MULTIBAND IMAGERY FOR CONCEALED WEAPON DETECTION (U)

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ABSTRACT (U)

(U) The fusion of visual and infrared sensor imagery for the detection of concealed weapons is demonstrated using several techniques. The fusion algorithms used are wavelet based fusion and Fuzzy Logic Approach (FLA) fusion. The FLA is presented as one of several possible methods for combining images from different sensors for achieving an image that displays more information than either image separately. Near infrared filters are used along with camcorders to capture images for later fusion. Metrics are suggested that could rate the fidelity of the fused images, such as, a textured clutter metric and entropy.

INTRODUCTION (U)

(U) Recent terrorist incited events, both at home and abroad, have created the need for the development of improved methods for the detection of concealed weapons to improve homeland security. The locations that require improved concealed weapon detection capabilities are many; airport gates, building entrances, borders, urban environments etc. Concealed weapon detection ideally should be reliable and fast, however, as with any imaging and detection technology, there are tradeoffs to consider that involve technical as well as social issues. Portability and imaging speed place constraints on the size and resolution of sensors and the computer systems that are used to control the imaging devices. In addition to size, public exposure to ionizing radiation is another issue that must be considered in technology choices that try to balance better concealed weapon detection rates with increased public safety and confidence.

(U) The authors have tested or obtained example imagery from sensors in several wavelength regimes for detection of concealed weapons and describe in this paper the sensor fusion of near IR and visible, near IR and far IR, mmwave and visual band imagery. Combined with the afore mentioned images, the authors have tested several computational methods to combine and enhance the images from the sensors, such as wavelet edge processing, fuzzy logic fusion, Gaussian Laplacian pyramid fusion, and others.

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(U)Method

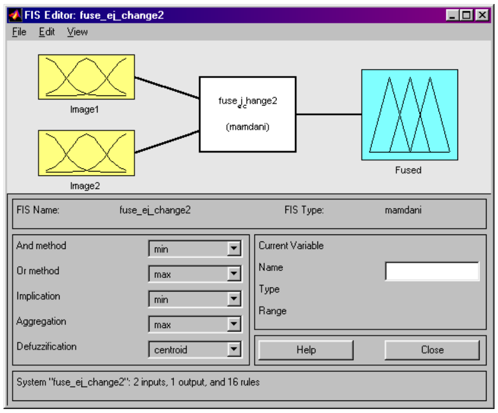
(U) The sources of imagery for sensor fusion were from sensors in the Visual Perception Laboratory at TACOM and raw imagery supplied from other laboratories. The images were then combined by using either the MATLAB Fuzzy Inference System (FIS) and the FuseTool interface. In his book Multi-Sensor Fusion [1], Brooks points out that Fuzzy logic is a technology that shows "promise for use with sensor problems." He goes on to mention, however, that because of the numerous forms of membership functions, methods of recombination, etc., it is difficult to know exactly which implementation is best suited for use in sensor fusion technology. The fuzzy logic approach to image fusion algorithm is described as one option for fusion below. Future papers will define and compare other methods and algorithms for image fusion.

(U) Fuzzy Logic Based Fusion

(U) A great deal of interest has been shown in the Fuzzy Logic Approach (FLA) during the last three decades for numerous technical areas [2, 3, 4, 5, 6]. A strong point of the FLA is that it permits the encoding of expert knowledge directly and easily using rules with linguistic labels. A weak point is that it usually takes some time to design and tune the membership functions that quantitatively define the parameters of interest. To enable a system or process to deal with system level uncertainties, researchers have incorporated the concept of fuzzy logic into many control systems. It has been found that artificial neural network learning techniques can automate this process and substantially reduce development time while improving performance [5]. In this paper, one of the techniques that the authors demonstrate sensor fusion for is the purpose of concealed weapon detection using the FLA.

(U) The basic algorithm for pixel level image fusion using the fuzzy logic approach is;

- Read first image in variable i1 and find its size (rows: z1, columns: s1).
- Read second image in variable i2 and find its size (rows: z2, columns: s2).
- Variables i1 and i2 are images in matrix form where each pixel value is in the range from 0-255. Use gray color map.
- Compare rows and columns of both input images, starting from the upper left. If the two images are not of the same size, select the portions which are of same size.
- Convert the images in column form which has C= z1*s1 entries.
- Make a Fuzzy Inference System file which has two input images, (See Fig.'s 1 and 2).
- Decide the number and type of membership functions for both the input images by adjusting the membership functions. Input images in antecedent are resolved to a degree of membership between 0 to 255.
- Make rules for two input images which resolves the two antecedents to a single number from 0 to 255.
- For num=1 to C in steps of one, apply fuzzification using the rules developed above on the corresponding pixel values of the input images which gives a fuzzy set represented by a membership function and results in output image in column format.
- Convert the column form to matrix form and display the fused image.



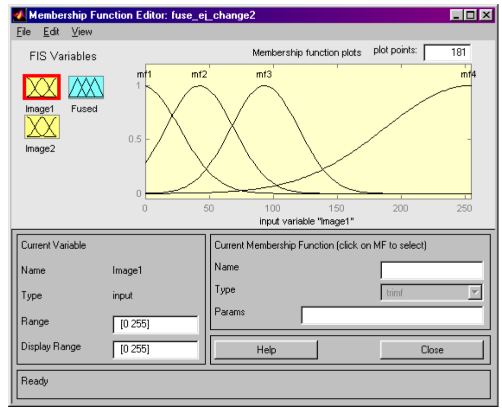


Fig. 1 (U) Mamdani FLA FIS

Fig. 2: (U) Mamdani MF's

<u>(U) Wavelet Processing of Fused Images</u>

(U) The computational method used by the authors to enhance the fused images is the application of wavelet processing. Wavelets have been used by the signal and image processing communities for several years now. A brief review of wavelets for image processing will be given below and then some examples of wavelet enhanced fused imagers will be shown.

(U) A fairly old method of computing a local spectrum is to apply the Fourier Transform (FT) to one specific piece of the signal at a time. This is the idea behind what is called the Windowed Fourier Transform (WFT). Basically, the implementation involves using a rectangular window to isolate a portion of the signal of interest, which is then Fourier transformed. As the window slides along to different positions, the WFT gives the spectra at these positions. This kind of analysis has a fundamental problem however, whose mathematics is similar to the Heisenberg Uncertainty Principle in Quantum Mechanics (QM). Multiplying the signal by a window function results in convolving or mixing the signal spectrum with the spectrum of the window. Add this to the fact that as the window gets smaller, its spectrum gets wider, and we have the basic dilemma of localized spectra: the better we determine the position of the signal, the poorer we localize the spectrum. This is analogous to the case in QM where increased precision in a description of say the momentum of an electron reduces the precision available of the position of that electron. Very accurate determinations can be made or computed, but both are not available to an unlimited degree of precision. Correspondingly, there is a fundamental physical limit to the degree of precision of the frequency content of a signal at a particular position [7,8].

(U) In 1946 Dennis Gabor [8] introduced a version of the WFT that reduced this uncertainty somewhat. The Gabor transform uses a Gaussian profile for the window since the Gaussian is the function that minimizes this uncertainty. However, the underlying idea of localizing a spectrum of a signal by windowing the signal needs to be reconsidered. Obviously, care must be taken in the selection of the signal. Careful attention to the placement of the window however is not an easy task for realistic time-varying signals. We are in fact trying to do two different things at once. Frequency is a measure of cycles per unit time or signal length. So that high frequency oscillations take much less signal length or time than do low frequency oscillations. High frequencies can be well localized in the overall signal with a short window, but low frequency localization requires a long window. The wavelet transform takes an approach that permits the window size to scale to the particular frequency components being analyzed.

(U) Wavelets are generally speaking, functions that meet certain requirements. The name wavelet originates from the requirement of integrating to zero by oscillating about the x-axis and being well localized [9]. In fact, there are many kinds of wavelets. There are smooth wavelets, wavelets with simple mathematical expressions, wavelets that are associated with filters, etc. The simplest wavelet is the Haar Wavelet.

(U) There are many important characteristics of wavelets that make them more flexible than Fourier analysis. Fourier basis functions are localized in frequency but not in time. Small frequency changes in a FT cause changes everywhere in the time domain. Wavelets are local in both frequency and scale by the use of dilations and in time by the use of translations. This ability for localization is useful in many applications. Another advantage of wavelets is coding efficiency. Many classes of functions can be represented by wavelets in a compact way. Functions that have discontinuities and sharp spikes take fewer basis functions to reach a similar approximation.

(U) Noisiness extends to the realm of image data sets. Noisy data sets can be cleaned up by using wavelets. Typically the speed of wavelets is also much faster than the fastest Fast Fourier Transform (FFT). The data is basically encoded into the coefficients of the wavelets. The computational complexity of the FFT is of the order of (nlog2(n)) whereas for most wavelets the order of complexity is of the order n. Many data operations, such as multiresolution signal processing can be done by processing the corresponding wavelet coefficients.

The basic flow of processing in wavelet analysis is shown below in Fig.3:

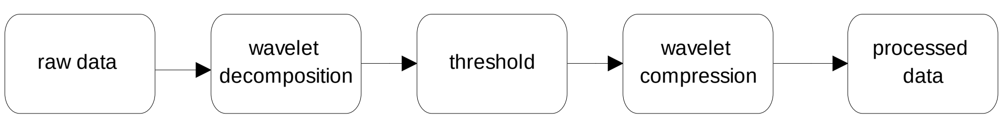


Fig. 3: (U) Wavelet processing flow diagram

(U) How wavelets work is best illustrated by way of an example. The simplest of all wavelets is the Haar wavelet [9]. The Haar wavelet, $\psi(x)$, is a step function that assumes the values 1 and -1. The Haar wavelet is more than 80 years old and has been used for various applications. It can be shown that any continuous function can be approximated by Haar functions. Dilations and translations of the function $\psi(x)$,

$$\psi_{jk}(x) = const\, \psi(2^j x - k) \tag{1}$$

(U) define an orthogonal basis in the space of all square integrable functions, $L^2(R)$. This means that any element of $L^2(R)$ can be represented as a linear combination of these basis functions. The orthogonality of the wavelets pair is checked by the following,

$$\int \psi_{jk}\psi_{j'k'} = \delta_{jj}\,\delta_{k'k'}, \qquad (2)$$

(U) whenever j=j' and k=k' is not satisfied simultaneously. The constant that makes the orthogonal basis orthonormal is $2^{j/2}$.

<u>(U) IMAGES</u>

(U) The figures below are samples of both the raw input images from several sensors and the fused images. Fig. 4 is the visible image of a black sweater suspended over a board. Beneath the sweater is a pair of metal office scissors that is not visible to the naked eye. In Fig. 5, the picture is a long wave infrared image of the scene. Since the scissors are being warmed by the sun outside, the infrared imager can form a reasonable good image based on the temperature difference between the sweater and the pair of scissors. The image in Fig. 6 was obtained using a near infrared filter with a commercial off-the-shelf (OTS) camcorder with night-shot capability. The outline and partial image of the pair of scissors can be seen through the sweater; in fact, both the handles and blades are clearly visible. Fig. 7 is a wavelet fused and enhanced image of Fig. 6. In this case, the enhanced image shows the outline of where the scissors are.

Fig. 4:(U) Visible image of covered scissors

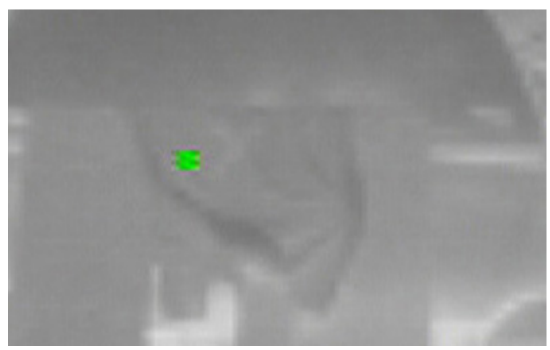


Fig. 5:(U) Far IR image of scissors

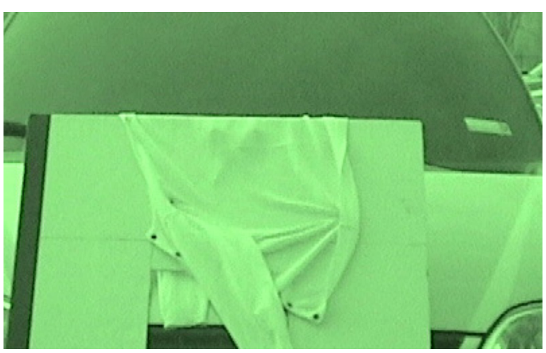


Fig. 6:(U) Near IR image of scissors

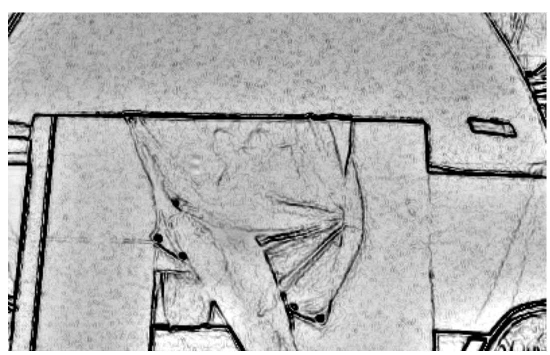


Fig. 7(U): Wavelet Fused near and far IR and enhanced image

Fig. 8:(U) visual image of pants

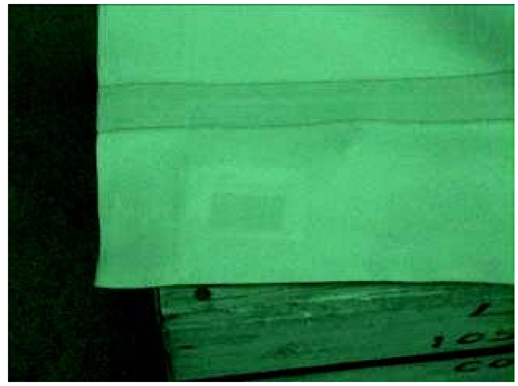


Fig. 9:(U) near IR image of bar pattern under pants

Fig. 10:(U)visual image[11]

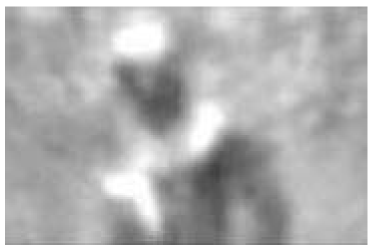


Fig. 11:(U)passive mmwave [11]

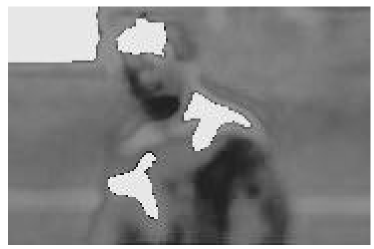


Fig. 12:(U)FLA fused

(U) Fig.'s 8 and 9 are the visible and near IR image of thick cotton pants that have a bar code paper under one of the pant legs. The camcorder with the near IR filter clearly detects the bar pattern under the pant leg. Future work will demonstrate the detectability of various concealed weapons. One of the benefits of using multi-band IR is that the imaging process is completely passive, no ionizing radiation is used or directed unto the people being scanned. The drawback with such a technique is that there is a loss in resolution and additional computer processing, be it some kind of edge enhancement or image processing such as sensor fusion must be used in order to detect a weapon, especially if thick clothing is covering the weapon. Fig.'s 10, 11 and 12, show the imaging of a concealed weapon with passive millimeter-wave (mmwave). [11] Passive millimeter-wave forms an image from the radiation emitted from the body by virtue of it's temperature, no additional incident radiation is needed. The image in Fig. 12 is fused using a Fuzzy Logic Approach (FLA) fusion algorithm to segment the location of the handgun.

<u>(U) How the Near IR filter works</u>

(U) The part of the electromagnetic spectrum that is visible to the naked eye lies between the wavelengths of 400nm to approximately 760nm. ($1nm=10^{-9}m$) Infrared rays have longer wavelengths than the visible band wavelengths, and range from 760 nm to 3000 nm, and are also sometimes called the short-wave IR or SWIR bands of the IR, or near-IR. The near-IR imager works by using a filter with a camcorder.[12] The near IR electromagnetic waves (EM) incident on the subject (2) from the source (1) penetrate the clothing because of their wavelength, are absorbed and re-emitted from the person, and then again pass out through the clothing (4) on the way to the camera and can be used to form an image on the CCD chip (5). The filter (6) used with the camcorder passes only the near IR EM radiation. Since most CCD chips used in OTS camcorders are sensitive to this part of the spectrum, an image can be formed. In some cases the image is good enough to see objects under layers of clothing, and sometimes additional image processing is needed to make the concealed object visible.

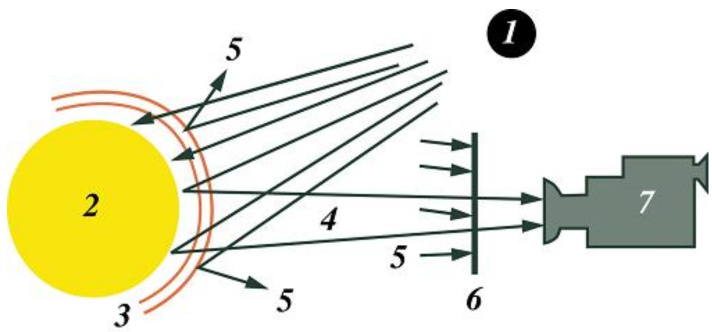


Fig 11: (U) Physical principle of near IR filter operation [12]

<u>(U) Analysis</u>

An entropy and texture based clutter metric were run over the images to see if there was a correlation of the visual quality of the fused imagery with the metrics. The entropy of an image is a measure of the information content, in terms of gray scale levels and is also related to the texture of the image. The maximum value the entropy metric can take on is eight and the minimum is zero. The equation used for the calculation of the entropy [10] is shown below,

$$H = -\sum_{g=0}^{L-1} p(g)\log_2 p(g)$$

where $p(g)$ is the probability of gray value g, and the range of g is [0,...,L-1].

MMW Weapon Images

Sensor	Entropy	Text Clut
Visible	6.653	59.17
Mmwave Radar	6.7709	61.64
Fused	7.1993	65.39

Scissor Images

Sensor	Entropy	Text Clut.
Visible	7.3932	44.02
IR	6.2709	16.42
Fused PCA	7.4658	66.75
Fused PCA edge	6.5238	89.82

Table 1: (U) Entropy and clutter metric values for sensor images

(U) Conclusions

(U) In summary, the authors have shown some of the sensor combinations and algorithms that can be combined to detect concealed weapons. Which sensors are used is going to be determined also by factors such as cost, perceived risk by the public, and the size of the device. Using passive infrared and or millimeter-wave multiband imagery with sensor fusion and edge enhancement it is possible, in some circumstances to detect a weapon concealed under light clothing. When imaging through thick layers and a high degree of resolution is required, the best sensor may be active millimeter-wave imagers, however, this capability brings with it greater cost. The authors have shown some of the imaging possibilities using passive infrared imagery and millimeter-wave wave images. Future research could show how the passive infrared sensors used with image fusion and processing algorithms can detect concealed weapons such as handguns.

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