Multi-Stage Processing of Time Series Aerospace Images for Obtaining Enhanced Forecast Land Cover Maps

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INTRODUCTION

Every year high accuracy and operative forecasting necessity of land cover change has been growing. At the same time the operative and accurate forecasting is not possible without joint using of the comprehensive technologies for time series (TS) remote sensing (RS) data interpretation, geoinformation systems performing complex spatial analysis of interpreted data, and comprehensive methods of spatial forecasting.

The task of interpretation of TS aerospace images, which in their turn can be used for forecasting, traditionally is solving with image processing, RS and mapping software such as ER Mapper (Earth Resource Mapping), ERDAS Imagine (ERDAS), Idrisi 32 (Clark University). This software based upon either parametric statistical methods using assumption about normal distribution of features or nonparametric methods that can produce acceptable results in few cases only. Besides the actual image processing RS, and mapping software do not use in full measure spatial (texture) information about classes on aerospace images.

While forecasting the behavior of complex systems such as mapping nature territorial complexes to which influence a lot of stochastic processes, basically stochastic forecasting methods have been using (Baker, 1989). The widespread among them are methods using markov chains. Markov chains have been used in a variety of fields and model changes on a variety of spatial scales (Baker, 1989). In order to markov model considers spatial interaction between classes on thematic map cellular automata (CA) are often applied (e.g. Park & Wagner, 1997). A parameter of CA is the distance of the neighbourhood from the central grid-cell. In majority cases of CA application for land cover and land use change modeling this parameter is taken equal for all types of classes. But such approach does not take into account features of spatial interaction of classes on thematic map (Verburg, 2003).

This paper introduces multi-stage automated algorithm of processing TS aerospace images. The algorithm should help overcome mentioned imperfections that allows to obtain more sophisticated forecast maps of land cover change using TS aerospace images. Next this paper shows the main points of multi-stages processing of aerospace images. The paper first describes in detail each stage with its methods and algorithms, applied forecasting with two alternative approaches of land use change to three TS aerospace images for 1998, 1999, 2000.

GENERALISED ALGORITHM OF OBTAINING FORECAST LAND COVER MAPS

Figure 1 shows that multi-stage algorithm of processing of TS aerospace images is an iterative procedure. The feature of the algorithm is joint using GIS, the advanced interpretation algorithm and the procedure of enhanced designing of forecast maps. The generalized algorithm of obtaining forecast land cover maps using TS aerospace images is shown in Figure 1.

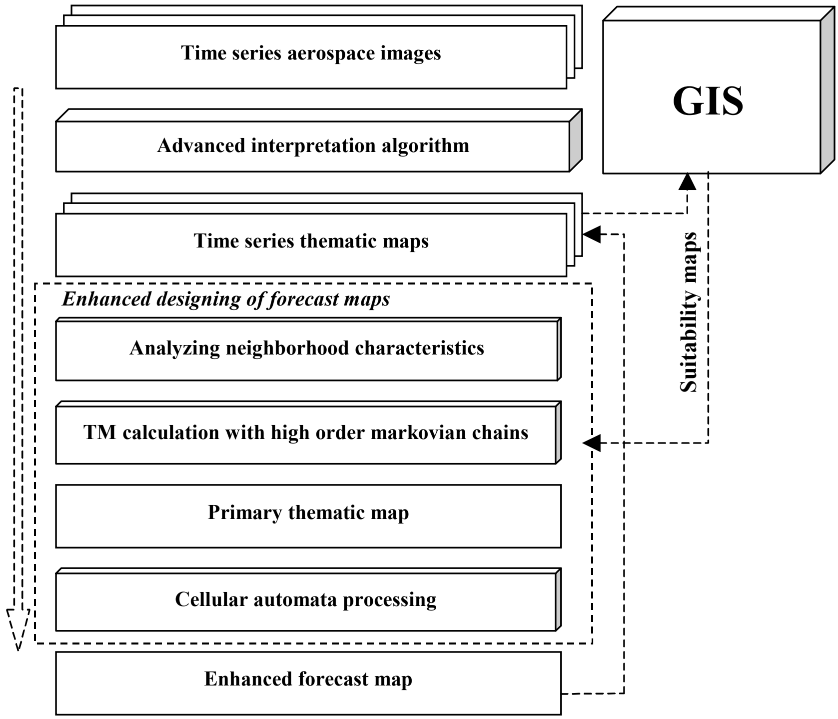


Figure 1: Generalized algorithm of obtaining land cover forecast maps.

Let's consider the stages of this generalized algorithm more detailed.

Interpretation algorithm of TS images

As was mentioned above, comprehensive image processing, RS and mapping software using texture information from processed aerospace image to some extent only. It could lead to unsatisfactory classification accuracy. In order to perform more flexible and accurate thematic processing of RS data the advanced parametric-nonparametric algorithm with use of spectral and spatial characteristics is proposed. This advanced interpretation algorithm of aerospace images presents complex procedure some details and features of that have been described earlier (Zamyatin & Markov, 2003; Markov et al., 2003; Markov et al., 2003). The general points of the interpretation algorithm of aerospace images allowing joint application of statistical parametric and nonparametric classification and artificial neural networks classification (ANN) will be underlined here (Figure 2).

Classification of aerospace images in the framework of the proposed approach might be represented in two sequential stages, where each phase is based on Bayesian decision rule. In the first stage, the posterior probability maps of each class from an aerospace image are designed with the use of either the statistical or the ANN classification with spatial feature space (which might be formed by two different ways). In the second stage these maps (layers) are to be used as prior probability maps of classes. In this case the feature space consists only of spectral features. In case of statistical classification the estimation of conditional probability density performs parametrically if the data fit the normal distribution. In all of the other cases it performs nonparametrically. In what cases data fits the normal distribution is defined for each dimension of feature space by the Pearson's chi-square criterion. In case of the ANN classification (the first stage), the statistical (parametric or nonparametric) density estimation will be applied in the second stage only. Nonparametric density estimation is performed by the original algorithm that contains modified Rosenblatt-Parzen and k - nearest neighbor density estimators. Application of such algorithm provides a computational performance increase in dozens times over traditional nonparametric density estimation algorithms.

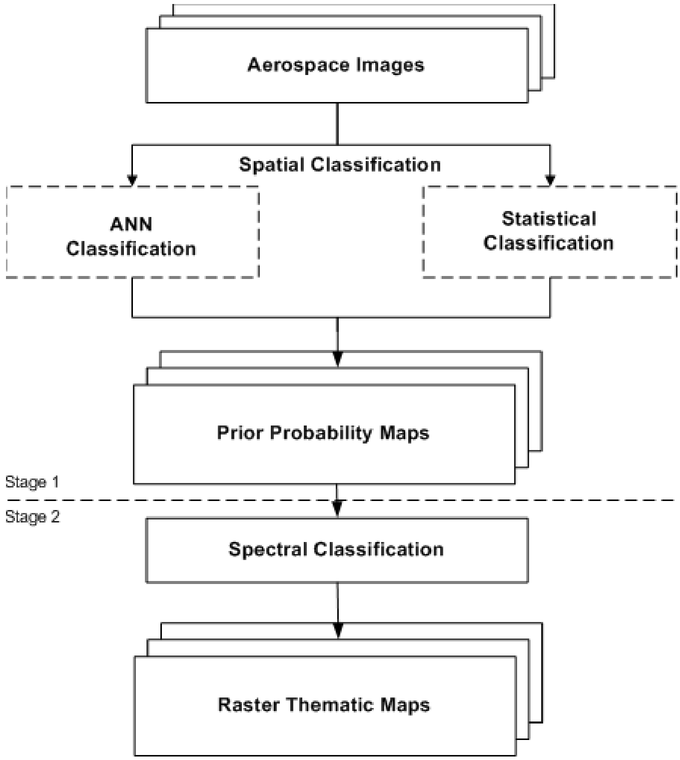


Figure 2: Generalized interpretation algorithm of obtaining thematic maps.

It was mentioned that the way of forming feature space using spatial features of classes is used in the first stage. The first way of forming feature space is used in case of statistical classification and it is based upon Haralick textural characteristics (Haralick et al., 1986) calculated by the first- and the second-order histograms for all aerospace image bands using characteristics from (Markov et al., 2003). The second way is applied for the ANN classification and it consists in way of forming the input ANN data vector. The vector contains the focal and its neighbor elements from all bands of aerospace image without special additional calculation of texture features and feature space optimization. Moreover application of ANN allows considering peculiar class information that could not be taken into account by traditional statistical methods. Stage-by-stage and separate using of spatial and then spectral features allows to decrease blur of obtained classification and to make it essentially accurate.

In order to make the process of ANNs topology and parameters definition easier and also to make the learning process of ANN more faster it is proposed to store and search existed ANNs in a database. The search might be done with test of sign-rank correlation between the investigated data sample and the ANN train data sample stored in the database. The possibility of ANN search makes the ANN learning more predictable and robust. That is why in case of successful search of the appropriate ANN for investigated data sample the designing of prior probability maps performs by ANN classification.

The advance interpretation algorithm repeats for all TS aerospace images. The preliminary investigation results revealed the developed classification algorithms are insensitive to data distribution and allow performing more flexible and accurate thematic processing of RS data using spectral and spatial characteristics compared to existing interpretation methods and actual image processing, RS and mapping software.

Enhanced designing of forecast maps

Figure 1 shows that the first stage of the enhanced designing forecast map procedure is the analysis of neighbourhood characteristics of land cover patterns. The purpose of this analysis is the determination of the optimal cell-grid size for every class. This parameter needs further for working of cellular automata. To characterize the neighbourhood of a location in a land cover map a measure that is based on the over- or under representation of different land cover classes in the neighbourhood of a location. This measure, the enrichment factor (Verburg et al., 2003), is defined by the occurrence of a land use type in the neighbourhood of a location relative to the occurrence of this land use type in the study area as a whole following (1):

$$F_{i,k,d} = \frac{n_{k,d,i} / n_{d,i}}{N_k / N} \tag{1}$$

$F_{i,k,d}$, characterizes the enrichment of neighborhood d of location i with land use type k. The shape of the neighbourhood and the distance of the neighbourhood from the central grid-cell i is identified by d (for instance d = 1 means grid-cell 3x3). $n_{k,d,i}$ is the number of cells of land use type k in the neighbourhood d of cell i, $n_{d,i}$ the total number of cells in the neighbourhood while N_k is the number of cells with land use type k in the whole raster and N all cells in the raster. The algorithm of enrichment factor calculation is repeated for different neighbourhoods located at different distances (in this case d=1,...,10) from the grid cell to study the influence of distance on the relation between land use types. The average neighbourhood characteristic for a particular land use type l ($\overline{F}_{i,k,d}$) is calculated by taking the average of the enrichment factors for all grid cells belonging to a certain land use type l, following (2):

$$\overline{F}_{i,k,d} = \frac{1}{N_l} \sum_{i \in L} F_{i,k,d} \tag{2}$$

where L is the set of all locations with land use type l and N_l the total number of grid-cells belonging to this set. The grid-cell of size d for each class type is fixed in case of maximum of the average enrichment factor. These values are to be used for every class in CA. In most land cover and land use change model first-order markov chains and only two classified images are used. Classified images are for the begin time (t_1) and for the end time (t_M) of studying interval and there are not taken into account aerospace images between this time interval. Such approach is widely used for designing forecast map based upon so-called transition probability matrix (TM) (3):

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & & & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{bmatrix}, \tag{3}$$

where N – the number of states. However, it is better constructing TM also use intermediate aerospace images with equal time interval between all images. This approach requires the using of high-order markov chains (Baker, 1989). In this case the states number in expression (3) would be N^M, where M – the number of TS images. Transition probabilities there depend not only on one (previous) state, but also on the $M - 1$ states, where M – the number of TS images. Automated examining of all precedent states from TS images should help to obtain more proper transition probability matrix.

Next TM and M thematic maps are used for designing primary thematic map. In order to do it is necessary examining all corresponding elements of the thematic raster maps. Each element presents by itself the M-dimensional vector $Tm^{i}_{j,k}$, where i = 1,…,M, j and к are the pixel coordinates. For each element the transition probability value is calculated and determined in what state the element $FTm_{j,k}$ will be on the forecast map FTm. A primary map, which is obtained this way, is very noisy because the elements of TM are not determined but stochastic.

In order to reduce the mentioned effect of "noise" typically a primary map is processed using CA (Verburg et al., 2003). CA allows to model behavior of complex system with simple rules. The most important parameters of CA are the size of neighborhood interaction and transition rules. As the size of the neighborhood interaction the optimal size of grid-cell for each class (d_i) is used. Talking about transition rules of CA it is needed to underline that there are a lot of different transition rules of neighborhood interaction.

There the algorithm of spatial interaction, described in (Turner, 1987) is used, and will only be summarized briefly here. Some number of neighbors of each cell in the land use matrix are examined, and a transition index is calculated for each cell. The index is a function of the number of neighbors of state j (n_j) and the probability of i going to j (p_{ij}), and is equal to the maximum value of n_j*p_{ij}, where j = 1, ..., N (number of states). The cell in the land use matrix that has the highest transition index is then changed to the appropriate new state. The transition indices are then recalculated, allowing a 'domino effect' to occur where patches can grow or shrink. If there are no neighbors of type j to effect a particular i, j transition, cells of type i are selected at random and changed to j. This may occur, for example, when urban land appears for the first time. During a simulation interval, a cell can be changed only once. This stage is the final one in multi-stage processing algorithm. The result of this stage is the thematic raster map FT^{M+1} (time t_M + 1). In general case in order to obtain the forecast map FT^{M+k}, where k = 1, ... ∞, the processed map FT^{M+k-1} is put as the thematic map T^{M+k-1}, and TM needs to be recalculated.

The multi-stage algorithm should help designing enhanced forecast maps using TS aerospace images and so called suitability maps. Figure 1 shows interpreted TS aerospace images (thematic maps) should be transferred to GIS for additional processing includes spatial analysis and designing the suitability maps for every thematic class. These maps contain the additional information about what classes more suitable for that location. For instance suitability maps could show that an urban could replace a highway with the zero probability, but could replace a forest with probability about fifty percents and so on. More accurate designing of suitability maps and finally more accurate forecasting could possible with using auxiliary data (socio-political, nature-climatic, slope maps and etc.) that is why in case auxiliary data is available it could be also used by multi-stage algorithm (Figure 1).

Advantages and disadvantages of multi-stage algorithm

Recently the first steps of automated forecasting tasks with RS data are made. In order to solve these tasks effectively it is needed the joint using of advanced interpretation software and comprehensive forecasting methods based upon complicated schemes and adaptive procedures. At the same time the effective solving of the tasks impedes by complexity and the low calculation performance of approaches proposed by different researchers.

The proposed multi-stage algorithm decides in general the task of joint application of the two traditionally complex procedures. The first one is the advanced interpretation using spectral and spatial feature spaces and the original parametric-nonparametric classification algorithms. The second one is the forecasting with use of high-order transition matrix and adaptive tuning of grid-cell size.

Comprehensive image processing, RS and mapping software does not have means of nonparametric classification and could take spatial features of objects into account to some extent only. Therefore interpretation of RS data with arbitrary distribution performed by one of the existing image processing, RS and mapping software could be significantly inaccurate and noisy. Such inaccurate interpretation results decrease the final forecast accuracy. The application of the original interpretation procedure in the framework of multi-stage algorithm allows significantly increase RS data classification accuracy compared to existing interpretation algorithms presented in comprehensive image processing, RS and mapping software. More accurate classification leads to more accurate thematic maps used further in the procedure of the enhanced designing of forecast maps.

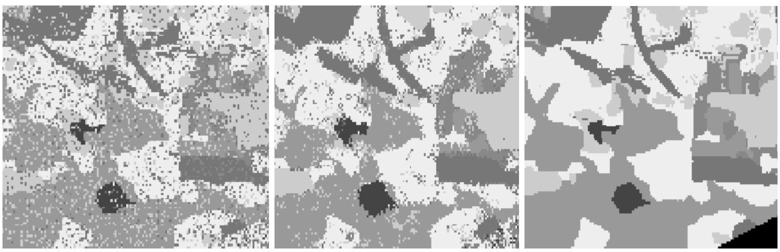
Moreover the enhanced designing of forecast map (Figure 1) is on the basis of high-order Markov chains and CA with tuning of adaptive grid-cell size. Application of high-order Markov chains in case of processing more then two aerospace images allows taking into account more complex regularity of classes change during period of time. Nowadays almost every time the information about the initial (first image) and the final (last image) states is used without any additional intermediate information. That approach is significantly easier in realization but it does not trace for complicated change in objects structure on an aerospace image and could decrease the final forecast accuracy. The application of "adaptive CA" allows taking into account spatial classes correlation to large extent.

Mentioned modifications, discriminating proposed multi-stage algorithm from the existing methods, allow performing more accurate forecasting. However it is reached by more complex and low performance procedures that are the main deficiency of the proposed algorithm. Moreover the traditional disadvantage of majority of forecasting algorithms is the lack of additional information such as suitability maps, digital elevation models, social, economics data that are urgent need to make the accurate forecasting. In some cases the information mining connects with many problems and expenses or even impossible at all. That could make difficult or impossible the appropriate forecast.

RESULTS AND DISCUSSION

Efficiency investigation of the discussed multi-stage algorithm performed with three multispectral aerospace images for 1998, 1999, 2000, obtained from satellite RESURS-O1 (spatial resolution 30 m). The forecast should be done at 2001. First of all in order to perform forecasting it is needed to classify the all aerospace images. The classification is to be done either with traditional maximum likelihood algorithm or with proposed complex parametric-nonparametric classification algorithm. Moreover the forecasting procedure requires a set of suitability layers containing the additional information about what classes more suitable for that location.

Figure 3 shows the fragments of forecast maps for 2001 obtained by three various techniques. Hence, Figure 3 a) shows the result obtained with using the first-order TM without using CA. In Figure 3 b) shown the result obtained with using the first-order TM and CA described in (Eastman, 2001). Furthermore, Figure 3 c) shows the result obtained by the proposed multi-stage algorithm.



a) b) c)

Figure 3: Different forecast maps obtained with different approaches.

Figure 3 a) obviously shows significant noise on the thematic map which leads to the significantly inaccurate forecast. The same technique but using CA significantly decreases the noise shows in Figure 3 b). Figure 3 c) shows the best forecast map compared to previous results. The results allow saying about the availability of the proposed multi-stage approach, and particularly about using high-order markov chains and the adaptive grid-cell size of CA, in tasks of forecasting with TS aerospace images.

CONCLUSION

Intensity of using RS data and GIS for tasks of ecosystem monitoring and land cover change forecasting has been growing every year. The requirements in comprehensive multifunctional systems allowing to solve these tasks accurately and operative have been increasing. This paper proposed the multi-stage algorithm of time series aerospace images processing based upon the advanced interpretation algorithm and the procedure of obtaining forecast maps which is used high-order markov chains and cellular automata with adaptive grid-cell size. The primary investigation results of the proposed approach show the availability of this one. But due to perform comprehensive research it is necessary to have a large amount of experiments with a lot of aerospace images and available additional information.

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