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Cognitive Aspects of Object Recognition – Recognition of Objects by Texture

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Abstract

To study human image cognition is more than ever an important topic since the number of vision-based materials has been increased over the years. Texture seems to be a powerful tool to describe the appearances of objects. Therefore, very flexible and powerful texture descriptors are of importance that allow to recognize the texture and to understand what makes up the texture. The most used texture descriptor is the well-known texture descriptor based on the co-occurrence matrix. We propose a texture descriptor based on random sets. This descriptor gives us more freedom in describing different textures. In this paper, we compare the two texture descriptors based on a medical data set. We review the theory of the two texture descriptors and describe the procedure for the comparison of the two methods. Polyp images are used that are derived from colon examination. Decision tree induction is used to learn a classifier model. Cross-validation is used to calculate the error rate. The comparison of the two texture descriptors is based on the error rate, the properties of the two best classification models, the runtime for the feature calculation, the selected features, and the semantic meaning of the texture descriptors. The medical data set was chosen since texture seems to play an important role in describing medical objects.

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Keywords: image cognition; object classification; texture description; random sets; co-occurence matrix, comparison of statistical texture

1. Introduction

To study human image cognition is more than ever an important topic since the number of vision-based materials has been increased over the years. Texture seems to be a powerful tool to describe the appearances of objects.

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Therefore, very flexible and powerful texture descriptors are of importance that allow to recognize the texture and to understand what makes up the texture. Texture becomes an important role to describe the appearance of different biological objects in images. Patterns on cells in cell images, on fungi images or polyp images can be described by texture.

Different texture descriptors have been developed over the past[1]. The most used texture descriptor is the well-known texture descriptor based on the co-occurrence matrix[2]. Although it works well on different applications we prefer to use our texture descriptor that is based on random sets[3] since this descriptor gives us more freedom in describing different textures.

In this paper we compare the two texture descriptors based on a medical data set. Related work on texture description is given Section 2. The theory of the texture descriptors based on Random Sets is reviewed in Section 3. The procedure for the comparison of the two methods is described in Section 4. The used data set of polyp images is derived from colon examination. We calculated the texture features based on the two methods for each image of the data set and learn a decision tree classifier. Cross-validation is used to calculate the error rate. Then we compare the properties of the two best decision trees, the runtime for the feature calculation, the selected features, and the semantic meaning of the texture descriptors. The results are presented in Section 5 and discussed in Section 6. Conclusions are presented in Section 7.

2. Related Work

Texture description methods are mainly classified into structural, statistical, model-based, and transform-based approaches[4-6]. Structural methods use texture elements to describe textures. It is good for image synthesis applications. Statistical methods use gray-level relationship between neighboring pixels to describe to local texture property in first-order, second-order, or higher-order statistics. The methods are good for invariant texture analysis and classification. Model-based methods model images as different probability or linear combination models[6] and use model parameters to describe their texture features, such as autoregressive models, fractal models[7], Gaussian-mixture models (GMM)[8], hidden Markov models (HMM)[9,10], Markov random fields (MRF)[11] and so on. The transform methods transfer images into a frequency domain to describe textures. The methods usually use Fourier, Gabor, or wavelet transform. An overview about older methods such autocorrelation and other is given in van Gool et. al[12] and Haralick[13].

Often the texture descriptors are compared on standard texture data sets but recently appeared work of texture description for real world problems such as description of objects in medical images, microscopic images for different purposes such as e.g. in system biology and for environmental applications, food inspection and so on. Texture became a valuable information about images. Researcher try to develop many new texture descriptor that take into account the variances of the texture, the spectral influences and so on. At lot of different methods exist and it is not easy to do a categorization of all these methods. We want to describe in brief the recent developments. Often that are variants of the above-described categories that have been evaluated on standard data sets. However nowadays, more work on real world applications appear.

Din-Chang Tseng et. al[14] developed a multiscale texture segmentation approach based on contextual hidden Markov tree (CHMT) model and boundary refinement. A hidden Markov tree (HMT) model is a probabilistic model for capturing persistence properties of wavelet coefficients without considering clustering properties. They have proposed the CHMT model to enhance the clustering properties by adding extended coefficients associated with wavelet coefficients in every scale.

Wesley Nunes Goncalves et. al[15] developed a method that is able to capture the details richness of the image surface. They estimated the fractal dimension by the Bouligand- Minkowski method due to its precision in quantifying structural properties of images. They validated their method on two standard texture datasets and the experimental results reveal that the methods is good enough to describe different data sets.

R. Mukundan[16] us orthogonal moment functions based on Tchebichef polynomials. They claim that the method is good because of their superior feature representation capabilities. They construct feature vectors from orthonormal Tchebichef moments evaluated on 5x5 neighborhoods of pixels, and encoding the texture information as a Lehmer code that represents the relative strengths of the evaluated moments. The features will be referred to as Local Tchebichef Moments (LTMs). The encoding scheme provides a byte value for each pixel, and generates a gray-level

LTM-image of the input image. The histogram of the LTM-image is then used as the texture descriptor for classification.

Yuhui Quan et. al[17] developed a statistical approach to static texture description, which combines a local pattern coding strategy with a robust global descriptor to achieve highly discriminative power, invariance to photometric transformation and strong robustness against geometric changes. They called their method pattern fractal spectrum that characterizes the self-similar behavior of the local pattern distributions by calculating fractal dimension on each type of pattern. Compared with other fractal-based approaches, the proposed descriptor is compact, highly distinctive and computationally efficient. The evaluation was done on a standard benchmark set.

Aujol et. al[18] explored in their paper various aspects of the image decomposition problem using modern variational techniques. They aim at splitting an original image f into two components u and v, where u holds the geometrical information and v holds the textural information. The modeling uses the total-variation energy for extracting the structural part and one of four of the following norms for the textural part: L2, G, L1 and a new tunable norm, suggested there for the first time, based on Gabor functions. They design tools for the TV -Gabor model.

Champion et. al[19] do texture modelling on a real world application for forest stand age from SAR images. The texture descriptors are calculated from statistics generated by the gray-level co-occurrence matrix for varying distance d, and orientation α, values used to calculate the matrix. It is found that texture descriptors contrast; inverse difference moment, homogeneity, and correlation are strongly influenced by the parameters (d, α) related to forest stand structure (forest rows, stand density) and image resolution. In contrast, the calculated energy and entropy from the co-occurrence matrix are observed to be highly correlated to stand age and displayed a stable performance whatever the distance and orientation parameters (d, α), thus rendering them a good contender.

Dharmagunawardhana et. al[20] proposed a novel robust texture descriptor based on Gaussian Markov random fields (GMRFs). A spatially localized parameter estimation technique using local linear regression is performed and the distributions of local parameter estimates are constructed to formulate the texture features. The inconsistencies arising in localized parameter estimation are addressed by applying generalized inverse, regularization and an estimation window size selection criterion. The texture descriptors are named as local parameter histograms (LPHs) and are used in texture segmentation with the k-means clustering algorithm. The segmentation results on general texture datasets demonstrate that LPH descriptors significantly improve the performance of classical GMRF features and achieve better results compared to the state-of-the-art texture descriptors based on local feature distributions.

Madzin et. al[21] deal with medical application, where the usage of multiple medical images generated by computer tomography such as x-ray, Magnetic Resonance Imaging (MRI) and CT-scan images is a standard tool of medical procedure for physicians. The major problems in analyzing various modality of medical image are the inconsistent orientation and position of the body-parts of interest. In this research, local descriptor of texture, shape and color are used to extract features from multi-modality medical image in patches and interest point's descriptor.

Palanivel et. al[22] use a Markov process with Bayesian Approach to analyze textures in the image and that are identified and distinguished from untextured regions with edges. The parameters of the model are estimated based on the Bayesian approach. They use two types of classification namely supervised and unsupervised classification.

Massich et. al[23] use Self-Invariant Feature Transform (SIFT), both as low-level and high-level descriptors, applied to differentiate the tissues present in breast US images. For the low-level texture descriptors case, SIFT descriptors are extracted from a regular grid. The high-level texture descriptor is built as a Bag-of-Features (BoF) of SIFT descriptors. Experimental results are provided showing the validity of the proposed approach for describing the tissues in breast US images.

Song et. al[24] presented a noise-robust descriptor by exploring a set of local contrast patterns (LCPs) via global measures for texture classification. To handle image noise, the directed and undirected difference masks are designed to calculate three types of local intensity contrasts: directed, undirected, and maximum difference responses. To describe pixel-wise features, these responses are separately quantized and encoded into specific patterns based on different global measures. These resulting patterns (i.e., LCPs) are jointly encoded to form our final texture representation. The evaluation has been done on two standard data sets and showed superior performance compared too many state-of-the-art methods.

Zhang and Pham[25] and Pham[26] tried to recognize the Subcellular Location Features (SLF) by three well-known texture feature descriptions., which are the local binary patterns (LBP), Gabor filtering and Gray Level Co-occurrence Matrix (GLCM), to recognize the cell phenotype images. Using the public benchmark 2D HeLa cell images, a high classification accuracy 96% is obtained with rejection rate 21% from the proposed system by taking advantages of the complementary strengths of feature construction and majority-voting based classifiers' decision fusions.

Marcos et. al[27] use Gray-Level Co-occurrence Matrices (GLCM), Log-Gabor Filters (LGF), Local Binary Patterns (LBP) and Discrete Tchebichef Moments (DTM) for pollen identification in microscopic images. Fisher's discriminant analysis and k-nearest neighbor were subsequently applied to perform dimensionality reduction and multivariate classification, respectively. They found that the combination of all the texture features resulted in the highest performance, yielding an accuracy of 94.83%.

Olveres et. al[28] use texture image segmentation for medical images. The noise inherent to images and the lack of contrast information between adjacent regions hamper the performance of the algorithms. The characterization of regions as statistical parametric models to handle level set evolution have been proposed. In this paper, they study the influence of texture on a level-set-based segmentation and propose the use of Hermite features that are incorporated into the level set model to improve organ segmentation that may be useful for quantifying left ventricular blood vessel. The proposal was also compared against other texture descriptors such as local binary patterns, Image derivatives, and Hounsfield low attenuation values.

Cai et. al[29] propose a novel phase-based texture descriptor for efficient and robust classifiers to discriminate benign and malignant tumors in breast cancer images. The phased congruency-based binary pattern (PCBP) is an oriented local texture descriptor that combines the phase congruency (PC) approach with the local binary pattern (LBP). The proposed PCBP texture descriptor achieves the highest values (i.e. 0.894) and the least variations in respect of the AUC index, regardless of the gray-scale variations.

Cheng et. al[30] propose a texture method based on the co-occurrence matrix to detect colorectal polyps in colonoscopy images. They used support vector machines for classification and achieve a sensitivity of 86,2%.

We have developed our own texture descriptor based on statistics that model the texture by a Poisson process after the image has been processed by a morphological operation. The remaining areas in the images can be described by first-order and second-order statistics as well as higher-order statistics if the number of remaining areas are large enough. The texture descriptor can be easily and fast computed and can handle different medical textures very well [31, 32]. These medical textures are often not easy to describe as it is in case of the Brodatz texture data set[1]. Our method has also explanation capability. A human can understand the differences in the texture by looking up the remaining images. If necessary, a symbolic description of the different textures can be found. Our texture descriptor has still some other properties that are of interest but here in this paper, we want to compare our texture descriptor to the co-occurrence matrix since it is from the category of statistic texture descriptors. The co-occurrence matrix is still the most used texture descriptor and we want to explore the differences between our texture descriptors and the co-occurrence matrix.

3. Texture Descriptor based on Random Sets

Boolean sets were invented by Matheron[31]. An in-depth description of the theory can be found in Stoyan et al[32]. The Boolean model allows to model and simulate a huge variety of textures e.g. for crystals, leaves, etc. The texture model X is obtained by taking various realizations of compact random sets, implanting them in Poisson points in R^n, and taking the supremum. The functional moment $Q(B)$ of X, after Booleanization, is calculated as:

$$P(B \subset X^c) = Q(B) = \exp(-\theta \overline{Mes}(X' \oplus \check{B})) \qquad \forall B \in \kappa \tag{1}$$

where κ is the set of the compact random set of R^n, θ the density of the process and $Mes(X' \oplus X)$ is an average measure that characterizes the geometric properties of the remaining set of objects after dilation. Relation (25) is the fundamental formula of the model. It completely characterizes the texture model. $Q(B)$ does not depend on the location of B, i.e., it is stationary. One can also provide that it is ergodic so that we can peak the measure for a specific portion of the space without referring to the particular portion of the space.

Formula 1 show us that the texture model depends on two parameters:

- the density θ of the process and

- a measure $\overline{Mes(X^{`} \oplus \check{B})}$ that characterizes the objects. In the one-dimensional space it is the average length of the lines and in the two-dimensional space $\overline{Mes(X^{`} \oplus \check{B})}$ is the average measure of the area and the perimeter of the objects under the assumption of convex shapes.

We consider the two-dimensional case and develop a proper texture descriptor.

Suppose now that we have a texture image with 8bit gray levels. Then we can consider the texture image as the superposition of various Boolean models, each of them having a different gray level value on the scale from 0 to 255 for the objects within the bit plane.

To reduce the dimensionality of the resulting feature vector, the gray levels ranging from 0 to 255 are now quantized into S intervals t. Each image f(x,y) is classified according to the gray level into t classes, with t={0,1,2,..,S}. For each class a binary image is calculated containing the value "1" for pixels with a gray level value falling into the gray level interval of class t and value "0" for all other pixels. The resulting bit plane *f(x,y,t)* can now be considered as a realization of the Boolean model. The quantization of the gray level into *S* intervals was done at equal distances. In the following, we call the image *f(x,y,t)* a class image. Object labeling is done in the class images with the contour following method. Afterwards, features from the bitplane and from these objects are calculated.

The list of features and their calculation are shown in Table 1. The first one is the density of the class image t which is the number of pixels in the class image, labeled by "1", divided by the area of the image. If all pixels of an image are labeled by "1", then the density is one. If no pixel in an image is labeled, then the density is zero.

Table 1. Texture Features based on Random Set

Description	Name	Type	Formula
Area in class image *t*	***Area_t***	num	$Area_t = \begin{cases} Area_t = Area_t + 1 & \text{if } f(x,y,t) = 1 \\ Area_t = Area_t & \text{if } f(x,y,t) = 0 \end{cases}$
Density in class image *t*	***Dens_t***	num	$Dens_t = \begin{cases} Dens_t = Dens_t + \frac{1}{A} & \text{if } f(x,y,t) = 1 \\ Dens_t = Dens_t & \text{if } f(x,y,t) = 0 \end{cases}$ with $A = \sum_{t=1}^{S} Area_t$
Number of objects	***Count_t***	num	*n(t)*
Mean area of objects in class image *t*	***AreaMean_t***	num	$\overline{A(t)} = \frac{1}{n(t)} \sum_{i=1}^{n(t)} A_i(t)$
Standard deviation of the area of the objects in class image *t*	***AreaStdDev_t***	num	$S(t) = \sqrt{\frac{1}{n(t)} \sum_{i=1}^{n(t)} (A_i(t) - \overline{A(t)})^2}$
The contour length of a single object is $u = l + \sqrt{2} \cdot m$ with *l* being the number of contour pixels having odd chain coding numbers and *m* being the number of contour pixels having even chain coding numbers.			
Mean contour length of objects in class image *t*	***ContMean_t***	num	$\bar{u}(t) = \frac{1}{n(t)} \sum_{i=1}^{n(t)} u_i(t)$
Standard deviation of the contour length of objects in class image *t*	***ContStdDev_t***	num	$S(t) = \sqrt{\frac{1}{n(t)} \sum_{i=1}^{n(t)} (u_i(t) - \overline{u(t)})^2}$

From the objects in the class image t, the area, a simple shape factor, and the length of the contour are calculated. According to the model, not a single feature of each object is taken for classification, but the mean and the variance of each feature are calculated over all the objects in the class image t. We also calculate the frequency of the object size in each class image t.

Depending on the number of slices S we get a feature set of 42(*S=6*), 84(S=12), 112(S=16).

4. Material and Application

We studied the performance of the two texture descriptors based on a data set of 344 images. These images come from an endoscopic video system used for colon examination[30]. The data set contains 283 normal tissue images and 61 polyp images (see Figure 1) in the form of sub-images of a size 33x33 that are derived from 37 original colonoscopic images. The polyps in the 37 original colonoscopy images were identified and selected by a “well-trained” medical expert. A polyp is split into as many as possible sub-images.

The 283 normal images consist of dark regions, reflections etc. of the 37 original colonoscopy images.

This presents a two class problem; one must decide if the image shows a polyp or not. The texture descriptions were calculated from these images. The resulting data set was used to train a decision tree based on the C4.5 algorithm[35]. Cross-validation was used to estimate the error rate.

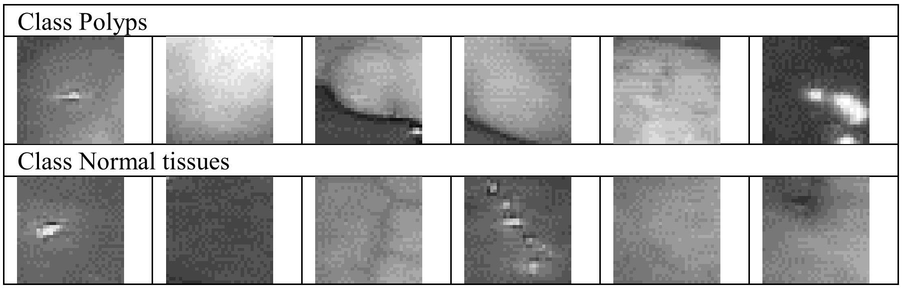

Fig. 1. Some Exemplary Images

5. Results

For the texture descriptor based on random sets the choice of S is important. On the one hand, we need a sufficiently large *S* to separate the classes. On the other hand, with increasing S also the number of features increases and we run into the curse-of-dimensionality problem.

Figure 2 shows the class images for some polyp images and some normal tissue images for *S=6*. Figure 3 shows the class images for some polyp images and some tissue images for *S=12*. Figure 3 shows that most pixels of normal tissue images are located in only a few lower 1-3 class images. In contrast to this, in the polyp images the pixels are distributed more across the class images.

For our tests we used S=6, S=12 and S=16. We have not yet developed a good procedure to estimate the number of S. The determination of the right number of S is still heuristic but in most of our applications S=12 turned out to be a good choice[3].

In the first test we used 30 polyp images and 30 normal tissue images as a data base. The results are shown in Figure 5. In the second tests we used all 344 images as a data base. The results are shown in Figure 6.

In both tests the texture descriptor based on random sets with S=12 is the best texture descriptor. The test shows that the choice of *S=6* is too small and the choice of *S=16* is already too large. This observation might already demonstrate the effect of the curse of dimensionality.

The texture descriptor based on random sets for S=12 has an error rate of 1.67% for the data set with 60 images (see Figure 5) with equally distributed number of polyps and normal tissue. Compared to this, the texture descriptor COO-1 has an error rate of 3.33% and COO-2 has an error rate of 10%.

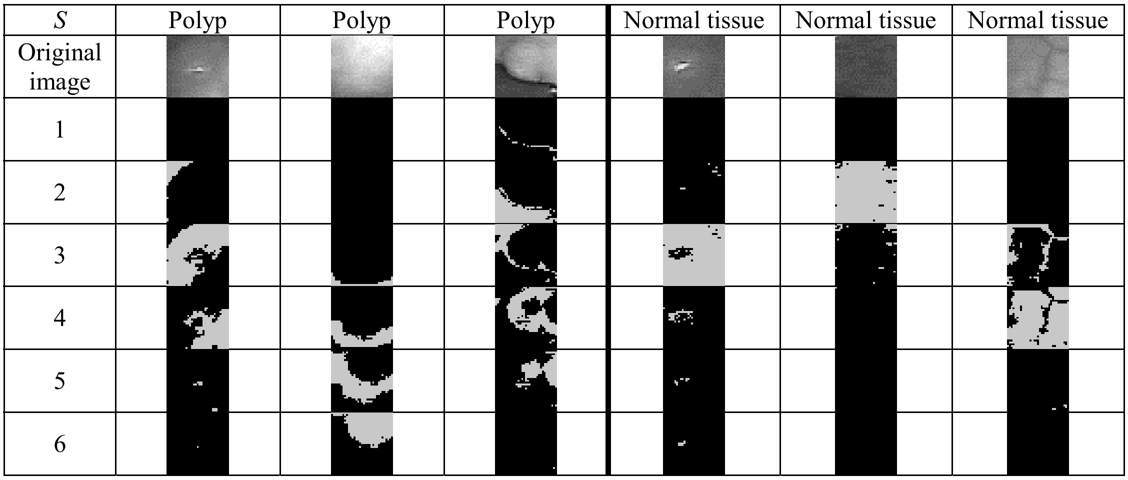

Fig. 2. The images f(x,y,t) with S=6

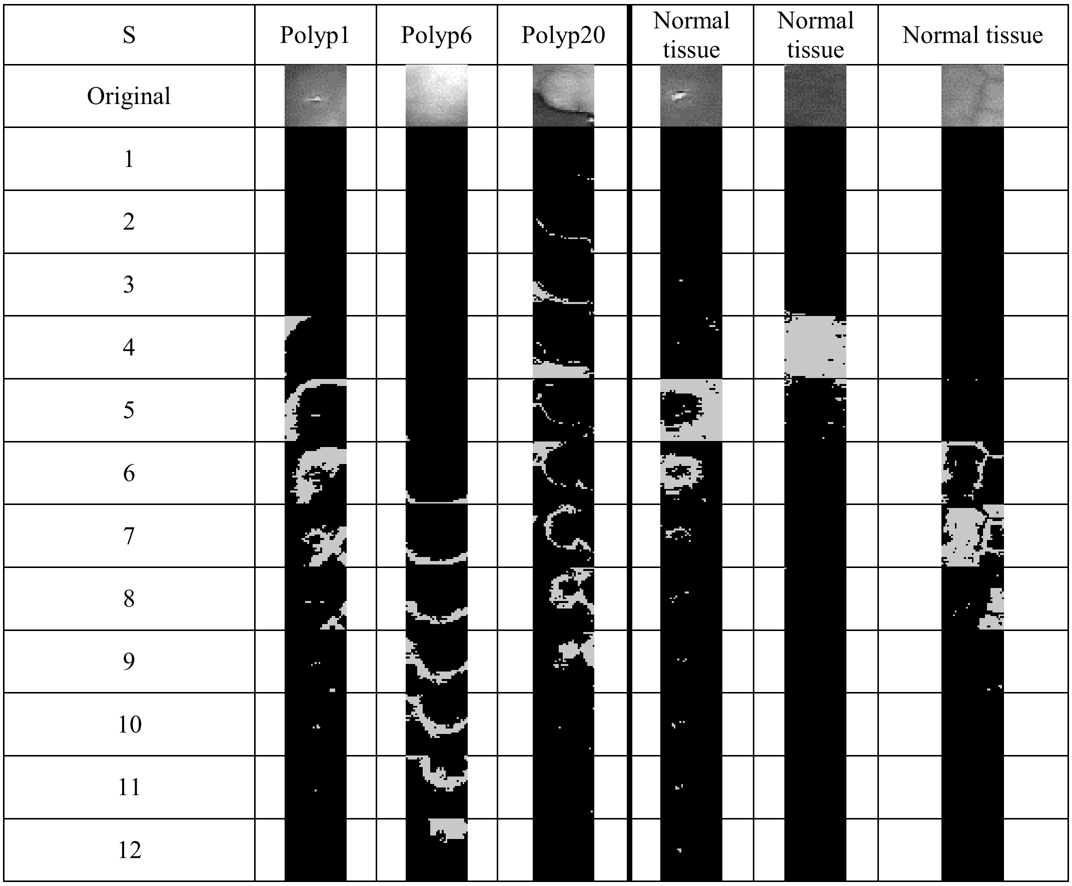

Fig. 3. The images f(x,y,t) with S=12

The texture descriptor based on random sets for S=12 has an error rate of 9.88% for the data set with 334 images (see Figure 6) with 283 normal tissues and 61 polyps. Compared to this, the texture descriptor COO-1 has an error rate of 13.37% and COO-2 has an error rate of 18.89%.

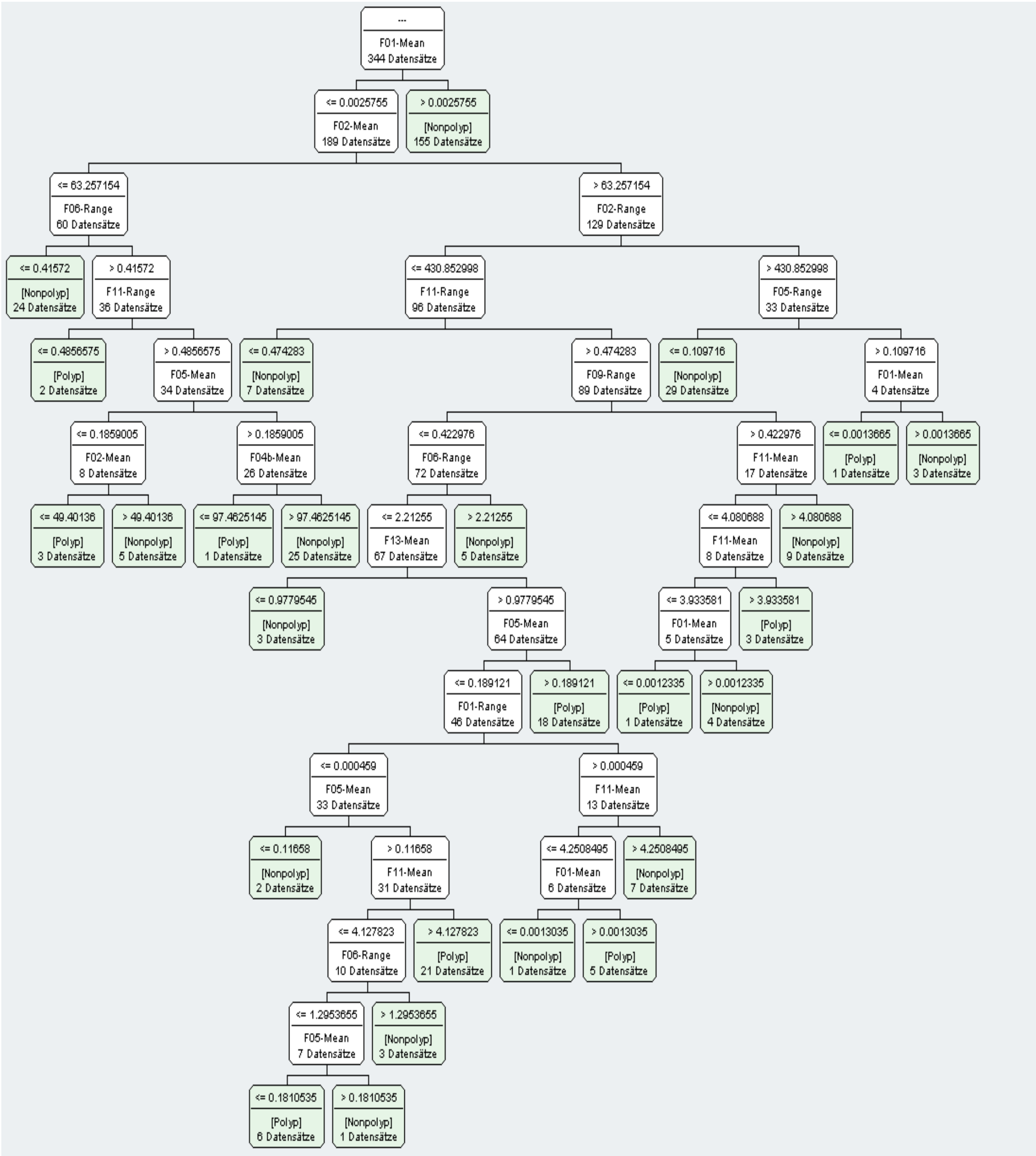

Fig. 4. Decision Tree for COO Feature Descriptor

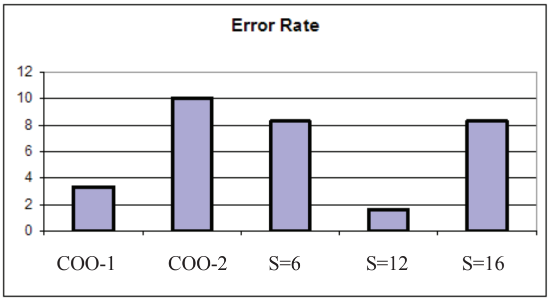

Fig. 5. Error rate (in percent) for Test 1

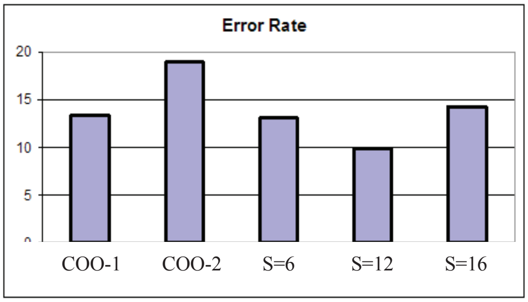

Fig. 6. Error rate (in percent) for Test 2

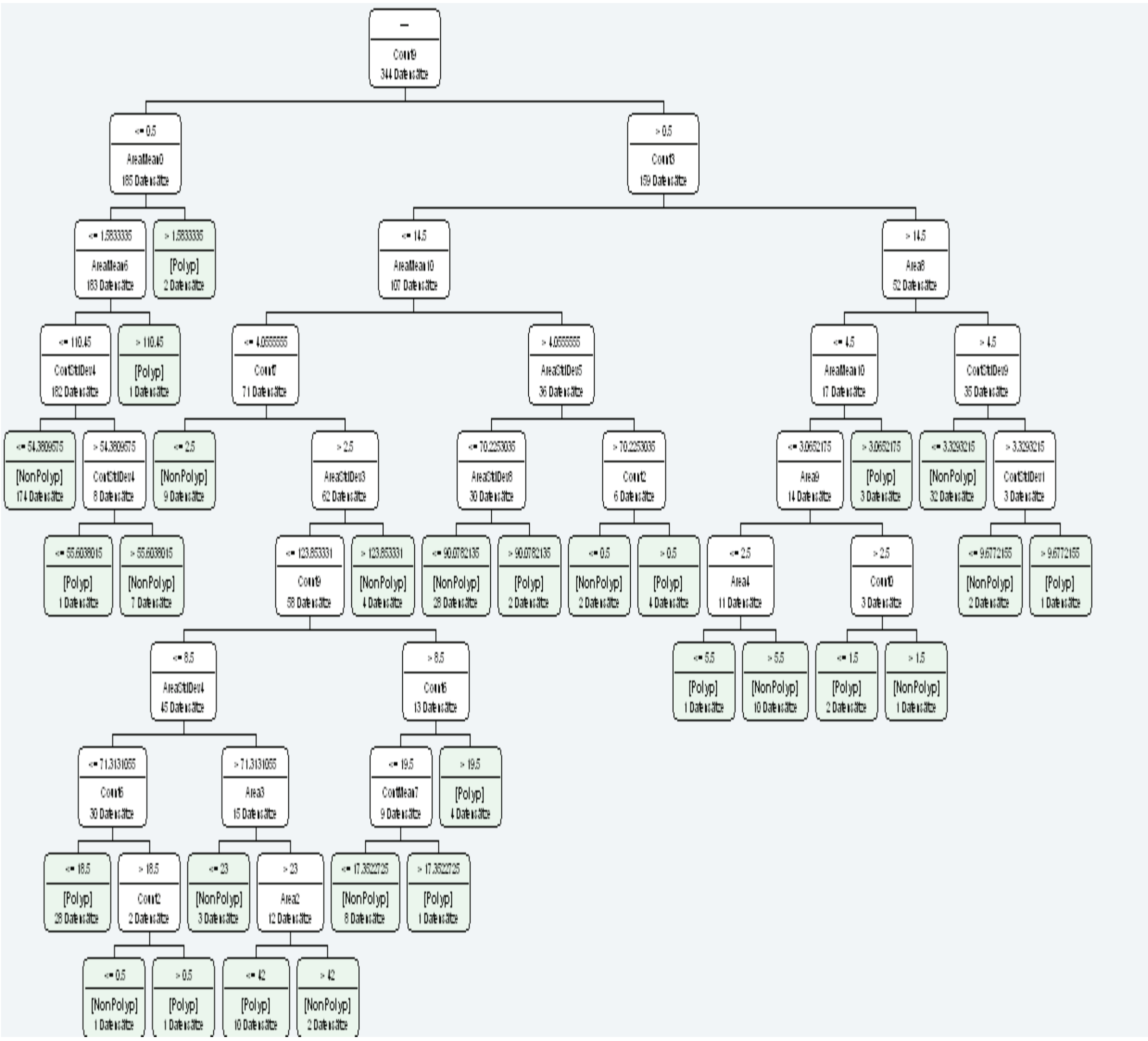

Fig. 7. Decision Tree for Texture Features based on Random Sets

Table 2. Run Time

Runtime	COO-1	COO-2	Texture Descriptor based on Random Sets
	91.03s	83.22s	13.75s

The resulting decision trees are shown in Figure 4 for COO feature descriptor and in Figure 7 for the texture features based on random sets.

The comparison of the two trees shows that the feature selection method during decision tree induction selects only 12 features from 26 features for COO texture descriptor and 22 features from 84 features for the texture descriptor based on random sets (see Table 1). The tree expands more in depth for the COO feature descriptor than for the texture descriptor based on random sets. The runtime of the program for the calculation of COO texture descriptor is 7-times longer than for the texture descriptor based on random sets (see Table 2).

The runtime of the program for the calculation of COO-2 texture descriptor is not as long but the error rate is much higher than that for COO-1.

6. Discussion

In this application the texture descriptor based on random sets outperformed the COO texture descriptor. The accuracy is 3.49 % higher than that of COO texture descriptor in case of COO-1 and 9.01% higher in case of COO-2.

Decision trees are sensitive to unbalanced class distribution. Therefore, the error rate in the second experiment rises since the ratio of the two classes is 1/5 in the data set. Nonetheless, the tendency of the error rate of the three descriptors is the same.

A further advantage of the texture descriptor based on random sets over COO texture descriptor is the reduced time required for computing the features. In addition, we can understand the semantics behind the numerical texture description. The texture features based on random sets have a semantic meaning and give an expert an understanding about texture (see Table 1).

The choice of the number of slices S emerges to S=12 in all the applications we have done. The number S=12 provides a feature set of 84 features. It might be that this is a compromise between a rich description of texture and the large feature set problem (curse-dimensionality).

The decision tree induction method performs feature selection during the tree building process. Therefore, the method can also be seen as a feature selector. The number of features selected for COO texture descriptor is always lower than the number selected for the texture descriptor based on random sets. The texture descriptor based on random sets may provide a more richer description of texture. Features from almost all slices are included in the decision.

7. Conclusion

To study human image cognition is more than ever an important topic since the number of vision-based materials has been increased over the years. We have studied the human image cognition based on texture for medical images. Texture seems to be a powerful tool to describe the appearances of objects. Therefore, very flexible and powerful texture descriptors are of importance that allow to recognize the texture and to understand what makes up the texture. We give in our paper the methodology how to study the human image cognition by automatically calculating texture descriptors from a set of images, using decision tree induction in order to learn the classifier, and recognizing the performance of the texture-based object recognition by performance measures such as accuracy, run-time, explanation capability.

Many texture descriptors are known from the literature[1]. The most used texture descriptor is the texture descriptor based on the co-occurrence matrix. We proposed a texture descriptor based on random sets[3] and in this paper compared both texture descriptors based on polyp images that were derived from colon examination. We learnt a classifier model based on decision trees. Then we compared both texture descriptors.

We have found that the texture descriptor based on random sets outperform COO texture descriptor based on the error rate, tree properties and the runtime. COO texture descriptor uses fewer features from the set of calculated texture features than the texture descriptor based on random sets. However, this might only demonstrate that COO texture descriptor has limited description power since the error rate is much higher than that for the texture descriptor based on random sets.

In addition, the texture descriptor based on random sets has semantic meanings. An expert can understand the properties of a texture when looking into the slices produced during the calculation of the texture features. The medical texture object are often not large objects. That limits the statistics we can use. Higher-order statistics make no sense since the number of objects gets less. Further work will study the behavior of our texture descriptor when the objects are large.

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