Detection of Buried Landmines using the Possibilistic Correlation-Dependent Fusion Methods

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Abstract: - Multi sensor fusion is an important component of applications for systems that use correlated data from multiple sensors to determine the state of a system. As the state of the system being monitored and many sensors are affected by the environmental conditions changing with time, the multi sensor fusion requires a correlation-dependent approach. The behavior of this approach should vary according to the correlation parameter. In this paper, we compare our possibilistic correlation-dependent fusion approach (PCDF) with the possiblistic combiner Dempster-Shafer. We use time-series infrared images of landmines buried in different types of soil.

Key-Words: - Image Fusion, Correlation, T-Norm, Dempster Shafer, time-series images of buried mines.

1 Introduction

Multi image fusion has become an active field of research as more and more applications such as medical imaging, security, avionics, surveillance and night vision utilize multi sensor imaging arrays. Such arrays provide a wider spectral coverage and reliable information even in adverse environmental conditions at a price of a considerable increase in the amount of data. Image fusion deals with the data overload by combining visual information from multiple image signals into a single fused image.

Detection techniques for buried low-metal landmines that are in development can be grouped into three main categories: (i) sensors that 'see' an image of the landmine through scattering, (ii) sensors that detect anomalies at the surface or in the soil, and (iii) sensors that detect the landmine explosives or chemicals that are associated with the explosives. Most if not all of these sensors are affected to some degree by soil conditions.

There is a general agreement that no sensor can by itself be used to find landmines under all conditions. Data fusion techniques are used to combine the information from different sensors to increase the probability of detection and decrease the false-alarm rate.

Most work on data fusion for landmine detection has involved data fusion at the decision level [2]. If the performance of the individual sensors is strongly correlated, then the sensor fusion algorithm may also need the correlation coefficients.

As a practical matter, models of sensor performance do not seem to be accurate enough to directly provide this information. Given that soil properties can have a very large influence on the ROC curve associated with a particular sensor [15], we suggest incorporating information about the change in the soil properties conditions in the area under investigation into the data-fusion process.

In [12], L. Kuncheva et al. consider two main issues in designing cluster ensembles "separately": (1) the design of the individual "clusterers" so that they form potentially an accurate ensemble, and (2) the way the outputs of the clusterers are combined to obtain the final partition, called the *consensus* function.

In our new cluster ensemble methods (PCDF, Possibilistic Correlation-Dependent Fusion) [10, 11] the two issues are merged into a single design procedure, i.e., when one clusterer is added at a time and the overall fusion function is updated according to the correlation between the two images to be fused. It is seen that correlation between two consecutive MWIR images is related to the environmental changes (temperature, water content, texture, bulk density).

2 Fusion Techniques

Fusion techniques can be seen as a *discriminant* function, $F(\vec{c})$ in image confidence space defined in such a way that:

$F(\vec{c}) \geq t \quad assign \;\; \vec{c} \rightarrow$ Object of Interest

$F(\vec{c}) < t \quad assign \;\; \vec{c} \rightarrow \text{Background}$

where $\vec{c} = (c_1, c_2, ..., c_R), c_i \in [0,1] \;\; \forall i \in [1, R]$ is an image output (confidence) vector with R the number of images and t the threshold. Image output vectors are defined only at locations where the images from co-registration and where image data is present.

The general layout of the image-fusion methods is shown in Figure 1. The input of each image-fusion method is a confidence level per grid cell.

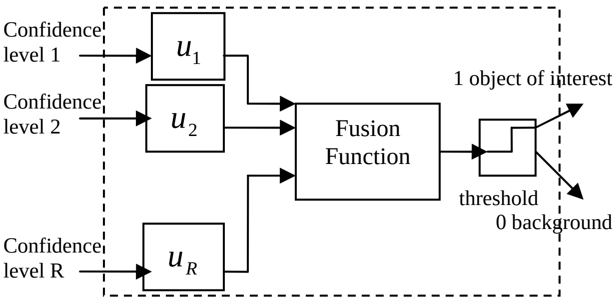

Figure .1. The generic image-fusion layout.

The output of the fusion process is one for detection and zero for no detection per ~~g~~rid cell. Each of the methods scales the influence of each of the images in a different way.

This mapping may remove the differences in definitions of the confidence levels. The mapped inputs are combined in a fusion function to acquire a single value per grid cell. The mapping functions and the fusion function are given in [1, 2, 3, 4].

3 The Dempster-Shafer Fusion Method

For application of the Dempster-Shafer theory to image fusion, three inputs per image are needed: the probability mass assigned to an object of interest $m(M)$, the probability mass assigned to background $m(\overline{M})$, and the unassigned probability mass $m(M \cup \overline{M})$. The sum of these masses always equals one, so there are only two *independent* masses ($m(M)$ and $m(\overline{M})$). The mass $m(M)$ represents a belief in an object of Interest, the mass $m(\overline{M})$ represents the belief in background, and the mass $m(M \cup \overline{M})$ reflects the uncertainty of the image. Each image produces one confidence level at each sample location, which must be mapped onto the three required probability masses. This is done by using the uncertainty as an optimization parameter.

The confidence levels for image i are mapped onto probability masses, using:

$$m_i(M) = (1 - u_i)c_i \quad (1)$$

$$m_i(M \cup \overline{M}) = u_i \quad (2)$$

with u_i the mapping parameter and c_i the confidence level for image i. The probability masses for image 1, 2,..,R are combined using Dempster's rule of combination:

$$m_{1,2,...,R}(M) = (m_{1,2,...,R-1}(M) + m_{1,2,...,R-1}(M \cup \overline{M})) * m_R(M) + m_R(M \cup \overline{M}) * m_{1,2,...,R-1}(M) \quad (3)$$

$$m_{1,2,..,R}(M \cup \overline{M}) = \prod_{i=1}^{R} m_i(M \cup \overline{M}) \quad (4)$$

with $m_{1,2,...,R}(M)$ the combined probability mass assigned to object of interest, and $m_{1,2,...,R}(M \cup \overline{M})$ the combined uncertainty mass. The output of the Dempster-Shafer fusion function is given by the three combined probability mass assigned to an object of interest plus half the uncertainty:

$$F(\vec{c}) = m_{1,2,...,R}(M) + \tfrac{1}{2} m_{1,2,...,R}(M \cup \overline{M}) \quad (5)$$

From the previous, we conclude that Dempster-shafer belief functions are assigned to independent sources of evidence and is known as a special case of possibilisty theory where correlation = 0 [8] and hence, it is not expected from this theory to have a good behavior in applications of high correlation data such as landmine detection. In later sections, we will present our PCDF approach sensitive to correlation.

4 The Possibilistic Correlation-Dependent Fusion Methods

We propose a general method for the fusion process, which can be used with image outputs that may exhibit any kind of (positive, neutral, or negative) correlation with each other. Our method is based on the concept of Triangular Norms, a multi-valued logic generalization of the Boolean intersection operator. With the intersections of multiple decisions one needs to account for possible correlation among the sources, to avoid under- or over-estimates. Here we explicitly account for this by the proper selection of a T-norm operator. We combine the outputs of the images by the generalized intersection operator (T-norm) that better represents the possible correlation between the images. This approach performs better for correlated satellite

images for environmental changes than the previous techniques [10-11].
The correlation affects the performance analysis [1]. The larger the correlation index, the larger the redundancy. In particular, the correlation index goes to zero if the individual incorrect answers are disjoint for all answers. In other words there is always at least one correct answer for any class.
The ρ correlation coefficient [6] gets larger as the number of wrong answers is the same for many answers. Let N^f be the number of experiments where all tools had a wrong answer, N_i^c be the number of experiments with combinations of correct and incorrect answers; c is the combination of correct and incorrect answers; n is the number of tools. The correlation coefficient is then

$$\rho = \frac{nN^f}{\sum_{i=1}^{2^n-2} N_i^c + nN^f} \quad (7)$$

N^f and N_i^c are computed using the correlation analysis matrix [5].
In our work, we suggest a new decision-level fusion method based on possibilistic fusion for a better representation of the correlation among images.
From the associativity of the T-norms, we can derive the associativity of the fusion by:

$$F(\vec{c}) = TNorm\,(TNorm\,(c_1, c_2), c_3) = TNorm\,((c_1, TNorm\,(c_2, c_3)) \quad (8)$$

with c_1, c_2, c_3 the confidence levels for three images and this equation (8) can be computed recursively for R images. For instance the operator $h(x, y, \alpha)$ is CIVB (Context Independent Variable Behavior) whose behavior depends on the value of α [7].
In our approach, we choose a suitable α to have a fusion technique sensitive to correlation.

1. *Generalized T-Norm Family:*
   - This family is increasing w.r.t. the parameter α
   - We choose α such that $\alpha = \rho$

$$TNorm(c_i, c_{i+1}) = \max[0, (c_i^{\alpha} + c_{i+1}^{\alpha} - 1)]^{1/\alpha}, \quad \alpha \neq 0 \quad \alpha \neq 1 \quad (9)$$

otherwise

$$TNorm(c_i, c_{i+1}) = \begin{cases} \max[0, (c_i + c_{i+1} - 1)] & \alpha = 1 \\ c_i * c_{i+1} & \alpha = 0 \end{cases}$$

(10)

2. *Schweizer-Sklar T-Norm Family:*
   - This family is a decreasing family w.r.t. the parameter α
   - We choose α such that $\alpha = 1 - (\rho / \infty)$

$$TNorm(c_i, c_{i+1}) = \frac{c_i * c_{i+1}}{\max(c_i, c_{i+1}, \alpha)}, \quad \alpha \neq 0 \quad \alpha \neq 1 \quad (11)$$

otherwise

$$TNorm\,(c_i, c_{i+1}) = \begin{cases} c_i * c_{i+1} & \alpha = 1 \\ \min(c_i, c_{i+1}) & \alpha = 0 \end{cases} \quad (12)$$

3. *Frank T-Norm Family:*
   - This family is decreasing family w.r.t the parameter α
   - We choose α such that $\alpha = 1/(1-\rho)$

$$TNorm\,(c_i, c_{i+1}) = \log_{\alpha}\left[1 + \frac{(\alpha^{c_i} - 1)(\alpha^{c_{i+1}} - 1)}{\alpha - 1}\right], \quad \alpha \neq 0, 1, +\infty \quad (13)$$

otherwise

$$TNorm(c_i, c_{i+1}) = \begin{cases} \max[0, (c_i + c_{i+1} - 1)] & \alpha = +\infty \\ c_i * c_{i+1} & \alpha = 1 \\ \min(c_i, c_{i+1}) & \alpha = 0 \end{cases}$$

(14)

4. *Hamacher T-Norm Family:*
   - This family increasing w.r.t. the parameter α
   - We choose α such that $\alpha = 1/(1-\rho)$

$$TNorm(c_i, c_{i+1}) = \frac{c_i * c_{i+1}}{\alpha + (1-\alpha)(c_i + c_{i+1} - c_i * c_{i+1})}, \quad (15)$$

$\alpha \neq +\infty \quad \alpha \neq 1$

otherwise

$$TNorm(c_i, c_{i+1}) = \begin{cases} \max[0, (c_i + c_{i+1} - 1)] & \alpha = +\infty \\ c_i * c_{i+1} & \alpha = 1 \end{cases} \quad (16)$$

5 Experiments on Real data

In the performance evaluation curve, the accuracy is compared to the correlation between different images of environmental changes. The images are acquired from http://apl-database.jrc.it/Home/sigdata.htm/ for landmine MWIR images in a sand lane, gravel lane, mixture lane.

These data were collected at Meerdael (Belgium) minefields on 1st, 2nd and 3rd of April 1998 using mid-wave infrared cameras - AGEMA (3um-5um). These images are chosen to prove the efficiency of the algorithm and its usefulness in the landmine detection applications [9, 13]. The accuracy here is defined by comparing the actual image (priori knowledge) with the fused image.

In order to create this comparison it is of extreme importance to have adequate simultaneous information on the detection rate over the entire diagram for the algorithm.

The data used for performance evaluation:

1. AGEMA MWIR image in a sand lane(referred to S row in table 1) acquired at date 01-04-1998 and times 21:34M and 22:04M
   Computed Correlation = 0.65631
2. AGEMA MWIR image in a gravel lane (referred to G row in table 1) acquired at date 02-04-1998 and times 20:49M and 21:23M
   Computed Correlation = 0.91762
3. AGEMA MWIR image in a mixture lane (referred to M row in table 1) acquired at date 03-04-1998 and times 21:19M and 21:48M
   Computed Correlation = 0.94982

DATA	**Accuracy of Techniques**				
	DS	**G**	**S-S**	**F**	**H**
S	-----	0.93757	0.93757	0.93757	0.93757
G	0.89795	0.92569	0.92569	0.92569	0.92569
M	0.9317	0.95358	0.95358	0.95358	0.95358

Table1. Accuracy gained by the Dempster Shafer technique and the different forms of the PCDF approach. The points (----) means that the algorithm fails to detect any of the object of interest.

The following figures show the output fused images using Dempster-Shafer and the PCDF (the four T-Norm CIVB forms gave appropriate results here)

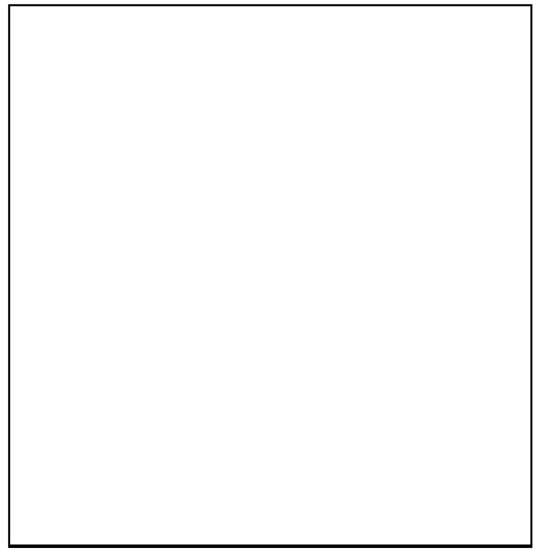

Figure 2.The output fused image using Dempster-Shafer (sand lane)

Figure 3.The output fused image using the PCDF (sand lane)

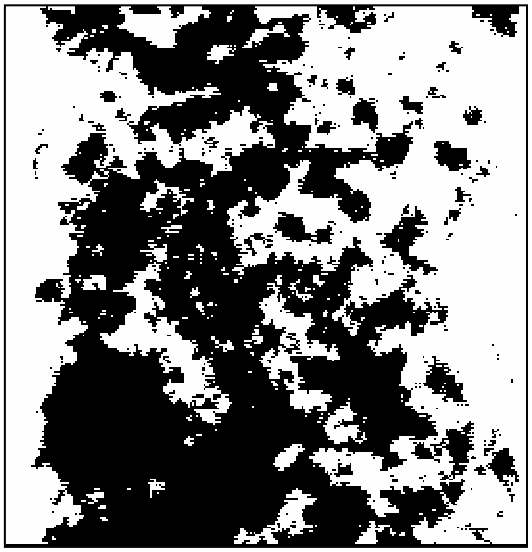

Figure 4.The output fused image using the Dempster Shafer (gravel lane)

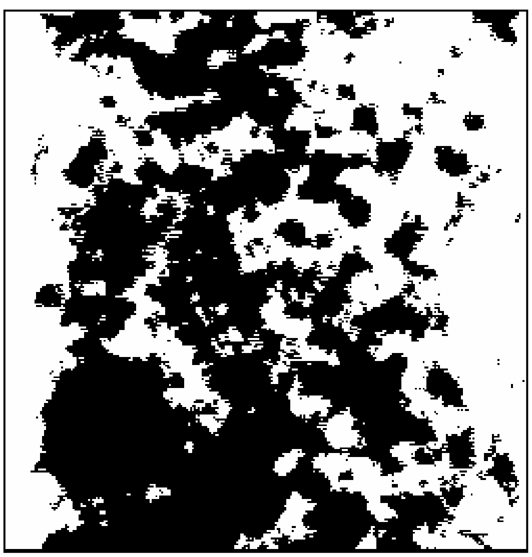

Figure 5.The output fused image using the PCDF (gravel lane)

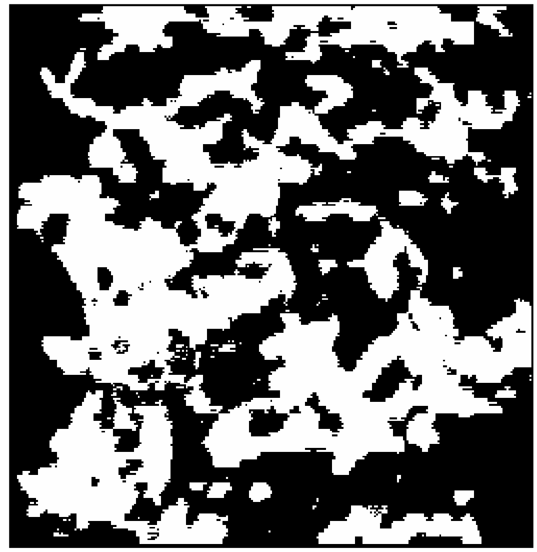

Figure 6.The output fused image using the Dempster Shafer (mixture lane)

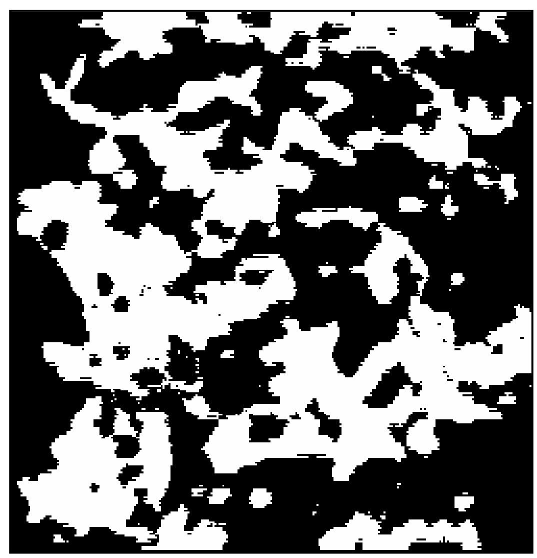

Figure 7.The output fused image using the PCDF (mixture lane)

5 Conclusions

We have proposed an approach based on possibility theory in this paper. The approach is based on computing the correlation among different images taken at different times to study the change of the environment and use it as a parameter in four T-Norm Correlation-Dependent fusion techniques to handle the problem of high correlation by introducing the correlation parameter in the fusion process.

6 Future Works

In this paper, we presented two types of T-Norm families which are increasing and decreasing w.r.t. the parameter α families. The behavior of the PCDF was the same when applied to time-series images of large changes of the environment (long periods of time proportional to the landscape acquired) while time-series images of small changes of the environment (short periods of time proportional to the landscape acquired)[11], the difference between both types of families is distinguished. For future work, we will focus on the comparison between decreasing and increasing T-Norms families and the choice of the suitable form of the PCDF Method in the application to a particular problem.

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