# Privacy Algorithm for Airport Passenger Screening Portal

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## ABSTRACT

A novel personnel surveillance system has been developed for airport security to detect and identify threatening objects, which are concealed on the human body. The main advantage of this system over conventional metal detectors is that non-metallic objects such as plastic explosives and plastic guns are detectable. This system is based on millimeter-wave array technology and a holographic imaging algorithm to provide surveillance images of objects hidden beneath clothing in near real-time. The privacy algorithm is based on image processing filters and artificial neural networks. The algorithm examines the millimeter-wave surveillance images to locate and segment the threats and place them on either a silhouette of the person or a wire-frame humanoid representation. In this way, all human features are removed from the final image and personal privacy is maintained. This system is ideally suited for mass transportation centers such as airport checkpoints that require high throughput rates. The system is currently under going evaluation. This paper reports on results from an earlier initial test of portions of the privacy algorithm that detect hidden plastic objects.

**Keywords:** airport security, weapons detection, neural networks, millimeter wave imagery, privacy

## 1. INTRODUCTION

Figures 1 and 2 illustrate two imaging systems for security applications. The systems employ a millimeter-wave (MM-wave) transceiver and array, high-speed digital signal processing computer, and a holographic imaging algorithm [1,2]. Because millimeter waves are, unlike x-rays, non-ionizing and therefore pose minimal health risks, they are ideally suited for surveillance of people. The array illuminates the person under surveillance with very low power millimeter waves, which readily penetrate clothing barriers and reflect off the body and concealed threats. These reflected signals are collected by the array and sent to a high-speed imaging computer where they are formed into very high-resolution radar images by the holographic imaging software [3,4]. After the holographic images are formed, they are sent to a video monitor where the system operator can detect and identify the concealed threats. Although this security system can detect and identify non-conventional concealed threats, it also displays human physical features in the imagery. This has delayed the full testing and implementation of this new scanning technology into airport checkpoints.

### 1.1. Imaging Portals

The Dual Planar Panel Portal (D3P) system, illustrated in Figure 1, provides a quick front and back scan of a person in near real-time. The person walks into the portal, pauses momentarily, and is scanned by two planar imaging systems that image the front and the back of the person. It is designed for use in security applications requiring high throughput such as airport security checkpoints, mass transit systems, and border crossings.

The Cylindrical Holographic Imaging System (CHIS), illustrated in Figure 2, provides a 360-degree scan of a person in near real-time. It is designed for use in high security applications such as prisons, secure facilities, and other tightly controlled areas which require a more detailed scan than provided by the D3P system. The person walks into the portal, pauses momentarily, and is scanned by a rotating imaging array which produces a series of images covering a full 360-degree view of the person. Since the person must stand stationary while the imaging array rotates around the person, it is useful in situations with low throughput and where time is not critical.

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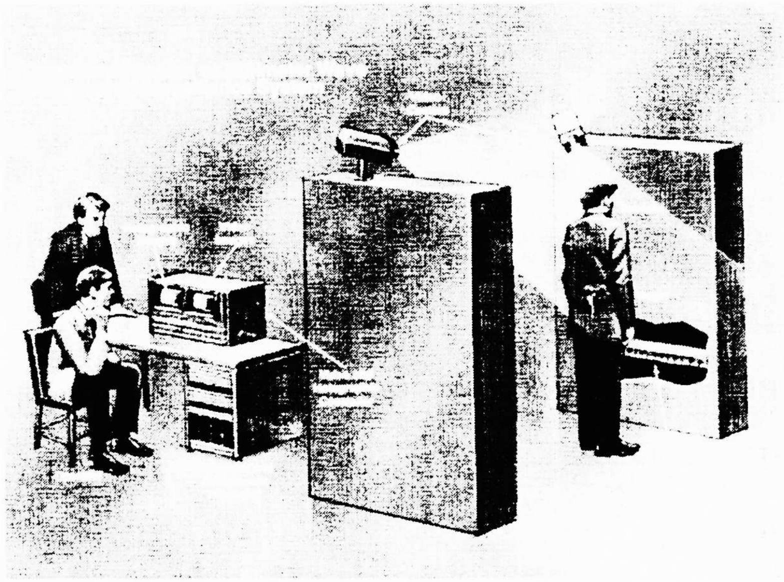

Figure 1. This figure illustrates the Dual Planar Panel Portal (D3P) system. The person walks into the portal, pauses momentarily, and is scanned by two planar imaging systems that image the front and the back of the person.

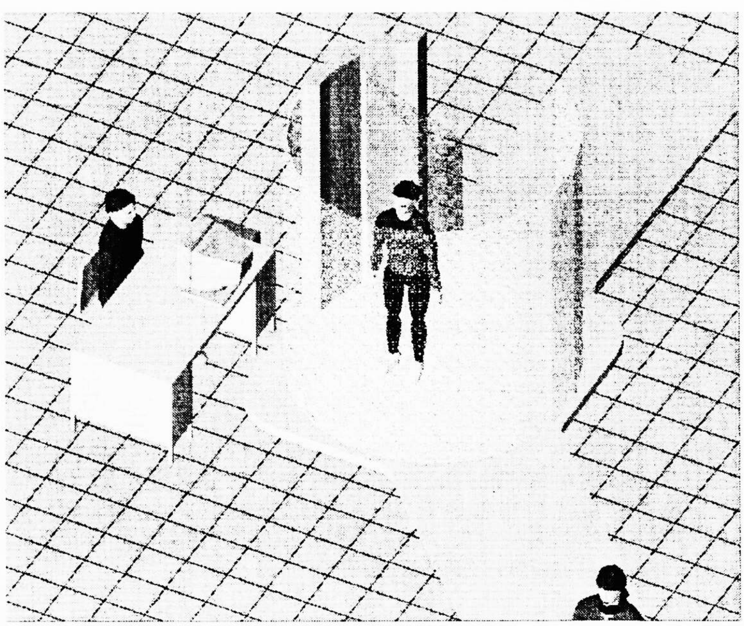

Figure 2. This figure illustrates the Cylindrical Holographic Imaging System (CHIS). The person walks into the portal, pauses momentarily, and is scanned by a rotating imaging array which produces a series of images covering a full 360-degree view of the person.

### 1.2. Privacy Concerns

There is a perceived public opinion that directly presenting the imagery data to the operator would be unacceptable because of personal privacy concerns. It is believed that public acceptance of this type of screening system would likely be greater if the imagery was presented to a computer pattern recognition or segmentation algorithm for threat detection and identification rather than to a human operator. In this scenario, the operator would be retained in the security activity to clear the alarms generated by the privacy algorithm from either false alarms or real threats. In 1997, work was initiated on a privacy algorithm for the holographic imaging systems with the near-term goal of developing software techniques to automatically segment concealed threats and innocuous items from the imagery and place these objects on a generic facsimile of a human.

The ultimate goal for the privacy algorithm is to eliminate from the imagery all human features that may be considered too intrusive. This paper details the initial privacy algorithm development and laboratory testing.

### 1.3. Privacy Algorithms

To eliminate privacy concerns, several techniques were applied to partially automate the detection of weapons in the imagery obtained from the holographic imaging system. All of these techniques are based on segmenting suspicious areas of the images and placing them on a silhouette, wire-frame rendered humanoid, or optical image of the person being scanned. This would alleviate privacy concerns by precluding the showing of the body parts of the person being scanned; instead, showing only detected items. This paper concentrates on techniques which use pattern/texture recognition or segmentation schemes of the image data to detect plastic objects, and reports preliminary test results from the application of pattern/texture recognition and segmentation schemes on data obtained from an operational test at the Seattle-Tacoma International Airport (Sea-Tac) in 1996 [5,6]. Additionally, this paper discusses work that was performed on the presentation techniques to the system operator that eliminate human features obtained in the MM-wave imagery.

## 2. THREAT SEGMENTATION WITH PULSE-COUPLED NEURAL NETWORKS

The first neural network based approach to the detection of threats included a Pulse-Coupled Neural Network (PCNN). A PCNN is a physiologically motivated information-processing model based on the mammalian visual cortex. The underlying model was proposed by Eckhorn to explain the experimentally observed pulse synchrony process found in the cat visual cortex.[7,8] This model is significantly different than other artificial neural network models in both its structure and operation. In the PCNN model, each neuron in the processing layer is directly tied to an image pixel or set of neighboring image pixels. Each neuron iteratively processes signals feeding from these nearby image pixels (i.e., feeding inputs) and linking from nearby neurons (i.e., linking inputs) to produce a pulse train. There is no training involved for the PCNN. Similarities in the input pixels cause the associated neurons to fire in synchrony indicating similar structure or texture. This synchrony of pulses is then used to segment similar structures or textures in the image. In this study, two PCNN algorithms were implemented. The first was based on the work of Shane Abrahmson.[9] The second was based on the work of Jason Kinser.[10]

In work reported earlier, we found that that PCNNs do well at contrast enhancement but require a good deal of manual intervention to produce the desired results [11]. They also do well at image segmentation when each segment is approximately uniform in intensity. However, when intensity significantly varies across a single segment, that segment does not properly separate from other objects. Due to the illumination method, the images produced with the millimeter scanner have varying contrast across a segment, which can result in improper segmentation. The best results with this PCNN approach yielded segmentation of major body parts (e.g., arms, legs, torsos), but not individual threats. Work was discontinued on PCNNs for this application.

Another complexity of PCNNs is properly setting the various parameters so that a uniform response is achieved over a set of imagery. The adjustable parameters include the number of nearby neurons (linking inputs), number of nearby pixels (feeding inputs), strengths of the linking and feeding connections, decay constants, and thresholds. For example, a set of parameters, which properly segment objects in one image, can fail on similar images. For our evaluation, we continually changed the parameters until we got the desired enhancement or segmentation.

## 3. SPECKLE DETECTION WITH MULTI-LAYER PERCEPTRONS

Plastic, ceramic, and other dielectric items are partially transparent to the millimeter-wave illumination. This often leads to a speckled texture on these items due to wave interference of the various coherent reflected and transmitted waves. Visually this appears as a granular texture. On the other hand, the MM-wave image texture of human skin is smooth and produces very little pixel-to-pixel variation. Since the texture produced by dielectrics is substantially different from that imaged from the human body, it may be used to segment dielectric items for subsequent removal and placement on a silhouette, wire-frame rendered humanoid, or optical image of the person being screened.

The speckle detection algorithm locates plastic objects on the subject being scanned by looking for speckle in the MM-wave image. This approach uses a multi-layer perceptron (MLP) neural network trained with the back-propagation of error algorithm on the texture of the speckle[12]. Several approaches to preprocessing and post-processing for use in the speckle detector were evaluated. Both median window and dilation filters were used to post-process the output of the speckle detector. Post-processing reduces noise and false alarms in the output images. Figure 3 shows a block diagram of the components in the speckle detector. The multi-layer perceptron neural network examines a 7-by-7-pixel region and determines if the kernel contains speckle. The output is thresholded and fed into a series of dilation and median window filters that remove individual and small areas of identified speckle, which are likely false alarms. To reduce the number of false alarms found in the imagery, a frame-to-frame consistency-checking algorithm was developed. This frame-to-frame consistency check is applied to the multi-frame cylindrical holographic imaging system (CHIS) but not the dual panel planar portal (D3P) system.

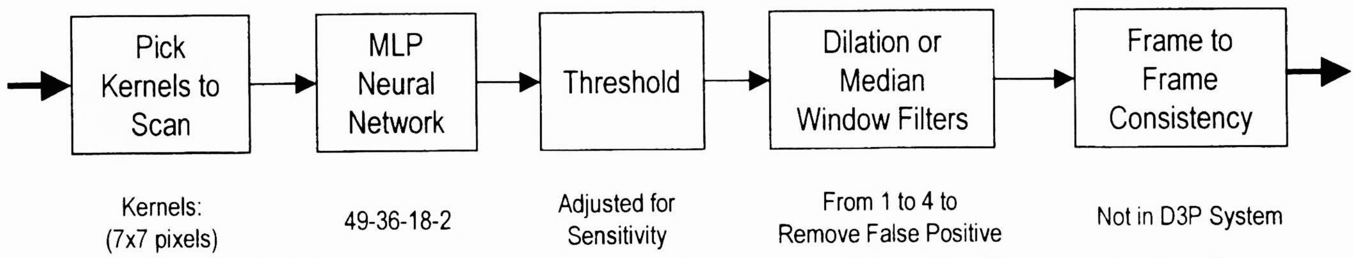


Figure 3. This figure is a block diagram of the speckle detection algorithm. The neural network portion operates as a kernel operator over the image. The output is then processed by several dilation or median window filters to remove false alarms and fill in false negatives within a detected threat region. The frame-to-frame consistency check is applied to the multi-frame cylindrical holographic imaging system (CHIS) but not the dual panel planar portal (D3P) system.

Figure 4 shows the initial results from this work on the detection of RDX explosives that are concealed on a man. Figure 4(a) shows the optical image and Figure 4(b) shows the MM-wave holographic image obtained with a single scan at Ka band (27 – 33 GHz). Figure 4(c) shows the results of the speckle detector on the plastic explosive. As can be observed from the Figure 4(c), the plastic explosive is shown in red (dark gray in this paper).

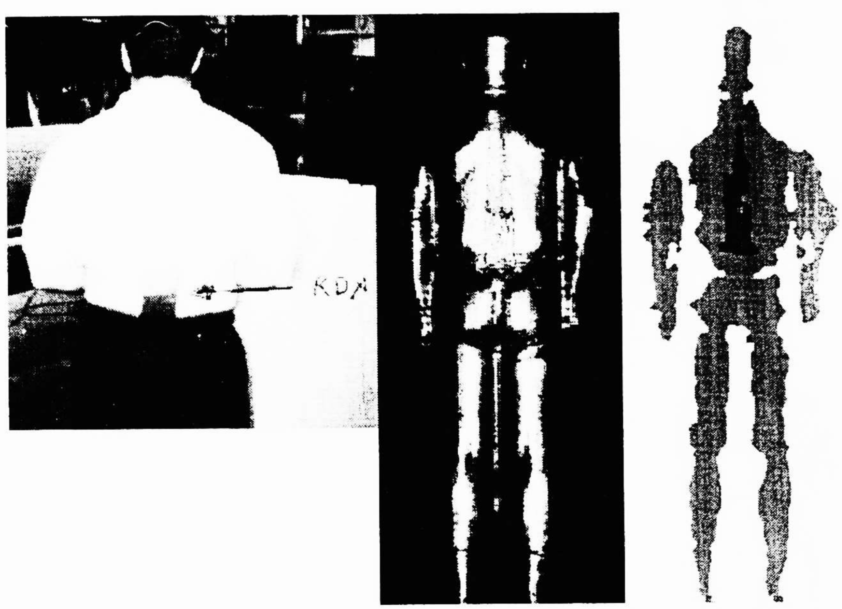

Figure 4. This figure shows the results of the speckle detection algorithm for detecting RDX explosive: (left) optical image, (middle) Ka-band holographic image (27 - 33 GHz), and (right) speckle detection results.

## 4. DISPLAY TECHNIQUES

A summary of display techniques for highlighting threats on the body is shown in Figure 5. Five potential techniques were explored and each one effectively removed privacy issues or human features from the MM-wave imagery. The first candidate display technique is shown in Figure 5(a). This technique thresholds the MM-wave image so that no detail of the person is in view except for their silhouette. It displays the threat in red (black in this paper) on the silhouette. The second candidate, shown in Figure 5(b), is similar to the first except that a cutout view from the MM-wave image is displayed on the silhouette. The third candidate, shown in Figure 5(c), is a generic silhouette. The fourth candidate, shown in Figure 5(d), uses a 3-D-rendered generic human model generated from wire-frame polygons to match the various views of the millimeter-wave scans. The fifth candidate is shown in Figure 5(e) and uses an optical image of the person and overlays the threat object from the privacy algorithm in red (black in this paper). In each of these display methods, the threat is placed on the silhouette, rendered humanoid, or optical photo at the location where the privacy algorithm detects the threat in the MM-wave imager. The generic silhouette is the likely candidate for the D3P system, which is a single frame (1 front, 1 back) imaging system. The 3-D rendered humanoid is the likely candidate for the CHIS approach, which is a 360-degree multi-frame imaging system.

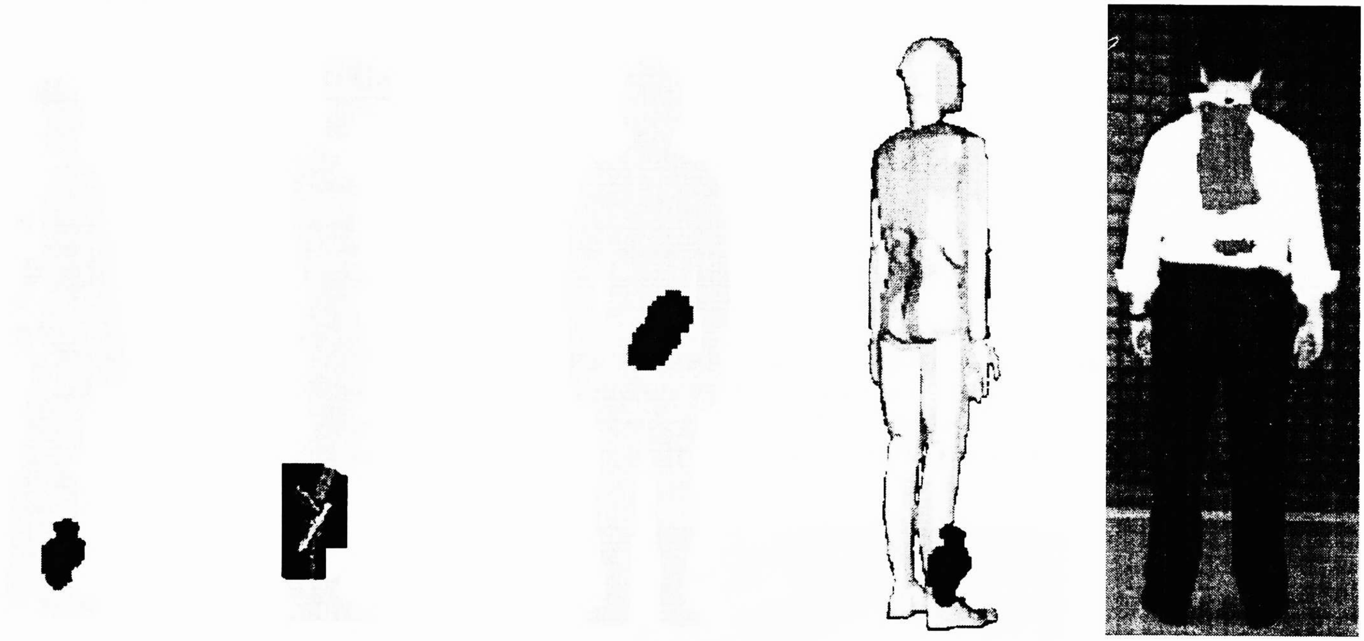

Figure 5. This figure illustrates several methods for displaying the detected threat. The first two on the left, 5(a) and 5(b), use simple thresholds of the millimeter wave image. The third method shown in the middle, 5(c), overlays the threat indication on a generic silhouette and is the likely candidate for the D3P system. The fourth method, 5(d), uses a rendered humanoid and is the likely candidate for the CHIS. Finally, the last approach, 5(e), overlays the threat on an optical photo.

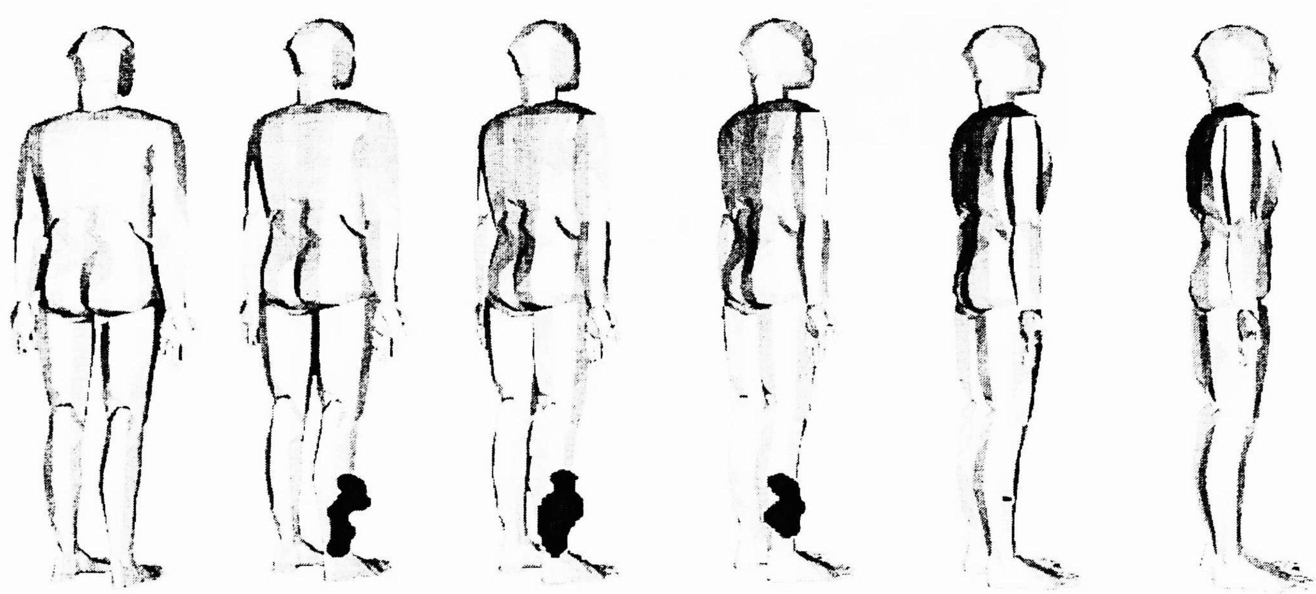

Figure 6. This figure shows a sequence of processed MM-wave frames from the Cylindrical Holographic Imaging System (CHIS) which indicate a potential threat object (flare gun) on the lower right leg.

The CHIS is more useful for high security applications where full body coverage (360-degree) of the person is needed for optimum threat detection. In this system, a 3D-facsimile of the human is necessary to show all sides of the person for accurate placement of the segmented concealed threat. Figure 6 illustrates a few frames from the CHIS indicating a flare gun on the lower leg as a red (dark gray in this paper) overlay on a 3-D-rendering of a generic human model.

## 5. INITIAL PERFORMANCE OF SPECKLE DETECTION ALGORITHM

Initial laboratory testing was performed on the speckle detection algorithm. This algorithm was trained to detect plastics in millimeter-wave holographic imagery by utilizing texture pattern recognition techniques to identify the plastics. It was trained and tested on a MM-wave database collected from the 1996 screener test conducted at the Seattle-Tacoma International Airport (Sea-Tac). Also, the results of the speckle detection algorithm were compared to the human screen tests on the same data.

The Sea-Tac database set contained 80 identical MM-wave cylindrical scans at both Ka-band (27 - 33 GHz) and Ku band (12 - 18 GHz). Forty of the scans contained no threat objects and the other forty contained threat objects. Sixteen of the forty threat scans contained plastic threat objects (flare gun or simulated plastic explosives) and the other twenty-four contained non-plastic threats (guns and a knife). The Ka-band and Ku-band training scans were not identical, however. The Ka-band had twenty-five training scans with nine containing plastic threats. The Ku band had twenty training scans with only five containing plastic threats. Of these five, only three could be used effectively to train the MLP neural network, which affected the results from the speckle detection algorithm Ku-band test set.

### 5.1. Ka-band Results

The results of the test on the Ka-band (27 - 33 GHz) scans with the human screeners and the speckle detector at two sensitivities are shown in Figure 7. At low sensitivity, the probability of false alarm is substantially lower for the speckle detector than the human screeners, but the detection probability is somewhat reduced. For the high sensitivity case, the probability of detection has increased, but so has the probability of false alarms. Overall, these results show comparable performance of the speckle detection algorithm to that of the human screeners for the detection of plastic threats.

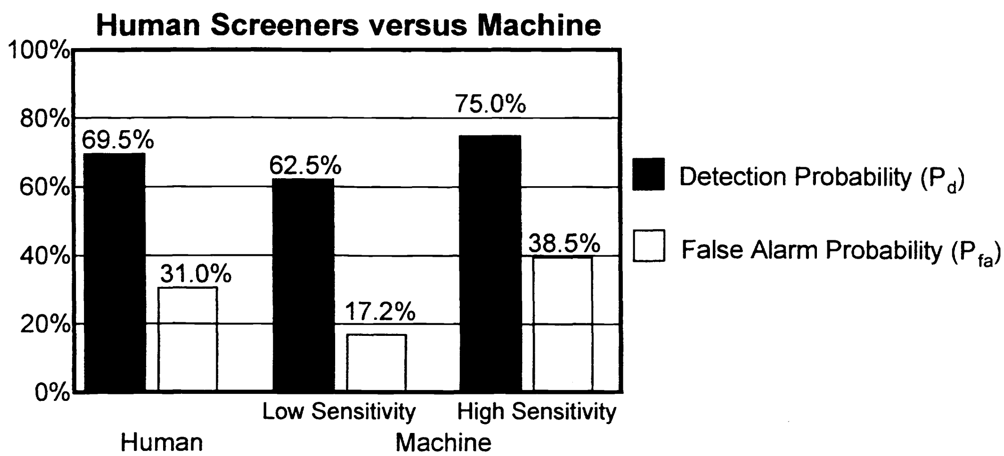


Figure 7. This figure shows the preliminary test results for human screeners and the machine based speckle detector on plastic guns and plastic explosives at low and high sensitivities with Ka-band scans.

### 5.2. Ku-band Results

Figure 8 shows results of a comparison of human screeners to the speckle detection algorithms with Ku-band (12 - 18 GHz) scans. The results in Figure 8 show that the Ku-band speckle detector preformed with a poorer detection rate detecting fewer concealed plastic threats than the screeners did when trained with the original training set. This can be attributed to the fact that there were a lower number of plastic explosive training scans for the Ku band than for the Ka band. To improve the training video set, five scans with plastic explosives from the set which were shown to the screeners were randomly chosen and used to train the neural network in the speckle detector. After training, a modified test was run and the results were much closer to the human screener results. The results of this modified test are also shown in Figure 8.

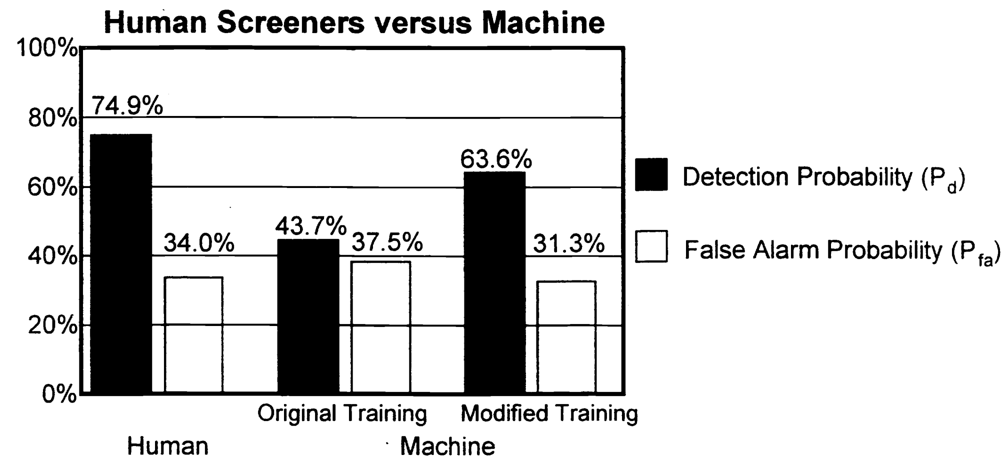


Figure 8. This figure shows the preliminary test results for human screeners and the machine based speckle detector on plastic guns and plastic explosives developed with the original training set and a modified training set with Ku-band scans.

## 6. DISCUSSION

While still in development, the research reported in this paper illustrates several technologies potentially important in the final implementation of an automated privacy algorithm for the millimeter-wave weapons screening system. The artificial neural network speckle detection algorithm is showing comparable results to human screeners for the detection of plastic threat objects and will likely show up in the final system. Since automation is the goal, these results show that nothing is lost with machine based screeners in the detection of plastic threat objects.

Current work, not reported here, involves combining depth information with intensity information and detecting man-made structure by using Fourier techniques. The depth information shows potential for finding concealed objects through the use of gradients and edge detection methods. Other techniques examined in this research, but not reported here include the use of dielectric measures. The dielectric measurements can detect threats and anomalies by themselves, but were not successful on humans because the contours of the body, which affect the measurement, produce a difficult inverse scatter problem. The results of these approaches will be reported in a later paper. Finally, the various approaches outlined here must be automated and integrated into a single software package for the scanner.

Information about artificial neural network developments at Pacific Northwest National Laboratory is available on the World Wide Web at: http://www.emsl.pnl.gov:2080/proj/neuron/neural/

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