Implementation of Pixel Level Color Image Fusion for Concealed Weapon Detection

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***Abstract*—Image fusion has various applications in the field of military, law and enforcement. Image fusion for Concealed Weapon Detection (CWD) has attracted lots of interest in the field of military. In this paper linear pixel level image fusion has been implemented using vector valued total variation algorithm (VTVA). It includes decomposition of covariance matrix of multispectral bands using cholesky decomposition. The decomposed data is linearly transformed and mapped. The statistical properties of the resultant fused image can be controlled by the user.**

Keywords—Concealed Weapon Detection(CWD), pixel level image fusion, VTVA

I. INTRODUCTION

Image fusion [4] is a process of merging two or more images taken from different sensors to form a fused image which is more informative and efficient compared to the source images. It's difficult to combine visual information simply by viewing multiple images separately by the human observer so we go image fusion. The pixel level image fusion performed on a pixel-by-pixel basis. It generates a fused image in which information associated with each pixel is determined. The performance of source image will be improved. In general pixel level fusion methods can be classified as linear and nonlinear methods.

In this paper the proposed algorithm is a linear pixel level image fusion. This method improves the visual quality of the fused image. The Concealed Weapon Detection (CWD) has been introduced in this paper, which detects the weapon or metal object hidden underneath a person's clothing. The research activities are going, on improving the quality of the fused image.

II. VECTOR VALUED TOTAL VARIATION ALGORITHM (VTVA)

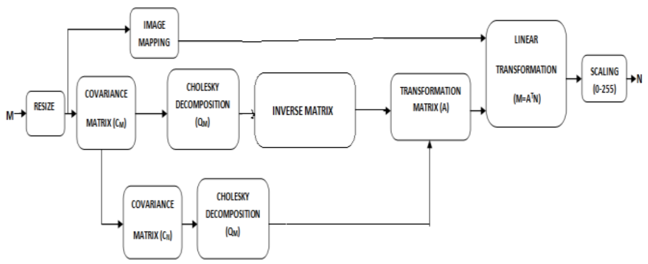

Fig .1. Block Diagram of VTVA

Statistical properties of multispectral data set with X * Y pixel per channel and k different channels can explored if each pixel is described by a vector whose components are the individual spectral responses to each multispectral channel

$$M = [M_1, M_2, M_3, ..., M_K]^T \qquad (1)$$

with mean vector given by

$$x_m = E\{M\} = \left(\frac{1}{X.Y}\right)\sum_{i=1}^{X.Y} M_i \qquad (2)$$

The mean vector is used to define the average or expected position of the pixels in the vector space.

A. Covariance matrix

The correlation between the multispectral bands can be defined by covariance matrix. If the off diagonal elements in covariance matrix are large then we can say that the multispectral bands are correlated with each other and diagonal elements of the covariance matrix are the variance. The covariance matrix is real symmetric and positive definite matrix. The covariance C_M can be obtained using equation

$$C_M = \frac{1}{X.Y}\sum_{i=1}^{X.Y} m_i\,\bar{m}_i - x_m {x_m}^T \qquad (3)$$

The correlation coefficient 'r' is obtained by dividing the covariance matrix elements with the standard deviation of the corresponding multispectral component ($r_{ij}=c_{ij}/\sigma_i\sigma_j$). The correlation coefficient matrix R_M has an elements the correlation coefficient between ith and jth multispectral components. The correlation coefficient matrix is shown below. The covariance matrix C_M and C_N are real and symmetric.

$$R_M = \begin{bmatrix} 1 & r12 & \cdots & r1k \\ r21 & 1 & r23 & r2k \\ \vdots & r32 & \ddots & \vdots \\ rk1 & rk2 & \cdots & rkk \end{bmatrix} \qquad (4)$$

The covariance matrix C_N can be obtained as the product of diagonal matrix and correlation coefficient matrix as below

$$C_M = E\,R_M\,E^T \qquad (5)$$

Where E is the diagonal matrix and

$$E = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & 0 & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_k \end{bmatrix} \tag{6}$$

B. Cholesky decomposition

The C_M and C_N can be transformed into upper triangular matrix Q_M and Q_N respectively by making use of cholesky transformation matrix. The cholesky decomposition is applicable only for the real, symmetric and positive definite matrix. A real symmetric matrix P can be decomposed by means of upper triangular matrix Q so that

$$P = Q^T * Q \tag{7}$$

The factorized C_M and C_N can be written as

$$C_M = {Q_M}^T Q_M \tag{8}$$

$$C_N = {Q_N}^T Q_N \tag{9}$$

C. Transformation matrix

The transformation matrix transforms the fused multispectral components into a RGB or color image. The transformation matrix A depends on the statistical properties of the original data set. The transformation matrix A can be obtained using the cholesky decomposition method. The relation between the covariance matrices be

$$C_N = A^T C_M A \tag{10}$$

substitute (8) and (9) in (10)

$${Q_N}^T Q_N = A^T {Q_M}^T Q_M A = (A Q_M)^T Q_M A \tag{11}$$

Thus,

$$Q_N = Q_M \; A \tag{12}$$

The transformation matrix can be written as

$$A = {Q_M}^{-1} Q_M \tag{13}$$

D. Linear transformation

The linear transformation is to map the input and output components.

$$N = A^T M \tag{14}$$

E. Scaling

The scaling scales the mapped image into the range [0-255]. The linearly transformed M must be scaled in order produce an RGB representation.

$${N_{ki}}^T = 255.\frac{N_{ki} - \min(N_{ki})}{\max(N_{ki}) - \min(N_{ki})} \tag{15}$$

Where min (N_{ki}) and max (N_{ki}) are the minimum and maximum values of transformed vector N_k respectively.

III. SIGNAL TO NOISE RATIO

The signal to noise ratio (SNR) is calculated as the ratio of rms value of the reference input and the rms value of difference between reference input and mapped output image.

The SNR for the fused image at the output can be calculated by as below

$$SNR = 10\log_{10}\frac{RMS\{\text{reference image}\}}{RMS\{\text{reference image} - \text{output image(bit\_length)}\}} \tag{14}$$

TABLE I. SNR VALUE IN DECIBELS VERSUS BIT LENGTH OF THE FUSED IMAGE

Table Head	SNR Value Of Previous Paper	SNR Value Of Proposed System
12-bit	77.20dB	72.8407dB
16-bit	98.15dB	73.1117dB

The previous SNR values and propose method values for 12-bit and 16-bit are shown in Table.1.

IV. EXPERIMENTAL RESULTS

Fig .2. Natural color image

Fig .3. Infrared image

Fig .4. Fused image 1

Fig .5. Fused image 2

First a natural color image is taken, the RGB components are separated from color image. Next a gray scale image is taken where we can see the weapon hidden inside the clothing. This is shown in the first two figures. Last two images are fused images where the weapon hidden is clearly seen. The resultant fused image's color is configurable. User can configure the color of the fused image.

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REFERENCES

[1] Dimitrios Besiris et.al. "An FPGA-Based hardware implementation of configurable pixel level color image fusion," IEEE Tras. Geosci. Remote Sens., vol. 50, no.2, pp. 0196-2892, Feb 2012 .

[2] V. Tsagaris and V. Anastassopoulos, "Multispectral image fusion for improved RGB representation based on perceptual attributes," Int. J. Remote Sens., vol. 26, no. 15, pp. 3241–3254, Aug. 2005.

[3] Mrityunjay Kumar, Member, IEEE, and Sarat Dass, Member, IEEE, "A Total Variation-Based Algorithm for Pixel-Level Image Fusion," Trans. image processing, vol. 18, no. 9, Sept 2009

[4] A. Goshtaby and S. Nikolov, "Image fusion: Advances in the state of the art," Inf. Fusion, vol. 8, no. 2, pp. 114–118, Apr. 2007.

[5] R. S. Blum and Z. Liu, Eds., "Multi-Sensor Image Fusion and Its Applications (Special Series on Signal Processing and Communications)". New York: Taylor & Francis, 2006.

[6] T. Stathaki, "Image Fusion: Algorithms and Applications,". New York: Academic, 2008.