COMBINING COMPARATIVE AND SIMULTANEOUS ANALYSIS APPROACHES BASED ON FUZZY INTEGRATION FOR CHANGE DETECTION

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ABSTRACT:

The purpose of this paper is to investigate the applicability of change detector combination for improving the performance of change detection in remotely sensed data. Thereby, outputs of two fuzzy change detectors based respectively on comparative analysis and simultaneous analysis approaches are combined to yield a single decision. Both change detectors utilize the squared Mahalanobis distance from the prototypes of classes to formulate the fuzzy membership model, while the combination is carried out by using the Sugeno fuzzy integral. This method combines the objective evidences in the form of fuzzy class membership values with subjective importance measures of each change detector. Bitemporal SPOT images covering a region of Algeria are used for evaluating the performance of the proposed scheme. Based on our experiments the effectiveness of the combination rule has been proved. Furthermore, the results obtained for several classes of change showed that it outperforms the individual change detectors by increasing the detection of nonspurious changes while reducing the number of false alarms.

1. INTRODUCTION

An important purpose in multitemporal image analysis is the detection of changes in land cover properties, which are caused by human activities and/or natural alterations. These changes are commonly profound and irreversible for years resulting thus in significant differences in remote sensing measurements between the different dates.

Various techniques have been developed in this field, which proceed typically by analyzing sequential images to extract areas of change. However, they differ in the manner with which the data are handled and also, in the nature of the resulting information. In addition to the simple detection of changes, we are mostly interested to know its precise nature. Therefore, interesting change detection techniques based on classification procedures seem to be the most appropriate. In this context, there are two possible ways to produce the change detection map. The first way is based on the comparative analysis of independently-produced classifications of images, while the second handles the spectral channels in the same classifier by using the simultaneous analysis approach. The first approach, called the post classification comparison, is usually used since it provides complete information over the land cover change. Unfortunately, this scheme suffers of many shortcomings such as errors in class assignment and missed changes within a single land cover class. These problems are related to the hard classification which fails when the spectral signature of a given class is too general to describe properly a pixel that is considered to be part of it (Bárdossy and Samaniego, 2002), or in the case of mixed pixels. When an individual pixel covers more than one land cover class, some proportions may undergo changes while the others remain unchanged. Therefore, any decision about the change is false. These limitations can be avoided by considering the concept of the fuzzy set theory, which allows the reasoning with the fuzzy class membership values of a given pixel in several classes. All fuzzy classifiers reported in the literature share the basic concepts provided by the fuzzy set theory, nevertheless there are large differences regarding how they handle the data in the training and validation stages (Bárdossy and Samaniego, 2002).

However, it is well known that two different change detectors trained on the same task will perform differently. Thus, since they are different they may offer complementary information about the changes to be detected. Based on this assumption, we investigate the applicability of the combination of change detectors. In classification and pattern recognition fields, the combination is used to achieve the best possible performance. Several methods are available but are diverse in the way they combine classifiers. Among them, the method based on the notion of the fuzzy integral and its associated fuzzy measures provide a useful way for aggregating information (Cho and Kim, 1995). This technique has been successfully used in different areas such as classification, digital handwritten recognition, and image sequence analysis (See: Cho and Kim, 1995; Cho, 1995; Verikas et al., 1999; Liu et al., 2001; Cho, 2002). In the present case, the fuzzy integral is used for combining the comparative and simultaneous analysis-based change detectors. In both systems, the squared Mahalanobis distance is used to formulate the fuzzy class membership model. In section 2, we describe the two fuzzy change detectors and introduce the notion of the combination by the fuzzy integral. Section 3 presents the experimental results and demonstrates the superiority of the combination scheme over the individual change detectors. In section 4 we give the main conclusions of the paper.

2. METHODOLOGY

2.1 Fuzzy classifier

The fuzzy classifier utilizes the squared Mahalanobis distance to formulate the fuzzy membership model, which is computed as follows:

$$h_{lk}=\frac{\left(\frac{1}{d_{lk}^2}\right)^r}{\sum_{j=1}^{c}\left(\frac{1}{d_{jk}^2}\right)^r} \quad (1)$$

where r = controls the amount of fuzziness.
c = number of classes of interest.
d_{lk} = Mahalanobis distance of the pixel l from the mean of the class k. It is computed by:

$$d_{lk}^2=(l-m_k)^T V_k (l-m_k) \quad (2)$$

m_k = mean vector of the class k.

V_k = inverse of the covariance matrix of the class k.

This model involves that for each pixel the sum of the fuzzy memberships in all classes is equal to one.

$$\sum_{k=1}^{c} h_{lk} = 1, \forall l \quad (3)$$

2.2. Change detection methods

2.2.1. Comparative analysis-based change detector

In this approach, the fuzzy classifier presented above is used to produce independent classifications for two images. Traditionally, (i.e. with hard classifiers) the change is detected if the labels of a given pixel in dates t_1 and t_2 are different. However, using fuzzy classifiers we do not have single class labels to compare. Instead, we have the degree of membership of each pixel in each of the classes of interest. In such a case arithmetic operators as well as ranking techniques do not lead to a result which can be considered as a membership value, despite of being real numbers comprised between 0 and 1. Consequently, we use triangular norms to define change and no change classes (Deer, 1998).

Hence, the fuzzy class membership of a pixel x in the class A at t_1 is described by $h_{xA}(t_1)$. Similarly, the membership in the class B at the date t_2 is described by $h_{xB}(t_2)$. To inspect at what point this situation is truth, we evaluate the fuzzy membership in the change class (A, B), that is defined as

$$Min(h_{xA}(t_1), h_{xB}(t_2)) \quad (4)$$

2.2.2. Simultaneous analysis-based change detector

This change detector considers the bitemporal space as a single date space. Thus, classes of interest are either change or no change classes. The situation in which the pixel x was in class A at t_1 and is in class B at t_2 is described by $h_{x(A,B)}(t_1, t_2)$ according to (1). In this case, covariance matrices and mean vectors of the Mahalanobis distance are computed using all spectral bands of the two images.

2.3. Combination scheme

The concept of the combination scheme is to pool decisions or classification scores from multiple information sources into a single composite score by applying a fuzzy integral with respect to a designated fuzzy measure. Thus, in this paper, we combine outputs of simultaneous analysis (*SA*) and comparative analysis (*CA*) based change detectors as shown in figure 1.

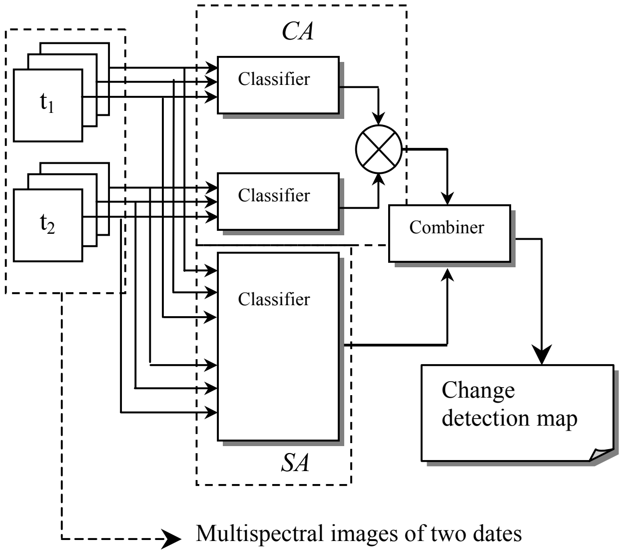


Figure 1. Description of change detector combination

The fuzzy integral combines objective evidences given in the form of fuzzy grade memberships, with a subjective evaluation of the reliability of individual change detectors. The concept of the fuzzy integral and the associated fuzzy measure was originally introduced by Sugeno in the early 1970's in order to extend the classical (probability) measure through relaxation of the additivity property (Cho and Kim, 1995). A formal definition of the fuzzy measure is as follows.

Fuzzy measure: let Z be a finite set of elements. A set function $g: 2^Z \rightarrow [0,1]$ with:

1. $g(\phi)=0$
2. $g(Z)=1$
3. $g(A) \le g(B)$ *if* $A \subset B$

is called fuzzy measure. This measure does not follow the addition rule. In other words, for two sets $A, B \subset Z$ and satisfying $A \cap B = \phi$, the equation (5) does not apply.

$$g(A \cup B) = g(A) + g(B) \quad (5)$$

To overcome this limitation, Sugeno introduced the so called g_λ fuzzy measure.

λ-Fuzzy Measure: Let $Z = \{z_1, \ldots, z_n\}$ be the set of available change detectors.

For each change detector z_i to be combined, we associate a fuzzy measure $g_k(z_i)$ indicating its performance in the class *k*. For a given pixel, let $h_k(z_i)$ be the objective evidence of the change detector z_i for the class *k*. The set of change detectors is then rearranged such that the following relation holds: $h_k(z_1) \geq \cdots \geq h_k(z_n) \geq 0$.

We obtain an ascending sequence of change detectors $A = \{z_1, \ldots, z_i\}$, so that $A_1 = z_1$ and $A_i = A_{i-1} \cup z_i$.

The fuzzy measures of the obtained change detectors are constructed as

$$
\begin{aligned}
g_k(A_1) &= g_k(z_1) \\
g_k(A_i) &= g_k(A_{i-1} \cup z_i) \\
&= g_k(A_i) + g_k(z_i) + \lambda g_k(A_{i-1}) g_k(z_i)
\end{aligned}
$$

For each class, λ is determined by solving an *n*-1 degree equation (Cho and Kim, 1995; Cho, 1995):

$$\prod_{i=1}^{n} [1 + \lambda g_k(z_i)] = 1 + \lambda \qquad (6)$$

Fuzzy Integral: for a given class *k* the Sugeno fuzzy integral is computed as

$$I_S(k) = \int h \circ g = \underset{i=1}{\overset{n}{Max}} [Min(h_k(z_i)), g_k(A_i)] \qquad (7)$$

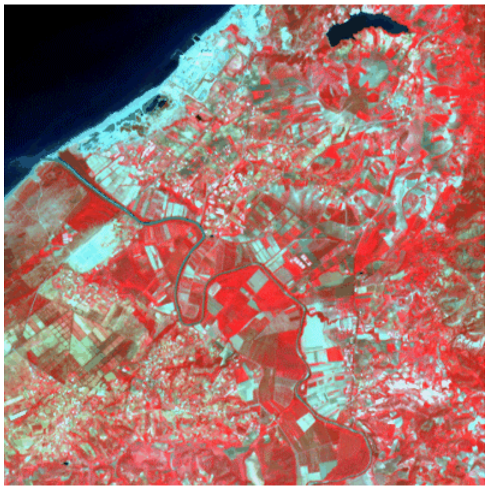
In the present case *n* is equal to 2. Also, the computation of the fuzzy integral would only require the knowledge of the importance of each source expressed by the fuzzy measure (Cho and Kim, 1995). These quantities can be computed by several ways. In this study, for each change detector the fuzzy measure is defined as being the fuzzy accuracy per land cover class computed on a validation set.

3. EXPERIMENTAL RESULTS

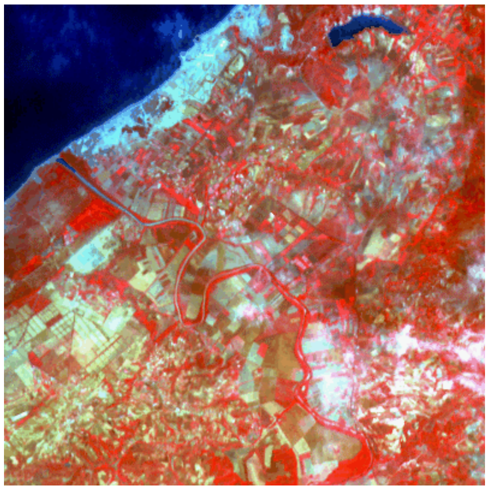
The study area is a portion of a coastal region located in the north of Algeria (Algiers), for which two SPOT images were selected to test the validity of change detector combination. The first image has been captured in May 1989, while the second image was captured in June 1991 (Figure 2). Due to the weak rainfall in this period, the study site has undergone important changes. Therefore, we were interested in those changes from water, construction, and vegetation to nakedly soil. However, the satellite data depict other changes caused by the presence of clouds in the second image. To avoid all surprising effect of this factor, an additional class '*X* ⇨ Clouds' was taken into account. *X* denotes whatever land cover class. Hence, the selected land cover categories are listed in table 1.

3.1. Quantitative evaluation

Unlike the hard classification techniques, the fuzzy set theory provides several measures for accuracy assessment beyond the standard error matrix. A number of approaches are available as the fuzzy distance measure and the fuzzy entropy. In this paper, we use the fuzzy accuracy (FA) per land cover class as well as the fuzzy overall accuracy (FOA), for performance evaluation (Bárdossy and Samaniego, 2002).



(a)



(b)

Figure 2. Coastal region of Algiers
(a : image of 1989, b : image of 1991)

Class labels	Description (1989 ⇨ 1991)
1	*Water ⇨ water*
2	*Vegetation ⇨ vegetation*
3	*Construction ⇨ construction*
4	*Soil ⇨ soil*
5	*Construction ⇨ soil*
6	*Vegetation ⇨ soil*
7	*Water ⇨ soil*
8	*X ⇨ clouds*

Table 1. Classes of interest

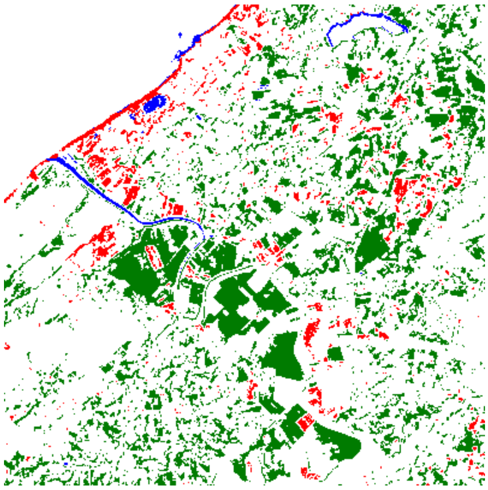
The two fuzzy change detectors used independent training data but they were evaluated on the same data set comparatively to the combiner. The derived FA and FOA measures from the different approaches are reported in table 2. As can be seen, the fuzzy integral outperformed the individual change detectors although the category water → soil has performed somewhat better with the simultaneous analysis based change detector. This empirical finding is due to the fact that the difference of performance between the two change detectors is important. In such a case the fuzzy integral produces an accuracy lower than that of the most precise change detector. In other classes the fuzzy integral gives the best fuzzy accuracy rates yielding to a significant improvement of the FOA rate. In fact, this combination rule tends to increase the overall fuzzy accuracy by equalizing the fuzzy accuracies in individual classes.

Class	CA (%)	SA (%)	FI (%)
1	98.38	89.06	100
2	67.54	73.00	87.30
3	78.52	75.52	90.74
4	83.91	75.94	97.20
5	61.84	82.61	86.76
6	77.21	80.90	88.84
7	17.65	49.69	46.08
8	75.90	66.78	87.39
FOA	70.56	74.43	86.56

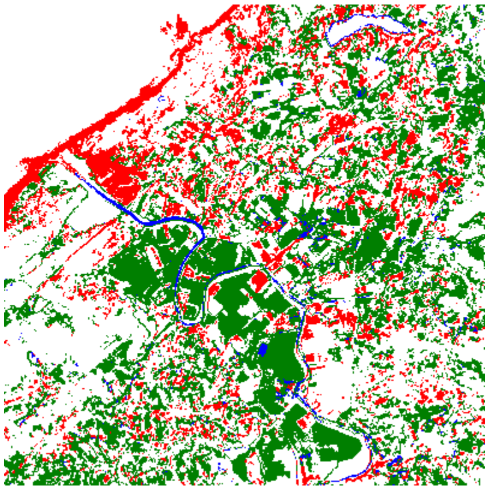
Table 2. Fuzzy accuracy values obtained for the individual change detectors against the combination process

3.2. Visual inspection

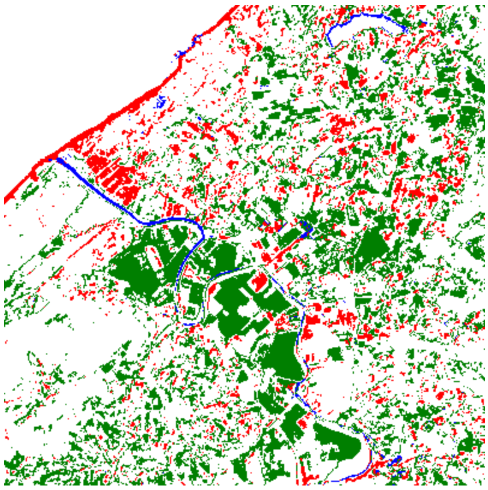
The visual inspection of the resulting change detection map indicates how the considered system generalizes. Since we are using fuzzy systems, the output is hardened by affecting each pixel to the land cover class which corresponds to the maximum fuzzy membership value. Thus, in the final change detection map, each land cover class takes a particular color. Figure 3 shows the resulting maps obtained for the two change detectors as well as the combined system. In this figure only the three change classes (Classes whose labels are 5, 6, 7) are depicted. As can be seen, the two change detectors produce considerable misclassification rates. According to figure 3.(a), the comparative analysis neglects an important change surface in the river and so detects badly the class water → soil. Moreover, it presents a considerable amount of omission in the class construction → soil. Instead, the simultaneous analysis based change detector presents important overestimation rates in the classes construction → soil and water → soil. In fact, errors in the class 5 are related to the clouds which were not selected as belonging to the class X → clouds, while errors in the class 7 are due to changes in vegetal areas which have not been considered in the training set. As shown in figure 3.(c), the fuzzy integral performs better, and can increase the detection accuracy in the different change classes while reducing the false alarm rate. This means that the fuzzy integral combines the two change detectors by extracting the correct decision from both so that it derives the best final decision.



(a)

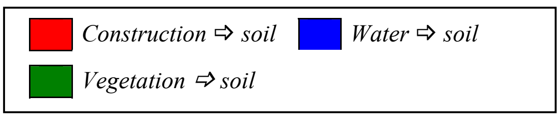


(b)



(c)

Figure 3. Change detection maps (a : Comparative analysis, b : Simultaneous analysis, c : Fuzzy integral)



4. CONCLUSION

In this paper, the applicability of change detector combination was investigated. Our assumption was that the change detection accuracy in remotely sensed data can be increased by combining different change detectors. Thereby, two fuzzy change detectors based respectively on the comparative analysis and the simultaneous analysis of multitemporal data were combined by using the fuzzy integral. Both change detectors used a fuzzy membership model computed by taking the squared Mahalanobis distance from the prototypes of the classes. Experiments using SPOT hrv data of the same area demonstrate that the combined change detection system with the fuzzy integral outperforms the individual change detectors. It increases the detection rate while reducing the number of false alarms. However, even though the usefulness of combining change detectors was highlighted, it has been shown that in a given land cover class, if one of the individual change detectors gives a very poor accuracy and the second gives an important accuracy, the precision of the combination system will be smaller than that of the most precise system (This is the case of the class 7). We think that this problem may be avoided when combining more than two change detectors.

5. BIBLIOGRAPHY

Bárdossy, A., Samaniego, L., 2002. Fuzzy rule-based classification of remotely sensed imagery, *IEEE Transactions on Geoscience and Remote Sensing*, 40(2), pp.362-374.

Carlotto, M. J., 1997. Detection and analysis of change in remotely sensed imagery with application to wide area surveillance, *IEEE Transactions on Image Processing*, 6(1), pp. 189-202.

Cho, S. B., Kim, J. H., 1995. Combining multiple neural networks by fuzzy integrals for robust classification, *IEEE Transactions on Systems, Man Cybernetics*, 25(2), pp.380-385.

Cho, S. B., 1995. Fuzzy aggregation of modular neural networks with ordered weighted averaging operators, *International Journal of Approximate Reasoning*, 13, pp.359-375.

Deer, P., 1998. Digital change detection in remotely sensed imagery using fuzzy set theory. *PhD Thesis*, Department of Geography and Department of Computer Science, University of Adelaide, Australia.

Lambin, E. F., Strahler, A. H., 1994. Change vector analysis in multitemporal space : a tool to detect and categorize land cover change processes using high temporal resolution satellite data. *Remote Sensing Environ*, 48, pp. 231-244.

Liu, Q. Z., et al., 2001. Dynamic Image Sequence Analysis Using Fuzzy Measures*, IEEE transactions on systems, man, and cybernetics-Part B: Cybernetics,* 31(4), pp. 557- 572.

Rosin, P. L., 2001. Robust pixel unmixing, *IEEE Transactions on Geoscience and Remote Sensing*, 39(9), pp. 1978-1983.

Verikas, A., Lipnikas, A., Malmqvist, K., Bacauskienne, M., Gelzinis, A., 1999. Combination of neural classifiers: A comparative Study. *Pattern Recognition Letters, Elsevier Science*, 2, pp. 429-443.