# **Imaging for Concealed Weapon Detection**

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# ABSTRACT

In today's world, security forms an integral part in every aspect of life. The detection of weapons concealed underneath a person's clothing is very much important to the improvement of the security of the general public as well as the safety of public assets like airports, building and railway stations, etc. Manual screening procedures for detecting concealed weapons are common in controlled access settings like airports, entrance to sensitive buildings and public events. It is desirable sometimes to be able to detect concealed weapons from a standoff distance, especially when it is impossible to arrange the flow of people through a controlled procedure.

In this project we propose an automated weapon detection using millimeter wave imagining method. The millimeter wave scans the entire body, without causing any side-effects, for concealed weapon. We enhance the millimeter wave image and follow it up with segmentation. The system has built-in intelligence to detect the concealed weapon after segmentation. We also use wavelet based fusing techniques to pin-point the position of the concealed weapon

## **General Terms**

Image Denoising, Algorithms et.

#### **Keywords**

Detection, Wavelets, Image segmentations, Fusion, Image Denoising.

# 1. INTRODUCTION

With the advent of modern sophisticated technologies the security threats are more enhanced and hard to detect. Even a small flaw in an otherwise foolproof system can bring down the entire system in no time. Hence security is of paramount importance. Various security systems have been developed and it's an ever continuing process.

There are various security systems like the metal detectors, body scanners, etc. that are being employed to counter the physical threats. But the perpetrators have found out some ways to escape from the radar.

# **1.1** Problems of existing methods of security mechanism.

Primary Concerns vs. Public Safety: For the system to be effective, security guards need to go about frisking security some of the people who pass through the detector to see if they have any dangerous or prohibited objects in their possession.

Fake Alarms: There may be number of legitimate medical reasons that a person has metal on his body. If the person sustained bodily injury and require metal device to be surgically installed within his body, the metal detector might go off, causing unnecessary fuss and subjecting the person to increased scrutiny and trauma.

Portability Issue: Most of the metal detectors are usually fixed at the particular place. As a result the perpetrators can become alert may avoid that path in order to escape from the jaws of the system. Hence it is not a foolproof security method. This is a cause of huge concern that needs to be addressed and also it necessitates for the development of system or rather a mechanism which is both efficient and effective in every aspect. One of the most recent advancement to tackle these problems has been the development of standoff methods of security surveillance by making use of special image sensors and principles of image processing. The method of standoff distance security surveillance has been fast gaining popularity because of the ease of the mechanism and also because it addresses all the concerns related to the conventional walk through metal detectors such as manual frisking, electromagnetic interference, false alarms and portability issues.

Also it is relatively easy to monitor several people at once scanning for traces of concealed weapons as opposed to the existing walk through metal detectors. The standoff distance security surveillance system involves two major steps

- 1. Capturing the image using special image sensor like infrared image and millimetre wave image.
- 2. Processing the captured image for Automatic detection of concealed weapons.

The process of captured image is the main challenge that defines the success of the phenomenon of standoff distance security surveillance system. As the image captured will be associated with lot of noises, several modifications will have to be made to the captured sensor image in order for the proper detection of weapons.

In this work, we propose to develop an image processing based mechanism for captured millimeter wave and visible images for concealed weapon detection. Since there is no human intervention, errors can be minimized, using our approach.

# **1.2** Millimeter wave image

The millimeter wave region of the electromagnetic spectrum is usually considered to the range of wavelengths from 10 millimetres (0.4 inches) to 1 millimeter (0.04 inches) i.e. millimeter waves are longer than infrared waves or x-rays, but shorter than radio waves or microwaves. The most attractive feature of millimetre waves, when compared with optical, infrared and terahertz waves is their ability to penetrate obstacles under low-visibility conditions such as in fog, ran, dust or fire where optical or infrared cameras cannot be used. A millimeter wave scanner is a whole-body imaging device used for detecting objects concealed underneath a person's clothing.

It has some disadvantages though. Millimetre waves can interface constructively or destructively to produce light and dark pixels known as speckle noise. It also causes shadows, wrinkles and other artifacts and may introduce blurring effect [5].

In this work, we use passive millimeter wave (MMW) image and visible image for the detection of concealed weapons. An example of MMW image is shown in Fig. 1.



Fig 1: MMW Images

## 2. DESIGN AND IMPLEMENTATION

Before an image is presented to a weapon detection system, it is desirable to pre-process the image to maximize its exploitation. Fig. 2 shows the various stages involved in image processing mechanism for the detection of concealed weapon.

Input image is usually affected by variety of degradations, which reduces the interpretability of the image. Hence in order to weed out the effects of noise and interference, we perform denoising and enhancement operations. Next we fuse image different information sources images for more informative. So here by fusing passive MMW image data and its corresponding electro-optical (visible) image, more complete information can be obtained; the information can then be utilized to facilitate concealed weapons detection.



Fig 2. Stages of processing

Next we perform the segmentation. The goal of segmentation is to simplify or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries cover the entire image, or a set of contours extracted from the image.

#### 2.1 Denoising

Image noise is random (not present in the object imaged) variation of brightness or information on images. Different noise may present in MMW images like, motion blur, speckle noise, additive Gaussian noise etc.

Denoising is the first pre-processing step to analyze the image. Removal of noise without deleting useful information and preserving original data is called denoising. As the wavelet theory is having lot of advantages in comparison with other transform, we in our project use Double density Wavelet Transform [6].

The flow chart of the denoising algorithm used is shown in the Fig 3.

Double-Density Wavelet Transform is a simple and elegant tool that can be used for many digital signal processing applications. The double-density DWT is an improvement upon the critically sampled DWT with important additional properties.

- i. It employs one scaling function and two distinct wavelets, which are designed to be offset from one another by one half
- ii. The double-density DWT is over complete by a factor of two.
- iii. It is nearly shift-invariant.



Fig 3. Denoising flow chart

#### 2.1.1 2-D Double Density DWT

To use double-density discrete wavelet transform for 2-D signal processing, we implement a two-dimensional analysis and synthesis filter bank structure. This gives rise to nine 2-D subbands, one of which is the 2-D lowpass scaling filter, and the other eight of which make up the eight 2-D wavelet filters, as shown in Fig. 4.

This returns the subband images as two variables: lowpass subband image and highpass subband images.

#### 2.1.2 Thresholding

Thresholding is a technique used for signal and image denoising, which is pioneered by Donoho[8]. When we decompose a signal using a wavelet transform, we are get a set of coefficients that correlates to the high frequency sub bands. These high frequency sub bands consist of the details in the data set. If these details are small enough, they might be emitted without substantially affecting the main features of the data set. Additionally these small details are often those associated with noise. Therefore, by setting these coefficients to zero, we are essentially minimising the noise. This becomes the basic concept behind thresholding – that is set coefficients that are less than a threshold to zero and use these coefficients in an inverse wavelet transformation to reconstruct the data set.



Fig 4: Filter bank for 2-D Images

There are two types of thresholding: Hard thresholding and Soft thresholding. In this work soft thresholding is proposed. It shrinks coefficients above the threshold in absolute value. The transfer function of the same is shown below.



2.1.3 Reconstruction

After thresholding, we implement the 2-D synthesis filter banks for the reconstruction of the denoising output image from the nine subband images. The inverse double-density DWT is computed using synthesis filter bank. This computes the inverse double-density DWT at the jth scale.

#### 2.2 Image Fusion

By fusing passive MMW image data and its corresponding electro-optical (visible) image, complete information of the person's image along with the concealed weapon can be obtained. This information can be used to segment the concealed weapon direction. Fusion of a visible image and its corresponding MMW image facilities recognition of a concealed weapon by locating the human subject(s) hiding the object. The fusion method incorporated here is a shift invariant extension of the discrete wavelet transform, which yields an over complete signal representation.

As for the DWT, each stage of the Shift Invariant Discrete Wavelet Transformation (SIDWT) splits the input sequence

into the wavelet sequence  $\omega_i$  (n) which is stored and the scale sequence Si(n) which is serves as input for the next decomposition.

$$w_{i+1}(n) = \sum_{k} g(2^{i}.k).S_{i}(n-k)$$
  
$$S_{i+1}(n) = \sum_{k} h(2^{i}.k).S_{i}(n-k)$$

The principle of SIDWT is shown in Fig 5.

Same SIDWT principle is implemented using Haar wavelet for Images. The 2x2 Haar matrix that is associated with the Haar wavelet is

$$H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

The filters, considered here would be

$$H1 = \begin{bmatrix} 0.5 & 0.5 \end{bmatrix}$$
$$G1 = \begin{bmatrix} 0.5 & -0.5 \end{bmatrix}$$



#### Fig 5. Principle of SIDWT

The couple of filters, when applied on the input images matrices, would produce 4 resultant matrices. The fourth matrix, which consists of high frequencies, would act as the input for the next level of decomposition. The other three matrices, consisting of the low frequencies, are used to produce 3 pyramids at each level. The re-composition process is performed with the help of the three pyramids formed at each level of decomposition. The reconstruction process is performed by superimposing the pyramids formed at each level to the undecimated image matrix at that level. The image decomposition and reconstruction is pictured in Fig. 6 and 7.

# 2.3 Segmentation and object extraction

Image segmentation refers to the process of portioning an image into groups of pixels which are homogeneous with respect to some criteria. Segmentation is area oriented instead of pixel oriented. The result of segmentation is the splitting up of image into concealed areas. Thus segmentation is concerned with dividing an image into meaningful regions. In this project, we first segment the fused image and extract the concealed weapons if any. Further if a weapon is found to be concealed then an alert message is given to the person checking.



Fig 6. Image decomposition and selecting coefficients



Fig 7. Reconstruction

Flow chart segmentation and weapon detection is shown in Fig 8.

Here we try to segment regions by identifying common properties. Or similarly, we identify contours by identifying differences between regions (edges). The simplest property that pixels in a region can share is intensity. So, a natural way to segment such regions is through thresholding the separation of light and dark regions. Thresholding creates binary images from gray-level ones by turning all pixels below some threshold to zero and all pixels about the threshold to one.

If g(x, y) is a thresholded version of f(x, y) at some global threshold T, then

$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) \ge T \\ 0 & \text{otherwise} \end{cases}$$



Fig 8. Segmentation and weapon detection

Otsu's method[8] is used to automatically perform histogram shape-based image thresholding or the reduction of a gray level image to a binary image. The algorithm assumes that the image to be thresholded contains two classes of pixels or bimodel histogram (e.g. foreground and background) then calculates the optimum threshold separating those two classes so that their combined spread (infra-class variance) is minimal.

In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two  $\sigma_{1}^{2}(t) = c_{1}(t)\sigma_{1}^{2}(t) + c_{2}(t)\sigma_{1}^{2}(t)$ 

classes: 
$$\sigma_w(t) = \omega_1(t)\sigma_1(t) + \omega_2(t)\sigma_2(t)$$

Weights  $\omega_i$  are the probabilities of the two classes separated by a threshold t and  $\sigma_i^2$  are variances of these classes. Otsu

by a threshold l and l are variances of these classes. Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance:

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = \omega_1(t)\omega_2(t) [\mu_1(t) - \mu_2(t)]^2$$

Which is expressed in terms of class probabilities  $\omega_i$  and class means  $\mu_i$ . The class probability  $\omega_1(t)$  is computed from the histogram as t:

$$\omega_1(t) = \Sigma_0^t p(i)$$

While the class mean  $\mu_1(t)$  is:  $\mu_1(t) = \left[ \sum_{0}^{t} p(i) x(i) \right] / \omega_1$ 

Where x(i) is the value at the center of the i th histogram bin. Similarly, we can compute  $\omega_2(t)$  and  $\mu_2$  on the righthand side of the histogram for bins greater than t. The class probabilities and class means can be computed iteratively. This idea yields an effective algorithm. By analyzing the shape and size of the extracted image, the object is recognized.

#### 3. RESULT





Visible image

Noisy input MMW image





Denoised MMW image

Fused image





Segmented image

Extracted object

# 4. CONCLUSION

Proposed method seems very robust and can detect weapons concealed if any. It can be used in public places without any hassles. It can also be used in the form of a network which can be literally foolproof. Can also be incorporated in binoculars and used in military applications. We can build intelligence into this system to detect the kind of weapon too.

#### 5. REFERENCES

- Hua-Mei Chen, Seungsin Lee, Raghuveer M Rao, Mahamed-Adel Slamani and Pramod K Varshney "Imaging for Concealed Weapon Detection" IEEE Signal Processing, March 2005
- [2] Ivan W. selesnick "*The Double-Density Dual-Tree DWT*", member IEEE.
- [3] Oliver Rockinger "Image Srquence Fusion Using a Shift-Invariant Wavelet Transform"
- [4] Oliver Rockinger, Thomas Fechner "Pixel-Level Image Fusion: The Case of Image Sequences"
- [5] http://www.academia.edu/2704626/compressive\_samplin g\_with\_unknown\_blurring\_function\_application\_to\_pass ive\_millimeter-wave\_imaging
- [6] http://eeweb.poly.edu/iselesni/DoubleSoftware/dintro.ht ml
- [7] D.L. Donoho, "De-Noising by Soft Thresholding", IEEE Trans. Info. Theory 43, pp. 933-936, 1993
- [8] Nobuyuki Otsu, "A Threshold Selection Method from Gray-Level Histograms", IEEE Tx on SMC, Vol. 9, No. 1, Jan 1979, pp 62-66.