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Research Article

Applying SGD Optimization Algorithm Method for Detecting and Localizing of Concealed Objects in Passive Millimeter-Wave Images

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Abstract: Millimeter waves have salient characteristics such as penetration through fabric fibers. These waves can be used to generate passive millimeter-wave images (PMMWIs) for detecting and localizing concealed objects under clothing. The obtained images have important applications in security systems and treat detection. These systems are installed in places such as airports, warehouses, and places that require high security. Passive millimeter-wave images are generated using passive scanners. The main challenges in these images are their incomprehensibility and low signal-to-noise ratio ant this avoids extracting good features from the images and reduces the accuracy of detecting and localizing concealed objects in the image. In this study, SGD Optimization Algorithm Method was used for detection and localizing after selecting highly ambiguous sample images. According to simulation results, our proposed method improves the classification process significantly.

Keywords: Treat Detection, Passive Millimeter-Wave Images, Passive Millimeter-Wave Imaging, Reduced stochastic gradient descent Algorithm

1. Introduction

Detecting concealed targets under the cloth by people is vital for public security. Millimeter-wave image systems can be used for imaging the concealed target regardless of privacy through material penetration except for water and metal [1-3].

Different from active modes, a millimeter sensor usually relies on its strong permeability and the targets can be detected using a passive millimeter imaging system. This makes fewer damages to human health and more fitted for security applications in places such as airports, metro stations, railway stations, conference locations, etc. [4-6].

However, some of the factors affecting the quality of image, shape, and size of concealed objects challenge this detection.

Several image processing techniques such as image elimination, image combination, classification, object detection have been developed and applied for PMMW in recent decades. However, imaging environment and hardware limitations usually lead to low spatial resolution and contrast with PMMW images. In addition, the information content of a single framework is less than smuggling and contains a lot of noise, so it is essential to obtain reliable and effective results by directly detecting smuggled goods per frame of the image. The above methods for processing PMMW data are mainly used for refinement and threshold segmentation. The edge detection to detect concealed objects of sequential images indicated their specific processing capacity to determine image sequencing. However, based on single-frame processing, most of these methods have two weaknesses.

The first is that with the increase in passenger flow application scenarios, the data processing speed is much slower to meet the requirements of target identification and real-time detection. The second is that object alignment extraction is not accurate enough which leads to ambiguity and the need for more calculations and identification costs [5].

For different properties of these objects, unfortunately, the quality of PMMW images is very poor [2]

As mentioned earlier, the quality of PMMW images is low and their resolution is low too; therefore, various preprocessing operations are used to increase the quality of PMMW images and reduce the effect of noise on the detection and localizing process. These operations include image smoothing, contrast enhancement, and more. Various filters are used to improve image quality. Two obvious examples of these filters are the averaging and median filters. Applying these filters to the image increases the signal-to-noise ratio, as well as increasing the image contrast, and finally increases the accuracy of detection operations. Researchers split the images into smaller pieces called patches to speed up the detection process. Then, image processing and detection operations are done on each of these pieces. Patches are always selected in different depending on the size of images. Because of the small size of risk and multiple risks in image in treat detection in an image thumbnail image using the Patch used blocks. Another point concerned by researchers in this field is to use of datasets that provide comprehensive, multiple, and highly diverse images. Despite the various potentials for security applications in this field, this field has not been concerned by the artificial intelligence community due to the lack of a comprehensive and complete database.

In this field, we will examine the work [1] where a comprehensive and different dataset is claimed and is the newest one in the literature.

Feature extraction through image patches is an important process in this field which means the detection process and provides required data for detection operation input. All the classifications used in this work need feeding through feature vectors. The pixel values that make up each feature vector are the same image patches that are divided into different components, and the local spatial information is evaluated and interpreted according to the degree of dependence between these components. The criteria suitable for a property vector are expressed in the following two terms:

- Explicit display of spatial information

- Uncorrelated separate properties in a subset of each patch and low similarity. In this literature, various techniques have been used for feature extraction. For example, Haar can be noted. Haar filters and local binary patterns are those that are most interested. Since the machine learning method is the basis of recent works, the detection operation is based on patch detection and classification functions. Applied classifications require significant features which are extracted through per patch for treat detection problem. Various classifications have been used in the literature which evaluates their performance based on various feature extraction in a different situation based on different parameters. Various parameters are involved in this evaluation including the area under the ROC curve, the number of true-positive detections, the number of false-positive diagnoses, etc. It is noteworthy that, the different evaluations are done in different parts of the body and the results are compared based on these parts. This study is organized as follows: the research literature is presented in section 2. The proposed method is presented in section 3. In section 4, the performance of the proposed method is evaluated and finally, the conclusion is presented in section 5.

Literature Review

Increasing the resolution of the images will overcome the limitations of the MMW imaging system. Researchers have demonstrated several power enhancement techniques such as interpolation and discrete wavelet transform (DWT) [7]. The main drawback of interpolation methods is a high-frequency component of the image due to smoothing at the edge of the image. Hence, DWT is used to increase the resolution as well as maintain the high-frequency components.

After removing the clutter and increasing the resolution, the distance is the target detection distance. Thresholding is one of the best ways to distinguish between target and background.

After reaching the threshold, the most important point is to identify the targets, such as targets like a blade or anything else or a bag of a feature. Blades can be distinguished with other bags of features such as a Diary cigarette box and matchbox based on the threshold of the image border. The size of the blade is less than a bag of features. First, the threshold of the image field is calculated, and if it is less than other bags of features, it is trained to reconstruct the image with ANN. So, ANN-based algorithm for identification of concealed blade is fixed orientation.

To achieve goal identification, 12 optionally selected data (75%) from a total of 16 samples used for ANN configuration education and the remaining 4 data (25%) were used for validation for the trained neural network. [14]

Non-positional averages [2], are used through scattered comparative representations [3]. However, to the best of our knowledge, there are no unpublished results on PMMWI decoupling. Blind deconvolution image at the moment is passive, although it has been applied extensively. In BID PMMWIs, retrieving is possible and there is no intensity from a single image due to noises. We assume that multi-frame blind image deconvolution methods can be used to estimate the system blur, which can be used to retrieve the observed images, to obtain more powerful images that can be used to improve the performance of threat detection systems.

Note that most multi-frame methods assume multiple views of a scene with different points. However, the PMMW system captures a variety of images that suffer from similar blurring. In this study, we propose the proposed method in [14] to propose a robust Bayesian blind-image deconvolution method to approximate the posterior blur distribution with the Dirichlet distribution.

Examples of images produced, simulating a person with concealed objects. Each image is PMM with a null point diffusion function (14) to account for the failure of the deconvolution imaging system. Its parameters were adjusted to a diameter of 60 cm from the lens and 5 m for the distance to the object (shadow image)

We simulated three unspecified scenarios. The first is a focused image, which means no motion blur effect is not considered than failure; the other two scenarios also add Gaussian blur with standard deviations of 1.5 and 2.5, respectively. For each scenario, we simulated a set of 36 blurred images by Gaussian noise from SNR 10 dB of noise for interior simulation of the PMWW camera. This noise is similar to what is found in real images [1]

This study also indicates a group of cs LR images through HR image reconstruction. The proposed method assumes that the estimated HR image is compressible, and as a result, complex, blurred, and low-sampling models are also compressible.

Then, they can be retrieved through their CS observation. However, a hybrid framework is presented following LR observation improvement and using the LR TO HR technique to retrieve LR and estimate HR simultaneously. This is a suitable method to estimate registration parameters in LR for HR issues and a previous strong scattered ad for the original image.

To generate all simulated images through the original image, we use the following method. Original image of human resource is randomly replaced at first and then in Horizontal and vertical form. Then, it is blurred using Gaussian blur with known variance. When it is low, a variable magnification factor p was sampled.

Using variable density ratio R, and finally, the Gaussian white noise is added to the CS by the variable observations of the signal-to-noise ratio (SNR). Various observations are generated using this method. We use the signal to noise (PSNR). An example of the degradation process is shown in Figure 2 in the cameraman image. As a performance measure, we use the Peak signal-to-noise ratio (PSNR).

2. Proposed Method

In this section, a method is proposed to increase detection accuracy. The reduced gradient method is an iterative optimization algorithm to optimize derivative function called objective function (cost function) which is a random approximation of the reduced gradient method. The random reduced gradient gives us an algorithm to obtain the minimum value of a function in several iterative loops and the values for which the function takes its minimum value. A recent paper [15] attributed the invention of this method to Herbert Robbins and Satin Monroe for the publication of an article on random gradient gradients in 1951.

The difference between random reduced gradient and the conventional reduced gradient is that, unlike conventional reduced gradient which used all educational data to optimize an objective function, random reduced gradient used a group of data selected randomly for optimization. This method is extremely used in statistical and machine learning issues.

In the first step, the images available in the dataset of millimeter-wave images are extracted and preprocessing operation is done using conventional methods such as median and averaging filters. In the second step, the image is segmented into different pieces and three zoning types are considered per piece. Then, using non-maximum suppression operations for each of these 3 regions, the percentage of overlap on the desired risk in the image is detected, and if any of these regions cover a high percentage of risk, we say that this region is at risk. Then we extract the properties of different regions of the image using two Haar filtering and LBP. The Haar filter uses different binary patterns, and the LBP method uses a circle to extract the image features and extracts the features on its perimeter. After these steps, we classify the data using the classifiers used in the best previous works. Acceptable results have been achieved using the SGD optimization algorithm in detecting concealed objects/

There always are some issues in statistical estimation and machine learning and it is needed to define a function like f through statistical data with one or several parameters (in coefficient or other shapes) and then these parameters are specified in the way that total (or average) of function values f is at least value for per statistical data.

Assume there is a set of statistical data and function f is defined for these data based on parameter θ. In this case, we obtain a function θ by inserting data I from dataset to function f and called $\mathcal{J}_i(\boldsymbol{\theta})$.

Now, the equation is simplified to finding θ which called minimum expression

$$\mathcal{J}(\boldsymbol{\theta}) = \left(\frac{1}{n}\right) \sum_{i=1}^{n} \mathcal{J}_i(\boldsymbol{\theta})$$

Or, in other words;

$$\mathcal{J}(\boldsymbol{\theta}) = \boldsymbol{E}[\mathcal{J}_i(\boldsymbol{\theta})]$$

$\mathcal{J}(\boldsymbol{\theta})$ is objective function of cost function.

To solve such a problem, conventional reduced gradients or in some cases random reduced gradients are used. In classical statistics, fields such as least squares or maximum likelihood estimation raise similar issues with sentence minimization. The problem of minimizing is also indicated in the principle of empirical risk minimization.

In most cases, the objective function is a simple function which applying a reduced gradient method is not complex or time-consuming. In this case, the conventional reduced gradient method is used like exponential family natural parameter used to evaluate economic functions. Since, conventional or random reduced gradient method requires the calculation of the objective function gradient in each loop, where the objective function parameters are large or the educational data set is very large, the calculation performed in each loop can be very time-consuming and complex. For this reason, random reduced gradients are used in these cases, which in each loop perform this operation only for a part of the educational data set that we have.

In the random reduced gradient method, in each loop, the operation is not performed on only one member of the educational data set, which is randomly selected in each loop, and instead is performed on a subset of it.

In the general implementation of a random reduced gradient, we first call the parameter vector, which is a vector that contains all the parameters of the cost function θ. We set θ to the desired vector, then for each update of this vector, we randomly select a member of the educational data set and subtract the vector of the cost function gradient at the point θ from θ at α.

$$\theta = \theta - \alpha \nabla_\theta \mathcal{J}_i(\theta; x^{(i)}, y^{(i)})$$

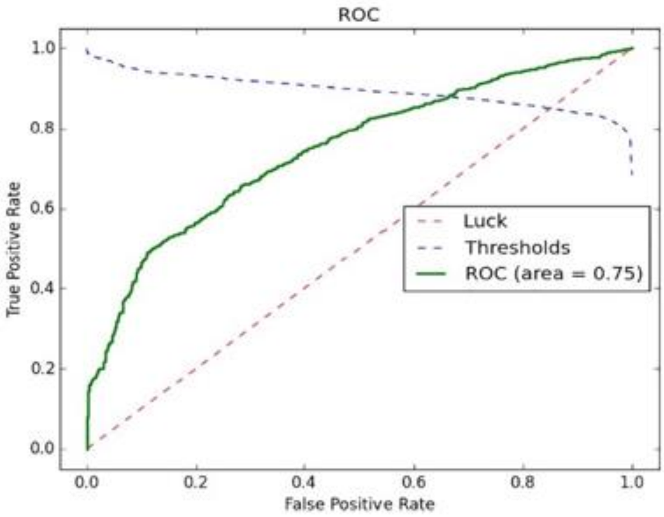
Where j is cost function and $(x^{(i)}, y^{(i)})$ is a member of educational data selected randomly. $\mathcal{J}_i(\theta; x^{(i)}, y^{(i)})$ Indicates expression i from objective function, a is a rate which is used to update θ and this is empirical. If this is small, it takes time to reach convergence, and if it is too large, convergence may not occur. [16]

Evaluation of Proposed Method

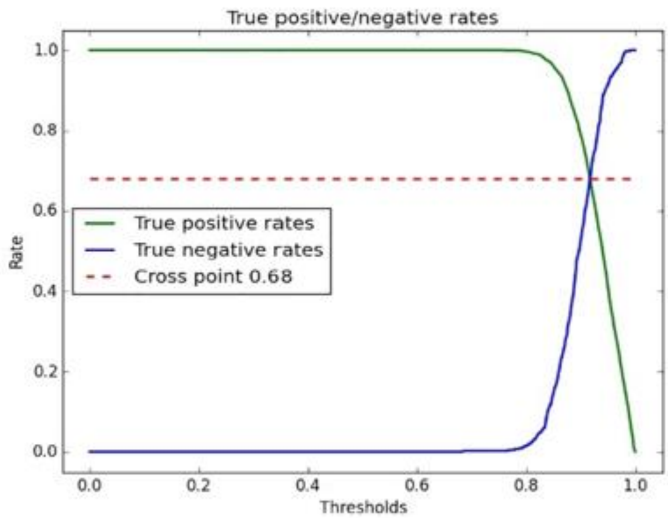
To evaluate classification algorithms (in this algorithm, the procedure is such that the classification algorithm is made by the educational data set and evaluated by the experimental data set) of the comprehensive k-Fold Cross Validation method, which divides the whole data set into k parts equally. The k-1 part is used as educational data set and the model is built based on it and the evaluation operation is performed with the remaining part. The process will be repeated k times so that each of the k parts is used only once for evaluation and accuracy is calculated for the constructed model. In this method, the final accuracy of the classifier will be evaluated equally to the average k of the calculated accuracy. The most common value for k in scientific texts is 5. However, the higher the k value, the accuracy of the classification algorithm is greater.

The methods for evaluation in this study are based on machine learning. The results obtained from these methods are shown in form of a table and image later. Tables indicate different parameters for each classifier in both preprocessing state and raw images have been compared in two types of Haar and LBP feature extraction and also examined together for better understanding of the results.

RF + Haar features on preprocessed images. Figure (1) shows the true and negative-positive rate curves for image classification.



A



B

Figure (1): (a) - roc diagram when classifying new images, (b) - accuracy on new images [1]

Their intersection point is slightly higher than 68% and defines the accuracy of the system for classifying new images. When FP = 1-TP, both false errors are equal. Although this rate may be considered low, it is important to note that the high slope of both curves (positive rates, negative rates) at the intersection indicates that it is possible to improve the true positive rate by increasing the small threshold, when fps increasing is cost-effective.

Figure (2) shows the lack of contrast in some images and. the difficulty of detecting some concealed objects without increasing the FP rate in the success of tree-based methods can be explained by the fact that both RF and ert mean square error using minimize group voting, which is an effective way to reduce noise in images. According to LBP, the errors in both tables have a large impact on the quality of this type of feature. However, LBP properties led to better detection of Haar properties while using parametric classifiers (LR, QLR, and SVM). FP scores were high enough to make them more competitive. These results clearly show the effect of noise on the behavior of classifiers and the importance of preprocessing when using LBP features.

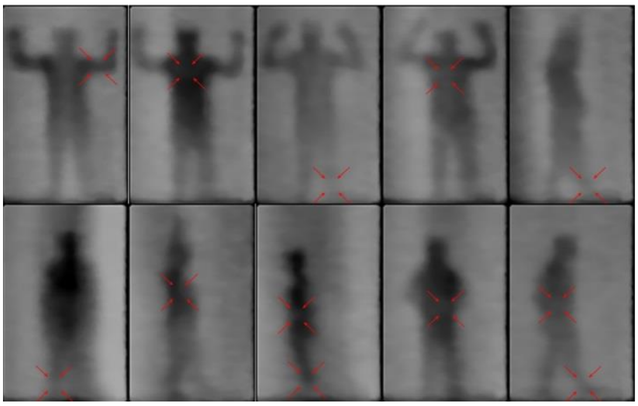
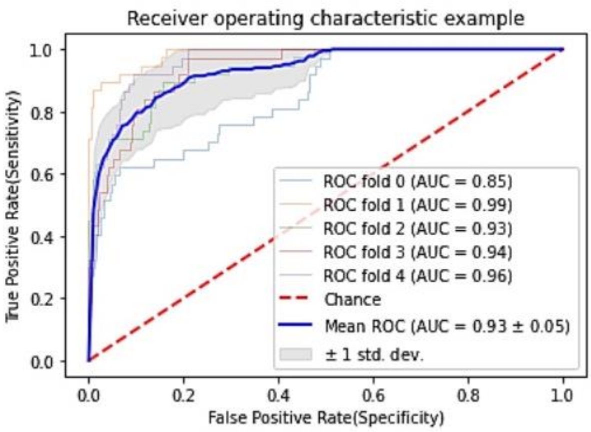


Figure (2) indicates examples of concealed objects where its RF cannot be detected, while the classifier for the same fp and fn is established. Red arrows indicate the location of objects. Linear methods are used as our basic in comparative study and SVM is a support-based approach. These three methods are in search of the best performance from a fixed set of possible functions. ADA, RF, and ert make the classifier simpler. RF and ert use different educational datasets for each member of the group, and ADA measures the training dataset with different values. In all cases, the amplitude of the detection function is normalized to [0, 1].

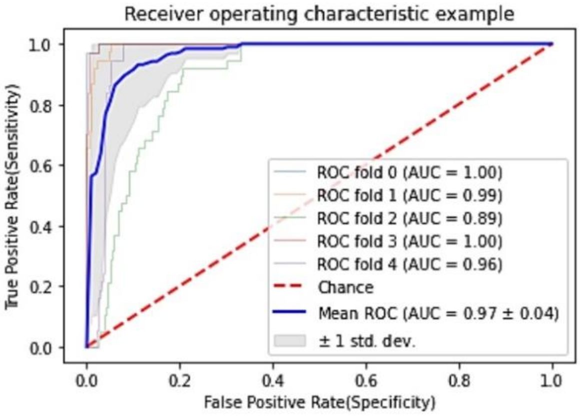
For each classifier M {LR, QLR, SVM, RF, ERT, corresponding image classification function F_D^M was performed on the images in each fold. Each loop contained approximately 600 images, all of which had the same aspect ratio with no threat, one threat, and two threats. For Adabost, we used asymmetric reinforcement (Viola and Jones, 2001) instead of a classification committee. Hyper-parameter estimation was performed using five-fold validation in each training loop. To reduce the time required to estimate each patch from each model, a subset smaller than the patch was selected. A uniform sample of the patch was used, using an additional factor reduction. This requires selecting a location for each image block. Finally, for each threat in an image, we added at least one piece that contained it in the training database. This ensured that all the threats in the database were included.

After implementing the basic article and achieving similar results, we tested different algorithms and machine learning methods. We tested different backup vector kernels and found that the kernel used in the base article had the highest performance. Other methods such as k nearest neighbor (KNN and other monitored methods such as SVD and the advantages and disadvantages of each were observed and tested.) Finally, we aimed to optimize objective function through the optimizer where optimizers have not been used there.

Although random reduced gradients have long existed in machine learning, they have recently received a great deal of attention for their use in large-scale learning. Another useful thing we found in the studies was that when our data is sparse, this optimizer dramatically improves the results. Random reduced gradient provides an algorithm to us for obtaining minimum function and the values take by minimum function through several iterative loops. Finally, this optimizer made significant improvements in the results.



(A)



(B)

Figure (3)- ROC Curve: A: SVM, B: SGD

3. Conclusion

Detection and localizing the objects under the cloth is very challenging and has important applications in the security field. In this field, passive millimeter-wave images are used. However, the quality of obtained images and unknown satiation, shape, and size of objects make some difficulties in concealing. In this study, a machine learning-based solution has been presented for localizing issues.

Our proposed method performs better than others. The effect of static noise on different classification algorithms has been discussed an accurate comparative study of classification techniques is presented through a comprehensive dataset. The low test cost of this solution allows it to be used in real-time applications.

This study aims to identify concealed objects in Iran. The main problem with this is the low SNR and static noise that distorts the image. Simple thresholding can be used for high-quality images.

In this study, a machine learning method was identified to detect work. This approach deals with the poor quality of passive images and uses threat detection methods to identify risks. Due to the lack of publicly available datasets, we have created one that, to the best of our knowledge, is the largest and has the most types and sizes of objects used for this purpose. Our proposed method is based on a classification committee based on two very unbalanced classes of image spots and has performed well in all experiments.

We compared different methods to estimate the classification function of images and showed higher efficiency through tree sets. On average, 94% of TP were indicated by distributing several true positive detections in the range of 1 to 7. The effect of image quality and extracted features have also been examined. The filtering method helps us in the detection process. Haar filtering which follows our task performs well for all classifiers.

The results show that large objects with low or zero emissions could be identified easily. The easiest place to track those was while objects were exposed to the camera in larger areas. Threats were more severe in the ankles, arms, and thighs.

Finally, a comparison between our diagnostic model and other approaches in the literature showed that our method relies less on the quality of the images observed. In addition, our method works very well when a large image training set is available, making a great performance prediction for a wide range of detection systems in realistic millimeters.

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