Emergency Decision Support Architectures for Bus Hijacking Based on Massive Image Anomaly Detection in Social Networks

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Abstract — **In bus hijacking, the availability of instant information in the scene may help the decision-making largely. In this paper, we discussed the significant value of the information acquisition in bus hijacking emergency from a qualitative analysis and quantitative description. Furthermore, we proposed an effective emergency decision support architecture for bus hijacking based on massive information in social networks. Last but not least, as to the core part of images discrimination, we build an image anomaly detection algorithm model. In the first step of the model, we conduct a Scale Invariant Feature Transform (SIFT) detection for images, and extract local feature descriptor; In the second step, the image feature vectors of the key points are subjected to further K-means clustering, so that we get the unified K-dimensional feature vectors; In the third step, we make the image classification with Support Vector Machine (SVM) classifier. This algorithm model achieves the image discrimination for bus hijacking emergency successfully, so that the information inside the bus could be transmitted to the outside effectively, and therefore provide a significant value for emergency decision-making.**

Keywords* — *Bus Hijacking Emergency; Image Anomaly Detection; Social Networks;

I. INTRODUCTION

In recent years, a series of unexpected emergency public security emergencies happened all around the world. These incidents result in a tremendous impact on people's lives. For instance, the Philippine tourist bus hijacking incident in August 2010, the Malaysia Airliner losing contact event in March 2014, criminals stabbing pupils incident in Jiangxi province China in October 2014, etc. Frequent occurrence of various public security incidents brings a serious challenge to government for rescuing management. Before the APEC meeting, the Chinese Snow Leopard Commando conducted a practical drill on November 3rd 2014. They chose bus hijacking incident as an example (Figure1). Clearly, emergency management in emergencies has become a hot topic in academic research [1].

Figure 1. The Chinese Snow Leopard Commando conducted a practical drill on November 3rd, 2014.(source: CCTV-13).

In emergency incidents, a common feature of public security emergencies is that the abductees are trapped in a relatively confined space, and the Emergency Decision Centre (EDC) outside the space cannot catch the details inside, so that it is difficult to make the most accurate judgment. We call it "a broken ring" in the access to information on emergency rescue. In the example of the bus hijacking in Philippine in 2010, the Hijacker closed all the windows as well as doors, and smashed the bus webcams (Figure2). Because of the failure of obtaining the detailed information of internal situation, an ineffective negotiation between government and the hijackers was conducted. Eventually, several hostages were shot dead with eight people killed and two seriously injured.

Figure 2. The Philippine tourist bus hijacking and rescue (source: http://news.163.com/photoview/00AO0001/10544.html).

It can be seen that obtaining the internal information in a closed environment with respect to this type of public transport security incidents has always been a difficult problem. In the APEC security practical drill, the Chinese Snow Leopard Commando detected the bus interior environment by remotely controlling the unmanned helicopter (Figure3), however it still remained a lot of risks in such approach. For example, the hijackers would probably shoot down the unmanned helicopter and be exasperated in the meantime.

Figure 3. Drill image of the Chinese Snow Leopard Commando for detecting the bus interior environment with unmanned helicopter before APEC conference on November 3, 2014 (source: CCTV-13).

However, with the rapid spread of the Internet and mobile networks, abductees with mobile communication

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devices could come into the most direct and effective source of internal information. It makes possible to connect the information inside and outside the bus by giving full play to the abductees and making use of advanced computer and internet technology to integrate massive network resources. Only in this way could it be possible to significantly promote the mastery of outside and inside situations, as well as connect the "the broken ring" in the chain of confined environment emergency rescue.

The second instance showed in Figure 4 indicates that in the Malaysia Airliner losing contact event in March 2014, a passenger post a hijacking picture via mobile phone. As is explained on website, the abductee might pull out the iphone5 from behind, and sent the message by logging in based on voice-activated approach.

Figure 4. Possible image related to the Malaysia Airliner losing contact event took by an abductee (authenticity of the image to be confirmed) (source: http://blog.sina.com.cn/s/blog_58d9fed20102emc6.html)

Nevertheless, in the research field of emergency management at this stage, the massive images in Social Network Services (SNSs) are not fully utilized. Without mining useful images accurately and efficiently in the social networks, some precious scene pictures, which may be taken with the risk of the abductees′ life, are lost in the networks. In other words, even if there is plenty of valuable information dealing with the emergency among the network, there is not a valid and reasonable mechanism to implement the monitoring and alerting function according to the existing emergency management systems [2]. Images generally contain more information than text, and it is hard for abductees to utter word in emergency situation. As a start of the emergency management system research, this article will only focus on images.

However, the significant contribution of this paper is to build an emergency decision support architecture for bus hijacking events with full use of sufficient images in social networks. The paper is organized as follows: Section 2 gives an accurate qualitative and quantitative analysis of the problem. Section 3 illustrates the innovative emergency decision support architecture for bus hijacking. Based on the key technology and difficulty in the architecture, Section 4 presents the effective images anomaly detection algorithm model to the core part. Section 5 shows an instant analysis and section 7 concludes.

II. Problem Structuring

A. Scenario Qualitative Analysis

We take the Philippine tourist bus hijacking incident as an instance in this paper. All the curtains in the tourist bus were closed according to the demands of the hijacker, and the doors were controlled as well. Therefore, the whole bus environment was confined and could not be observed by outside, which could be described as Confined Space Scene (CSS) [3]. Under this circumstance, the EDC could not get detailed interior environment information and could only negotiate with hijacker through a narrow access, which was preponderant for the hijacker, while the EDC was in a passive status. However, acquiring interior information of CSS would help convert a passive status to a state of advantages for the EDC.

In some situations, several abductees inside the bus will risk their lives to take some photos of inner condition by mobile phones, and upload them to social networks. Generally speaking, compared with other forms of data sources, images have an advantage in high-speed, large amount of information, convenient to transform, etc. Thus it becomes the best approach to help the outside get the interior information of the bus. To be specific, the images transmitted to the outside by mobile phones mainly concludes the information set of $I(i_1,i_2, \dots , i_N)$:

i_1: the number of abductees in the bus;
i_2: the positions of abductees in the bus;
i_3: the genders and features of abductees;
i_4: the number of hijackers;
i_5: the weapons of hijackers;
i_6: the positions of hijackers in the bus;
i_7: the internal environment features of bus.

The primary values of aforementioned images for decision-making by EDC at least include:

- Knowing the numbers of hijackers, and estimating the order of severity, range of influence, and level of emergency.
- Providing a more straightforward rescue direction when the EDC masters the abductees' positions to avoid accidentally injuries when taking actions.
- Knowing the position of the hijackers will help aiming and shooting of snipers.
- Distinguishing physical rescue obstacles in the bus from the internal environment in images so that preventing unnecessary rescue practices.

In conclusion, it is a significant component for the emergency information acquisition to supplement the "the broken ring," which implements the successful transmission of the precious images from the interior of the bus to outside in emergency rescue process effectively. Nevertheless, there is not a reliable method to achieve the transfer process according to existing researches and practices. The EDC tends to get close to the bus by unmanned aerial bus or on the pretext of negotiation nowadays, but the information is limited and it is difficult in practice. As a consequence, this paper will make full use of IT technology, and further propose an effective management system to supplement "the broken ring" [4].

B. Problem Quantitative Description

Assuming that the EDC gets an emergency alert at time t_1, because the temporary information is incomplete, the EDC can only predict the emergency level as well as status at time t_2 ($t_2>t_1$) in common sense and experience, and further take corresponding actions. When the emergency plan is implemented until the time $t_1+\Delta t$ ($t_1<t_1+\Delta t<t_2$), the EDC gets more amount of information I, and masters more accurate details on the spot. Therefore, decision-makers can adjust the emergency plan at time t_1, and make a more precise emergency project [5].

In this process, we set $S = \{ s_1, s_2, \ldots, s_L \}$ as level sets of an emergency, in which s_j and s_k represent the jth and kth levels, respectively. If $j < k$ and $s_j < s_k$, it means the level of s_j is lower than that of s_k. Moreover, each emergency level has a corresponding emergency plan, described as $X = \{ x_1, x_2, \ldots, x_L \}$, in which x_j represents the emergency plan corresponding to level s_j. In addition, there is a start-up cost vector for each emergency plan, indicated as $C = \{ c_1, c_2, \ldots, c_L \}$, in which c_j represents the start-up cost of plan x_j. When $j < k$ and $c_j < c_k$, the lower the level is, the less the plan will cost.

Setting a_j^o as the effect of dealing with level s_o emergency with plan x_j, and the value of a_j^o is defined as below:

If $s_j \geq s_o$, and $a_j^o > 0$, it means that emergency plan x_j can completely control the level s_o, even beyond the expected effect. Furthermore, the greater the difference between s_j and s_o, the larger the value of the corresponding a_j^o is. It means the better effect for the plan x_j to the emergency level s_o.

If $s_j < s_o$ and $a_j^o < 0$, it means that emergency plan x_j cannot meet the expected consequence for level s_o, and the greater the difference between s_j and s_o, the less the value of the corresponding a_j^o is, representing that the worse effect for the plan x_j to the emergency level s_o [6].

In summary, the function relationship among a_j^o, C, and $s_j - s_o$ is illustrated in Figure 5.

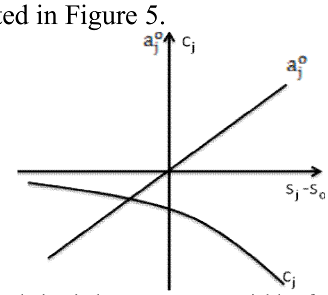

Figure 5. Relation judgment among variable a_j^o, C and sj - so.

Next, we introduce a utility function $U(c_j, a_j^o) = mc_j + na_j^o$ (m and n are constants) for evaluating the effect in the condition of dealing with level s_o emergency with plan x_j, and start-up cost c_j. As we all know, the value of a_j^o is related to the amount of information I. The more sufficient information the EDC obtains from t_1 to $t_1 + \varDelta t$, the more accurate will the estimate for a_j^o be. If $U(c_j, a_j^o)$ is larger, the effect of emergency decision is better.

In this function, the core factor that matters the result of the function is that whether the emergency plan x_j best matches the emergency situation s_o or not. Furthermore, the amount and quality of information obtained from t_1 to $t_1 + \varDelta t$ determines this core factor to some extent. The more amount of the information, the more precise the judgment will be. Therefore, the utility function $U(c_j, a_j^o)$ is larger.

III. Emergency Decision Support Architecture for Bus Hijacking

In general, the whole emergency decision support architecture is illustrated in Figure 6.

Assuming that the computer server has crawled large amount of images resources from SNSs in the emergency management system, and further an SNSs vast images pool comes into being, which can be indicated as,

$$P = \begin{bmatrix} x_{11}, x_{12}, x_{13}, & \cdots & x_{1M} \\ \vdots & \ddots & \vdots \\ x_{N1}, x_{N2}, x_{N3}, & \cdots & x_{NM} \end{bmatrix} \quad (1)$$

where P represents a set of SNSs images pool, and the P vector set concludes N rows, meaning that this images pool concludes N images, and each row represents the basic information of the corresponding image. Simultaneously, P vector set concludes M columns, meaning this images pool includes M types of image information. For instance, the first column concludes the GPS (Global Positioning System) information of the image, the second column contains the post time, the third column indicates the transmitting port information, and the forth column includes the identification information, etc. In general, the SNSs images pool concludes consistent information for each image $\vec{p}_i = (x_{i1}, x_{i2}, \ldots, x_{iM})$.

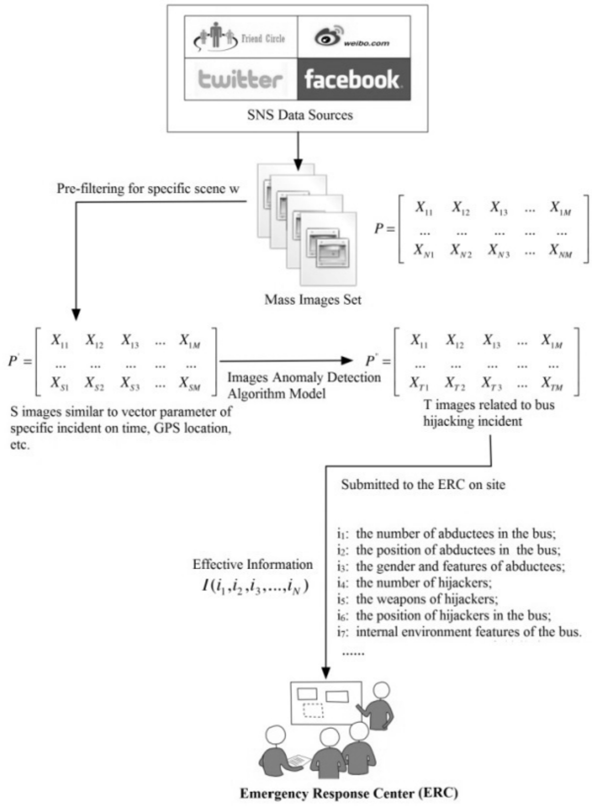

Figure 6. Emergency Decision Support Architecture for Bus Hijacking

In practice, for any emergency scene $\omega \in \overline{\Omega}$, we extract the essential information of it, and filter each image $\vec{p}_i$ in the existing SNS images pool. Taking the Philippine tourist bus hijacking incident as an example ω, we should set the GPS information x_{i1} = be near Reno grandstand in Manila downtown Philippine, x_{i2} = be two hours earlier of the incident to instant. In this example, it is from 7:00am, August 23, 2010 to present [7]. In this way, we give the specific value to each factor of the scene ω image vector, and sort out new images pool P' based on network auxiliary information. In a word, it extracts images with similar information like similar post location, post time, and so on.

Whereas the images pool P' still contains an amount of noises, it needs to further extract an images pool P'' with T images, which strong correlated to the Philippine tourist bus hijacking incident from pool P' with S images, and S ≤ T, i.e., extract from P' $= \begin{bmatrix} x_{11}, x_{12}, x_{13}, & \cdots & x_{1M} \\ \vdots & \ddots & \vdots \\ x_{S1}, x_{S2}, x_{S3}, & \cdots & x_{SM} \end{bmatrix}$ and get P'' =

$$\begin{bmatrix} x_{11}, x_{12}, x_{13}, & \cdots & x_{1M} \\ \vdots & \ddots & \vdots \\ x_{T1}, x_{T2}, x_{T3}, & \cdots & x_{TM} \end{bmatrix}, S \le T.$$

This process could further be converted into a problem of image recognition and classification, which means how to extract the images related to a specific incident only according to the image itself based on computer technology. For example, we should extract images related to the Philippine tourist bus hijacking incident among many images posted near Reno grandstand and from 7:00am, August 23, 2010 to present in this case. Therefore, it demands an effective monitoring and alert model to implement a specific selection from a lot of images.

After obtaining the effective images pool P" with S images, the system will transmit pool P" to the EDC on site, and the EDC further extracts valuable information $I(i_1, i_2, \ldots, i_N)$ from S images, which may contain i_1 (the number of abductees in the bus, i_2 (the position of abductees in the bus), i_3 (the gender and features of abductees), i_4 (the number of hijackers), i_5 (the weapons of hijackers), i_6 (the position of hijackers in the bus), and i_7 (internal environmental features of the bus), etc. The EDC can make the maximal use of information in emergency decisions.

In conclusion, the most significant and difficult step during the whole valuable information extraction process is that how to further distinguish the images relevant to a specific incident ω among plenty of preselected images. As a consequence, we propose an anomaly detection algorithm model in allusion to specific emergency incidents.

IV. Anomaly Detection Algorithm Model based on SIFT Features and SVM Classification

The key point of anomaly detection algorithm is to label the images automatically, and the fundamental difficult is that there is obvious semantic gap between low-level visual feature extracted by computers and high-level semantic interpretation of image content by users [8]. In order to eliminate the semantic gap, the existing approaches dedicate to build a mapping relation between visual features and semantic labels with the help of a set of artificial labeled training data, and subsequently add correlated labels to new images according to the mapping relation [9]. In particular, the widely acknowledged solution at present is to utilize SIFT (Scale Invariant Feature Transform) descriptors to get image features, and use SVM (Support Vector Machine) as dominating classifier [10].

In this paper, we make an innovative practice for the widely accepted algorithm to emergency anomaly detection, and propose an anomaly detection algorithm model based on image data aimed at specific emergency scenes. The model is illustrated in Figure 7. The method and the technology route of each module will be introduced next.

A. Image Features Extraction Based on SIFT

SIFT is a local feature descriptor in the field of image processing, which was proposed by David G. Lowe in 2004. The algorithm shows strong robustness in the scale of image scaling, rotation, transformation, even brightness change and affine transformation. There are four steps in SIFT feature extraction algorithm [11].

1) Extremum detection in scale space

We subsample the images repeatedly so that it can get a series of images of a pyramid. The definition of two-dimensional Gaussian filtering function is,

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{\frac{-(x^2+y^2)}{2\sigma^2}} \quad (2)$$

where σ represents the variance of Gaussian function.

An N×N image I(x, y) can be expressed in different spatial scales, which is named Gaussian Image. The Gaussian Image is obtained by a convolution between an image and Gaussian kernel,

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (3)$$

where σ is called scale space factor. The greater the value of σ is, the smoother the image is. Large-scale corresponds to overview of the image, while small-scale corresponds to details of the image. DoG operator is defined as,

$$D(x, y, \sigma) = [G(x, y, k^{\sigma}) - G(x, y, \sigma)] * I(x, y) \quad (4)$$

In order to detect the local extremum points of D(x, y, σ), it demands a comparison between each point in DoG scale space and 26 points adjacent to its scale and position one by one. If pixel (x, y) is a possible SIFT key point, it must be an extremum point among the ambient 26 neighboring pixels (9 points in the last scale + 8 points in the same scale + 9 points in the next scale). All the local extremum points constitute a SIFT key points alternative set.

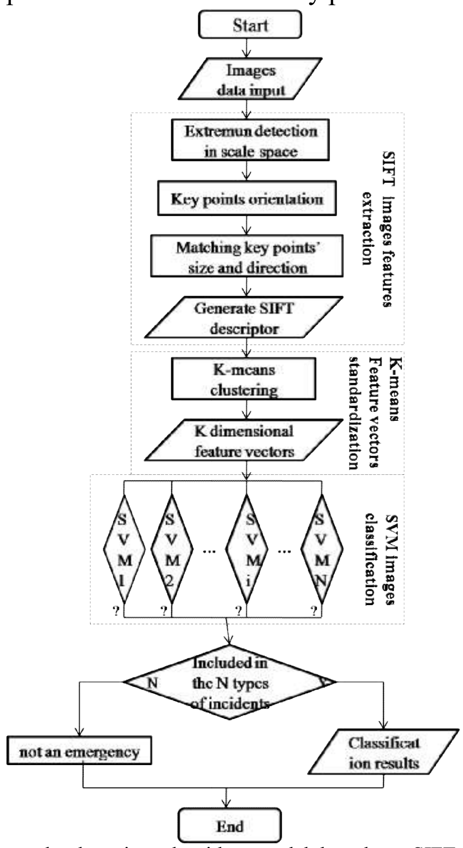

Figure 7. Anomaly detection algorithm model based on SIFT features and SVM classification.

2) Key point orientation

There are another two steps for all key points obtained from extremum detection to confirm its validity: the first step is to inspect an obvious discrepancy among its surrounding pixels, and the second step is to get rid of unstable edge response points (for there is a strong edge response effect for DoG operator).

3) Matching key points' size and direction

For the sake of operators' rotation invariance feature, it determines the main direction with the help of gradient histogram. The module value and direction of gradient at point (x, y) can be calculated as,

$$m(x, y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2} \quad (5)$$

$$\theta(x, y) = \tan^{-1}\frac{L(x,y+1) - L(x,y-1)}{L(x+1,y) - L(x-1,y)} \quad (6)$$

It should take into account each key point's gradient direction in its neighboring window. However, the peak of the histogram represents the neighboring gradient's main direction of the key point, as well as the main direction of the key point itself. We assign a direction parameter for each key point so that the operator has the feature of rotation invariance.

4) Generate SIFT descriptor

In order to guarantee the rotation invariance feature, firstly, the coordinate axis should be rotated to the direction of the key point. We take an 8×8 window centered on a key point, and segment the window into 2 × 2 child windows, then collect the orientation histogram of each child window.

The direction of each child window is decided by its 4 × 4 small blocks with the method above. However, the direction of each key point in the image is determined by 2 × 2 = 4 seed points' directions, and there are 8 directions information for each seed point, therefore there are 4 × 8 = 32 dimensions for each key point.

In the process of actual calculation, a description of 4 × 4 = 16 seed points is generally used for the sake of enhancing the robustness of matching. In this way, the 16 × 8 = 128 dimensional data come into being for each key point, which constitute the 128 dimensional SIFT feature vector.

B. SIFT Features Clustering Based on K-means Algorithm

Each image becomes a set of many SIFT key points after being extracted by SIFT algorithm. Furthermore, each key point equals to a 128 dimensional feature vector, and depicts the feature information of a portion of the objects in the image, such as the borders of an object, image gray change border, etc. However, the number of key points for each image generated by SIFT algorithm is diverse, while it demands an integrated and standardized characteristic form for image tag library applied to image processing in emergency management system [12]. Therefore, we bring a K-means algorithm into use for SIFT features clustering, and standardize the clustering with the Euclidean distance. The distance between SIFT feature vector X and the ith clustering centre is as,

$$D_i = \sqrt{\sum_{j=1}^{128} (x_j - k_{ij})^2} \quad (7)$$

where x_j represents the jth dimension of vector X, and k_{ij} is the jth dimension of the ith clustering center. Multiple iterative calculations of K-means algorithm are used to get the K clustering center, in which the value of K is determined by an overall consideration of multiple tests as well as clustering speed and classification accuracy.

For an image with N SIFT key points, firstly we analyze the distribution of N key points on the K clustering centers so that could bring the corresponding distribution vector feature of this image into being. The specific jth feature distribution vector is calculated as,

$$v_j = \frac{\sum_i^N s_{ij}}{N} \quad (8)$$

where $s_{ij} = \begin{cases} 1, & \text{the ith key point in the jth center} \\ 0, & \text{else} \end{cases}$

In conclusion, the algorithm converts the image with N SIFT key points into a K dimensional feature distribution vector, which represents the classification feature of the image and further becomes the feature vector of SVM algorithm next.

C. Image Classification Based on SVM Classifier

SVM is a dichotomy classifier algorithm preponderant in small-sample set, non-linear and high dimensions identification proposed by Vapnik in 1995 [13]. In the process of concrete realization shown in Figure 8, we divide the procedure into two portions of "Offline images training" and "Online images discrimination."

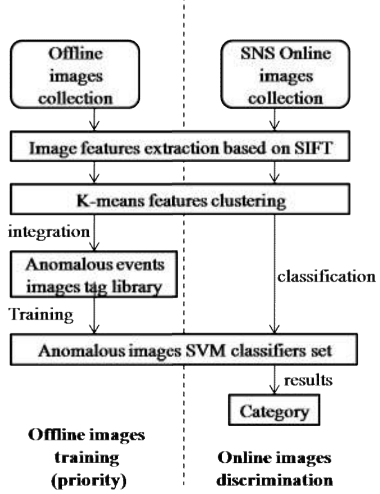

Figure 8. Anomaly detection method of image data based on the network.

For the offline images training part, we collected plenty of images involving bus hijacking related images as well as irrelevant ones, we divided and labeled them manually, then preprocessed the images with SIFT and K-means, and finally trained the SVM classifier with them separately.

Then for the online images discrimination part, we mixed the related and irrelevant images together, after preprocessing of SIFT and K-means, we classified them with the already trained SVM classifier, and made statistic and analysis on the results to evaluate the effect of our algorithm.

Futhermore, the model can be further extended in other scenes. It collects images respectively according to different scene ω in scenes set $\overline{\Omega}$, then trains the corresponding SVM classifier so that it can constitute a more comprehensive emergency anomaly detection model for abundant scenarios.

V. INSTANCE ANALYSIS

In this instance analysis section, we took our proposed emergency decision support architecture into an accurate situation of a tourist bus hijacking incident to prove it more feasible.

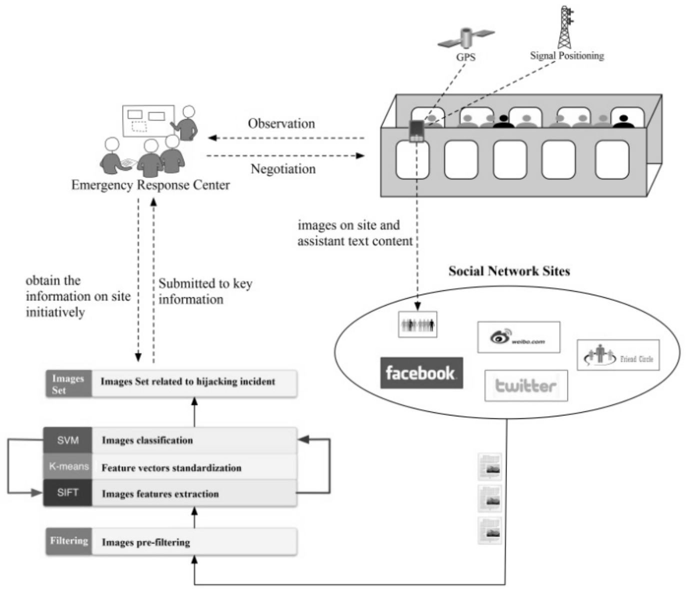

Figure 9. Optimized emergency response process based on access to effective images information.

As is illustrated in Figure 9, tourists inside the bus uploaded the interior circumstance images to twitter or facebook, etc. The real-time emergency management system collected variety of images timely and stored them to the database. When the EDC needed the inner condition images, they logged in the system based on our emergency decision support architecture, and set the specific factor according to the events' situation, finally picked up desirable images after SIFT—K-means—SVM disposal. However, the essential images will be transmitted to EDC and be helpful to the decision.

Moreover, we also made a further experimental verification to our anomaly detection algorithm model to testify its validity.

Firstly, we collected 1058 images related to bus hijacking incident and 3128 ordinary images from news websites, sina microblog, tencent microblog, etc. as the images set. Furthermore, we divided the 1058 related images and 3128 not-related images into training set V1 and testing set V2. To be specific, it concludes 858 related images and 2128 not-related images in the training set V1, while the remaining 200 related and 1000 not-related images in testing set V2 are used to verify the training consequence. The assignment approach is indicated in Tables I.

TABLE I. TRAINING ASSIGNMENT RESULTS OF SVM CLASSIFICATION IMAGES SET FOR BUS HIJACKING IMAGES

	Training set V1	**Testing set V2**	**Total**
Images related to hijacking incident	858	200	1058
Images not related to hijacking incident	2128	1000	3128
Total	2986	1200	4186

Secondly, we used Java program language in Eclipse environment for developing the model in this paper, and modified factors of the existing java package of SIFT feature extraction and K-means clustering algorithm for a better adaption to our experiment. In the process, the standard K dimensional feature distribution vectors are stored in a .txt document after SIFT and K-means processing for image, which is the input of SVM classifier as well.

Thirdly, we adopted the LIBSVM package (a software package in java program language) developed by Professor Zhiren Lin in Taiwan University to carry out training and testing classification in Matlab (a mathematical software). The training and testing classification results are illustrated in Table II.

TABLE II. SVM CLASSIFIER TEST RESULTS FOR BUS HIJACKING IMAGES

SVM classifier	**Actual number**	**Test number**	**Correct test number**
Images related to hijacking incident	200	184	165
Images not related to hijacking incident	1000	1016	808
Total	1200	1200	973

Finally, for the sake of further illustration of SVM classifier effect, we calculate the accuracy rate and recall rate of distinguishing images related to hijacking incident with SVM classifier. The result is shown in Table 3.

TABLE III. DISCRIMINANT EVALUATION RESULT OF HIJACKING INCIDENT IMAGES

	Accuracy rate	**Recall rate**
Images related to hijacking incident	89.7%	82.5%
Images not related to hijacking incident	79.5%	80.8%

In general, the average level of accuracy rate is 60%-85%, while results might be diverse from images qualities. However our tests showed a better result compared with ordinary outcome, the effect of discrimination with our SVM is great, the anomaly detection algorithm model based on SIFT features and SVM classification is feasible and reliable.

VI. CCONCLUSION

With the rapid popularization of internet and mobile internet, it becomes an inevitable essential research direction for optimizing emergency management with fully use of computer technology and massive internet resources. In addition, there are an increasing number of security threat events for public transportations. Therefore, we provided a detailed analysis of these emergencies and discovered the drawback of information access between inside and outside of buses. Based on this, we proposed an emergency decision support architecture for transmitting interior information to the outside of confined bus space effectively, which helped the EDC make more reasonable decisions. Furthermore, we proposed an anomaly detection algorithm model aiming at hijacking incident images for implementing the core portion of the architecture, and solved the difficulty of identifying specific emergency related images automatically by computer science. Ultimately, we made an optimized solution in the use of emergency decision support architecture we proposed for specific instance efficiently, and additionally made an experiment for verifying the anomaly detection algorithm model, which gets an ideal result and confirms the feasibility of the model.

However, the solution and algorithm model presented in this paper can be further extended in other emergent scenarios similar to bus hijacking incidents. Such as the hijacking incidents in kindergartens and elementary schools, partial or total collapse of residential building caused by gas explosion or earthquake, etc.

REFERENCES

[1] W. Fan, “Advisement and suggestion to scientific problems of emergency management for public incidents,” Bulletin of National Natural Science Foundation of China, 2007, 21(2):71-76.

[2] Y. Jiang, Z. Fan, and M. Su, “Study on the dynamic method for emergency, decision,” Chinese Journal of Management Science, 2011, 19(5): 104-108.

[3] M. Grathwohl, F. D. B. D. Beuvron, and F. Rousselot, “A new application for description logics: disaster management,” Proc. Int Workshop Description Logics, Linkoping, 1999.

[4] J. H. Canós, G. Alonso, and J. Jaén, “A multimedia approach to the efficient implementation and use of emergency plans,” IEEE Multimedia, 2004, 11(3):106-110.

[5] D. H. Liu, and Y. Su, “Scenario optimal model of social mediation, information warning and police deploy in mass incident,” Systems Engineering-Theory & Practice, 34(10):2609-2618.

[6] D. Mendonca, G. E. G. Beroggi, and W A Wallace, “Decision support for improvisation during emergency response operations,” Int Journal Emergency Management, 2001, 1(1):30-38.

[7] L. Zhang, T. Chen, and J. Huang, “Emergency network model and algorithm based on min-max regret robust optimization,” Chinese Journal of Management Science, 2014, 7:131-139.

[8] W. Fu, C. Qin, and J. Liu, “Matching and location of image object based on SIFT algorithm,” Chinese Journal of Scientific Instrument, 2011, 32(1):163-169.

[9] J. A. Starzyk, and H. He, “Spatio–temporal memories for machine learning: A long-term memory organization,” IEEE Trans Neural Networks, 2009, 20(5):768-780.

[10] R. Wu, S. Li, and F. Zou, “In age retrieval based on SIFT features,” Application Research of Computers, 2008, 25(2):478-481.

[11] D. G. Lowe, “Distinctive image features from scale-invariant keypoints,” Int Journal of Computer Vision, 2004, 60(2): 91-110.

[12] S. Zhang, and Z. Zhan, “Research on classification system based on SIFT features and support vector machine,” Computer Knowledge & Technology, 2012, 8(17) : 4277-4280:

[13] G. Guo, S. Z. Li, and K. L. Chan, “Support vector machines for face recognition,” Image & Vision Computing, 2001, 19(9): 631-638.