

SLIDING WINDOW FOR RELATIONS MAPPING

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ABSTRACT

In the contribution a new way of the correlation approach with sliding window is addressed for the inside relations mapping and the use of the method for training, learning and for the image classification is presented. The sliding context window with defined step is a tool that makes it possible to precise our knowledge about the relations inside the data structure and to improve the object mapping into the proper feature space. We present the correlation and operator design of the local context mapping for the purposes of the analysis and preprocessing.

We compute the correlation of pairs of pixels from the neighbourhood we assume it belongs to the same object as well as the correlation between image plains or channels which can be considered to be a spatial neighbourhood of investigated object. The operator design requires the collaboration with principle component analysis (PCA) to interpret and analyse variance-covariance structures.

The important phase of the processing is the contextual feature space modelling and the optimal set of features selection. It means to compute the within-class as well as between-class distances and use the rule to order the features according to diminishing significance with regard to the given training sets.

1 INTRODUCTION

1.1 Context

In the last decade the strong development of information technologies is running. Computers have penetrate into all spheres of our life and information have become to be the goods, very looking out and very expensive. The huge amount of available information surrounding us and another ones flowing from internet still stress the importance of the context. The whole technology of geographical information systems is build on the efficient use of the content of the context.

The context can stay as the resource as well as the means and the context understanding can be applied on the large hierarchy of levels. In case of the image we can take into the consideration the context coming from the surrounding of pixel, context between primitives, context among objects, between spectral channels or image plains and their combinations and moreover the whole image can be understood as the result of all possible contextual relations.

We are able even use the information from very different sources and model or change the requested contextual feature space.

Contextual information can be taken into account in a number of ways (Haralick, 1973). It can be considered, when the feature space is constructed, as a part of mapping of the object into a vector space. We include the features that hold information about arrangement and cross-relations in the neighbourhood (Swain, 1980). Another way is to use the context sensitive preprocessing within the image enhancement and reconstruction or even in the course of the classification or post-classification..

We will discuss the case when the contextual information is drawn from the neighboring pixels tend to be the same object and applied in the phase of preprocessing, training, learning and image classification.

1.2 Context types

The use of context improves the object content specification, increases the level of understanding and makes it possible to achieve higher accuracy of classification on one hand but the context itself is often very vague and fuzzy quantity which can be quantified with high difficulties and which is noted to be heavy defined (Haslett J. 1985).

In practical applications the different types of context are distinguished:

Spatial (local context) – the distance dependent relations and/or directional, properties of neighborhood or its form, inside point of, border point, ...

Attribute (logical) context – simultaneous occurrence of selected properties, definite combination of properties or nonexistence of the given type relation or relations.

Temporal context – flowing from the time dependent behavior of selected objects.

Thematically oriented context or the combinations of contexts mentioned above.

With increasing complexity of processed image (of data structure) the importance and also the variability of the context rapidly increases.

2 CONTEXTUAL MODELING

2.1 Correlation design

In the field of remote sensing and image analysis of natural scenes we often meet the objects with large variability of tones, for example forest, urban areas and so on. Commonly we can say the objects the dominant property of which is the texture. Many approaches have been developed using namely second order statistics to describe and interpret the objects corresponding to the classes of nature objects where the context relations play the significant role. The goal of our approach is to avoid the computation with the large and sparse matrices and the loss in information which follows the image re-scaling.

The proposed model prefers the possibility to extract features directly from the original image $F(x, y)$ using sliding window $2W+1$ with the sliding step $q = (q1, q2)$, where $q1, q2$ denote the horizontal and vertical parameter of sliding. Roughly speaking, the limit case $q1, q2 = 1$ is usually used when the multi-channel image is processed where the multi-spectral and spatial feature spaces are combined and the values $q1, q2 = 2W+1$ are set on to achieve the second marginal case where the non-overlapping sub-images are considered and processed. This approach is obviously used with the single-channel data structure. All possibilities within these boundaries can be applied with respect to the performed data structures.

We propose to consider the joint probability distribution function with parameterization by the covariance matrix CM to map the context relations in the defined neighborhood because the non-parametrical approach is not operational enough. For the common case we consider the arbitrary network of selected points (given by the mask) instead of stable surroundings as usual.

If we denote the number of mask points as $NMSK (>1)$, than the elements of CM are given as:

$$CM_{RS} = \left[\frac{\sum_{j,k} F_R(j,k)F_S(j^*,k^*) - \sum_{j,k} F_R(j,k) \cdot \sum_{j,k} F_S(j^*,k^*) / \sum_{j,k} 1}{\sum_{j,k} 1} \right] / \sum_{j,k} 1, \quad (1)$$

where the indexes $R, S \in \langle 1, NMSK \rangle$, $R \neq S$ denote the position in the mask and the relation between (j, k) and (j^*, k^*) is uniquely defined.

The sums are normalized by the number of involved pixels. The elements CM_{RS} gives the correlation of gray values between positions R and S of given mask.

To map and to analyze the objects on given data structure we are interested not only in the relations inside the definite neighborhood of pixel or sub-image. We can combine this approach with the possibility to obtain information about the relations between image plains or channels belonging to the same investigated scene. It means to consider the covariance between the same places of different image channels but from the point of view of object oriented approach we can without the restriction investigate in the same way the relations between different places of different image plains.

The common formula will be given as follows:

$$CM^{ab}(\Delta x, \Delta y) = (\sigma^a \sigma^b \sum_{x,y} 1)^{-1} \sum_{x,y} (F^a(x, y) - \mu^a)(F^b(x + \Delta x, y + \Delta y) - \mu^b) \quad (2)$$

where $a, b \in \langle 2, \dots, n \rangle$, n is the number of spectral channels or image plains. The sum is normalized by the number of involved pixels from the considered region.

From the symmetry of $CM^{ab}(\Delta x, \Delta y)$ with positive and negative transitions it follows, that we compute only one half of elements defined in formula (2). All coefficients are normalized and encoded and the set is usually fulfilled by the current statistical values as mean and standard deviation over the used mask or standard rectangular neighborhood. The sliding factor can help us to control the amount of generated features with respect to the available training sets and precise the learning.

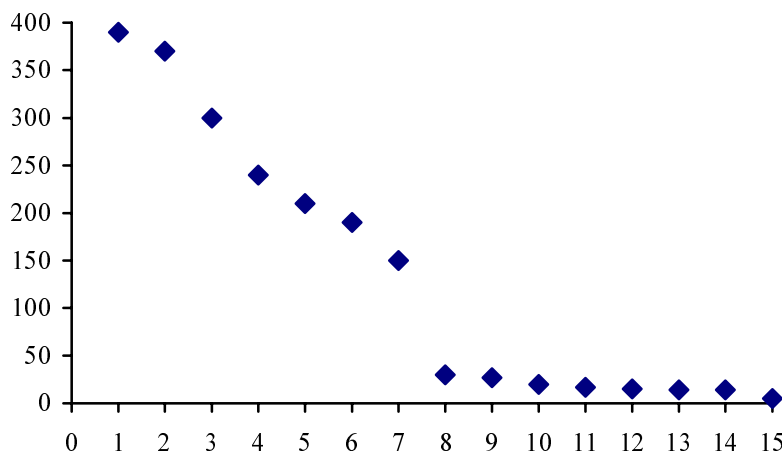
The sliding window can be also successfully used to investigate the features stability. In the course of the training the influence of determined size of window on the dynamics of within-class and between-class distances is tested and the size is selected to maximize the between-class ones.

2.2 Operator design

This approach is used when it is not desirable from different reasons to extract features directly from the original image structure. In that case it is useful to apply the context sensitive type of preprocessing to achieve more convenient and proper image data structure for further analysis (Nguyen Hong, Ocelikova, 1999). The great number of context sensitive operators is well known and moreover here is the place to generate the special approaches exactly prepared to conform to our data (Connors, Trivedi, 1984).

Frequently used are: two channel Laplacian product with changing size of neighborhood, the enhancement operators with two sizes of neighborhood with different stress application, the nonlinear hierarchical boundary evaluation, the edges with defined background and so on.

The phase of preprocessing contains also the test of new image plains information quality using *principle component transformation (PCT)* procedure and consequent analysis. The arrangement of ordered eigenvalues usually gives the answer on the question how many components - new image plains - is useful to continue with, where i -component is the linear combination of i -eigenvector with image data set.



Graph 1.: Eigenvalues ordered with diminishing value with the visible jump.

		0	0	-1	0	0
		0	0	0	0	0
H	=	-1	0	5	0	-1
		0	0	0	0	0
		0	0	-1	0	0

Table 2.: H is an example of preprocessing operator (4-multiple of extended Laplacian is added).

It is well known, that considering the random data structure the eigenvalues are laying nearly on/or around the line parallel with x-axis. Quite another situation is when we are dealing with real data structure. It is reasonable to stop the selection of the new components in the place of jump (see graph 1) which represents the change in behavior and significant decrease of information.

3 FEATURE SELECTION

The proposed approach can produce a large number of features and the use of effective feature selection algorithm is the significant phase of the processing. Roughly speaking, the local context evaluation and analysis could not be used without the efficient tool which is able to select and order features according to their diminishing significance with the respect to the training sets. It means to select couples of pixels from the neighborhood where the correlation relations are enough discriminative.

In (Klimesova, 1998) the method of the feature selection is published where two different measures of cumulative between-class distance are considered. The algorithm has been derived to select an optimal set of translations for computing of the correlation function between couples of pixels, based on 2D auto-correlation function, for the purposes of texture analysis, it means for the single-channel context evaluation.

Mentioned algorithm gives the set of features ordered according to their diminishing significance with regard to the training sets.

The distance of classes ω_i, ω_k at feature f_j is defined as

$$d_{ikj} = \left[\left(\mu_{ji} - \mu_{jk} \right) / \left(\sigma_{ji} + \sigma_{jk} \right) \right]^2 \quad \text{for every } f_j.$$

The time complexity estimation of the selecting algorithm is $O((n+q).R^2)$ and the estimation of the space complexity is equal to $O((R+n)^2)$, where R is the number of classes and n is the number of features.

4 EXPERIMENTS AND RESULTS

The use of contextual features is strongly recommended to precise the classification procedure in case of objects with large variability of gray values. Namely the objects of natural scenes can be more exactly specified using this model (objects like: forest, crop, urban areas, meadows, vineyards, ...) Namely the classes with nearly the same mean value and great enough the variance value ask for the contextual information incorporation.

On the other hand the combination of spectral and contextual feature space with strong accent of context requires usually the hierarchical approach of classification with consequently applied masking technique.

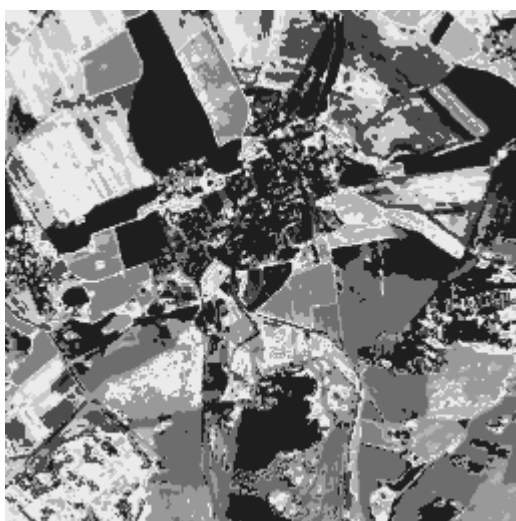


Fig.3.: Multispectral classification of Landsat TM scene by maximum-likelihood method.

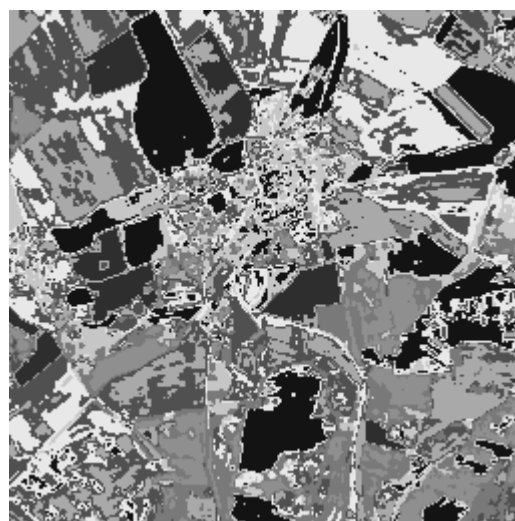


Fig.4.: Spectral-correlation feature space used in the procedure of maximum-likelihood classification.

The result of contextual classification is shown on fig. 4, where the neighborhood of size 7×7 has been used with sliding step equal 1. The more homogenous compact objects can be detected but also the dividing line caused by border effect.

5 CONCLUSIONS

In this paper the new method of image processing and analysis is proposed where the contextual information is used on different levels of performance. The covariance parameterization of JPD function is described including the design of within image and between image context understanding. It is shown, that the recognition of object with great variance of gray levels can be done more exact and consistent when the context is taken into consideration. The features resulting from the neighborhood context evaluation have been used to the recognition of agricultural landscape of Landsat TM scene. The method is computationally efficient and may have numerous practical applications in the field of pattern recognition, computer vision and remote sensing.

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