Possibilistic Fusion for Landcover Mapping using Correlated Satellite Imagery for Environmental Change

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Abstract: - To acquire detection performance required for an operational system in the detection for satellite image for environmental change, it is necessary to use multiple images over years to know the environmental changes over years. This paper describes a method for decision-level fusion technique where the fusion can compensate for correlation among images. The fusion is done using possibilistic combiners based on T-norms families that better represent the correlation of images. This technique was applied to Nile River Delta, Egypt (1973, 1987). These images show the dramatic urban growth within the Nile River delta and the expansion of agriculture into adjoining desert areas.

Key-Words: - Decision Fusion, Correlation, naive Bayes, Dempster-Shafer, voting, linear discriminant, T-Norm, Satellite Imagery for environmental change.

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 with the direct aim of preserving the full content value of the multi sensor information.

The production of land cover / land use maps is a common application of multi spectral satellite images. There are numerous examples of land cover maps derived from multi spectral satellite imagery at global, regional and local level. The most widely used approach is to classify each image pixel as an independent observation, regardless of its spatial context. Recently, at local level, a number of data sources have been used to derive land cover products, including Land sat TM data for high resolution studies.

These studies have been carried out for a number of different applications, including estimation of biomass and vegetation mapping. It was evaluated the potential of ASTER VNIR (Visible and Near Infrared) and SWIR (Short Wave Infrared) sensors for land cover mapping. Information in the VNIR image contributed to the enhancement of vegetation and water classes. Rock and soil units were enhanced due to the contribution by the information in the SWIR images.

One of the main problems when generating land cover maps from digital images is the confusion of spectral responses from different features. Sometimes two or more different features with similar spectral behavior are grouped into the same class, which leads to errors in the final map. The accuracy of the map depends on the spatial and spectral resolution and the seasonal variability in vegetation cover types and soil moisture conditions. Attempts have been made to improve the accuracy of image classification.

Our aim in this paper is to develop a new approach for multi spectral image fusion or satellite imagery for environmental change based on possibility theory. This approach is expected to handle the problem of correlation which degrades the performance fusion.

This approach will then be used to the Nile River Delta, Egypt (1973, 1987). These images show the dramatic urban growth within the Nile River delta and the expansion of agriculture into adjoining desert areas.

2 Background

Fusion techniques [3, 4, 5] can be seen as a *discriminant* function, $F(\vec{c})$ in satellite image confidence space defined in such a way that:

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

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

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.

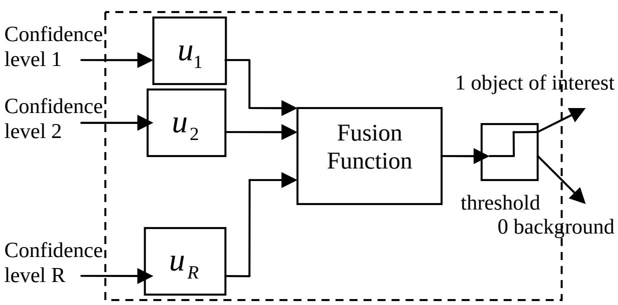

Figure 1. The generic decision-level image-fusion layout.

The output of the fusion process is one for detection and zero for no detection per grid ~~c~~ell. 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 Table 1.

Method	**Mapping Function**	**Fusion Function**
naive Bayes	linear scaling around 0.5	product
Linear discriminant	linear scaling	summation
Dempster-Shafer	uncertainty level	Dempster's rule of combination
Voting	threshold	Summation
Rule-Based	linear scaling	Disjunction of conjunction clauses

Table 1. The different functions for scaling the input and combining these into a single (fused)

3 T-Norm Fusion

We propose a general method for the fusion process, which can be used with satellite 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.

3.1 The Triangular-Norm

A triangular norm (briefly t-norm) is a binary operation T on the unit interval [0, 1] as follows $T : \forall(x, y) \in [0,1]^2, \max(0, x + y - 1) \leq xy \leq \min(x, y)$ The T-norm operation is commutative, associative, monotone and has 1 as neutral element, i.e., it is a function $T : [0,1]^2 \rightarrow [0,1]$ such that for all $x, y, z \in [0,1]$:

(T1) $T(x, y) = T(y, x),$

(T2) $T(x, T(y, z)) = T(T(x, y), z),$

(T3) $T(x, y) \leq T(x, z),$ whenever $y \leq z,$

(T4) $T(x,1) = x,$

In I. Bloch [10], T-norms were considered as fuzzy CICB operators which satisfy the requirements of the conjunction operators. There exist a lot of parameterized T-norm families of operators which range continuously from one operator to another depending on the value of the parameter. This parameter can be used to express correlation as explained in later sections**.**

3.2 Correlation of Image-Decision Fusion

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 [8] 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

$$\rho = \frac{nN^f}{\sum_{i=1}^{2^n-2} N_i^c + nN^f} \quad (12)$$

3.3 The T-Norm fusion technique for correlated images

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:

$$F(\vec{c}) = TNorm(TNorm(c_1, c_2), c_3) = TNorm(c_1, TNorm(c_2, c_3)) \quad (13)$$

with c_1, c_2, c_3 the confidence levels for three images and this equation (13) 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 [10]. According to [11], Dempster-Shafer is a special case of possibilitic fusion where correlation = 0 and the function is equal to the product xy. From this, we can choose a suitable α to have a fusion technique sensitive to correlation.

- Schweizer-Sklar: $TNorm(x, y) = \dfrac{xy}{\max(x, y, \alpha)}$, which ranges from product xy for $\alpha = 1$ to $\min(x, y)$ for $\alpha = 0$ (this family is decreasing w.r.t. the parameter α)
  - We choose α such that $\alpha = 1 - (\rho / \infty)$
- Generalized: $TNorm(x, y) = \max[0, (x^\alpha + y^\alpha - 1)]^{1/\alpha}$, which ranges from $\max(0, x + y - 1)$ for $\alpha = 1$ to the product $\alpha = 0$ (this family is increasing w.r.t. the parameter α)
  - We choose α such that $\alpha = \rho$
- Family of Hamacher $TNorm(x, y) = \dfrac{xy}{\alpha + (1-\alpha)(x + y - xy)}$, which ranges from $\max(0, x + y - 1)$ for $\alpha = +\infty$ to the product $\alpha = 1$ (this family increasing w.r.t. the parameter α)
  - We choose α such that $\alpha = 1/(1-\rho)$
- Family of Frank:

  $$TNorm\ (x, y) = \log_\alpha [1 + \frac{(\alpha^x - 1)(\alpha^y - 1)}{\alpha - 1}]$$

  ,which is equal to the "min" for $\alpha = 0$, to the product for $\alpha = 1$ and to $\max(0, x + y - 1)$ for $\alpha = +\infty$ (this family is decreasing family w.r.t the parameter α)
  - We choose α such that $\alpha = 1/(1-\rho)$

4 Performance Evaluations

In the performance evaluation tables, the accuracy is measured by comparing the best image - image which gives the minimum error when applying the clustering technique- with the output fused images.

We applied the T-Norm algorithm to the Nile River Delta, Egypt (1973, 1987) images which show the dramatic urban growth within the Nile River delta and the expansion of agriculture into adjoining desert areas as in the following images acquired from the site http://edcwww.cr.usgs.gov/earthshots/slow/Nile/Nile

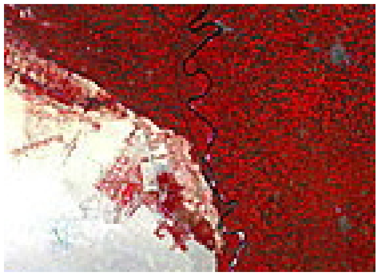

Figure 2. West Delta-Nile1973

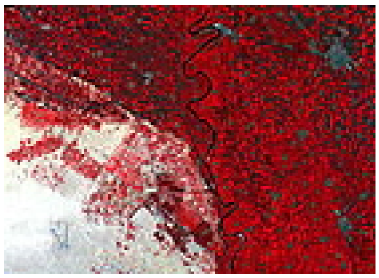

Figure3.West Delta-Nile 1987

Correlation = 0.95777

Technique	Accuracy
T-Norm(S-S)	0.9699
T-Norm(G)	0.96986
T-Norm(H)	0.9699
T-Norm(F)	0.96986

Table 2. Performance Fusion table for West Delta Nile images (73-87)

The following figures show the output fused image of West Delta Nile using different T-norm families:

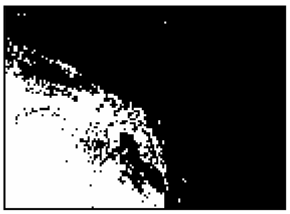

Figure 4.Generalized

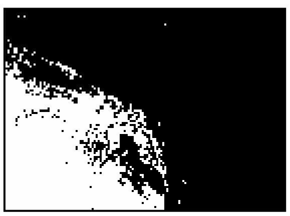

Figure 5.Schweizer-Sklar

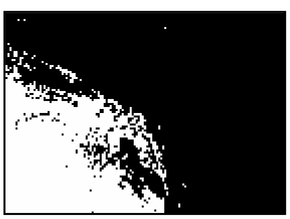

Figure 6.Hamacher

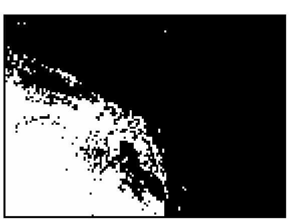

Figure 7.Frank

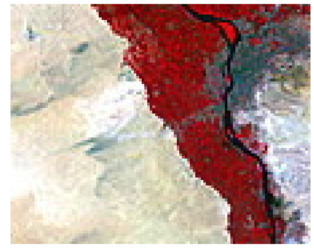

Figure 8.Cairo-Nile 1973

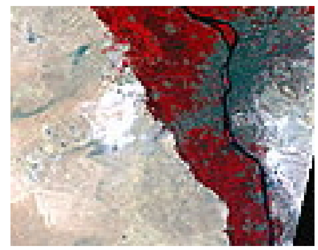

Figure 9.Cairo-Nile 1987

Correlation = 0.96806

Technique	Accuracy
T-Norm(S-S)	0.97431
T-Norm(G)	0.97431
T-Norm(H)	0.97431
T-Norm(F)	0.97431

Table 3. Performance Fusion table for Cairo Nile images (73-87)

The following figures show the output fused image of Cairo Nile using different T-norm families:

Figure 10. Generalized

Figure 11.Schweizer-Sklar

Figure 12.Hamacher

Figure 13.Frank

5 Conclusions and Future Work

We have proposed an approach based on possibility theory in this paper. The approach is based on calculating the correlation among different images taken at different times to study the change of the environment and use it as a parameter in four CIVB T-Norm techniques to handle the problem of high correlation. This approach shows high performance for correlated satellite images for environmental changes. When the correlation is very high (almost 1), there is no difference of accuracy between T-norm families applied.

For future work, we can search for more strict definition of a confidence level based on a statistical foundation to be used in the fusion techniques.

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