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A STUDY ON OPTIMIZATION METHODS OF X-RAY MACHINE RECOGNITION FOR AVIATION SECURITY SYSTEM

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Abstract- ***Traditional X-ray machine image recognition methods for airport security system have difficulties in recognition and are prone to result in recognition errors due to the impact of placing angle, density and volume of detected objects. This paper accurately describes the image features of X-ray machine visual image, carries out SVM classification after a visual dictionary is formed and enhances the accuracy of image discrimination by means of robust acceleration. The experimental results indicate that both identification efficiency and accuracy are improved to some extent.***

Index terms: Image features visual dictionary robust acceleration optimization.

I. INTRODUCTION

Since the operators of airport security system tend to make mistakes in the discrimination of X-ray machine images and thus lead to insecurity, the accurate discrimination of the images of dangerous items are of paramount significance to ensure the safety of aviation. The images of dangerous items on the computer screen are different owing to their different volume, density and position, so it is highly difficult to accurately identify the dangerous items.

For instance: A pistol is placed in the same case, but compared with image B, image A and C, due to different angles, are difficult for operators to make an accurate judgment with reference to figure 1.

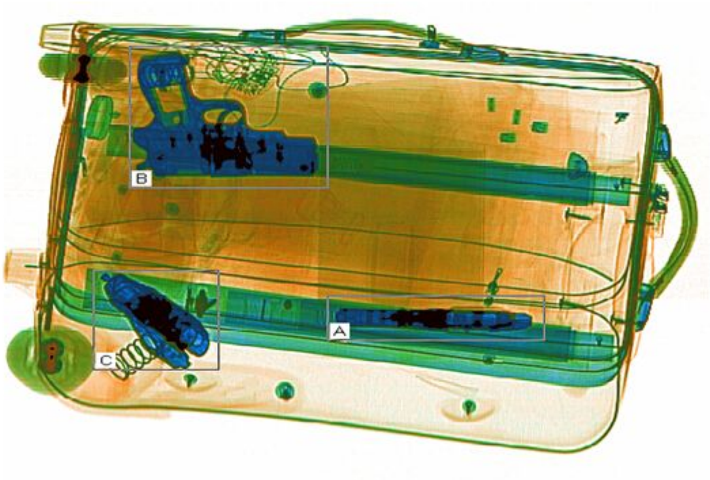

Figure 1: X-ray machine image of the same pistol in the same case from three different placing angles

II. LITERATURE REVIEW

In the paper of Maryam Jaberi, traditional SIFT feature extraction method of image feature was employed [1]. M.G. Ponomarev put forward the SIFT method for extraction of X-ray machine image feature of metal parts [2]. In the paper of Ashnil Kumar and Jinman Kim, robust acceleration method was proposed to improve SIFT [3]. Qizhi Xu, Yan Zhang and Bo Li et al. significantly enhanced the accuracy of image matching through image normalization and image classification techniques [4]. Jang Seo and Hee Jung Park presented SIFT method for improving feature extraction of two-dimensional space of an image [5]. Melloni, P.

Bestagini et al. believed that SIFT and SURF methods for extraction of image feature have limitations, so SVM method is proposed for classification [6].

The research purpose of this paper is to accelerate and optimize images of X-ray machine and improve the check efficiency and quality of operators.

Ideas of this paper: Image feature extraction of dangerous items is first conducted; SIFT method is used to extract key points in the images; then SURF method is adopted to carry out robust acceleration and optimization for image recognition and thus to establish a visual dictionary of images of dangerous items; finally SVM is utilized for image classification.

III. RESEARCH METHODS

3.1 Image feature extraction

Extraction of image feature [7] refers to the extraction of image information using a computer in order to determine whether the points of each image belong to an image feature. Results of feature extraction are to divide points on the image into different subsets which tend to belong to isolated points, continuous curves or continuous areas.

The extraction process of feature points of BoW model refers to (Figure 2)

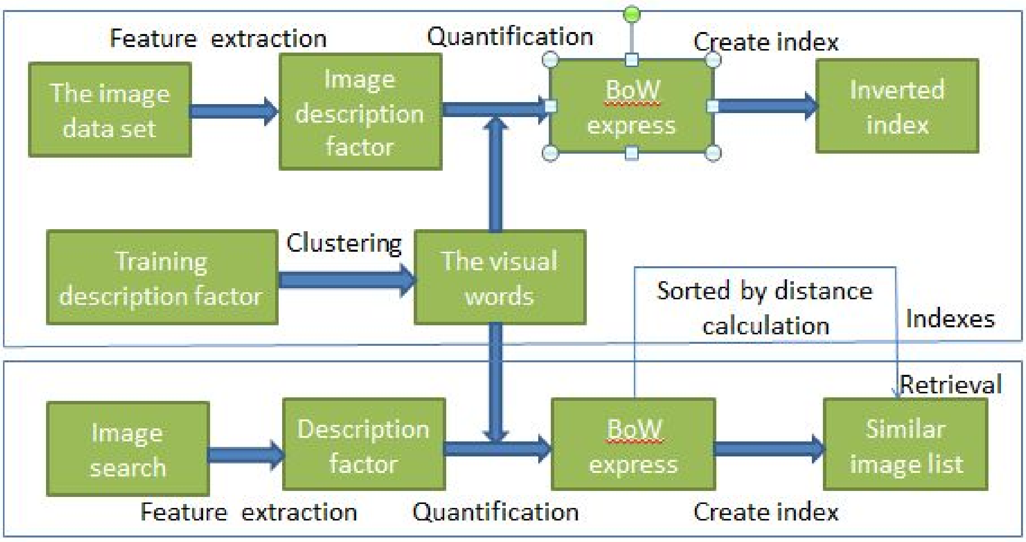

Figure 2: The framework of bow model retrieval

3.2 BoW model

BoW model, also known as Bag of Features algorithm [8], is a simple hypothesis in natural language processing and information retrieval. In BoW model, words are seen as a collection of unordered vocabulary and the order of grammar or even words is ignored.

BoW bank of X-ray machine images established in this paper maps the two-dimensional image information of these words into a visual collection of keywords and carries out image feature-based X-ray machine image extraction of dangerous items including pistols and cutting tools (see Figure 3 and Figure 4). We conducted image feature-based X-ray machine image extraction of dangerous items including pistols and knives (see Figure 3 and Figure 4).

Figure 3: The pistol in the visual words features of X- ray machine screen

Figure 4: The sword in the visual words features of X- ray machine screen

3.3 Steps of Bag of words algorithm

1. The extraction of image block. This process is to input image sampling which could be dense or sparse. Its purpose is to divide the image into small image blocks to facilitate computer processing.

2. Image block representation. This process of image block representation as the feature vector has some characteristics, such as color histogram or local features.

3. Generated codebook. The feature extraction before a process is of large amounts, but there is a lot of redundant information. So this process can be seen as a step to deal with feature redundancy by using the clustering process in other codebook generation algorithm to code in the past.

4. Feature encoding. The process of image features using codebook fitting code length is equal to the size of the codebook, and the code value is usually equal to the amplitude of the corresponding fitting code book (or factor). Linear fitting method of feature code can use the traditional one, but in recent years has been proved to obtain sparse coding method for the discriminative coding and better robustness to image classification.

5. Pool features. This process is a process to get the further joint of corresponding coding composed of a new feature. This process can be combined by average pooling, the maximum pooling and other ways.

We use the bag of words model generation process to represent the characteristics of the visual vocabulary as is shown in Figure 5.

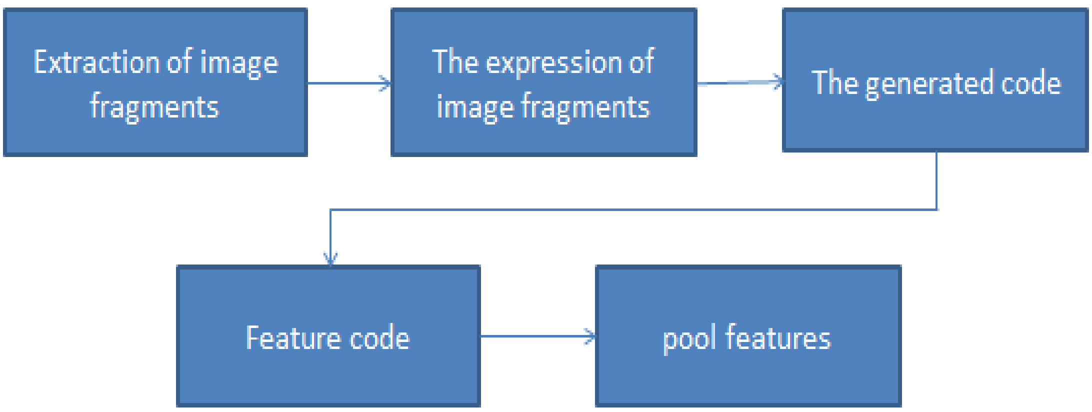

Figure 5: The bag of words algorithm steps

3.4 Visual Dictionary

Visual Dictionary [9] is an image modeling approach in areas such as image classification and retrieval. This approach is derived from dictionary expression in the area of document analysis, where document is described as the vector of keyword frequency in the dictionary. Based on image representation method of visual dictionary, we consider the collected images as a collection of a series of unordered local features and only emphasize the apparent description information of each local visual feature while ignoring the spatial relationship between local visual features, thus providing an effective expression method for appearance scene model for closed-loop visual detection. Visual dictionary for cutting tools in the image bank of X- ray machine are shown in Figure 6.

Figure 6: Various cutting tools image combination in the X machine on the screen of visual words

The visual dictionary is constructed for an image, the visual features of each sub region to each word channel visual dictionary of projection and the distribution characteristics of vocabulary in each feature of the calculation area. Given a V dimension:

$P=\{P_1, p_2, \cdots, p_v\}$. For a feature descriptor for $p(x)$ of the definition of super pixels x, the distribution of p in the dictionary on the characteristics of is $\theta(x)=(\theta_1(x), \cdots, \theta_v(x))^T$, $\theta(x)$ is a vector of v dimension, draw:

$$\theta_i(x)=c(x)\mathrm{e}^{-\frac{\|p(x)-p_i\|_2^2}{2\zeta^2}} \tag{1}$$

In Type (1), ζ is the distance between the visual vocabulary of the maximum value, $c(x)$ is the normalized factor, makes the $\sum_{i=1}^{v}\theta_i=1$

According to equation (1) statistics for frequency information of each image visual word, the image of the Bag of Words distribution histogram is regarded as another feature of image.

Extraction of visual bag of words model from the training image set image low-level features requires the use of an unsupervised algorithm. For instance, K means clustering algorithm and the clustering number is given the clustering center of these low level features.

Given a set of observations: The sequence of $(\times 1, \times 2, \ldots, \times n)$. K means clustering is divided the n observations to the K sequence. $S = \{s_1, s_2, \cdots, s_k\}$, $(k < n)$, See formula (2), where μ_1 is the mean of s_1 .

$$\arg\min \sum_{i=1}^{k} \sum_{x_{j\in} \in s_i} \left\| x_j - \mu_i \right\| \tag{2}$$

3.5 SIFT algorithm

Scale-invariant feature transform (SIFT) is a computer vision algorithm used for the detection and description of local features of the images. It searches for extreme points at the spatial scale and extracts invariants of the image's position, scale and rotation. The algorithm was introduced by David Lowe in 1999 and refined and summarized in 2004 [10].

SIFT algorithm matches the features of the same scenes in two images and establishes correspondence between them.

A brief summary of SIFT's idea is as follows: Scale space representation of images is first set up; then the feature points of the image's scale space is detected and the main direction of the feature points is defined; finally feature vector description factors are generated.

3.6 SURF (Speeded-up Robust Feature) algorithm

3.6.1 Principle of SURF

The principle of SURF algorithm is to detect feature points through fast Hessian detectors and to make quick calculations on the basis of integral image. Main direction and description factor of each feature point are determined through calculation and wavelet transform; then matching between feature points of images is achieved through the Euclidean distance between description vectors. Not only can this algorithm meet the requirement of accurate matching, but owns the advantage of small-amount and fast calculation.

3.6.2 SURF algorithm flow

Three key steps of SURF algorithm are as follows:

1. Image convolution is completed with integral image;
2. Eigenvalues are detected with Hessian matrix;

3. Use distribution-based descriptors (local information)

This figure we use to achieve this flow is as follows (see Figure 7).

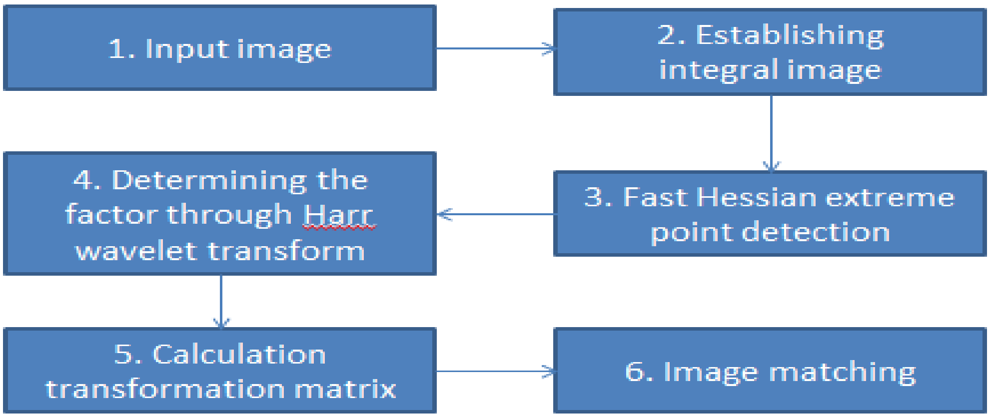

Figure 7: The basic framework of SURF

3.7 Support Vector Machine (SVM)

3.7.1 Classification principle of SVM

Support Vector Machine (SVM) proposed by Vapnik takes training errors as the constraint conditions for optimization problems and the minimization of confidence interval value as optimization objective. That is, SVM is a learning method based on minimization criterion for structural risk, so it can more accurately describe the image features and can resist the influence of changeable position and background information.

The core idea of SVM takes structural risk minimization as its principle, makes non-linearly separable data linear and separable by mapping the data of input space into high-dimensional feature space through kernel function, and allows the distance of the above two kinds of data from this space to be largest through constructing low VC-dimension optimal classification hyper-plane in high-dimensional phase space. The purpose of SVM algorithm is, in fact, to search the optimal classification hyper-plane that can minimize the structural risk.

With regard to the two kinds of classification, training sample sets are given: $T=\{(x_1,y_1),x_{2,}y_2,\cdots,(x_n,y_n)\}$, where $x_i \in X = R^n$ is sample vector, $y_i \in Y=\{+1,-1\}$ is category number and n is the number of samples. It is assumed a mapping $\varphi(x_i)$ exists. When data x_i is mapped from the original feature space X to the high-dimensional feature space F and slack variables ξ_i are introduced, then the original problem of SVM can be expressed as follows:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \quad \text{s.t.}\{^{y_i(w\bullet\varphi(x_i)+b)\le 1-\xi}_{\xi_i\ge 0}\ ,\ i=1,2,\cdots,n \tag{3}$$

The dual problem of original problems can be deduced through Lagrange function method:

$$\max -\frac{1}{2}\sum_{i=1}^{n}\sum_{i=1}^{n}\alpha_i\alpha_j y_i y_j k(x_i,x_j)+\sum_{i=1}^{n}\alpha_i \ \text{s.t.}\begin{cases}\sum_{i=1}^{n}\alpha_i y_i = 0\\ 0\le\alpha_i\le C\end{cases},\quad i=1,2,\cdots,n \tag{4}$$

Where: $k(x_i,x_j)$ refers to positive kernel function of Mercer theorem, polynomial kernel function (POLA), Gaussian radial basis function (GRBF), Sigmoid kernel function, etc. [11].

The classification process of SVM is indicated in (Figure 8).

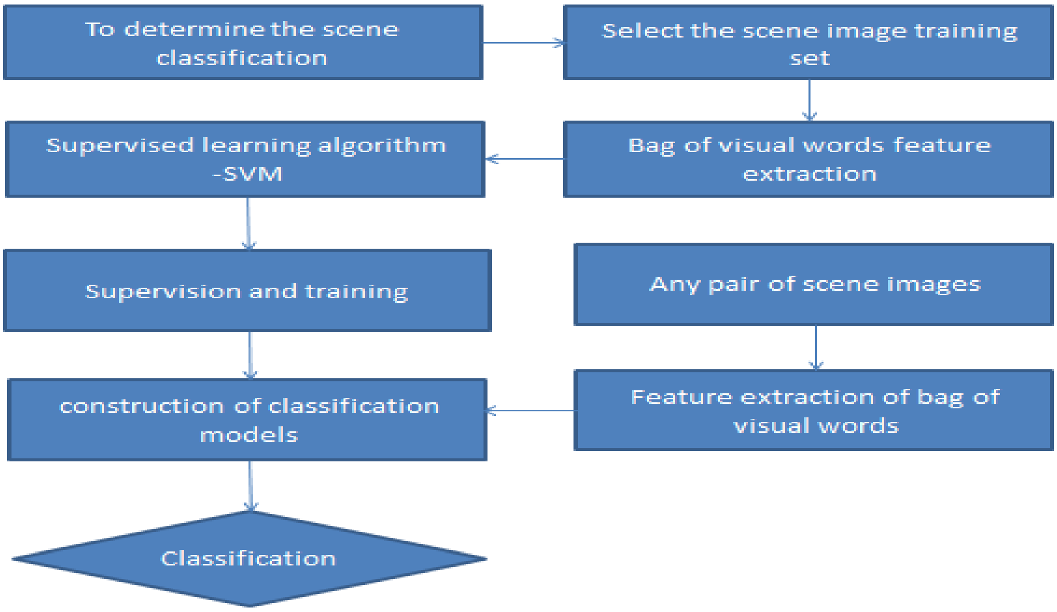

Figure 8: SVM Image classification system based on the bag of words model

3.7.2 Kernel function

Kernel function can be an alternative to dot product algorithm in classification and regression problems, solving them by mapping the problems into higher dimensions. The function is thus not only a key to Support Vector Machines, but also widely applied in other realms.

With the help of the machine learning method, the learning-based method learns the congruent relationships between two-dimensional observations and three-dimensional attitudes from the prepared training samples of different attitudes. The decision rules or regression function thus acquired are then applied to the samples, whose results are used in the attitude estimation of the samples later. The learning-based method generally adopts holistic observational characteristics, so there is no need to detect or identify the subjects' partial characteristics, hence the method's greater robustness. The method is deficient, however, in obtaining the dense samplings needed by the continuous estimation in higher dimensions, thus providing no guarantees for the precision and continuousness of the attitude estimation.

3.7.3 Multi-kernel learning method

Support Vector Machines have powerful capabilities of data calculation and problem analysis. The key to these capabilities lie in the use of the relatively easy kernel functions in the calculations, thus avoiding inner product algorithm within the characteristics space, as well as the space design. The application of kernel functions makes it easy to extend the application of linear SVM to nonlinear SVM.

In the early stages of kernel method's development, machine learning was usually carried out by unitary kernel function, namely using only one kernel function in the learning process. Since SVM performance was greatly affected by kernel functions and parameters, it varied greatly with the different points of application and the change of kernel functions. Moreover, unitary kernel method was proved not ideal in handling the samples, when the sample characteristics contained heterogeneous information, the sample size was huge, the multi-dimensional data was irregular, or when the multi-dimensional sample distributed unevenly.

With the above deficiencies in mind, we adopt a combined kernel method, i.e. multiple kernel learning (MKL). Multiple kernel learning refers to the use of multiple kernel functions in the learning process.

The success of Support Vector Machine (SVM) has led to the rapid development of kernel methods, which have then permeated themselves into many fields of machine learning little by little. With SVM as its key algorithm, Kernel Method (KM) is a new machine learning method that combines statistical theories with kernel technologies. KM is what bridges linearity and non-linearity. By introducing kernel functions into the scene ingeniously, the method effectively avoids dimensional disasters without increasing the computing complexity.

MKL, on the other hand, is a more flexible kernel learning method, the theoretical and practical applications of which in recent years have proved its better performance over that of the unitary kernel method. The most important issue in MKL is how to obtain the characteristics space for the kernel combination, namely obtaining weight coefficients through the optimization of algorithms. This research mainly makes use of a combined kernel method featuring the weighted sum method, also called Multiple Kernel SVM (MKSVM), to make the classifications. The results are then compared with those obtained from unitary kernel SVM classifiers that are based on radial basis kernel functions and polynomial kernel functions. It is shown that MKSVM has a higher classification precision rate.

In the learning process, there are two kernel combination strategies: one is comprised of unitary kernel function and diverse parameters; the other of multiple kernel functions and diverse parameters. Basis kernel function adopts essentially RBF kernel function and POLY kernel function, as is expressed in the following:

$$k(x,) = \exp(-\|x-z\|^2 / 2\sigma^2) \tag{5}$$

$$k(x,z) = (x \cdot z + 1)^p \tag{6}$$

In the expression, σ is the Gaussian kernel parameter, while p is the polynomial coefficient.

The SVM learning results can be expressed by a linear combination:

$$f(x) = \mathrm{sign}[\sum_{i=1}^{n} \alpha_i y_i k(x_i, x) + b] \tag{7}$$

$$x_i(i = 1, 2, \cdots n),\ y_i = \{\pm 1\}$$

In expression (7), α_i is the Lagrange multiplier, b is the classification threshold value, $x_i(i = 1, 2, \cdots n)$ refers to the training sample, $y_i = \{\pm 1\}$ the training category, and n is the sample point.

MKL solves the typical problems within the more complex heterogeneous datasets, by handling them into convex combinations through multiple kernel functions, so that the problems are transformed into traditional kernel functions.

$$k(x_{i,} x_j) = \sum_{k=1}^{K} \beta_k k_k(x_i, x_j) \tag{8}$$

$$\beta_k \le 0\ ,\quad \sum_{k=1}^{K} \beta_k = 1$$

In expression (8, K is the number of sub kernel functions, β refers to the weight values of sub kernel functions, and $k(x_{i,} x_j)$ represents the sub kernel function. Many kernel functions and parameters can be chosen as the sub kernel function, transforming the various sub kernel functions into a multiple kernel function. Even if the sub kernel function is not optimal, the optimum value β can be obtained through learning and training, so is a relatively ideal classification. It is thus clear that the combination of multiple kernel functions, compared with unitary kernel function, can be popularized more easily and boasts a higher robustness.

MKSVM Classification:

According to Mercer's theorem and features, if K_1 and K_2 are kernels in the expression $X \times X$, $X \in \mathrm{R}^n$. The following function is also a kind of kernel function:

$$1)\ K(x,z) = K_1(x,z) + K_2(x,z) \tag{9}$$

$$2)\ K(x,z) = aK_1(x,k) \tag{10}$$

If the expression $X \times X$ has such a kernel function M in it, it can be inferred from 1) and 2) that the following function is also a kernel function:

$$K(x,z) = \sum_{m=1}^{M} d_m K_m(x,z), d_m \leq 0, \sum_{m=1}^{M} d_m = 1 \tag{11}$$

Expression (11) is the most generic of all combinations of multiple kernel functions, as well as a weighting linear convex combination of the basis functions. In the expression, K_m represents the basis kernel function, M refers to the number of basis kernel functions, and d_m is the weight coefficient.

The SMKL problem can be expressed as the following:

$$\min_{w_m,b,\xi,d} \frac{1}{2}\sum_{m=1}^{M}\frac{1}{d_m}\|w_m\|_{H_m}^2 + C\sum_{i=1}^{n}\xi_i$$

$$\text{s.t.}\begin{cases} y_i(\sum_{m=1}^{M} w_m \bullet \varphi(x_{i)} + b) \geq 1-\xi_i \\ \xi \leq 0 & i=1,2,\cdots,n \\ \sum_{m=1}^{M} d_m = 1, d_m \geq 0 \end{cases} \tag{12}$$

We now rephrase expression (12) into an optimization problem with d_m as its variable:

$$\begin{cases} \min_d J(d) \\ \text{s.t.} \sum_{m=1}^{M} d_m = 1, d_m \geq 0 \end{cases} \tag{13}$$

$$J(d) = \begin{cases} \min_{w_m,b,\xi} \frac{1}{2}\sum_{m=1}^{M}\frac{1}{d}\|w_m\|_{H_m}^2 + C\sum_{i=1}^{n}\xi_i \\ \text{s.t. } y_i(\sum_{m=1}^{M} w_m \bullet \varphi(x_i) + b) \geq 1-\xi_i \ , \ i=1,2,\cdots,n \\ \xi_i \geq 0 \end{cases} \tag{14}$$

Since the problem in expression (14) is a standard SVM problem, as well as an optimization problem containing the variable d_m , we can now transform $J(d)$ into a maximum-minimum problem:

$$L(w_m,b,\xi,\alpha,v) = \frac{1}{2}\sum_{m=1}^{M}\frac{1}{d}\|w_m\|_{H_m}^2 + C\sum_{i=1}^{n}\xi_i + \sum_{i=1}^{n}\alpha_i(1-\xi_i - y_i(\sum_{i=1}^{n} w_m \bullet \varphi_m(x_i)+b)) + \sum_{i=1}^{n} v_i\xi_i \tag{15}$$

In the expression x_i and v_i are Lagrange coefficients. We now calculate the differentials of w_m, b, and ξ in expression (15):

$$\begin{cases} \nabla_{w_m} L\left(w_m, b, \xi, d, \alpha, v, \eta\right) = \frac{1}{d_m} w_m - \sum_{i=1}^{n} \alpha_i y_i \varphi_m\left(x_i\right) = 0 \\ \sum_{i=1}^{n} \alpha_i y_i \varphi_m\left(x_i\right) = 0 \\ \nabla_b L\left(w_m, b, \xi, d, \alpha, v, \eta\right) = \sum_{i=1}^{n} x_i y_i = 0 \\ \nabla_\xi L\left(w_m, b, \xi, d, \alpha, v, \eta\right) = C - x_i - v_i = 0 \end{cases} \tag{16}$$

Substitute (15) into (16), and the result is:

$$i = 1, 2, \cdots, n \tag{17}$$

Expression (17), containing the kernel combination $k(x_i, \mathrm{y}_i) = \sum_{m=1}^{M} d_m k_m\left(x_i x_j\right)$, is the dual form of the standard SVM problem. If α^* is one of expression (9)'s optimum solutions, for the given d_m, there deduces

$$J(d) = -\frac{1}{2}\sum_{j=1}^{n}\sum_{i=1}^{n} \alpha_i^* \alpha_j^* y_i y_j \sum_{m=1}^{M} d_m k_m(x_i x_j) + \sum_{i=1}^{n} \alpha_i^* \tag{18}$$

If expression (18)'s optimum solution α^* has nothing to do with d_m, the differential calculus of $J(d)$ and d_m is the following:

$$\frac{\partial J(d_m)}{\partial d_m} = -\frac{1}{2}\sum_{j=1}^{n}\sum_{i=1}^{n} \alpha_i^* \alpha_j^* y_i y_j k_m(x_i x_j) \tag{19}$$

We can infer that expression (25) is the grad of the objective function $J(d)$. If every basis kernel function satisfies Mercer's theorem's positive definite kernel requirements, it can be inferred that $J(d)$ is a strictly convex optimization problem, which can also be differentiated. After calculating $J(d)$'s grad, update the values that meet the constraints of d based on the grads' descent direction:

$$d_m^l + \gamma_l D_l \rightarrow d_m^{l+1} \tag{20}$$

In expression (20), γ_l represents the updated step length. We can calculate D_l, which is the grads' descent direction, by uni-dimensional linear search.

We can sum up the MKSVM classification algorithm as the following:

Step 1. Set the initial value of d_m : $d_m^1 = \frac{1}{M}$, $(m = 1, 2, \cdots, M)$. M refers generally to the number of kernel functions.

Step 2. In the t-th iteration, use expression (1)'s kernel combination $k(x_i, y_i)$, together with the calculation method of standard SVM, to calculate $J(d)$.

Step 3.Calculate grads and grads direction D_l and the optimal step length γ_l by expression (5).

Step 4. Update the value of d_m^{l+1} and set up new combined kernel functions through expression (6).

Step 5. Decide if the conditions to stop the iteration have been fulfilled. If not, repeat step 2 to step 4, until the conditions are fulfilled.

Conditions to stop the iteration include duality gap (GP), KKT condition, as well as when Δ_d has reached the threshold value and the maximum iteration number.

The expression of DG is:

$$\max_m \sum_{j=1}^{n}\sum_{i=1}^{n}\alpha_i^*\alpha_j^* y_i y_j K_m(x_i x_j) - \sum_{j=1}^{n}\sum_{i=1}^{n}\alpha_i^*\alpha_j^* y_i y_j \sum_{m=1}^{M} d_m^* K_m(x_i x_j) \le \varepsilon \quad (21)$$

In expression (21), ε refers to the threshold value.

3.7.4 MKSVM Classification Problems

It is known that the multiple-class classification problems are dealt with by establishing high dimensional classification platforms through the combination of two classifiers. The commonly used methods are one-against-all method (OAA) and one-against-one method (OAO). If there are k classes of data, OAA method needs to train k classifiers, while OAO method needs $k(k-1)/2$ classifiers. The MKSVM multi-class classification problems can also be solved by the two classifiers separately, the difference being that MKSVM defines another objective function $J(d)$, which can be obtained by summing every value of the objective functions within the two classifiers:

$$J(d) = \sum_{k\in K} J_K(d) \quad (22)$$

In the expression, K represents the set of the two classifiers, and $J_k(d)$ refers to the ordinal number k of the value of the objective functions within the two classifiers. If the objective functions have been updated in the algorithm of the multiple kernel SVM classifier, the grads of $J(d)$ are:

$$\frac{\delta J}{\delta d_m} = -\frac{1}{2}\sum_{k\in K}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_{i,k}^*\alpha_{j,k}^* y_i y_j K_m\left(x_i, x_j\right) \quad (23)$$

In the expression, $\alpha^*_{i,k}\alpha^*_{j,k}$ represents the Lagrange coefficient contained in the k decision function containing $j(i)$ samples.

We can classify SVM supervised vision package based on the characteristics are summarized as follows as shown in Figure 9.

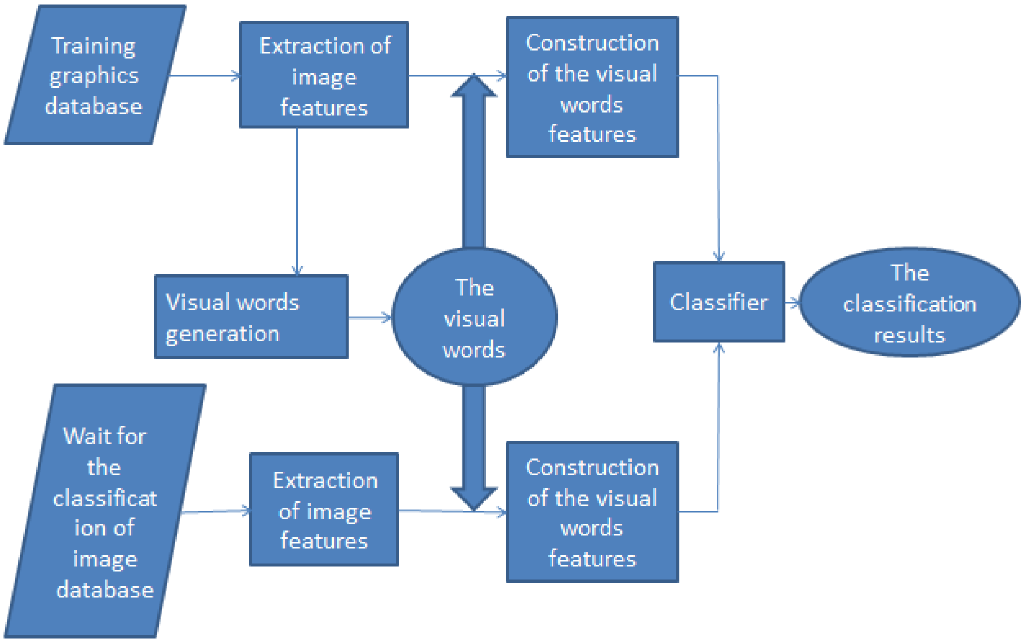

Figure 9: Classification of supervised training framework based on the feature of bag of visual words

3.7.5 SVM classification of visual model for X-ray machine images

Since SURF algorithm is utilized to accelerate the identification of images of dangerous items by X- ray machine and SVM classification method is also used, detection and matching time and performance, compared with traditional methods, are considerably improved, with shortened time of the whole matching process and relatively accurate calculation results. This process is indicated in Figure 10.

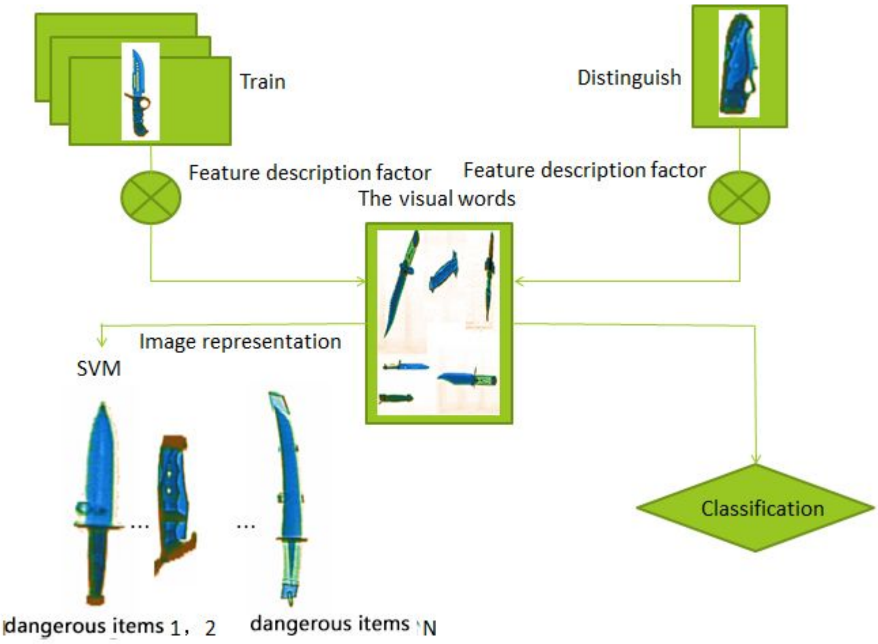

Figure 10: The basic classification of dangerous items in the bag of words model of security

IV. EXPERIMENTAL RESULTS AND ANALYSIS

An experienced operator at a certain hub airport in South China was invited. 15 kinds of dangerous items were selected and placed in accordance with 5 different angles when passing the conveyor belt of the X- ray machine, which was designed to test his identification results of the images of dangerous items. Subsequently, he was offered one-month training in image classification. In the test after the training, his identification results of the 5 kinds of dangerous items were enhanced to a various degree.

The vertical axis in Figure 11 represents the identification results of the images of the 15 kinds of dangerous items before and after training. Percentile system is adopted with a full mark of 100. The horizontal axis indicates the comparison of discrimination results of X-ray machine images of 15 different dangerous items in six different angles. It can be observed that the difficulty of image discrimination increases.

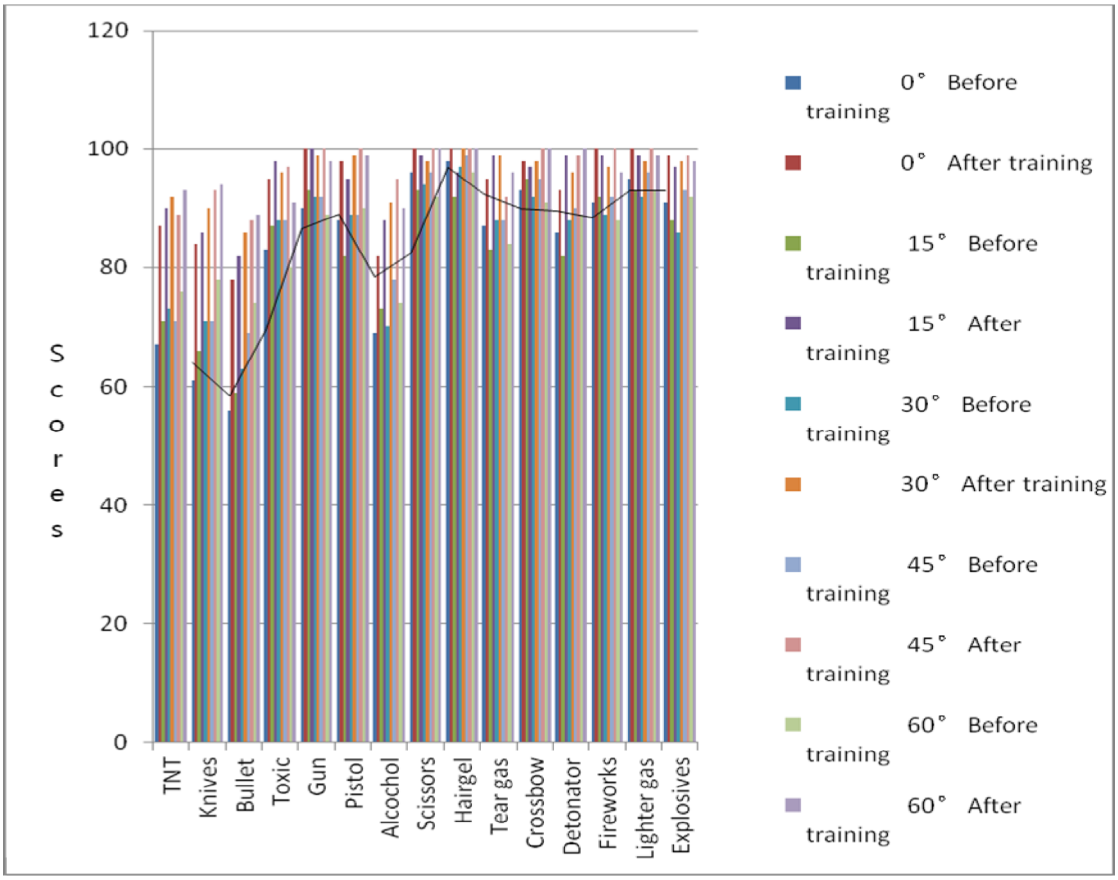

Figure 11: Result comparison graph of operators before and after training

We employ ROC curve to test the identification results of dangerous items image before and after training [12]. ROC curve reflects the curves which are characterized by sensitivity and specificity and dynamically change with the changes in determination values, so it can make objective and accurate judgment of the image discrimination level of X- ray machine and therefore make the image training of X-ray machine more scientific. In this paper, DPS statistical software [13, 14] is used to analyze the training results and thus obtain ROC curve in Figure 12. In Figure 12, the solid line represents the theoretical value, whereas the dotted line suggests 95% confidence interval. The area under ROC curve can be seen to be 0.801, suggesting that the trained operator achieved relatively satisfactory results of image recognition.

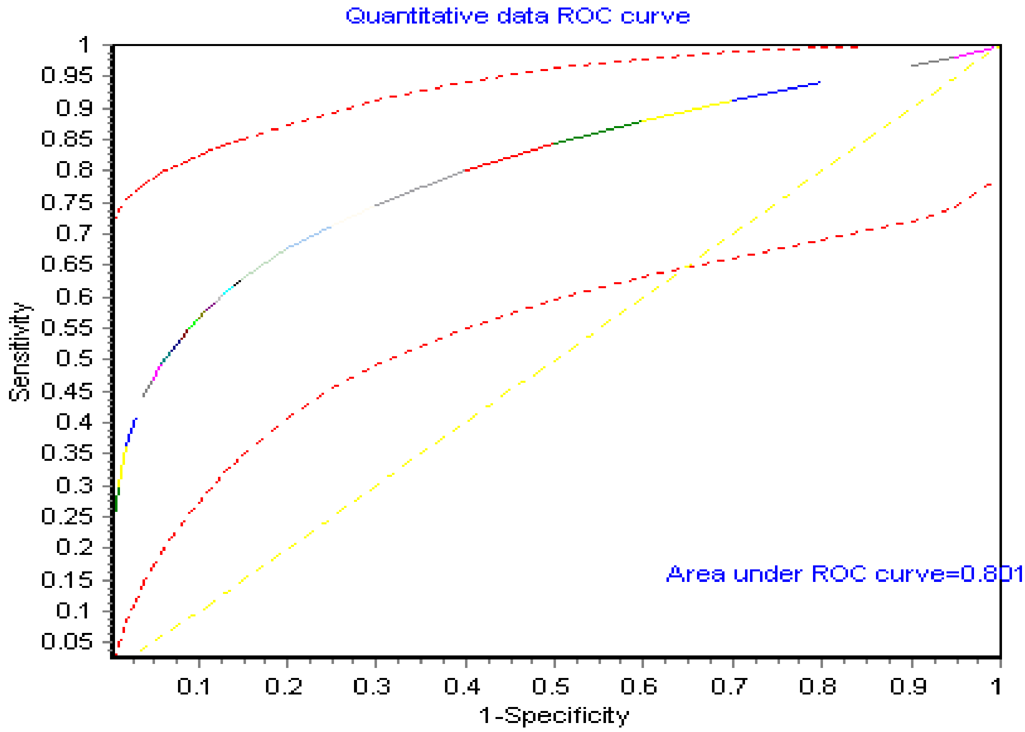

Figure 12: ROC curve of image recognition level of the operator

V. CONCLUSION

This paper makes improvement in BoW model for X-ray machine images and conducts summarization of visual dictionary for image features from different angles; also, it perfectly combines classified visual words with training of operators and carries out targeted training. According to the experiment, the image recognition level of the operator after training is enhanced.

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