SEATH - A NEW TOOL FOR AUTOMATED FEATURE EXTRACTION IN THE CONTEXT OF OBJECT-BASED IMAGE ANALYSIS

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ABSTRACT:

In order to avoid the time-consuming trial-and-error practice for seeking significant features for optimal class separation in object-based classification, an automatic feature extraction methodology, called SEaTH has been developed. SEaTH calculates the SEperability and the corresponding THresholds of object classes for any number of given features on the basis of a statistical approach. The statistical measure for determining the representative features for each object class is the mutual separability of the object classes. Subsequently, SEaTH calculates those thresholds which allow the best separability in the selected features. The methodology and its application to a case study on an Iranian nuclear facility are presented. With regard to the automation of object-based image processing, aspects of standardization and transferability are discussed.

1. INTRODUCTION

Feature recognition is an essential part of object-based image analysis. A comprehensive feature extraction methodology is the precondition for successful work with image objects. Given the large number of possible features for object description, it is necessary to identify the characteristic, significant features for object-classes of interest. Questions like: "Which of the numerous possible features are most characteristic for which object class?" or "Is the feature I have chosen really the best possible feature?" have to be answered. These and other problems demand a consistent procedure for selecting object features as well as a quality measure for features. The methodology should be able to identify the most salient features for each object class and should also allow a comparison of their suitability.

Since the availability of high-resolution satellite imagery, the use of remote sensing data has become very important for nuclear verification and safeguards purposes.[1] According to the expected technical improvements regarding the spatial and spectral resolution, satellite imagery can build the basis of complex systems in the future for recognizing and monitoring even small-scale and short-term structural features of interests within nuclear facilities. Examples are construction of buildings, plant expansion, changes of the operational status, planning of underground activities etc. Large volumes of satellite data require a high degree of automated image processing, analysis and interpretation. Though it seems to be overconfident to replace an image analyst completely by a software system, there certainly exist opportunities to obtain faster and more precise image analysis results. These include for example the pre-selection of relevant objects or the automatic detection and classification of changes.

When adapted to high-resolution imagery, the traditional pixel-based image processing algorithms are sometimes limited. Especially if small structural objects are to be detected, object-based procedures seem to be more precise and meaningful. In comparison to the purely spectral-based features used within the pixel-based approaches, the inclusion of features such as the size or orientation of an object, its shape or texture and its relations to other objects on the same or at different scales, considerably extends the possibilities for image analysis. Computer driven, object-based image analysis is in a first approximation comparable to visual perception. An image interpreter recognizes, along with the color of an image, also the shapes, textures and coherent regions present within it, and associates meaningful objects and their contextual relations. A similar goal is intended in object-based image analysis, although the complexity and effectiveness of human perception is of course far from being achieved. The extraction of the objects from the analyzed image occurs at the lowest level by segmentation, at which stage the primary segments should ideally represent the real world objects. The feature analysis provides the basis for the preparation of a ruled-based classification model resulting in a classified image. In this paper we emphasize the important step of feature analysis.

[1]The work presented in this paper has been carried out in the context of nuclear verification and international safeguards, in support of the International Atomic Energy Agency (IAEA). The developed feature analysis tool can, of course, be used in any classification context.

2. SEATH ALGORITHM

Generally, a semantic class can be described by its characteristic features and their distribution in the feature space. Using an object-based approach to analyze an image, there are many possible features to take into consideration in order to describe the object classes of interest. Therefore it is necessary to determine the prominent features for each object class for the succeeding image analysis (Nussbaum, Niemeyer, and Canty, 2005).

The feature analyzing tool SEaTH (*SEparability and THresholds*) identifies these characteristic features with a statistical approach based on training objects. These training objects represent a small subset out of the total amount of image objects and should be representative objects for each object class. The statistical measure for determining the representative features for each object class is the pairwise separability of the object classes among each other. Subsequently, SEaTH calculates the thresholds which allow the *maximum* separability in the chosen features.

2.1 SEparability

The identification of the characteristic features is a problem of probability density estimation. On the basis of representative training data for each object class, the probability distribution for each class can be estimated and used to calculate the separability between two object classes. Under the assumption of normal probability distributions, the *Bhattacharyya distance* B can be used as a suitable separability measure. B is justified as a measure of separability from the Bayesean decision rule for misclassification probability. For the derivation of the Bhattacharyya distance see (Bhattacharyya, 1943) or (Fukunaga, 1990). For two classes (C_1, C_2) and one feature it is given by

$$B = \frac{1}{8}(m_1 - m_2)^2 \frac{2}{\sigma_1^2 + \sigma_2^2} + \frac{1}{2} ln[\frac{\sigma_1^2 + \sigma_2^2}{2\sigma_1\sigma_2}], \quad (1)$$

where m_i and $\sigma_i^2, i = 1, 2$, are the mean and the variance, respectively, for the two feature distributions. If the means coincide, the first term in (1) vanishes, whereas the second term vanishes if the two feature distributions have equal variances.

Figure 1 shows the probability distribution exemplified for two object classes C_1 and C_2 and three notional features A, B and C. In feature A both object classes show a *partial separability*, this means that there is an area where the probability distributions of the object classes (C_1 and C_2) overlap in their feature characteristic. Given feature B this overlap is so large that its use for for classification would result in a huge object misclassification rate. This feature therefore provides *poor separability* relative to object classes C_1 and C_2. The ideal case is represented by feature C. Here the object classes have no overlap in the feature characteristic it is therefore well-suited for classification: the feature has *complete separability*.

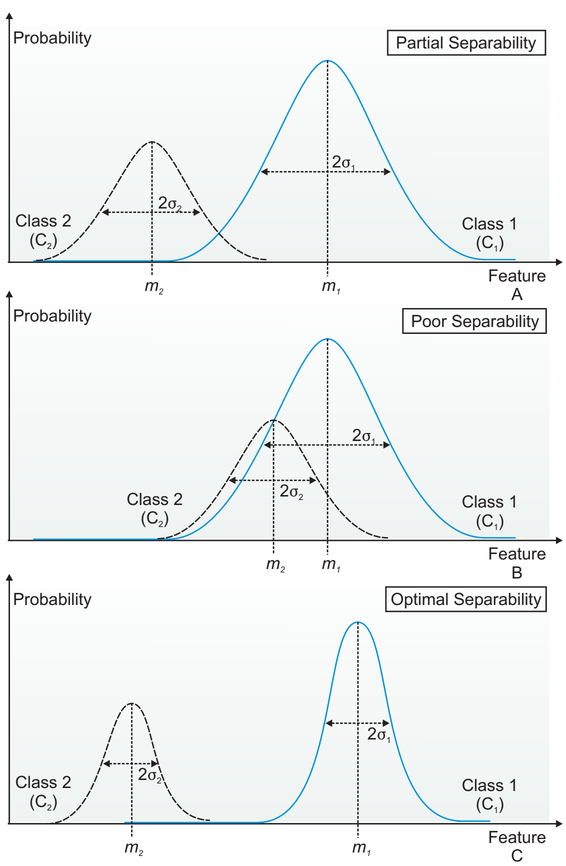

Figure 1. Examples of probability distributions

An more useful measure for separation in classification contexts is the *Jeffries-Matusita distance* J which has, unlike B, a finite dynamic range. This allows a better comparison of the feature analysis results to identify that feature which has the separability. The Jeffries-Matusita distance measures the separability of two classes on a scale $[0 - 2]$ in terms of B:

$$J = 2(1 - e^{-B}). \quad (2)$$

Complete separability of the two classes with respect to the analyzed feature is indicated by $J = 2$. That is to say, on the basis of the training objects used, there will be no misclassifications if this feature is used for classification. The lower J is, the worse is the separability and the higher the number of misclassified objects. SEaTH calculates the separability for any number of given object classes and object class combinations.

2.2 THreshold

Besides determining the features separating optimally the object classes among each other, it is essential to know also the decision threshold for the maximum separability. The knowledge of the optimum threshold is necessary for the assembly of a ruled-based classification model.

The optimum threshold is also calculated by SEaTH. A Gaussian probability mixture model of the form

$$p(x) = p(x|C1)p(C1) + p(x|C2)p(C2)$$

is fit to the frequency distribution of a feature for two object classes $C1$ and $C2$, where $p(x|C1)$ is a normal distribution with mean m_{C1} and variance σ_{C1}^2 and similarly for $p(x|C2)$. The decision threshold which minimizes the error probability is obtained by solving

$$p(x|C1)p(C1) = p(x|C2)p(C2). \quad (3)$$

for x. Taking logarithms,

$$\frac{1}{2\sigma_{C2}^2}(x - m_{C2})^2 - \frac{1}{2\sigma_{C1}^2}(x - m_{C1})^2 = log[\frac{\sigma_{C1}}{\sigma_{C2}} * \frac{p(C2)}{p(C1)}] =: A \quad (4)$$

with solutions

$$x_{1(2)} = \frac{1}{\sigma_{C1}^2 - \sigma_{C2}^2}\Big[m_{C2}\sigma_{C1}^2 - m_{C1}\sigma_{C2}^2 \pm \quad (5)$$

$$\sigma_{C1}\sqrt{(m_{C1} - m_{C2})^2 + 2A(\sigma_{C1}^2 - \sigma_{C2}^2)}\Big]. \quad (6)$$

The relevant solution of the two can be determined by requiring that it lie between the two means m_1, m_2 of the probability distributions. Thus, for the example in Figure 2, x_1 is the correct choice. Since the distributions are only partially separated (see section 2.1), there will be some misclassifications when using this feature for classification of unknown object classes. Given the validity of the normal approximation assumption, SEaTH will minimize their number.

To identify the best features for the classification SEaTH calculates the separability and the corresponding threshold for every object class combination and for every feature. Any number of object classes and features can be analyzed. The results of SEaTH are presented in tables. An interpretation of the results allows a fast preparation of a classification model, with statistically optimized features and thresholds.

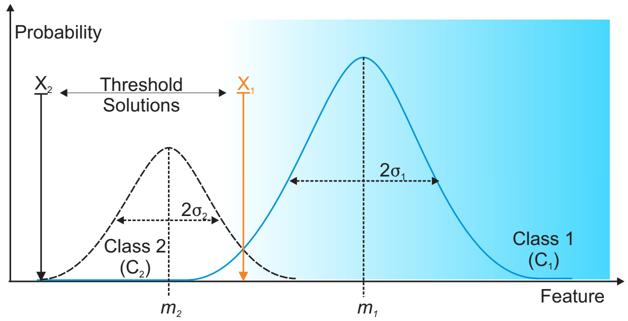

Figure 2. Threshold identification

3. SEATH VALIDATION

The SEaTH Algorithm was validated by performing an accuracy assessment for an object-based analysis of an aerial image acquired over the Research Center Jülich (FZJ) in September 1998. The image has a ground resolution of 1.25 m. Ground truth data were available for the entire scene.

The image analysis process was carried out with the software eCognition (Baatz, Heyen, and Hofman, 2004). All image object were considered in the accuracy assessment, except for those image objects representing mixed classes. Figure 3 shows the original aerial image of the FZJ.

Figure 3. Research Center Jülich, September 1998

In this scene, the object classes BUILT-UP, FIELDS, FOREST, MEADOWS, STREETS and SHADOWS were classified. The class BUILT-UP contains buildings and sealed surfaces which are not streets. A very simple segmentation procedure was applied, with only one scale level: scale factor 50, shape factor 0.3, compactness 0.5. Nevertheless most of the expected objects are well-represent as individual segments.

The segmentation results in almost 2500 image objects. For the SEaTH analysis about 2% of the total number of image objects were selected as training data, i.e. approximately ten objects for each class. eCognition enables the user to select feature characteristics for the training objects. For the validation 74 spectral, shape and texture features were taken into account. The training data set was then analyzed with SEaTH, which calculated, for every object class combination, the separability and thresholds for each of the 74 features (see Table 1).

Spectral features
Mean *Channel 1,2,3*
Stddev *Channel 1,2,3*
Ratio *Channel 1,2,3*
Max.Diff.
Brightness
Shape features
Area (m^2)
Length (m)
Width (m)
Length/width
Compactness
Elliptic Fit
Rectangular Fit
Border length (m)
Shape index
Density
Main direction
Asymmetry
Texture features
GLCM Homogeneity (all dir.) *Channel 1,2,3, all dir.*
GLCM Contrast (all dir.) *Channel 1,2,3, all dir.*
GLCM Dissimilarity (all dir.) *Channel 1,2,3, all dir.*
GLCM Entropy (all dir.) *Channel 1,2,3, all dir.*
GLCM Ang. 2nd moment (all dir.) *Channel 1,2,3, all dir.*
GLCM Mean (all dir.) *Channel 1,2,3, all dir.*
GLCM StdDev (all dir.) *Channel 1,2,3, all dir.*
GLCM Correlation (all dir.) *Channel 1,2,3, all dir.*
GLDV Ang. 2nd moment (all dir.) *Channel 1,2,3, all dir.*
GLDV Entropy (all dir.) *Channel 1,2,3, all dir.*
GLDV Mean (all dir.) *Channel 1,2,3, all dir.*
GLDV Contrast (all dir.) *Channel 1,2,3, all dir.*

Table 1. Features used for image analysis with SEaTH

Table 2 lists the two "best" of the given 74 features for each object class combination. In general the first few features with maximum separability are sufficient for classification, especially if the classification model is to be applied to other image data. For reasons of transferability, it is wise to keep the number of characteristic features low. A subsequent interpretation of the SEaTH results finally leads to the compilation of a ruled-based classification model.

Here are some examples of how to read Table 2: the object class BUILT-UP is best separated from the class FOREST (line 1) with the feature *Ratio Channel 2*. This feature nearly holds a *complete separability* (1.99). All image objects with a feature characteristic in *Ratio Channel 2* smaller (column: *omen*) than 0.352 (column: *threshold*) should be assigned to the class BUILT-UP. This statement can easily be implemented as a classification rule in eCognition; The best features for separation of FOREST from MEADOWS (line 10) are texture features. Every image object with a *GLCM Dissimilarity Chan. 2* feature characteristic *greater* than 12.92 belongs to the class FOREST, otherwise it will be classified as MEADOWS.

The result of the object based classification is shown in Figure 4. The class WATER has been classified manually since it corresponds to only one image object.

In remote sensing the accuracy assessment is important for the evaluation and the comparison of classification results. A good overview of general techniques, accuracy measures, the construction of an error matrix and the sampling problem can be found in (Congalton, 1991). For the accuracy assessment of the object-oriented classification based on the SEaTH results the *overall accuracy* as well as the *users*- and *producers accuracy* were calculated.

Object Class Combination	Separability	Omen	Threshold
BUILT-UP. from FOREST			
Ratio Chan. 2	1.99	small	0.352
Ratio Chan. 1	1.95	great	0.309
BUILT-UP. from STREETS			
Density	1.69	great	1.105
Length (m)	1.17	small	150.901
BUILT-UP. from MEADOWS			
Ratio Chan. 2	1.85	small	0.351
Max.Diff.	1.80	small	0.107
BUILT-UP. from FIELDS			
Ratio Chan. 3	1.97	great	0.311
Ratio Chan. 1	1.89	small	0.345
SHADOWS from BUILT-UP			
Mean Chan. 2	1.98	small	94.810
Mean Chan. 1	1.98	small	85.900
SHADOWS from FOREST			
GLCM Ang. 2nd (a.d.) Chan. 2	1.41	great	0.0006
GLCM Ang. 2nd moment (all dir.)	1.37	great	0.0007
SHADOWS from STREETS			
Mean Chan. 1	2.00	small	117.769
GLCM Mean (all dir.) Chan. 1	2.00	small	121.413
SHADOWS from MEADOWS			
Mean Chan. 2	1.96	small	93.979
GLCM Mean (all dir.) Chan. 2	1.94	small	99.268
FOREST from STREETS			
GLCM Mean (all dir.) Chan. 1	2.00	small	120.944
Mean Chan. 1	2.00	small	130.044
FOREST from MEADOWS			
GLCM Dissim. (all dir.) Chan. 2	1.99	great	12.920
GLDV Mean (all dir.) Chan. 2	1.99	great	12.920
FOREST from FIELDS			
GLCM Dissim. (all dir.) Chan. 2	1.99	great	13.333
GLDV Mean (all dir.) Chan. 2	1.99	great	13.333
STREETS from FIELDS			
Ratio Chan. 3	1.97	great	0.316
Max.Diff.	1.94	small	0.078
STREETS from MEADOWS			
Ratio Chan. 2	1.92	small	0.344
Max.Diff.	1.89	small	0.074
MEADOWS from FIELDS			
Ratio Chan. 1	1.82	small	0.345
Ratio Chan. 2	1.52	great	0.361

Table 2. Summarized result of the SEaTH analysis

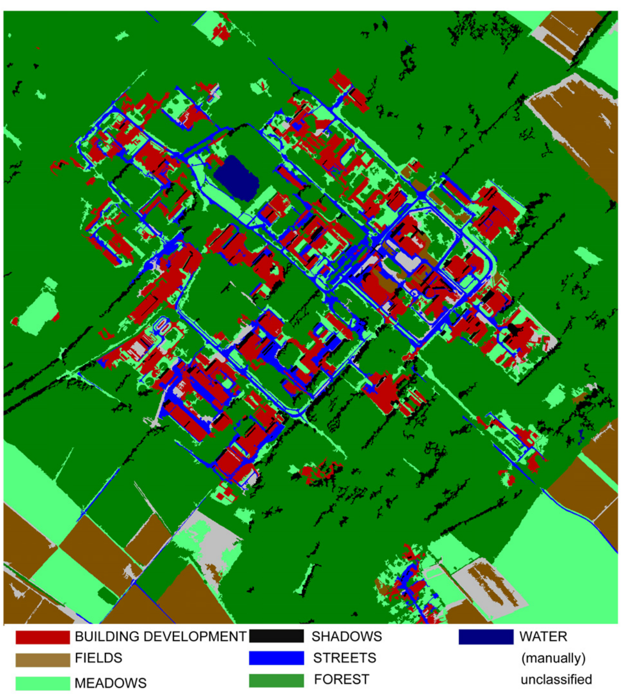

Figure 4. Classification of the ariel image acquired over the FZJ

Results are presented in a common error matrix, which specifies the ground truth data in columns and the classified objects in rows against each other (see Table 3). The diagonal of the matrix shows the correctly identified objects (here in boldface). Due to space considerations, the reference object data in the columns are represented by numbers which represents the object classes. The number is equivalent to the numbers given in the rows of the classified objects.

	1	2	3	4	5	6	Sum
BUILT-UP (1)	**188**	0	7	0	0	2	197
FOREST (2)	2	**1393**	0	5	0	5	1405
STREETS (3)	7	0	**84**	0	0	0	91
MEADOWS (4)	4	3	7	**144**	0	1	159
FIELDS (5)	0	0	2	6	**46**	0	54
SHADOWS (6)	1	26	0	0	0	**87**	114
UNCLASS.	2	1	3	5	5	0	16
Sum	204	1423	103	160	51	95	2036
Producer Accuray	0.92	0.98	0.81	0.90	0.90	0.91	
User Accuray	0.95	0.98	0.92	0.91	0.85	0.76	
Overall Accuracy	0.95						

Table 3. Accuracy assessment of the FZJ classification

Since there are ground information data for every of the 2036 reference objects taken for the accuracy assessment, the confidence level is 100%. The *overall accuracy* for the classification based on SEaTH is 95%. The producer accuracy amounts to 90% or better for all object classes, except for the object class STREETS with a producer accuracy of only 81%. In all other object classes, over 90% of the reference objects where identified correctly, in the case of FOREST even 98%. The worst result, obtained for the object class STREETS, was predictable on the basis of the SEaTH results, given the separability of the classes BUILT-UP and STREETS of 1.69. The reliability of the classification is represented by the *user accuracy*, which is 90% for most of the classes over 90%, except for the object classes FIELDS and SHADOWS. With regard to nuclear verification the class BUILT-UP is particularly important, for example to confirm State declarations regarding new construction.

4. TEST CASE IRAN: ARAK

In this section the SEaTH methodology is applied to an actual test case, the nuclear installation at Arak in the Iran. Since the Iran is a member of the Non-Proliferation Treaty (NPT), International Atomic Energy Agency (IAEA) Safeguards measures are being applied to the site. The facility Arak contains a Heavy Water Production Plant, a 40 MWt Research Reactor as well as hot cells under construction.

Site area monitoring was carried out on the basis of ASTER satellite data at 15m ground resolution. For observation of individual facilities over time, high spatial resolution Quickbird images at 0.6m ground resolution have also been used (Niemeyer and Nussbaum, 2006). This case study uses two Quickbird images acquired over the facility from 12 June 2004 and 20 June 2005. In the following, we will focus on the extraction of an object-based classification model using the results of the feature analysis tool SEaTH. The other steps (preprocessing, classification and change detection) will only be mentioned briefly.

The pre-processing of the satellite images consisted of automated image-to-image-registration (Lehner, 1986) and wavelet-based image sharpening (Ranchin and Wald, 2000). For reasons of transferability of the classification model, relative radiometric normalization was also applied to the data sets (Canty, Nielsen, and Schmidt, 2004).

Figure 5. QUICKBIRD image of the Arak Facility, 12 June 2004 - pre-processed, original image provided by Digital Globe

The extraction of the objects is carried out by the multi-scale segmentation within eCognition with standardized parameters (Baatz and Schaepe, 2000). The SEaTH analysis is carried out for two segmentation levels. On a higher level the big real world objects e.g. great buildings where analysed followed by the lower level where small structures are represented e.g. watchtowers.

Spectral	Shape
Mean *Channel 1,2,3,4, NDVI*	Area (m)
Stdev *Channel 1,2,3,4, NDVI*	Length (m)
Ratio *Channel 1,2,3,4, NDVI*	Width (m)
Max. Diff.	Length/width
Brightness	Compactness
	Elliptic Fit
	Rectangular Fit
	Border length (m)
	Shape index
	Density
	Main direction
	Asymmetry
Texture	
GLCM Homogeneity (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	
GLCM Contrast (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	
GLCM Dissimilarity (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	
GLCM Entropy (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	
GLCM Ang. 2nd moment (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	
GLCM Mean (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	
GLCM StdDev (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	
GLCM Correlation (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	
GLDV Ang. 2nd moment (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	
GLDV Entropy (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	
GLDV Mean (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	
GLDV Contrast (all dir.) *Channel 1,2,3,4, NDVI, all dir.*	

Table 4. Features used for image analysis with SEaTH

Feature extraction and semantic modelling is implemented on the basis of representative training objects for each of the defined object classes: BACKGROUND, BUILT-UP, SHADOWS, TARMAC STREETS, VEGETATION and WATCHTOWERS. Table 4 gives an overview of the analyzed features. SEaTH now calculates for each possible combination of two object classes their separability in any feature plus the corresponding threshold (see. Sect.2.). An interpretation of the SEaTH results leads to the compilation of a rule-based classification model and finally to a classified image. The model itself will not presented here, however Figure 6 shows the site classification for June 2004.

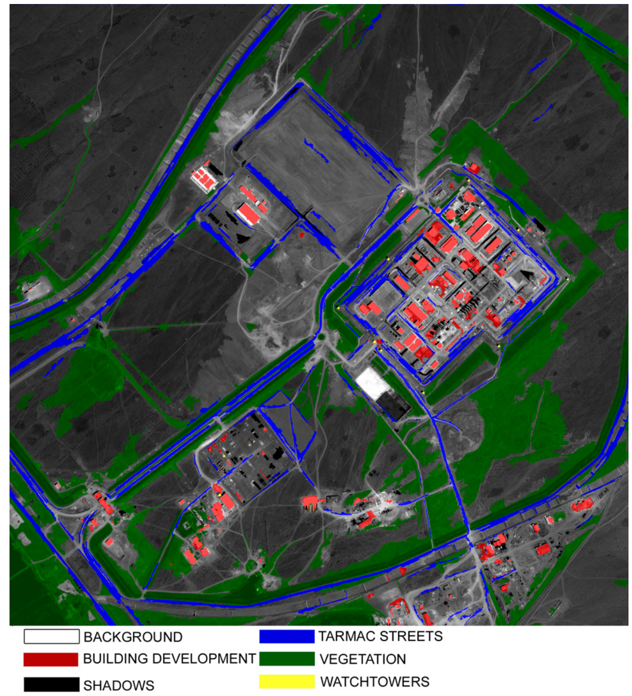

Figure 6. Classification of the Arak Facility, 12 June 2004

At first view, the results seem coherent, with none of the salt and pepper effects that appear often in pixel-based approaches. Most of the objects are classified correctly. An accuracy assessment was carried out as explained in section 3. Here 260 reference objects from a total of 9000 image objects were considered. The overall classification accuracy is 92%. Table 5 also shows the calculated user and producers accuracy for each class. In particular the good accuracy achieved in the class BUILT-UP is important for Safeguards related purposes.

	1	2	3	4	5	6	Sum
TARMAC STREETS (1)	**42**	0	2	1	0	1	46
VEGETATION (2)	0	**47**	0	0	0	2	49
SHADOWS (3)	0	0	**45**	0	0	0	45
BUILT-UP (4)	4	0	0	**47**	0	0	51
W-TOWERS (5)	0	0	0	2	**10**	0	12
BACKGR. (6)	4	3	3	0	0	**47**	57
Sum	50	50	50	50	10	50	260
Producer Accuracy	0.84	0.94	0.90	0.94	1.00	0.94	
User Accuracy	0.91	0.96	1.00	0.92	0.83	0.82	
Overall Accuracy	0.92						

Table 5. Accuracy assessment of the Arak 2004 classification

The question whether the features identified with SEaTH are ”key features“ for the analyzed object classes is a question of transferability. For an automated monitoring regime, it would be beneficial if the created classification model can be applied as an reference model for all other scenes of the Arak site or, even better, for other facilities.

The results of a temporal transferability test of the classification model is presented in Figure 7. Here the classification model from Arak 2004 is applied to a pre-processed Quickbird image of the Arak facility from 20 June 2005. Choosing nearly the same acquisition dates (both in June) and keeping the exact model, the achieved classification result is, with an overall accuracy of 91%, quite satisfactory.

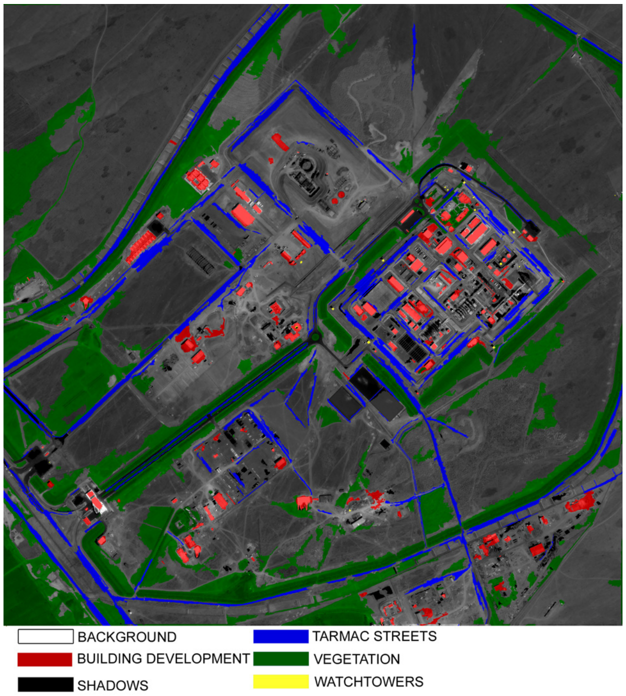

Figure 7. Classified image of the Arak Facility, 20 June 2005

5. CONCLUSIONS AND FUTURE WORK

A comprehensive feature analysis is essential for the work with image objects. It utilizes the advantage of a wide feature basis of objects and provides the fundament for a successful classification. The feature recognition and analysis Tool SEaTH has been described, validated and exemplified for a case study on the Iranian Facility of Arak. SEaTH is a very useful tool in the context of feature analysis. It is able to evaluate statistically any number of given features for object classes of interest. The results of SEaTH allow an optimized object-oriented classification which minimizes the misclassified rate.

The features identified with SEaTH produce a good classification result for the Arak site and even the temporal transferability of the classification works very well. In future work SEaTH will be improved regarding features wich are not approximately normal distributed. Other investigations belonging to the temporal transferability of training objects for the SEaTH analysis will be carried out.

In all, SEaTH shows promising results in the field of feature recognition for Nuclear Safeguards related purposes. In the given case study the buildings could be identified correctly, and this information can be used in combination with a change detection technique for nuclear verification. In future work on nuclear verification a comprehensive change detection and interpretation system has to be developed. To this end, characteristic features for different facility types in different geographical/political areas are urgently needed. Moreover, automatic procedures for geometric registration, radiometric normalization, image fusion/sharpening have to be developed and/or improved.

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