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Concealed Weapon Detection: A Data Fusion Perspective

Zheng Liu* and Todd Macuda†
National Research Council, Canada

Zhiyun Xue‡
Lehigh University, Bethlehem, PA 18015

David Forsyth§
Texas Research International, Inc., Austin, TX 78733

and

Robert Laganière¶
University of Ottawa, Canada.

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The purpose of the paper is to address the problems of multisensor security system for concealed weapon detection from the perspective of data fusion. This paper overviews the concealed weapon detection techniques and the state-of-the-art of both signal processing and data fusion algorithms for concealed weapon detection and identifies how they are incorporated into the concealed weapon detection application. The discussion clarifies the functionality and role of data fusion for concealed weapon detection. The expectation for technical advances is presented as well.

I. Introduction

TERRORIST events lead to an increasing requirement for the enhancement of national homeland defense and security. In light of new threats, there are needs for improved surveillance and screening systems in airport facilities, government buildings, transportation security, and many other milieus. The National Institute of Justice (NIJ) of the U.S. Department of Justice released a guide to the technologies of concealed weapon and contraband imaging and detection (CWCID) in 2001 [1]. Each technique has its advantages and disadvantages. Each sensor can be optimized for somewhat different operating range and environmental conditions, and effective combination of such sensors will extend the capabilities of the individual ones and reduce the false call rate of concealed weapon detection (CWD). Thus, the appropriate combination of selected techniques can improve the overall performance of current surveillance system. The technique, namely "data fusion", can be employed to deal with a hybrid system and achieve this objective [2].

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* Institute for Aerospace Research, National Research Council, 1200 Montreal Road, Building M-14, Ottawa, Ontario K1A0R6, Canada. zheng.liu@nrc-cnrc.gc.ca
† Institute for Aerospace Research, National Research Council, 1200 Montreal Road, Building M-14, Ottawa, Ontario K1A0R6, Canada.
‡ Department of Electrical Engineering and Computer Science, Lehigh University, Bethlehem, PA 18015.
§ Texas Research International, Inc., Austin, TX 78733.
¶ School of Information Technology and Engineering, University of Ottawa, Canada.

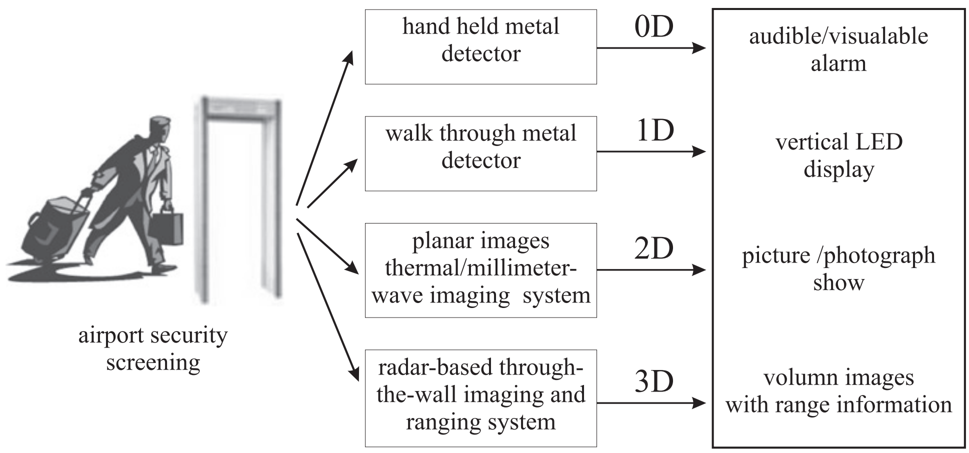


Fig. 1 The data format of a CWCID system.

Depending on the specific technique, the information can be acquired in the format of zero-, one-, two-, or three-dimensional data [1]. Figure 1 illustrates this concept. Although high-dimensional data may provide more useful information, it increases the computational intensity and complexity while coarse information in a reduced dimension may be obtained with equipments at a lower cost. With the development of new imaging sensors, such as infrared (IR) cameras, millimeter wave (MMW) radar, and night-sight cameras; appropriate combination of the available imaging sensors can generate a composite image with more complete information and detailed content from the images acquired by multiple image sensors or make a decision with higher reliability. The fusion can be implemented at the pixel level and higher level. Pixel-level fusion of multisensor images will provide the operator a comprehensive observation. The output of high-level fusion may help the operator make decisions and judgments. With the preprocessing algorithms, multiple features extracted from multimodal sensors and the fusion results can be further used as inputs for the tracking system. The fusion of multisensor images for CWD has attracted more attention recently. With the current wide use of camera-based security systems, there is an enormous potential market for applying multiple image modalities for the enhancement of existing surveillance systems.

The interface design of the multisensor system will provide the flexibility to integrate the system into the existing surveillance network as an independent module and work with other modules cooperatively. Such functionality will make the multisensor CWD system deliverable to most of the surveillance applications.

The intent of this paper is not to evaluate different fusion algorithms for CWD; it aims at addressing the issues relevant to the fusion algorithm development and performance assessment. Fusion of the heterogeneous modalities of sensors or data may provide an efficient solution to many applications but not all. This depends on what techniques are involved and how to fuse them properly.

The rest of the paper is organized as follows. Currently available CWD techniques are briefly described in Sec II. The state-of-the-art on data fusion for CWD is reviewed in Sec. III. The relevant issues are discussed in Sec. IV. The recommendation for future study is provided in Sec. V. The summary of this paper can be found in the last section.

II. CWD: The Techniques

The NIJ's report provided a brief description of the physics of each CWD technique. We summarize those CWD techniques in Table 1. There are ongoing efforts to pursue reliable, efficient, low cost, and privacy-protected CWD techniques.

AKELA developed a portable CWD system based on electromagnetic resonance [3]. The detector employed a radar to sweep through a range of frequency between 200 MHz to 2 GHz and the signature of the resonant response was used to identify the size, shape, and physical composition of the object. This is a nonimaging approach and only zero-dimensional information is available. The ongoing efforts include the design of Terahertz stand-off imager [4]. A performance trade-off study has been carried out by Spore Corp. An ultrasound hand-held detector with LED indicators was developed [5,6]. However, the performance of the detector needs to be further improved. Another

Table 1 The techniques for CWD [1]

Physical principles	Technical implementation	Acquired information	Notes
Acoustic reflectivity of material	Acoustic-based hard object detector	Object size	
Interaction of the time-varying magnetic field	Walk-through metal object detector	Detect presence	Electrically conductive or magnetizable material
	Hand-held metal object detector	Detect presence	Used in close-proximity situations
	Magnetic imaging portal	Image of the objects	Lower spatial resolution (current 2001)
Interaction with the magnetic field of the body	Nuclear magnetic resonance imaging body cavity imager	Objects hidden deep within the body	Expensive and high cost for operating
Changes in local magnetic field of the earth	Gradiometer metal detector	Presence and location of ferromagnetic object	Subject to false positives caused by vibration and movement
	Gradiometer metal object locator	Track and locate ferromagnetic objects	Can be used to track a close metal object or in a few meters way
Interference of two beams of electromagnetic waves	Microwave holographic imager	Accurate surface image of a person	The target must be stationary
Measuring dielectric constant of materials	Microwave dielectrometer imager	Surface image of a person	Stationary object
Back scattering	X-ray imager	Detailed anatomical information	Exist privacy issue
Reflections of the microwave energy by objects	Microwave radar imager	Presence and distance	Through-the-wall capability
Measuring the time interval between pulses and the resonance of reflecting objects	Pulse radar/swept frequency detector/electromagnetic pulse detector	Electromagnetic signature for comparison and judgement	Use the electromagnetic signature of the object
Measuring reflected energy of a pulse illuminating signal	Broadband/terahertz-wave imager	Distance and size	Exists safety issue
Measuring the energy reflected from objects	MMW radar detector	Distance and an image	
Detecting the MMW energy emitted by objects	MMW imager	Surface image	Stationary object and weapon-to-body temperature issue
Measuring the temperature	IR imager	Surface image	Clothing may influence the result

effort is to use ultrasonics to generate a lower frequency acoustic wave that is able to penetrate clothing [7]. The weapon is detected by analyzing the acoustic difference with tissue.

Currently, the study on CWD data fusion mainly focuses on the MMW image and IR image. Because weapons vary broadly in terms of size and materials, imaging system is the strongest candidate for weapon detection [8]. MMW imaging is able to detect the passive radiation of objects at longer wavelengths (1–10 mm), because all materials above absolute zero exhibit black body radiation [9]. The active MMW sensor generates and transmits MMW energy to illuminate the scene and detects the reflected energy to create an image. The passive MMW sensor detects only the naturally occurring MMW emissions and reflections from objects in the scene to form an image [10]. The passive MMW imaging technique can rapidly detect concealed weapons and contraband under clothing [11]. The MMW sensor should be operated in the regions with better atmospheric transmission. The “Vela 125” from Millivision is such an imaging system [12]. The active MMW system developed by the Pacific Northwest National Laboratory in the U.S. can acquire a crisp image in three dimensions by using a linear array of 128 antennas [13,14]. An algorithm for protecting privacy was developed, where a wire-frame humanoid was presented with threats highlighted [15].

The temperature received by the MMW sensor can be expressed as [16,17]

$$T_{\mathrm{rec}}(\varepsilon, \mu, \theta, \alpha) = RT_{\mathrm{ill}} + \epsilon T_{\mathrm{obj}} + tT_{\mathrm{back}} \tag{1}$$

where $T_{\mathrm{rec}}(\varepsilon, \mu, \theta, \alpha)$ is the received temperature, T_{ill} the temperature of the illumination, T_{obj} the temperature of the object and T_{back} the temperature of the background. The reflectivity R, the emissivity ϵ, and the transimissivity t are related as

$$R + \epsilon + t = 1 \tag{2}$$

These three coefficients depend on the physical characteristics of materials and geometrical aspects of the scene defined by the dielectric constant ε, the permeability μ, the angle of incidence θ, the angle between the electric field and the plane of incidence α, and the polarization p [17]. The report on the advances of MMW-based techniques can be found in [6,17,18]

IR imaging is similar to MMW imaging in that the signal response is a function of the temperature of the elements in a scene [9,19]. IR radiation is electromagnetic radiation of a wavelength longer than that of visible light, but shorter than that of microwave radiation. It is categorized into five groups: 1) near IR (0.75–1.4 μm), 2) short wavelength IR (1.4–3 μm); 3) mid wavelength IR (3–8 μm); 4) long wavelength IR (8–15 μm); and 5) far IR (15–1000 μm). In [19], the use of uncooled bolometer array operated in the far-IR band was reported. It is believed that longer wavelength is more efficacious for detection of weapons. External illumination must be applied due to the rapid reduction in sensitivity.

III. Fusion for CWD: State-of-the-Art

The CWD has benefited from the development of data fusion techniques. A number of publications have reported the progresses [20–22]. A tutorial overview of development in imaging sensors and processing was published by Chen et al. [21] on IEEE Signal Processing Magazine in 2005. This article depicted a general picture for the research and development of CWD. In this paper, we will focus on the fusion perspective.

A. The Signal Processing Techniques

The CWD images come with background noises and clutter, which directly lower the probability of detection (POD). Before any further analysis, preprocessing should be applied to tackle this problem. Lee et al. [23] proposed a method to simultaneously suppress noise and enhance object for passive MMW video sequences. They adopted undecimated wavelet transform to achieve enhancement via multiscale edge representation. A motion compensated filtering was applied for temporal denoising. Ramac et al. [24] employed the gray-scale morphologic filtering technique to remove the clutter and spots in IR and MMW images. The clutter herein refers to the irrelevant details such as shadows, wrinkles, and artifacts.

Slamani et al. [25] proposed a mapping procedure consisting of three stages. The first stage is threshold computation, which segments the original image into a number of binary scenes. A low-pass filer and a high-pass filter are used to group pixels and detect edges for each scene in the second stage. At the third stage, a composite is obtained

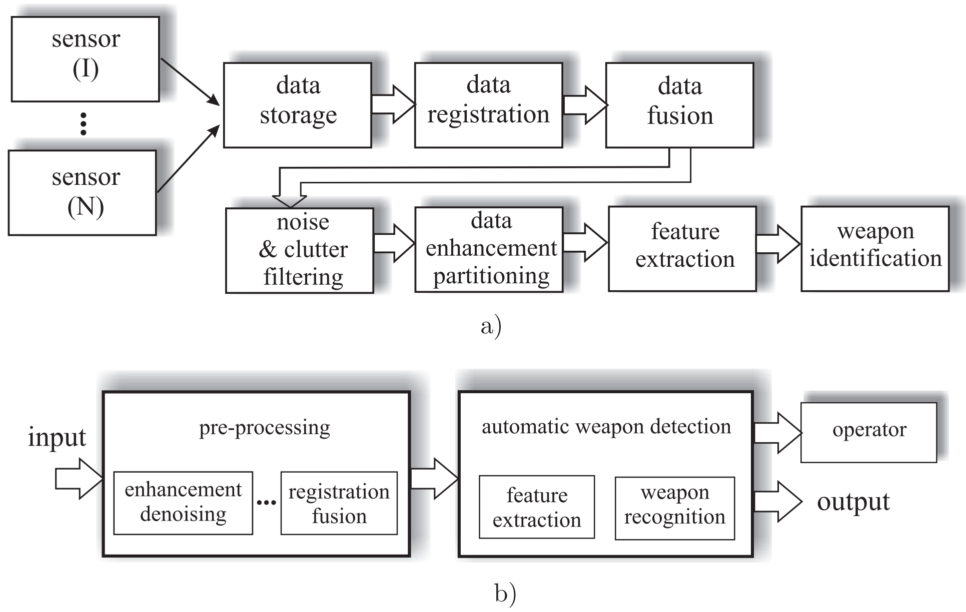


Fig. 2 The signal processing procedures for CWD: a) Slamani's procedure [20] and b) Vashney's procedure [26].

by summing all the processed sub-images together. This procedure actually accomplished a clustering of pixels with common features and will directly affect the systematic performance.

To identify the procedure of processing CWD data, let us look at the flowchart in Fig. 2. The first one in Fig. 2a was proposed by Slamani et al. [26]. The authors proposed another one (Fig. 2b) in their recent publications [20,21]. The second procedure is preferred in most cases, because the preprocessing needs to apply before any further analysis is carried out. The pixel-level image fusion will retain salient features no matter if these features are relevant or not. Such prominence will be presented in the final fusion result.

Another critical issue should be addressed is image registration. The registration process assures each pixel from different images corresponds to the same physical point on the object so that the images can be compared or operated pixel-by-pixel. Chen and Varshney [27] proposed an algorithms to register IR and MMW images. The extracted body silhouettes are used as control points and the mutual information is to measure the match between the input and reference. Yasuda et al. [28] used a test chart made of heated wires to calibrate IR and visual camera successfully for the segmentation of human in a video sequence.

While it would be impossible to discuss all the signal processing techniques for CWD, because the processing algorithms vary with the detection techniques and applications. We hope to provide a general picture of what have been achieved in this research field so far from the discussion in this section.

B. The Data Fusion Algorithms

The contributions of data fusion techniques to a CWD application is demonstrated with Fig. 3. The fusion can be implemented from two aspects: integration and discrimination. In Fig. 3a, the fusion operation can combine the complementary information from two sensors, e.g., the face and moon. In Fig. 3b, one sensing technique can discriminate A and B from C while the other technique can separate A and C from B. The fusion operation can fully discriminate the three components.

Felber et al. [29] implemented a CWD system based on radar and ultrasound sensors. According to the authors of [29], the idea for fusing these two types of sensors is to have the radar acquire concealed weapon at long ranges and seamlessly hand over tracking data to the ultrasound sensor for high-resolution imaging on a video monitor. The frequency-agile radar will achieve a high POD while the active ultrasound sensor array can obtain a centimeter-resolution image of the weapon at the range of a few meters. However, this paper did not demonstrate how the

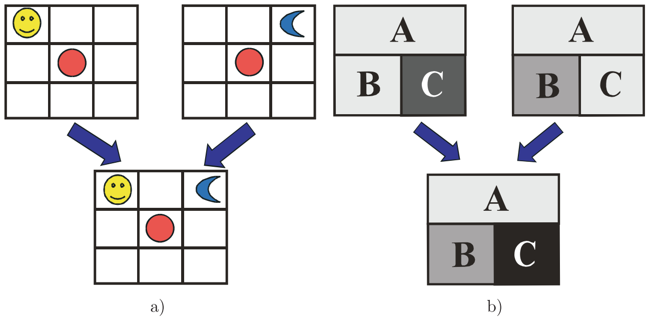


Fig. 3 Data fusion for CWD: a) integration and b) discrimination.

detection could benefit from both techniques in detail. Experimental results on fusing these two techniques were not available at the time the paper was published.

It is claimed that the fusion of MMW image and its corresponding IR or electrooptical image can achieve more complete information [21]. The IR imagers cannot penetrate heavy clothing but operate at reasonably a longer range whereas MMW sensors have a good penetration at a short range [30]. A visual image does not provide any information about the concealed weapons. However, the facial pattern of the suspicious may be available. Thus, the fusion of visual image with other image modalities such as MMW image can provide information of both the personal identification and concealed weapons. As a result, the concealed weapon can be easily located in the fused image that is most suitable for human perception.

Most fusion algorithms for CWD are implemented at pixel level with multiresolution analysis (MRA) approaches. The principle for MRA-based methods is that the image features can be easily accessed and manipulated by representing the image in the transform domain. The methods vary with the basis functions and fusion rules. An excellent review of the MRA based pixel-level fusion can be found in reference [22]. Piella's overview is another good reference [31]. The fusion procedure is illustrated in Fig. 4. The input images $I(x, y)$ are first represented in the transform domain, i.e., a sum over a collection of functions $g_i(x, y)$

$$I(x, y) = \sum_i y_i g_i(x, y) \tag{3}$$

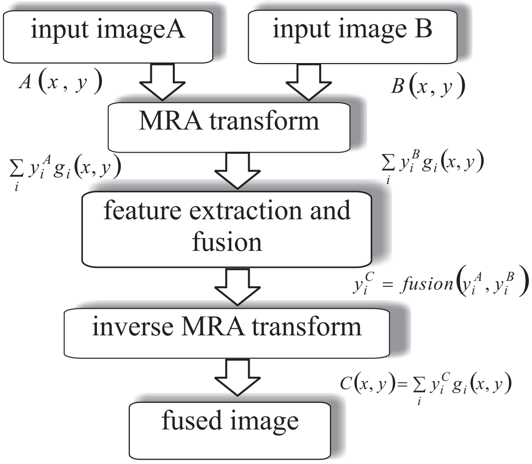


Fig. 4 The procedure of MRA-based pixel-level fusion.

Table 2 The summary of the image fusion techniques for CWD

Image modality	Method	Achievement	Reference
Fusion of two IR images	Spline wavelet transform and Burt's fusion rule [32]	Obtain more complete and detailed information	Üner et al. [33], Slamani et al. [34]
Fusion of IR and MMW images		Facilitate the shape extraction process	Slamani et al. [26], Varshney et al. [30]
Fusion of IR and visual images	Comparison of 15 MRA fusion algorithms	Retain the fidelity of facial pattern and highlight the concealed weapons	Xue et al. [35]
	Color-channel fusion		Xue et al. [36]
	Expectation maximization (EM) algorithm		Yang et al. [37]
	EM and hidden Markov model		Yang et al. [38]
	Region-based EM algorithm		Yang et al. [39]
	Image mosaic		Liu et al. [40], Blum et al. [41]

where y_i are the transform coefficients and can be obtained by projecting the image onto a set of projection functions, $h_i(x, y)$

$$y_i = \sum_{x,y} h_i(x, y) I(x, y) \tag{4}$$

The fusion rule is applied to y_i based on the measurement of image features and characteristics of $g_i(x, y)$. After applying the inverse transform, the fused image is obtained.

For pixel-level fusion, the outcome of the fusion process is also an image, which should be more suitable for further analysis. The current available fusion techniques for CWD application are summarized in Table 2. The details will not be repeated herein and readers are referred to the listed references for more information. In the following, we will discuss the fusion results listed in this table.

Although the authors claimed that the detection performance could be improved by analyzing fused images, there was a lack of solid evidences to support such claims. There needs a quantitative metric, such as POD that can assess the fused result in terms of the improved detection performance, when the data from two detection techniques are fused. For the reliability study, much data needs to be generated to achieve a good POD curve and such study may raise a cost efficient issue.

While the detection techniques is approaching advanced stage, the privacy protection issue comes into view. Fortunately, the fusion of visual image and long-wavelength image will take into account this problem. In the results of [40,41], only the suspect regions for concealed weapons were highlighted in a visual image. An example is given in Fig. 5. The examples of fusion with MMW image or IR image are shown in Figs. 5a and 5b, respectively. The detected weapon area is embedded to the visual image with the multiresolution mosaic technique. The detection of weapon was implemented by unsupervised fuzzy c-means clustering algorithm. The pixel aggregations with highest intensity value were classified as weapon region.

Therefore, the CWD fusion techniques fall into two categories: one is the fusion for visualization (integration); the other is the fusion for detection (discrimination). There is a simple rule to identify the difference. When the fusion is carried out with a visual image input, this is for visualization. Otherwise, the fusion is for detection. However, these two concepts are not mutual exclusive and the CWD system can also be a hybrid one. The visualization is to show the detected weapon. If there is no consideration for the detection, the visualization might not be helpful as expected.

IV. Data Fusion for Detection

A. The Reliability of Detection

The terminology "CWD" indicates the most important task, i.e., detection. Therefore, the assessment of the CWD techniques and fusion algorithms will concentrate on the performance of detection. The reliability of detection for

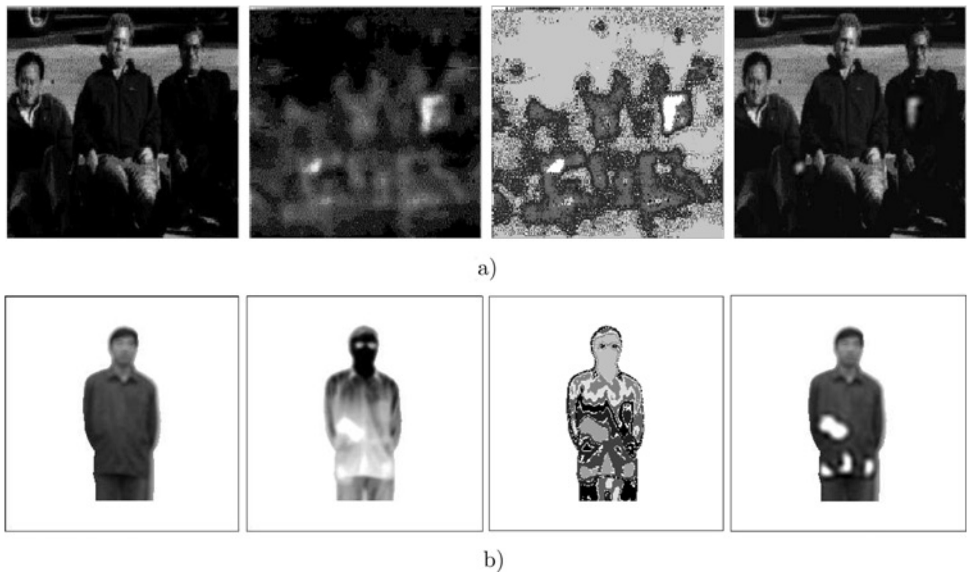


Fig. 5 Fusion examples for CWD: a) MMW + visible image and b) IR + visible image (from left to right: visible image, MMW/IR image, segmented image, and synthesized image) [40].

CWD has not been explicitly addressed and explored so far. In [21], Chen used the plot of POD against probability of false alarm to assess the performance of different shape descriptors. This plot actually illustrated the relationship between accuracy and reliability and did not reflect the impacts of physical variables affecting reliability of detection, such as the size of the concealed weapon, the thickness of the clothing, the stand-off distance, the environment temperature, human factors and so on. The reliability can be estimated by a POD curve.

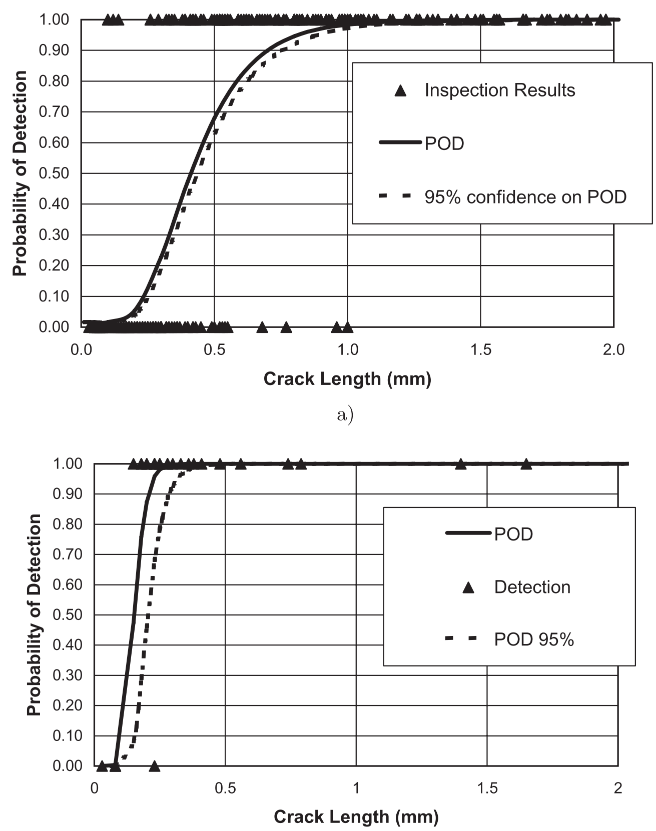
The terminology "POD" appears frequently in research literatures of nondestructive evaluation/inspection (NDE/NDI). It is a measure of the ability of a technique to detect specific defect size of a particular component [42,43]. Continuous POD curves can be estimated from models or experiment or a combination of both. Therefore, properly using the POD metric can evaluate the CWD techniques or fusion algorithms in a specific situation. The POD curve is expressed as a plot of the dependence of the POD of a flaw on a characteristic size of the flaw. For an NDI application, the inspection results are recorded in either "hit/miss" or "a-hat vs a" formats [44]. Figures 6a and 6b show the typical "hit/miss" and "a-hat vs a" POD curve, respectively. We may find the corresponding concepts in a CWD application. As defined in NIJ guide [1], detection gives the operator information on the presence of objects in the detection space. Such indication consists of the hit/miss results. The characteristic size of concealed weapon can be the amplitude, area, diameter, aspect ratio, and so on. These characteristics can be derived from the detection results with processing algorithms. With the POD study, we can understand how the other variables like heavy clothing influence the POD curves. From now on, we use the terminology "characteristic size (a_i)" instead of "crack size" in the following discussion.

For the hit/miss data, the log-logistic and log-normal models are suggested [46]. According to Berens and Hovey [47], the log-logistic function is as follows

$$P_i = \frac{\exp(\alpha + \beta \ln(a_i))}{1 + \exp(\alpha + \beta \ln(a_i))} \tag{5}$$

where P_i is the POD for concealed weapon i, a_i is the characteristic size, α and β are constant parameters defining the curve. The constants can be estimated with two approaches, i.e. regression analysis and maximum likelihood estimation (MLE) [43]. The log-normal function is

$$P_i = 1 - Q(z_i) \tag{6}$$



a)

b)

Fig. 6 Typical POD chart for NDE applications: a) hit-miss POD curve [44] and a-hat vs a POD curve [45].

where the standard normal variate z_i is $z_i = (\ln(a_i) - \mu/\sigma)$, $Q(z)$ is the standard normal survival function, and μ and σ are the location and scale parameters of the POD curve. Similarly, the MLE method can be applied to find parameter μ and σ.

Care must be taken when a-hat vs a POD is generated. In this case, a-hat ($\hat{a}$) stands for the signal response. As mentioned before, such response may be represented in different formats, but there is no guarantee that the POD relation exists. Thus, the characteristic size and signal response should be carefully selected. The "a-hat vs a" POD function is a cumulative normal distribution function and can be expressed as

$$\mathrm{POD}(a) = \Phi\left[\frac{\ln a - (\ln a_{\mathrm{dec}} - \beta_0)/\beta_1}{\delta/\beta_1}\right] \tag{7}$$

where a_{dec} is the decision threshold and parameters β_0, β_1, and δ can be estimated by using the regression analysis or MLE methods.

Although these concepts are well established in the field of NDE/NDI, the reliability study for CWD has not been reported so far to the authors' knowledge. There are a number of variables that contribute to the change of the POD curve. These factors are condition dependent, i.e., the technique itself and the application environment. The objective assessment for CWD techniques and algorithms can be implemented with the POD study. A performance model for each CWD technique should be built. With the established model, the need for fusing multimodal detecting data can be identified.

B. A Second Look on Fusion

As described in the previous section, either data fusion or the signal processing algorithms serve for the detection. As described in Sec. III.B, the fusion is implemented at pixel level. The procedure for the implementation is shown in Fig. 7a. The fully registered images are fused and then segmented or partitioned to indicate the concealed weapon. Even if the segmentation is successful, it is still needed to identify which segmented block is the suspect region for the concealed weapon. No suggestion has been proposed so far.

In [40], Liu et al. proposed a new architecture of signal processing for the CWD application. We demonstrate this concept with Fig. 7b. In this case, the fusion algorithm is to facilitate the classification process that highlights the concealed weapon regions. The detection algorithm is based on the physical phenomenon, for example, the difference in emissivity. Image clustering algorithms like the one described in [48] may act an important role for this. For each pixel, it can be classified as either a weapon or a background from the measurements. The output of the classification or detection algorithm is not a binary result (hard decision), e.g., zero or one. It could be a value between 0 and 1. Therefore, the fusion algorithms at decision level, such as Dempster–Shafer theory, Bayesian inference, or fuzzy set theory, can be applied. Herein raises another question, i.e., which data source should be given more preference. This needs the knowledge of running conditions, which may include the environmental parameters and past performance records. The fusion result is rather explicit and the weapon region can be easily detected by

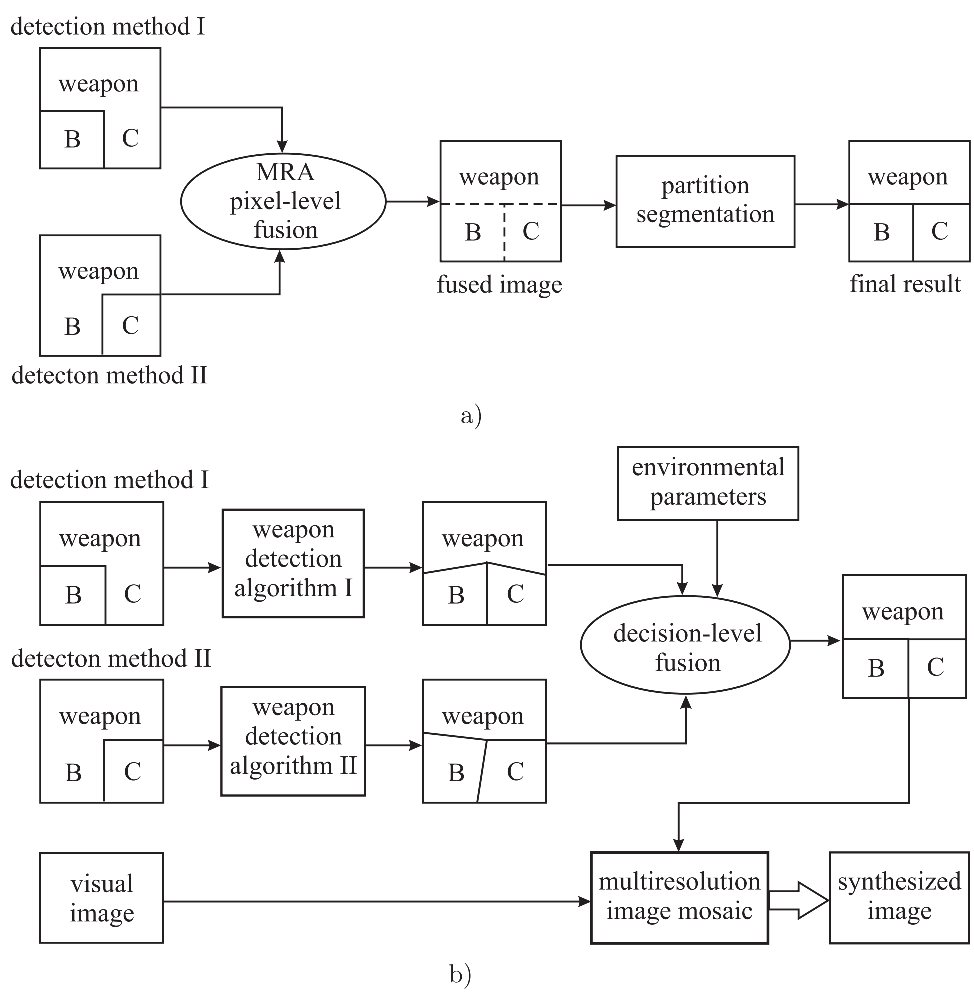


Fig. 7 The data fusion procedure for CWD: a) pixel-level fusion for CWD and b) decision-level fusion procedure for CWD.

applying certain threshold value. The detected weapon region can be further embedded into a visual image. The benefit of this operation is two-fold. The information from visual image can be integrated and privacy is protected from voyeurism.

The reliability study will provide another chance to improve the performance of detection through fusion operation. For each individual detection method, if the POD result is available and we know how the environmental variable influence the curve, we can tune the fusion parameters to give preference to one information source in a specific condition. The implementation of such mechanisms remains a topic for future research.

C. The Human Factor Issue

There will be several human factors issues associated with the CWD application. The visual imagery presented by the CWD will be different from everyday visual displays. That is, the imagery will not appear exactly in the same colors, contrast and details we normally associate with other display systems and natural visual image conditions. As a consequence, this imagery may affect the human users capacity to detect and recognize objects. Thus, there will be a visible impact on the user and this will affect their performance in relevant tasks such as identifying weapons and related materials. Although there will likely be a myriad of perceptual effects using the CWD, according to Klock the primary issues to be considered initially include [49]:

- *Usability*: the ease with which the human user can interface with hardware and software in the CWD system;
- *Training*: timeliness to use the system well and interpret imagery;
- *Efficiency and system effectiveness*: how rapidly can the imagery be interpreted and how accurate is detection and recognition of objects.

There are several other human factors considerations in the development of the CWD. Changing the device characteristics and will have a direct impact on POD and the human user POD curves. It is important to note, that the POD curves for the engineering characteristics will have to be validated against human user PODs. It will be necessary to review the optimal display characteristics (e.g., hardware and software) to best enhance performance in the general four areas described above. This use of sensors in security applications is a relatively new application and will require domain expertise from several areas including, physics, engineering, psychology, and law enforcement professionals.

V. What Is the Next?

The other consideration is how to integrate the multisensor CWD system to work with the existing surveillance system. Besides the implementation of the CWD functions, the multisensor system can also provide complementary information for the task of identifying or tracking in the surveillance process as well. This will enhance the surveillance to be more adaptive to the variations of the environment. However, the potential attacks include a wide variety of chemical, biological, radiological, or nuclear (CBRN) weapons [50]. Therefore, the weapon detection will not be limited to the techniques mentioned in Sec. IV. What is the next beyond CWD?

The national security networks will employ tens of thousands of sensors for detecting weapons, monitoring and protecting critical infrastructures [51]. In order to share sensor data and information, both the sensor interface and data format need to be standardized. The network should be capable of web-based discovery, access, control, analysis, management, and visualization of connected sensors, sensor-derived data repositories, and sensor-related processing capabilities [51]. The opened network should be able to interconnect the sensors seamlessly. IEEE 1451 is such an interface standard for smart transducers.** The goal is to achieve sensor-to-network plug-and-play and interoperability [51]. The sensor information provides the basis for risk management of homeland security, e.g., estimating the likelihood of threat to an asset, individual, or function. At this level, a more general term “information fusion” is more suitable.

VI. Summary

The core of CWD is the capacity to detect and recognize weapons. The CWD sensor and display system must have the capacity to separate the weapons from other objects and items. There are defined homogeneous featural

** http://ieee1451.nist.gov/

characteristics of pixels such as intensity that could be used. Segmentation of imagery, clustering, and thresholding techniques will contribute to this process.

Although CWD is in its infancy, this application may benefit from the fusion of multiple sensors and detection modalities. The data available suggest that pixel-level image fusion can facilitate the segmentation process and ultimate detection of weapons from other objects. There seems to be an obvious advantage to fusing the partitioned results at the decision level and this remains a topic for future investigation.

The quantitative assessment of CWD techniques and fusion algorithms has not been fully explored. A reliability study can provide an objective evaluation of the performance of a CWD system. There is currently no report that describes a comparison study of different CWD systems. It will be necessary to investigate the variables that influence the POD in real operational scenarios. These studies should address engineered device characteristics and human performance limits. This paper is to highlight and emphasize these issues contributing to the performance of a CWD system. The CWD functionality should be integrated as one part of a nation wide risk management system.

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Gerard Parr
Associate Editor