillance video is limited. Compared with traditional video multi-frame super-resolution approach, face super-resolution based on samples introduces the learning-based method to enhance image's quality, which is the current research focus [14]. This approach uses sample database's prior knowledge to restore the missing information caused by low definition, which can offer more useful information to enhance images'

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

definition. And structure similarity among face images makes this approach more feasible. At the same time, compared with traditional interpolation technology and reconstruction technology, the approach of face super-resolution based on samples will not cause obvious error diffusion effect with magnification of images which is extremely important for enhancing quality of surveillance video of very low definition. Therefore, the author is going to make a detailed study of the research status of face super-resolution based on samples, and consider robustness of complicated degradation factors for surveillance on the foundation of traditional face super-resolution technology.

2.2 Research Status of Single-Mode Face Super-Resolution

Face super-resolution (single-mode face super-resolution), also called face hallucination technology, referring to the approach of restoring high definition face image from low definition face image by making use of prior information of sample database. Training sample database can be classified into three kinds according to its method of constructing prior model [15]. The first kind is the global face approach based on global face model. The second kind is the partial face approach based on partial face model. The third kind is the mixed model approach based on the combination of the first two kinds.

In 2005, Wang and Tang in Chinese University of Hong Kong put forward a new face hallucination algorithm based on feature transformation. This approach uses Principal Component Analysis (PCA) to synthesize input low definition images into linear expression of low definition images in sample database. And expression coefficient of low definition samples are directly mapped to image space of high definition samples. Then images of high definition are synthesized. This approach can not only enhance recognition rate, but also the subjective quality. Experiments also proved that this method had certain robustness to Gaussian white noise [16]. But the anti-noise type of this approach is too simple, which limits its application.

In 2008, Jeong-Seon Park and others in Chonnam National University put forward the idea of reconstructing high definition face image from single frame low definition face image by means of PCA synthetic method of iteration error back projection and morphable face model. This approach renews high definition image by comparing reconstructed iteration error, and gradually compensates high definition image error. Simultaneously, this approach introduces and expands morphable face model, which decompose sample face into shape vector and texture vector. Then both of the vectors are separately synthesized, and finally the texture is transformed according to shape information [17]. This approach can also use face images' shape and texture information at the same time, which can make the synthesized images more accurate. Compared with traditional PCA decomposition, the experiment result has been enhanced. But this method needs to use optical flow to calculate face images' shape field. This step may be influenced by various noises, and the calculation is also very complicated.

In recent years, Chinese scholars have started researches on global face super-resolution. In 2006, Huang hua and some other people put forward the reconstruction approach of face image super-resolution based on particle filter. This approach describes face image super-resolution as Bayesian probability estimation problem of texture and location parameters, and put the process of image registration and pixel fusion in super-resolution reconstruction into a unified probability estimation framework. This approach also uses parameter estimation algorithm based on particle filter to estimate texture and location parameters at the same time, and to realize super-definition reconstruction of face images. This approach solves the problem of estimating motion field and clear high definition images at the same time [18]. In 2008, Liu ju and some other people in Shandong University put forward face super-resolution algorithm based on independent component analysis. This approach acquires weight coefficient by means of MAP and linearly combines independent components to reconstruct high definition images, which maintains global structure and high frequency information. Experiment result proves this approach has certain robustness under the condition of gesture, expression and illumination changes. In 2010, Zhang xuesong, Jiang jing, Peng silong and some others thought face image blocks as certain signal classifications, and used Principal Component Analysis to calculate training face image blocks' feature subspace. They also unified traditional reconstruction constraint and face image blocks' orthogonal complement feature subspace constraint in Bayesian framework, and put forward a regularized method of face image SR. This algorithm has great ability of denoising and deblurring, and its reconstruction effect is better than SR result using classical Laplacian regularization operator. But the experiment was done in the environment of uniform blur and Gaussian noise, which didn't take more

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

complicated environment factors in reality into consideration.

3. GLOBAL FACE SUPER-RESOLUTION APPROACH BASED ON SHAPE LIMITATION

Global face super-resolution is the approach of using face images' global structure features to reconstruct low definition face images. Since PCA model can analyze sample data's features and realize the function of removing data redundancy and noise, PCA is a commonly used data analysis method in global face super-resolution approach. Approaches of this kind are also called face or feature transformation approach. The most classic feature transformation face super-resolution approach is put forward by Wang xiaogang and his colleagues. This approach firstly uses PCA to decompose low definition image set which high definition image sets in sample database correspond with into low-dimensional feature subspace. Then images are input and draft synthesized into linear expression of face, and representation coefficients are mapped to high definition images' high-dimensional feature space. Finally, high definition reconstructed images are synthesized, and high-dimensional features that exceed certain threshold (which is decided according to variance) are truncated. This approach makes use of the relation between low definition sample and high definition sample images, and takes the role of low-level feature in synthesizing high definition face images.

3.1 Reconstruction Model of Face Super-Resolution

Classical face super-resolution reconstruction model is based on image restoration's MAP (Maximum A Posteriori) framework, and combines information in face sample database at the same time. Assume objective high definition face image is defined as matrix Z, low definition face image as Y. And assume that surveillance image is influenced by add-noise. Then image imaging model can be expressed as:

$$Y = DBZ + n$$

In the expression above, B is lens optical blur matrix, D is sampling matrix decided by CCD size, n is noise matrix. On the condition of knowing low definition image, according to maximum a posteriori principle and Bayesian theory, we can get:

$$\hat{Z} = \arg\max_{Z} p(Z \mid Y) = \arg\max_{Z} \frac{P(Y \mid Z)P(Z)}{P(Y)}$$

In the expression, P(Z) and P(Y) separately represent prior probability of high definition image and low definition image. P(Z|Y) represents posterior probability we desire. P(Y|Z) represents conditional probability of high definition image Z degrades to low definition image Y. In terms of MAP formula, ignoring terms unrelated with Z, we can get super-resolution's cost function:

$$\hat{Z} = \arg\min \|Y - DBZ\|^2 + \lambda\rho(\mathrm{Z})$$

In the function above, $\rho(Z)$ is high definition image's prior regularization item. λ is parameter balancing reconstruction error and prior item. Many prior regularization items have been put forward. In order to simplify the calculation but not lose generality, we use Laplace function as regularization item.

Since there is great structure similarity among face images, face super-resolution technology can enhance face images' definition by studying information in high definition sample face database. We use PCA to decompose database and acquire face image W. Assume $Z = \overline{m} + We$, in which $\overline{m}$ is average face image in database, e represents unknown coefficient vector, then formula can be rewrite as:

$$\hat{e} = \arg\min(\|Y - DB(\overline{m} + We)\|^2 + \|\Gamma(\overline{m} + We)\|^2)$$

3.2 Algorithm of Face Super-Resolution Limited by Shape Model

Similarly, we can rewrite formula as:

$$\hat{c}' = \arg\min(\|Y - DB(\overline{m} + Lc')\|^2 + \|\Gamma(\overline{m} + Lc')\|^2)$$

In the formula, L is sample image residual, c' is the coefficient corresponding with L. Since image is closely related with its corresponding shape, coefficients of image shape and image are also closely related. We combine the two coefficients of the sample into a long vector b, whose form is:

$$b = \begin{pmatrix} c' \\ c \end{pmatrix}$$

Using PCA to decompose the coefficient matrix made up of by long vector, we can get a unified coefficient model:

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$b = \mathrm{Qi} = \begin{pmatrix} \mathrm{Q}_{c'} \\ \mathrm{Q}_{c} \end{pmatrix} i$$

In the expression above, Q is the matrix composed by feature vectors of database coefficient matrix, and i is the unified vector after the change of image and shape coefficients. Then we can get the cost function of face super-resolution based on shape semantics model:

$$X = \arg\min_X \|L - D_l X\|_2^2 - \lambda_1 \|R - D_l X\|_2^2 + \lambda_2 \|Y - D_h X\|_2^2$$

3.3 Purpose and Theory of the Experiment

Purpose of the experiment: Firstly, the author wants to prove that composite coefficients of face shape and face image have consistency, which means shape information can be used to constrain image's reconstruction. Then the author tries to prove that the algorithm put forward in this thesis has better robustness to low quality input face image by means of separately comparing the objective and subjective quality of the results of traditional global face super-resolution algorithm and face super-resolution algorithm based on shape model constraint raised in this chapter. Experiments separately prove that algorithm's test image is sample image, or images took in built darkroom environment are effective.

Theory of the experiment: The key point of science in face super-resolution principle based on shape model is to prove image's texture content and its shape have relativity. When the content of image is unclear, contour shape can be used to restore image information. Use contour semantic point's coordinates vector to represent shape. Since the data of image information and shape information are of different dimension, it's hard to compare them. Therefore, image and shape information need to be transformed in the first place. Mapping image and shape information to image sample database and corresponding shape sample database, we can acquire coefficients of same dimension and then compare their root-mean-square error (RMSE). If RMSE is smaller, then two groups of coefficients are more consistent, the image and shape they represent have more relativity, and it's more feasible to use contour shape to restore image information.

As to the algorithm experiment put forward, we not only follow the experiment standards of international colleagues, selecting images from the samples as input test images after processing; in order to prove the algorithm is also effective to images taken in reality, we also build a darkroom simulating night surveillance environment where images are taken as input. We realize three algorithms' results. The first method is the most commonly used interpolation, the second method is the latest global face approach, and the third method is the algorithm put forward in this chapter. Same Set up same sample database images, input test sequence, same output image definition. Compare the subjective and objective quality of the three algorithms' results to explain different algorithm's reconstruction effect of low quality images.

4. ROBUSTNESS FACE SUPER-RESOLUTION ALGORITHM BASED ON POSTERIOR INFORMATION

In order to construct the ideal low definition dictionary D_l mentioned above, we put forward the idea of generating high definition image sample database, ideal low definition image sample database and spot surveillance noise image sample database by collecting posterior image information on the spot. Then use information of these sample databases to train robust high and low dimensional dictionary. Among them, high definition image sample database consists of clear high definition images, and deal low definition image refers to low definition image without noise influence. When low definition image with complicated noise subtracts ideal low definition image, spot surveillance noise image can be get. According to super-definition goal, operation of dictionary construction must satisfy the following requirements: 1. In order to guarantee completeness of dictionary, ideal low definition images can be synthesized by low dimensional dictionary. 2. In order to make sure that dictionary has sparse characteristics, composite coefficients of low dimensional dictionary must be sparse. 3. In order to make dictionary have robust function to surveillance strong noise, low dimensional dictionary can only sparsely represent ideal low definition images and not noise images. 4. In order to make composite coefficients of high and low dimensional dictionaries have direct mapping relation, composite coefficient of low dimensional dictionary must can be directly mapped to high dimensional dictionary and be able to compose corresponding high definition image. In terms of these principles, our minimizing objective function based on posterior information can be expressed as:

$$\sum_{i=1}^{N} \|l_i - D_l \alpha_i\|_2^2 - \lambda_1 \sum_{i=1}^{N} \|r_i - D_l \alpha_i\|_2^2 + \lambda_2 \sum_{i=1}^{N} \|Y_i - D_h \alpha_i\|_2^2 \ \text{subject to } \forall \mathrm{i},\ \|\alpha_{\mathrm{i}}\|_0 \le M$$

In this function, l_i represents ideal low definition

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

image block, D_l is low dimensional dictionary sparsely representing ideal low definition image blocks, α_i represents sparse composite coefficient of image block, r_i is noise image block, Y_i is high definition image block, D_h is high dimensional dictionary sparsely representing high definition image blocks, λ_1, λ_2 are weighting factors, $\|\cdot\|_2$ represents l_2 norm operation, $\|\cdot\|_0$ represents l_0 norm operation. In objective function, the first item is binding term of dictionary completeness, the second item is binding item of coefficient sparsity, the third item is binding item of dictionary to surveillance noise robustness, the fourth item is binding item of consistency of coefficients of high and low dimensional dictionaries. In the calculation process, we use high definition face sample images' blocks collected on the spot as variable Y_i, and use low definition blocks sampled in Y_i as l_i. At the same time, we collect spot surveillance low definition face images corresponding with high definition face samples. r_i is high definition block subtracts spot surveillance low definition block.

As to cost function , assume X is matrix composed of α_i vector; L is matrix composed of ideal low definition blocks; R is matrix composed of noise image blocks; Y is matrix composed of low definition image blocks. Then the cost function can be rewritten as:

$$\|L - D_l X\|_2^2 - \lambda_1 \|R - D_l X\|_2^2 + \lambda_2 \|Y - D_h X\|_2^2 \quad \text{subject to } \|X\|_0 \le M$$

Therefore, cost function consists of three vectors X, D_l and D_h. We need to fix two vectors at the same time and use cyclic iteration for solution. Vector D_l and D_h 's initial value are standard sample database. We also use WOMP algorithm put forward in part 3 to solve X. But the steps need to be changed:

$$X = \arg\min_X \|L - D_l X\|_2^2 - \lambda_1 \|R - D_l X\|_2^2 + \lambda_2 \|Y - D_h X\|_2^2$$

Obviously, as to variable X, only when λ_1 does not exceed 1, then cost function represented by expression is still a convex function. Then steepest descent method can be used for solution. Similarly, we can solve and get D_l and D_h . And atom collection based on posterior information can be acquired.

When we use the method described above to get sparse dictionary and since dictionary is sparse robust to surveillance noise, we can use the following cost function to calculate each block in actual surveillance images sparsity coefficient.

$$\|\tilde{y} - D_l \tilde{x}\|_2^2 + \|\tilde{x}\|_0$$

Considering that the low definition blocks actually input are influenced by real noise, this thesis put forward the robustness tensor approach based on posterior information learning. Assume that image tensor block $y_i \in R^{m_1 \times m_2 \times m_3 \times m_4 \times m_5}$ is divided into two parts. One part is the ideal face image tensor block $l_i \in R^{m_1 \times m_2 \times m_3 \times m_4 \times m_5}$ only consists of clear content. The other part is the real noise image tensor block $r_i \in R^{m_1 \times m_2 \times m_3 \times m_4 \times m_5}$. For instance, $y_i = l_i + r_i$. While as to ideal face image block l_i, we assume tensor atom ground $U_{id}, U_{pose}, U_{\exp}, U_{res}, U_{pix}$ exist, and content of l_i can be sparsely represented by these atom grounds, the formula is the following:

$$l_i = a_i \times_1 U_{id} \times_2 U_{pose} \times_3 U_{\exp} \times_4 U_{res} \times_5 U_{pix}, \quad \text{subject to: } \|a_i\|_0 \le T$$

In order to construct ideal multi-mode atom ground $U_{id}, U_{pose}, U_{\exp}, U_{res}, U_{pix}$, we also generate high definition image tensor sample database, ideal low definition image tensor sample database and spot surveillance noise image tensor database by means of collecting spot posterior image information. And then we use information of these tensor sample database to further train robust multi-mode atom ground. Among them, high definition image tensor sample database consist of clear high definition images of different mode; ideal low definition image tensor sample database consist of multi-mode low definition images without noise influence. Spot surveillance noise image tensor can be got when low definition image tensor with complicated noise subtract ideal low definition image tensor. According to goal of face super-resolution, construction of robustness multi-mode atom ground must satisfy the following requirements: 1. in order to guarantee completeness of atom ground, ideal low definition image tensor blocks can be synthesized by low dimensional atom grounds. 2. In order to make sure that atom ground has sparse characteristics, composite coefficients of low dimensional atom ground must be sparse. 3. In order to make atom ground have robust function to surveillance strong noise, low dimensional atom

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ground can only sparsely represent ideal low definition image tensor blocks and not noise image tensor blocks. In terms of these principles, minimizing objective function based on posterior information can be expressed as.

5. CONCLUSION AND PROSPECTS

Face super-resolution technology of surveillance image is a new research subject, which also has many deficiency and difficult problems. Research and exploration in this field will continue. Although this thesis makes a research on surveillance image robustness face super-resolution technology from several aspects and has got some achievements, there are also many limitations. In the future, the following problems need to be solved:

(1). Further research on shape semantic model. This thesis use position of semantic point to describe shape. Accuracy of shape depends on that of points. But shape semantic points are marked by human, which will influence the accuracy of model. Method of automatic or semi-automatic shape marking to increase model accuracy need further study.

(2). In the current approach based on posterior information, many high and low definition images of face need to be taken on the spot for training dictionary, which increases the complexity of image processing each time. Method of increasing utilization ratio of posterior information to decrease scale of obtaining spot image information needs further study.

(3). at present, in robustness of multi-mode tensor, we only study the multi-posture super-resolution. Effectiveness of other modes such as expression and illumination needs further research. And since calculation complexity and memory consumption of multi-mode face super-resolution are high, we can only do with small samples. Face experiments of real shoot also have the problem of posture registration. Non rigid body characteristic of face makes the data after registration less reliable. All these problems need further study.

(4). Current face super-resolution is mainly used for subjective identification in criminal investigation. If sample database is enlarged to large-scale portrait database of suspects, we can consider combing the approach put forward with identification technology to enhance the accuracy of face recognition of surveillance images.

REFRENCES:

[1] D. COMANICIU, P. MEER. Mean shift analysis and application [J]. Proceedings of the Seventh IEEE International Conference Computer Vision 1999: 2: 1197-1203.

[2] Yilmaz A, Shafique K, Shah M. Target tracking in airborne forward looking infrared imagery. Int'l Journal of Image and Vision Computing, 2003, 21(7):623−635.

[3] Comaniciu D,Ramesh V,Meer P.The variable bandwidth mean shift and data-driven scale selection[A].8thIntl Conf on Computer Vision[C].2001,1:438-445.

[4] Comaniciu D, Meer P.Mean shift: A robust application toward feature space analysis [J].IEEE Trans on Pattern Analysis and Machine Intelligence, 2002, 24(5):603-619.

[5] Peng NingSong, Yang Jie, eta. Automatic Selection of Kernel-Bandwidth for Mean-Shift Object Tracking [J]. Journal of Software，2005，16（9）：1542~1550.

[6] Shi Ying Adaptive feature-spatial representation for mean-shift tracker. Proceedings - International Conference on Image Processing, ICIP. 2008, 2008, pp: 2012-2015.

[7] Li Peihua. An adaptive binning color model for mean shift tracking. IEEE Transactions on Circuits and Systems for Video Technology, September 2008, pp: 1293-1299.

[8] Tang Wei-Qin, Chen Rong-Qiu, Zhang Yin. Study on Path Optimization of Emergency Material Transportation with Interval Time. 4th International Conference on Wireless Communication, Networking and Mobile Computing, 2008. pp: 1-4

[9] Zhu Xiao-ning, Du, Wen. Study on the Mode of Social Emergency Early Warning Management Based on Grid. International Conference on Management Science and Engineering 2007. pp:2463-2468

[10] Mou Zhenhua, Li Meiling, Liu Yongjun. Study on Emergency Traffic Organization of Urban Road Traffic System under Abnormal State. International Conference on Management and Service Science 2009. pp:1-4

[11] Tang Hong, Zhao Lindu. Knowledge Management System of Intercity Emergency analysis [J].IEEE Trans on Pattern Analysis and Machine Intelligence, 2002, 24(5):603-619.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[12] Peng NingSong, Yang Jie, eta. Automatic Selection of Kernel-Bandwidth for Mean-Shift Object Tracking [J]. Journal of Software，2005，16（9）：1542~1550.

[13] Shi Ying Adaptive feature-spatial representation for mean-shift tracker. Proceedings - International Conference on Image Processing, ICIP. 2008, 2008, pp: 2012-2015.

[14] Li Peihua. An adaptive binning color model for mean shift tracking. IEEE Transactions on Circuits and Systems for Video Technology, September 2008, pp: 1293-1299.

[15] Tang Wei-Qin, Chen Rong-Qiu, Zhang Yin. Study on Path Optimization of Emergency Material Transportation with Interval Time. 4th International Conference on Wireless Communication, Networking and Mobile Computing, 2008. pp: 1-4

[16] Zhu Xiao-ning, Du, Wen. Study on the Mode of Social Emergency Early Warning Management Based on Grid. International Conference on Management Science and Engineering 2007. pp:2463-2468

[17] Mou Zhenhua, Li Meiling, Liu Yongjun. Study on Emergency Traffic Organization of Urban Road Traffic System under Abnormal State. International Conference on Management and Service Science 2009. pp:1-4

[18] Tang Hong, Zhao Lindu. Knowledge Management System of Intercity Emergency Decision Making World Congress on Software Engineering 2009. pp: 365-369