ESTIMATION OF TRANSITION POSSIBILITIES FOR FUZZY MARKOV CHAINS APPLIED TO THE ANALYSIS OF MULTITEMPORAL IMAGE SEQUENCES

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ABSTRACT:

This work presents a decision fusion, cascade multitemporal image classification approach that takes into consideration information acquired at different dates for the classification of an individual image. If compared to conventional monotemporal image classification, multitemporal classification enables the exploration of a richer set of attributes in the classification process. The proposed multitemporal classification approach is based on the concept of Fuzzy *Markov* Chains (FMC), which supports explicit representation of temporal knowledge, and is part of a recent line of studies on FMC for land use/cover classification of remotely sensed images. This work investigates a key aspect of FMC-based methods – the estimation of the transition possibility matrix. Such matrix defines the possibilities for objects of a certain class to change into objects of different classes in a certain time period. This paper presents a summary of an experimental study aiming at investigating the practical implications and the impact over the classification accuracy of alternative methods for the estimation of the transition possibility matrix within the FMC-based cascade multitemporal classification framework. More specifically, direct estimation is compared to extrapolation of matrixes computed for shorter time intervals. The herein presented experimental results indicate that direct estimation and extrapolation can lead to comparable results in terms of *Kappa* index.

1. INTRODUCTION

Recent advances in remote sensing (RS) technology, especially with respect to orbital platforms have provided a growing supply of images. Such advances alongside with the availability of free of charge RS images have contributed to the increasing research interest in automatic classification of land cover/use and its temporal dynamics.

Nevertheless, the inspection of the literature brings about the conclusion that, nowadays, the most usual approach for the automatic classification of a series of multitemporal RS images is, still, monotemporal classification (Lillesand et al., 2004; Mather, 2005). As the main limitation of such approach, it can be mentioned the usage of data obtained on a single date.

An alternative to the monotemporal approach is multitemporal classification. The main difference resides on the fact that, in order to improve the quality of the result, multitemporal classification relies on information obtained on different dates, exploring, therefore, a larger and richer set of attributes.

Among the works that explicitly model temporal knowledge for automatic classification of multitemporal images series, Fuzzy Markov Chains (FMC) has been employed in (Campos *et al.*, 2005; Costa *et al.*, 2007; Mota *et al.*, 2007, Costa *et al.*, 2009; Feitosa *et al.*, 2009, Feitosa *et al.*, 2011, Alves *et al.* 2011). The multitemporal model proposed in such works has brought about a knowledge-based approach which is able to capture the correlation between temporal and spectral information. It also should be mentioned that the results of these studies have been consistently better than that produced by monotemporal classifications.

This work investigates a key aspect of the recent line of studies that use FMCs as the basis of multitemporal cascade-classification methods, namely, the estimation of the transition possibility matrix **T** that defines the possibilities for objects of a certain class to change into objects of different classes in a certain time period. In the FMC scheme, the transition possibility values are used to update the classification of an object in the past through a temporal transformation. The updated classification is subsequently combined with the fuzzy monotemporal classification for a later point in time in order to provide a multitemporal classification for the object at this later time.

The transition matrix relating time instances t and $t+k.\Delta t$ can be directly estimated based on samples collected from images acquired directly at t and $t+k.\Delta t$. A transition matrix estimated this way is denoted henceforth as $\mathbf{T}_{t\rightarrow t+k}$.

Avranchenkov and Sanches (2002) introduced an alternative procedure to the extrapolation of $\mathbf{T}_{t\rightarrow t+k}$ from images acquired at time instants separated by Δt, for example, at t and $t+\Delta t$, i.e., $\mathbf{T}_{t\rightarrow t+1}$. Formally, the extrapolation corresponds to k-th fuzzy power of $\mathbf{T}_{t\rightarrow t+1}$, symbolized by $\mathbf{T}^{k}_{t\rightarrow t+1}$.

This paper presents a summary of an experimental study aiming at investigating the practical implications and the impact over the accuracy of such alternative methods for the estimation of the transition possibility matrix within a FMC-based cascade

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multitemporal classification framework. More specifically, direct estimation is compared to extrapolation of another matrix computed for a shorter time interval. Therefore, this paper analyses the impact of employing $\mathbf{T}^{k}_{t\rightarrow t+1}$ as an alternative to the transition matrix $\mathbf{T}_{t\rightarrow t+k}$ for the multitemporal classification at dates t and $t+k$.

Additionally, the stability of the estimation is also investigated by employing the transition matrix estimated for a certain pair of dates in the mutititemporal classification of another pair dates, with the same time interval.

2. FUZZY MARKOV CHAINS

The multitemporal classification approach herein presented employs Fuzzy Markov Chains (FMC) to model temporal knowledge. By and large, Markov Chains can be described as a temporal sequence of random variables corresponding to the possible states of a system (Ching, 2006).

The most important difference between conventional and fuzzy Markov chains resides in the values assumed by the variables. While in FMCs such values express fuzzy membership degrees, in conventional Markov chains they represent probabilities. As a consequence, FMC underlays a possibilistic modelling of the problem, which is more flexible than traditional probabilistic approach. The reader interested in a more general description of FMC can refer to Avrachenkov and Sanchez (2002).

A pictorial counterpart of the transition matrix of a FMC is the state transition diagram (STD). As presented in Figure 1, a STD can be described as a weighted directed graph that models valid temporal transitions. In such diagrams, vertices represent states, while edges indicate the valid transitions.

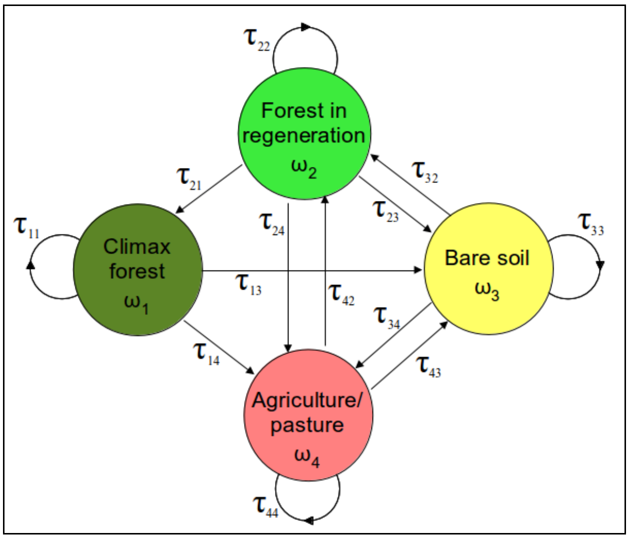

Figure 1. State transition diagram

In this context STD vertices model land cover/use classes which occur in the target area. The set of classes $\Omega = \{\omega_1, \omega_2, \ldots, \omega_c\}$ is invariable along the time, where c represents the number of distinct classes.

The so-called transition matrix, $\mathbf{T} = \{\tau_{ij}\}$, where i e j belongs to the set $\{1, 2, \ldots, c\}$, represents a core component of a FMC. Such matrix is equivalent to a fuzzy binary relation defined in the universe $\Omega\times\Omega$. Every transition matrix element, τ_{ij}, corresponds to a STD edge weight whose value belongs to the interval [0, 1]. The element τ_{ij} expresses the possibility of an object of belonging to class ω_i at instant t and to class ω_j at instant t+1. Both ω_i and ω_j belong to Ω, while t and t+1 represent two consecutive time instances separated by an arbitrary interval. It should be stressed that, in order to simplify the STD, zero-weight edges are not drawn.

The temporal transformation carried out by the FCM can be described as follows. Given the fuzzy vector ${}^{t}\boldsymbol{\alpha} = [{}^{t}\alpha_1, {}^{t}\alpha_2, \ldots, {}^{t}\alpha_c]$, which expresses the degree of membership of an object to each class in set Ω at time t, and the transition matrix $\mathbf{T}$, it can be derived ${}^{t+1}\boldsymbol{\beta} = [{}^{t+1}\beta_1, {}^{t+1}\beta_2, \ldots, {}^{t+1}\beta_c]$, which correspond to estimates of the object's memberships at time t+1. Such estimation process is realized by the transition law of the FMC, described by Equation (1).

$$ {}^{t+k}\beta_j = \perp \left[\underset{\forall i \in \Omega}{\top} ({}^{t}\alpha_i, \tau_{ij}) \right] \tag{1}$$

where $\top$ and $\perp$ represents respectively a *t-norm* and a *s-norm* operators (Klir and Yuan, 1995). Such operation can be described in a more concise manner as in Equation (2)

$$ {}^{t+k}\boldsymbol{\beta} = {}^{t}\boldsymbol{\alpha} \circ \mathbf{T}_{t\rightarrow t+k}, \tag{2}$$

where "∘" denotes a fuzzy operation analogous to conventional matrix multiplication, where the product is replaced by a *t-norm* operator and the summation is replaced by an *s-norm* operator.

In this paper two alternatives to the estimation of $\mathbf{T}$ are investigated. More specifically, direct estimation is compared to extrapolation of a matrix computed for a shorter time interval. In other words, this paper analyses the impact of employing $\mathbf{T}^{k}_{t\rightarrow t+1}$ as an alternative to the transition matrix $\mathbf{T}_{t\rightarrow t+k}$ for the multitemporal classification of date $t+k$. Such powers of $\mathbf{T}_{t\rightarrow t+1}$ can be computed recursively as presented by equation (3).

$$ \begin{aligned} \mathbf{T}^{2}_{t\rightarrow t+1} &= \mathbf{T}_{t\rightarrow t+1} \circ \mathbf{T}_{t\rightarrow t+1} \\ \mathbf{T}^{k}_{t\rightarrow t+1} &= \mathbf{T}^{k-1}_{t\rightarrow t+1} \circ \mathbf{T}_{t\rightarrow t+1} \end{aligned} \tag{3}$$

where "∘" is the same operator employed in Equation (2).

3. MULTITEMPORAL CLASSIFICATION METHOD

The multitemporal classification procedure is depicted in Figure 2. The decision process takes into account two sources of information about the objects:

(a) the fuzzy membership vector, ${}^{t+k}\boldsymbol{\alpha}$, obtained based on attributes measured on time $t+k$ and;
(b) the crisp vector, ${}^{t}\mathbf{w}$, which represents the classification of the segment on time t, i.e., a vector

with the value one in the position that corresponds to the correct class and zero in all other positions.

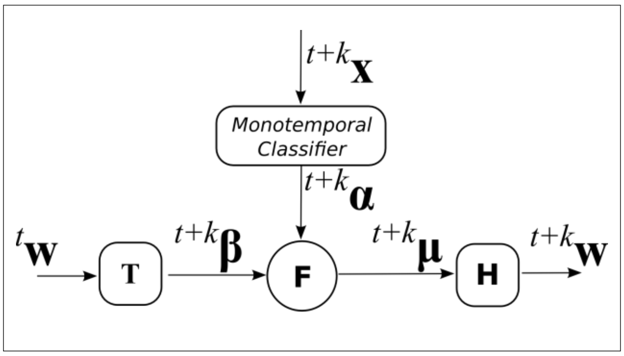

Figure 2. Multitemporal objects classifier

The vector ${}^{t}\mathbf{w}$ is submitted to the temporal transformation $\mathbf{T}$, bringing about ${}^{t+k}\boldsymbol{\beta}$, which can be understood as an up to date version of ${}^{t}\mathbf{w}$. In order to calculate ${}^{t+k}\boldsymbol{\mu}$, referred as multitemporal membership vector, it is necessary to combine vectors ${}^{t+k}\boldsymbol{\beta}$ and ${}^{t+k}\boldsymbol{\alpha}$, what is done by the fusion function **F,** which corresponds to a simple product. The hardening function (defuzzyfier) **H** calculates ${}^{t+k}\mathbf{w}$, that represents the decision taken to the segment under analysis, i.e., a vector with the value one in the position corresponding to the classification result and zero in all other positions.

Considering a pair of time instances t and $t+k$, the temporal transformation performed by the FMC can employ transition matrixes estimated directly from data acquired at those same instances or – and this is the main subject of investigation in this work – employ transition matrixes estimated from data acquired at other pairs of dates, either directly or using powers of **T**.

4. EXPERIMENTAL DESIGN

4.1 Reference Data

The study area corresponds to a rural region situated in the west of the Londrina city, in the state of Paraná, Brazil. The area encompasses the Mata dos Godoy Natural Park and two private owned farms adjacent to the Natural Park. The vegetation present in this area is among the last reminiscences of the Subtropical Forest that covered most of Paraná State. This reminiscent is subjected to anthropic activity pressures, since it is circumscribed by areas used for agriculture and cattle farming. The main reason for choosing this particular study area was the occurrence, in the last two decades, of important land cover changes. The following classes were considered in the experiments: climax forest, forest in regeneration, bare soil and agriculture/pasture.

The image temporal series used in the experiments consists of five Landsat 5 TM images, taken at August 1989; July 1994; July 1999; July 2004; and May 2009, from which composites of bands 5, 4 and 3 respectively on channels R, G and B were derived.

The images were segmented using the region growing algorithm implemented in the SPRING software. The segmentation procedure was similar to the one used in (Feitosa et al., 2010) – all bands from all images were stacked together, and the resulting image was submitted to segmentation. In this way the objects subjected to classification have the same extent for all considered points in time.

4.2 Experimental Procedure

The estimation of $\mathbf{T}_{t\rightarrow t+k}$ is made in a supervised approach by a genetic algorithm whose objective function maximizes the *Kappa* agreement index. Such process considers for each object its correct classification at time instances t and $t+k$. Objects are randomly partitioned into two subsets, training and test. The results presented in the next section are related to test subset. More specifically, results are the mean of 200 distinct set selection rounds. The monotemporal classifier is a fuzzy classifier based on the Bhattacharyya distance (Bhattacharyya, 1943), while the *t-norm* and the *s-norm* fuzzy operators employed are, respectively, the product and the maximum. All experiments were implemented in Matlab.

The reader will notice that the image sequence is inverted in the experiments. It was a resource necessary to improve the estimation of transitions that start from class agriculture/pasture which is only present in the latter dates. It must be mentioned the absence of theoretical restrictions for such inversion.

The experiments that follow are organized in order to favour the comparison of the accuracy provided by $\mathbf{T}_{t\rightarrow t+k}$ and $\mathbf{T}^{k}_{t\rightarrow t+1}$, where $k \in \{1, 2, 3, 4\}$. For each value of k it is presented a distinct bar plot. The abscissae of all plots are labelled after the dates being classified. About the bars, each bar colour refers to a distinct pair of dates, while their heights express the mean *Kappa* agreement index. Accordingly, the ordinate axis is graduated in terms of *Kappa*. As a reference for accuracy evaluation, blue bars represent the monotemporal classification.

In addition, the experimental arrangement underlies evaluating the stability generalization, accuracy variation among subgroups of outcomes that have the same value of k. The relevance of such analysis is figuring out if the usage of a **T** matrix for the same interval but estimated for distinct dates is a valid alternative. Next section also evaluates the limitations of the multitemporal knowledge contribution as the value of k grows.

5. RESULTS AND DISCUSSION

The subsections that follow present the results for k equal 1, 2, 3 and 4, respectively. Then it is presented a general analysis of these outcomes.

5.1 Experiments for *k*=1

Figure 3 presents the results of the multitemporal classification for k=1 as well as the ones produced by the monotemporal classifier.

The analysis of Figure 3 leads to the conclusion that the multitemporal approach for k=1 performed consistently better than the monotemporal approach. More specifically, the mean increment in the value of *Kappa* index of multitemportal approach in relation to the monotemporal was 0.18, while the respective standard deviation was only 0.03. Besides, results employing the transition matrix specifically estimated for the date under analysis were in all cases superior to the ones using other matrices.

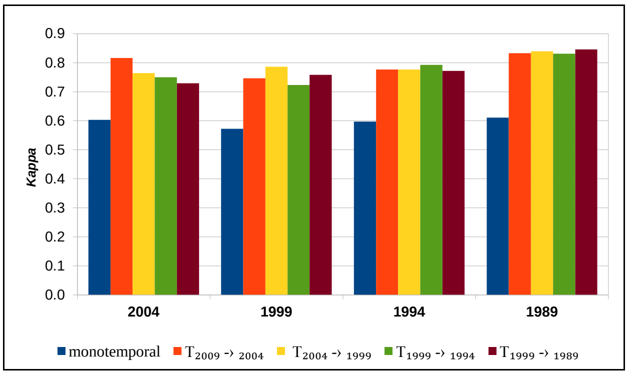

Figure 3. Results for k=1

5.2 Experiments for *k*=2

Figure 4 presents the results of the multitemporal analysis for k=2 as well as the monotemporal classifier outcomes.

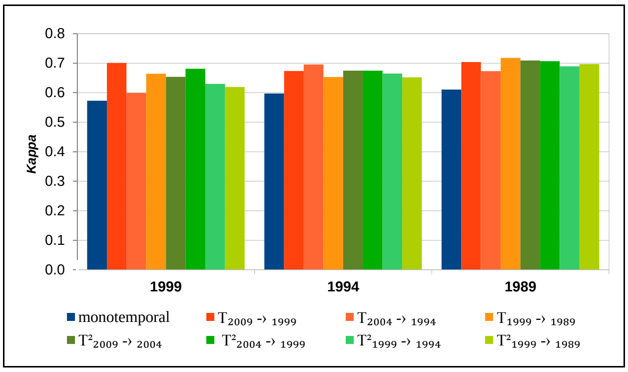

Figure 4. Results for k=2

Looking at Figure 4, one can observe that the multitemporal approach for k equal to 2 led both for direct estimation and for extrapolation of a matrix computed for a shorter time interval to better results than the monotemporal approach. In other words, $T_{t \rightarrow t+2}$ and $T^2_{t \rightarrow t+1}$ overcame the monotemporal results. The mean increments of *Kappa* index in relation to the monotemporal were respectively 0.092 and 0.078, while the standard deviations were 0.03 and 0.019. Thus, on one hand, $T_{t \rightarrow t+2}$ led to a more accurate, while $T^2_{t \rightarrow t+1}$ led to more stable results.

Other important aspect that should be mentioned is that, for all target dates, the results employing the transition matrix estimated directly for the specific date under analysis were again superior to the ones obtained with the remaining matrices.

5.3 Experiments for *k*=3

Figure 5 presents the results of the multitemporal analysis for k equal to 3 as well as the outcomes of the monotemporal classifier.

Looking at Figure 5, one can observe that the multitemporal approach for k equal to 3 led only in 75% of the cases to better results than the monotemporal approach. That occurred both for $T_{t \rightarrow t+3}$ and $T^3_{t \rightarrow t+1}$. The biggest increment in terms of Kappa was just of 0.05. The only classification where the multitemporal approach performance overcame the monotemporal in all cases was of the image acquired in 1994.

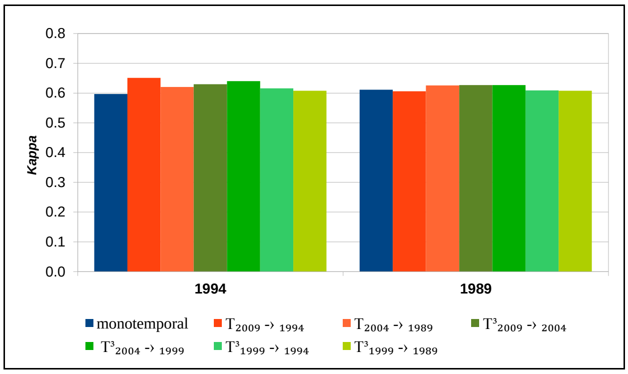

Figure 5. Results for k=3

5.4 Experiments for *k*=4

Figure 6 presents the results of the multitemporal analysis for k equal to 4 as well as the ones produced by the monotemporal classifier.

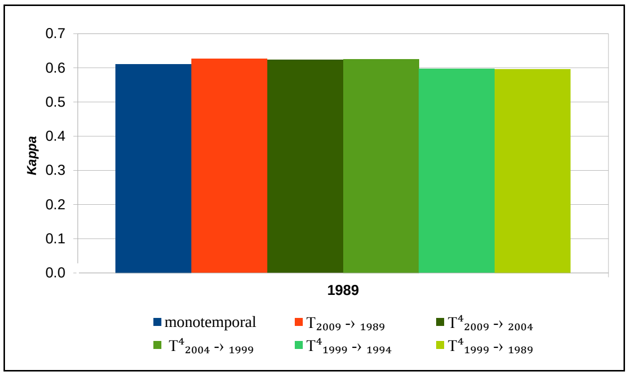

Figure 6. Results for k=4

Looking at Figure 6, one can observe that the performance of the monotemporal and multitemporal approaches are in general almost equivalent. However, $T^4_{t \rightarrow t+1}$ led in 50% of the experiments to inferior results than the monotemporal approach.

5.5 Overall analysis

A number of regularities can be identified in results presented in the above subsections:

(a) the multitemporal classifications $T^k_{t \rightarrow t+1}$ e $T_{t \rightarrow t+k}$ tend to outperform their monotemporal counterpart, particularly for small values of k;

(b) as expected the maximum performance was always attained when the transition matrices were directly estimated upon the sources of information being combined by the multitemporal method;

(c) otherwise, the extrapolation delivers similar results as the direct estimation;

(d) the performance variation obtained by the multitemporal approach and conclusion (c) may indicate that the proposed approach has consistent generalization stability;

(e) since the multitemporal approach results degenerate as far as *k* value is increased, it seems to be a temporal limit to the usefulness of the temporal knowledge.

6. CONCLUSIONS

This work was dedicated to multitemporal image classification. If compared to the monotemporal classification, the multitemporal classification permits the usage of a larger and richer set of attributes. The herein employed multitemporal classification approach exploits Fuzzy *Markov* Chains (FMC) for the explicit representation of temporal knowledge. It takes part in a recent line of studies on this field.

In this work a key aspect of FCM-based methods – the estimation of the transition possibility matrix – was investigated. Precisely, direct estimation was compared to extrapolation of matrixes computed for different time intervals.

The herein presented experimental results indicate that direct estimation and extrapolation can lead to similar results in terms of *Kappa* index. The proposed approach has shown consistent generalization stability, although it seems to be an upper *k* limit for the usefulness of the temporal.

The next step of this research is the investigation of the behaviour variation as well as the herein employed study area is split up into two regions: national park and private area.

We expect that the temporal dynamics related to the classes of interest in these two sub regions is more stable (when compared to the whole region) and can, therefore, lead to better results for larger *k* values.

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