Coarse Classification of Teeth using Shape Descriptors

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ABSTRACT

This paper presents the problem of coarse classification in an application to teeth shapes. Coarse classification allows to separate a set of objects into several general classes and can precede more detailed identification or narrow the search space. Features of an object are mainly determined by its geometrical aspects, therefore we investigate the use of shape description algorithms, namely the Two-Dimensional Fourier Descriptor, UNL-Fourier Descriptor, Generic Fourier Descriptor, Curvature Scale Space, Zernike Moments and Point Distance Histogram. During the experiments we examine the accuracy of classification into two classes: single-rooted teeth and multi-rooted teeth—each class has five representatives. We also employ an additional step of data reduction. Reduced representations are obtained in three ways: by taking a part of an original representation, by predefining a shape description algorithm parameter or by applying an additional step of data reduction technique, i.e. the Principal Component Analysis or Linear Discriminant Analysis. Euclidean distance is used to match final feature vectors with class representatives in order to indicate the most similar one. The experimental results proved the effectiveness of the proposed approach.

Keywords

teeth separation, coarse classification, shape descriptors, data reduction, dental radiographs

1 INTRODUCTION

The application of teeth as a biometric feature is accepted worldwide and appreciated especially in the field of forensic odontology, which is the science of dentistry related to law. Various forms of dental evidence are used in the identification process, such as entire dentitions, tooth fragments, bite mark impressions, dental treatment histories, including dental radiographs, dentition anomalies and dental works. Full permanent dentition consists of 32 teeth divided into four groups: 8 incisors, 4 canines, 8 premolars and 12 molars. The size of upper and lower teeth of the same type varies. Upper incisors are bigger than lower incisors, while upper molars are smaller than lower molars. All first molars are larger than second and third molars, and third molars are the smallest molars in the mouth, but generally molars are the largest teeth of the permanent set of teeth. All incisors, canines and premolars are single-rooted, while lower molars are double-rooted, and upper molars are triple-rooted. Upper molar roots are more or less fused [Gra00].

Radiographic dental images are extensively used in the analysis and identification of human, and X-ray imaging enables to obtain a considerable amount of data. Various types of radiographs can be obtained (depending on the view and the part of the mouth that is being imaged), however not all of them are equally often utilized in the identification process [Vin08]. Three types of dental radiographs—periapical, bitewing and panoramic radiographs—are presented in Figure 1. Periapical radiography produces intraoral radiograph images that most frequently depict three or four teeth with surrounding tissue and are mainly used in diagnosis. A bitewing radiograph is used to depict some of the teeth in left or right side of the jaws, namely molars, premolars and canines [Che08]. The third type of radiograph is an orthopantomogram, which is a panoramic, two-dimensional view of the full dentition, both jawbones and supporting structures from ear to ear.

The major sources of dental features are bitewing and panoramic radiographs. The most distinguishable substances visible on dental radiographs are dental

Figure 1: Sample radiographs: a) periapical [Jai05], b) bitewing [Che09], c) panoramic [Jai05].

fillings, especially amalgam restorations [Phi09]. Although dental restorations pay a significant role in the identification process, due to improved dental care and minimal restorations (modern filling materials have poor radiographic characteristics), other oral features are assessed during the identification [Pre01], such as the shape of teeth, both crown and root, and teeth appearance (grey level). This reason, coupled with the significant amount of dental records and low efficiency of manual methods, has led to the development of automatic identification techniques, and ultimately to the creation of automated dental identification systems. Given an input image, usually a postmortem radiograph, a search is performed in order to find the best matching antemortem radiograph in the database. This problem can be therefore considered as an image matching and retrieval problem [Mar11]. Moreover, the use of dental biometrics, compared to other biometric visual features (such as fingerprints [Yan10] or ear shape [Sul15]), can be performed regardless of the condition of soft tissues.

An automated dental identification system consists of three main steps: feature extraction, atlas registration and matching of dental radiographs [Che09]. Teeth classification is an important step preceding teeth numbering and subsequent matching, and its importance stems from several reasons. Firstly, the quality of classification affects subsequent processing steps. Secondly, due to the diversity of human dentition, particularly in molars appearance—the shape of crowns and roots and the number of the roots—person identification can be limited solely to the use of molar features. This approach also narrows the search space and reduces the computation time at matching stage. Bitewing radiographs are usually used for teeth classification into molars and premolars, and the results of the classification are then verified to check if they follow specific patterns. However, bitewing projection provides only partial information about an individual dentition and panoramic radiographs should be considered, particularly in the classification of teeth into four classes (molars, premolars, canines and incisors, eg. [Nas08]) or three classes (e.g. [Jai05]).

This paper considers and examines the problem of tooth shape classification using various approaches based on shape description algorithms. Panoramic radiographs are used as input images for tooth contour extraction. Contours are then represented using shape descriptors and divided into two classes—molars (multi-rooted) and non-molars (single-rooted) based on the similarity to the previously prepared templates. It is desired to find the best solution for this classification task, combining the highest percentage of classification accuracy and the smallest size of shape description.

The remaining part of the paper is organised as follows: the second section describes some related works on representation and classification of tooth contours. The third section contains the description of the proposed approach and presents algorithms selected for the experiments. The fourth section presents experimental conditions and results, and the last section summarizes and concludes the paper.

2 RELATED WORKS

This section presents some works concerning methods which are used for shape representation/feature extraction and teeth classification. We are mostly interested in applications of various shape description algorithms to teeth silhouettes. The second area of interest is a matching process performed during classification stage. Moreover, we intent to find an appropriate solution for obtaining small and compact representations. Several approaches that meet some of these requirements are presented below.

In [Mah05], Mahoor and Abdel-Mottaleb provided the solution for teeth classification and numbering in bitewing radiographs. Teeth are classified using the Bayesian classification into molars and premolars and later an absolute number is assigned to each tooth according to the common numbering system. The approach is based on tooth contours and two different kinds of Fourier descriptors are used as features for the classification—complex coordinates signatures and centroid distance of the contours. The arrangement of the teeth is taken into consideration in order to correct any misclassifications and to perform teeth numbering.

In [Bar12], Barboza et al. proposed the use of two different shape descriptors as biometric features for human identification. The authors used a graph-based algorithm for tooth contours extraction from panoramic radiographs. Tooth contours were represented using the Shape Context and Beam Angle Statistics (BAS) descriptors. Slightly better results were obtained for the matching of BAS representations. The majority of failures were attributed to the radiographs with poor segmentation.

Raju and Modi [Raj11] introduced a novel approach to feature extraction based on the multiple features of tooth shape and texture. The shape analysis is performed using Fourier Descriptors, and the texture analysis utilizes Grey Level Co-occurrence Matrix and its various properties such as Energy, Contrast, Correlation and Homogeneity. For feature matching the mean square error is calculated between the query and database radiographs.

Pattanachai [Pat12] proposed the use of Hu's moment invariants as tooth features and the Euclidean distance for feature matching. Another moment-based approach is described in [Gho12]. Ghodsi and Faez proposed the Zernike Moments for shape description in two steps: high-level features were used to reduce search space and low-level features were matched using the Euclidean distance.

In [Kuo10], Kuo and Lin presented a method for dental work extraction from bitewing radiographs which comprises two stages: the location of the coarse contours of all dental works and the utilization of region growing technique to obtain complete dental works. The matching approach uses two metrics: frequency domain based on Fourier Descriptors and spatial domain based on the relative size of the misaligned region between two matched dental works.

Nassar et al. [Nas08] proposed a two-stage approach to the automatic classification of teeth into four classes, i.e. molars, premolars, canines and incisors. In the first stage, some appearance-based features are used to assign initial classes, while in the second stage a string matching technique is used for class validation and assigning of tooth numbers. The method used in the second stage is based on teeth neighbourhood rules. The classification approach is applied for periapical and bitewing radiographs, achieving an accuracy rate of 87%.

Arifin et al. [Ari12] proposed a novel method for classification of teeth into molars and premolars on bitewing radiographs. The approach utilizes a support vector machine for classification and mesiodistal neck detection for feature extraction.

In [Als12] Al-sherif et al. proposed the utilization of appearance-based Orthogonal Locality Preserving Projection algorithm for assigning initial classes to teeth on bitewing radiographs. Later, a string matching technique is used to validate initial classes and finally to assign tooth numbers. The proposed approach achieved classification accuracy of 89%, which was enhanced by class validation to the overall accuracy of 92%.

Yuniarti et al. [Yun12] proposed a system for human identification, which utilizes the binary SVM method for teeth classification into molars and premolars using three tooth features: area, a ratio of height to width and centroid. Next, the numbering is applied to avoid incorrect teeth patterns. The accuracy of the SVM classification amounted to 89.07% and was subsequently improved to 91.6% by pattern correction.

3 THE PROPOSED APPROACH

In the paper, an approach based on the classification of teeth extracted from panoramic radiographs into single-rooted and multi-rooted teeth classes is proposed. The main goal of this classification is to narrow the number of teeth used for identification. Due to the fact that shape of molars is more diversified and varies visibly from (bi)cuspids and incisors, high classification accuracy values are expected. Panoramic radiographs are less frequently utilized for human identification due to uneven illumination and magnification as well as teeth occlusion they are more difficult to process. Nevertheless, orthopantomograms are still a valuable source of dental data, because they illustrate teeth with crowns and roots, their relative positions in the mouth and surrounding structures on a single image.

All tooth shapes were obtained from panoramic radiographs using the approaches proposed by Frejlichowski and Wanat in [Fre10b, Fre11a, Fre11b]. Three stages were involved in the preparation of tooth shapes for experimental databases: image enhancement, radiograph segmentation, and extraction of tooth contours. The enhancement of image quality was performed using the Laplacian Pyramid Decomposition. As a result, images had improved contrast, sharper edges and the difference between teeth and surrounding bones was more visible [Fre10b]. Image segmentation was performed on the basis of the locations of areas between necks of teeth, which were used for determining separating lines [Fre11a]. For tooth contour extraction a novel method was utilized. An image was segmented using the watershed algorithm and resulting regions were classified as belonging to the tooth or to the background by means of a fitness function. Regions, considered as belonging to the tooth, had their pixels set to 1, whereas other regions were rejected. Afterwards, the remaining regions were processed by means of dilation and traced to find external boundaries. Tooth contours were smoothed using Gaussian filtering [Fre11b]. The resulting list of points for each tooth was plotted on the image plane and saved.

In the next step, each tooth contour is represented using selected shape descriptor—six various description algorithms were chosen, namely the Two-Dimensional Fourier Descriptor (2DFD) [Kuk98], Generic Fourier Descriptor (GFD) [Zha02], UNL-Fourier Descriptor (UNL-F) [Rau94], Curvature Scale Space (CSS) [Abb99] with an additional Fourier Transform step, Zernike Moments (ZM) [Yan08] and Point Distance Histogram (PDH) [Fre10a]. In the proposed approach, the classification is based on feature matching using the Euclidean distance. Each of the two classes is represented by five binary tooth shape images, i.e. templates. The database consists of test objects, i.e. binary tooth shape images extracted from panoramic radiographs. Properly prepared description vectors of test objects are matched with template description vectors—the nearest template indicates the class of the test object. A brief description of applied algorithms is provided below.

Owing to its useful properties, the Fourier Transform is widely used in pattern recognition. The Two-Dimensional Fourier Descriptor applies Fourier Transform to a region shape (a contour with its interior) and the resultant representation has the form of a matrix with absolute complex values [Kuk98]. The UNL-Fourier descriptor is composed of the UNL (named after Universidade Nova de Lisboa) descriptor and Two-Dimensional Fourier Transform. The use of the UNL results in a Cartesian image containing the unfolded shape contour as it is seen in polar coordinates—the rows represent distances from the centroid, and the columns the corresponding angles. Then the Two-Dimensional Fourier Descriptor is applied to obtain the UNL-F representation. The Generic Fourier Descriptor is a region-based Fourier Descriptor that utilizes the transformation to the polar coordinate system. All pixel coordinates of an original region shape image are transformed into polar coordinates and new values are put into a rectangular Cartesian image [Zha02]. The row elements correspond to distances from the centroid and the columns to corresponding angles. As a result, an image of a transformed shape is obtained and the Two-Dimensional Fourier Transform can be applied.

The Curvature Scale Space is a contour shape descriptor based on multi-scale representation and curvature. CSS representation is obtained by tracking zero-crossing points of the curve while it is iteratively smoothed by Gaussian function. At each level, as the Gaussian kernel width increases, the curve becomes smoother and the number of zero crossing points on the curve decreases. The generation of subsequent, smoother curves is called an evolution. If the locations of the curvature crossing points are known, the results can be displayed on the image plane called a CSS image. The column elements of the CSS image refer to the representative contour points and row elements corresponds to the Gaussian kernel widths [Abb99]. Instead of extracting the maxima of the CSS contours, the CSS image is represented as a binary image, and the Two-Dimensional Fourier Transform is applied as an additional step.

The Zernike Moments are orthogonal moments which can be derived using Zernike orthogonal polynomials. The Zernike polynomials are a complete set of functions orthogonal over the unit disk $x^2 + y^2 < 1$. The Zernike Moments are rotation invariant and resistant to noise and minor variations in shape [Yan08].

The Point Distance Histogram is a contour-based shape descriptor which utilizes the transformation of contour points from Cartesian to polar coordinates. As a result, the representation of a shape is invariant to translation and scaling provided that normalization is applied. In order to obtain basic shape representation, the centroid is calculated. Next, the shape contour is transformed into polar coordinates, and new coordinates are put into two vectors—Θ^i for angles and P^i for radii. Values in Θ^i are converted to the nearest integers. In the next step, the elements of Θ^i and P^i are sorted according to increasing values in Θ^i and denoted as Θ^j and P^j. If there are any equal angle values in Θ^j, only the value with the highest corresponding radii value in P^j is left. These transformations produce a vector consisting of no more than 360 elements, and only P^j is further processed (denoted as P^k). The P^k vector is normalized according to its highest value. The elements in P^k are assigned to bins in a histogram (ρ_k to l_k). In the next step, the values in bins are normalized according to the highest one and final histogram is obtained [Fre10a].

The Principal Component Analysis is an unsupervised, linear dimensionality reduction technique. It enables the construction of low-dimensional representation of the data, which describes the most variability of the original data. Dimensionality reduction is obtained by finding a linear combinations of the original variables, which are uncorrelated and are characterised by the highest variance. These combinations are called principal components. For instance, the second component is linearly combined with the second highest variance value and is orthogonal to the first component. In many cases, a small number of first components reflects the highest variability of the data. The remaining components are deleted—although this results in data reduction, the loss of information is small [Fod02]. In the proposed approach, a matrix of feature vectors is used as an input for PCA—one row corresponds to one feature vector. After the PCA is applied, a new set of data is obtained. Then each row corresponds to the reduced feature vector, which contains from 1 to 10 principal components.

The Linear Discriminant Analysis is applied as a supervised data reduction technique. It is used to find a linear combination of features which best explains the data and preserves information about class labels. In other words, the method is focused on finding such data transformation that will maximize the separation between classes and minimalize the separation within classes [Cun07]. In practice, an input matrix is the same as the one used for PCA, and in addition the vector of class labels is given. Moreover, from an algorithmic point of view, LDA utilizes PCA as a step, therefore a various number of principal components can be used in the experiments. However, the final reduced representation includes two LDA components due to the consideration of the two-class classification problem.

The main focus of the proposed approach is to choose shape features that will ensure accurate classification. However, an attempt is made to maximally reduce the size of the shape description vector in order to minimize the storage space and to reduce the matching time. Therefore, various sizes of feature vectors were prepared for the experiments. The first set of experiments included the original shape representations. For the Zernike Moments and Point Distance Histogram the representations were generated using various orders and numbers of histogram bins respectively. For other shape descriptors using the Two-Dimensional Fourier Transform, which produces a coefficient matrix, various subparts of the original matrix were taken into account. In the subsequent experiments an additional data reduction step is performed prior to feature matching and two techniques are utilized—the Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA).

4 EXPERIMENTAL RESULTS

The main goal of the experiments was to choose the best shape description method for teeth classification into multi-rooted and single-rooted classes. The shape representation should be compact, therefore the descriptions were reduced in various ways. The experimental database consisted of 903 tooth contour images, extracted from panoramic radiographs of 30 different persons. Ten other tooth shapes were extracted from a separate set of radiographs and prepared for the template database (see Figure 2). Each class was represented by five template images. Since the original classes were known, it was possible to obtain a percentage accuracy of the classification.

In total, eighteen experiments were performed. During each experiment, various shape descriptions' sizes (or variants) were taken into consideration, as well as the different number of principal components if it was applicable. Firstly, all shapes in the database and the templates were represented by the same variant of the shape descriptor. Secondly, the Euclidean distance between each test object and template was calculated. The template with the smallest dissimilarity value indicated the class of the test object (the closest match). Finally, the classification accuracy as well as the ratio of correctly classified shapes to the number of all known class members was estimated for each class.

The first set of six experiments concerned the utilization of shape descriptors and their various variants, parameters or sizes. The representations obtained using shape

Figure 2: Templates used in the experiments: single-rooted class representatives are shown in the first row, whereas multi-rooted class representatives are presented in the second one.

description algorithms utilizing the Fourier Transform were manually reduced to smaller sizes by selecting square subparts of the Fourier coefficient matrix. The experiment using the PDH descriptor was performed for various numbers of histogram bins, whereas the experiment that utilized the Zernike Moments was carried out for the moments of various orders. All features used in the first set of experiments are considered as 'original'. The highest percentage accuracy values of each experiment and various description parameters are tabulated in Table 4.

The best results, exceeding the accuracy of 90%, were obtained for 2DFD, GFD and ZM, however they concerned the classification into single-rooted class. The classification accuracy to multi-rooted class was worse and not satisfactory. The highest accuracy value reached 81% and was observed in the experiment utilizing CSS+2DFD. For this reason, it was assumed that the manual selection of the size of the description vector is inefficient—it was probably caused by the fact that the original shape representation either contains additional information which worsen the results, or the feature vector could not appropriately reflect all distinctive and important shape features. Therefore, two additional sets of the experiments were performed.

In the second set, the Principal Component Analysis step was added. All shapes were represented by the ap-

Shape Descriptor	Class	Accuracy	Variant
2DFD	Multi-rooted	61.5%	2×2 subpart
	Single-rooted	93.7%	15×15 subpart
CSS	Multi-rooted	81.4%	10×10 subpart
	Single-rooted	73.5%	25×25 subpart
GFD	Multi-rooted	61.8%	2×2 subpart
	Single-rooted	93.2%	10×10 subpart
UNL-F	Multi-rooted	68.8%	5×5 subpart
	Single-rooted	86.2%	15×15 subpart
PDH	Multi-rooted	72.8%	2 bins
	Single-rooted	79.4%	50 bins
ZM	Multi-rooted	60.2%	1st order
	Single-rooted	94.0%	8th order

Table 1: The experiments utilizing shape descriptors.

propriate shape description vector in the same way as before, however the smallest shape representation size had to be larger than the largest number of target principal components. Afterwards, all shape representations were reduced to one to ten principal components. Finally, matching was performed on the basis of reduced representations, and the percentage classification accuracy was estimated for the combination of each shape description vector size and each number of principal components. The highest accuracy values of each experiment are provided in the Table 4.

The best classification results were obtained in the experiment using CSS+2DFD. The accuracy values were nearly equal for both classes and amounted to 93.4% for the multi-rooted class, and 95.7% for the single-rooted class. The second rank was scored by the PDH descriptor which achieved accuracy at the level of 91.2% for molars and 92.5% for incisors and (bi)cuspids. The results obtained for the other descriptors are more varied between classes.

In the third set, the experiments were carried out in the same way as before, with the difference that instead of the PCA, the LDA method was used. The experiments were performed for one to ten PCA components. All of the matched feature vectors had two elements after reduction, due to the fact that classification into two classes by means of LDA produces shape description composed of two components. The highest percentage classification accuracy values are tabulated in Table 4.

The experimental results obtained with the use of LDA instead of PCA resulted in a slight improvement. This time the highest accuracy value achieved 96.9% for the experiment utilizing 2DFD and for single-rooted classification. Unfortunately, the application of 2DFD for multi-rooted teeth classification yielded poor results. The best overall effectiveness of the classification to both classes can be attributed to the Point Distance Histogram (95.2% and 92.5%).

Table 4 and Table 4 contain a summarized representation of best results. Each row contains the best percentage accuracy values obtained for a particular shape descriptor in its original form and with the application of additional data reduction step. 'Variant' refers to the sizes or parameters of the feature vectors that were matched during experiments. The results are presented separately for each class.

Taking into consideration the accuracy values together with the sizes of the feature vectors, the best solution was obtained in the experiment combining PDH and LDA. The feature vector had only two elements and the percentage classification accuracy reached 95.2% for multi-rooted teeth class, and 92.5% for single-rooted

Shape Descriptor	Class	Acc.	PCA input	PCA output
2DFD	Multi-rooted	60.5%	15×15 subpart	2
	Single-rooted	94.2%	5×5 subpart	5
CSS	Multi-rooted	93.4%	10×10 subpart	6
	Single-rooted	95.7%	75×75 subpart	10
GFD	Multi-rooted	69.7%	5×5 subpart	2
	Single-rooted	93.7%	25×25 subpart	7
UNL-F	Multi-rooted	80.0%	100×100 subpart	3
	Single-rooted	94.0%	15×15 subpart	7
PDH	Multi-rooted	91.2%	75 bins	1
	Single-rooted	92.5%	200 bins	2
ZM	Multi-rooted	60.3%	9th order	1
	Single-rooted	94.5%	8th order	4

Table 2: The experiments utilizing shape descriptors and the Principal Component Analysis.

Shape Descriptor	Class	Acc.	LDA input	LDA PCA
2DFD	Multi-rooted	61.2%	10×10 subpart	2
	Single-rooted	96.9%	5×5 subpart	6
CSS	Multi-rooted	79.8%	10×10 subpart	5
	Single-rooted	81.9%	20×20 subpart	7
GFD	Multi-rooted	78.2%	5×5 subpart	2
	Single-rooted	92.5%	5×5 subpart	1
UNL-F	Multi-rooted	77.0%	5×5 subpart	3
	Single-rooted	83.9%	15×15 subpart	7
PDH	Multi-rooted	95.3%	200 bins	3
	Single-rooted	92.5%	200 bins	2
ZM	Multi-rooted	64.0%	8th order	8
	Single-rooted	94.5%	10th order	4

Table 3: The experiments utilizing shape descriptors and the Linear Discriminant Analysis.

teeth class. Consequently, this approach is regarded as the best solution for classifying molars.

5 CONCLUSIONS

In this paper, an approach for tooth shapes classification to multi-rooted and single-rooted teeth classes is proposed. The approach utilizes a combination of six various shape descriptors and three different data reduction techniques. The experiments were performed using 903 test objects and 10 templates, where one class was represented by five templates. Test objects were extracted from 30 panoramic radiographs and templates were extracted from other randomly selected orthopantomograms. In order to assign a class to a test object, the Euclidean distance between a particular test object's description vector and all templates' description vectors was calculated. The nearest template indicated a class of the test object. The experimental results were evaluated in terms of two factors: the highest classification accuracy and the smallest description vector size. The best results were obtained for PDH+LDA with the accuracy of 95.2% for multi-rooted teeth classification and 92.5% for single-rooted teeth classification. The results are satisfactory, however further improvements are still necessary.

It is important to emphasize the purpose of such classification. Panoramic radiographs are not as popular in human identification as bitewing radiographs, probably due to teeth occlusion and blurry areas. However, they still form a good source of dental data, and in some cases may be the only source available. The proposed classification approach divides teeth into two groups. Knowing that molars have more diversified shapes, the binary tooth images classified as multi-rooted teeth can be applied as a database for person identification. In this case, the proposed approach plays a role of a coarse classification and a search space reduction, which are performed before an exact identification.

	Multi-rooted class		
	original	PCA	LDA
2DFD	61.5%	60.5%	61.2%
variant	2×2	2	2
CSS	81.4%	94.0%	79.8%
variant	10×10	6	2
GFD	61.8%	69.0%	78.2%
variant	2×2	2	2
UNL-F	68.8%	80.0%	77.0%
variant	5×5	6	2
PDH	72.0%	91.2%	95.5%
variant	2 bins	1	2
ZM	60.2%	60.3%	64.0%
variant	1st order	1	2

Table 4: Summary results for multi-rooted class.

	Single-rooted class		
	original	PCA	LDA
2DFD	93.7%	94.2%	96.6%
variant	15×15	5	2
CSS	73.5%	95.7%	81.9%
variant	25×25	9	2
GFD	93.2%	93.7%	92.5%
variant	10×10	7	2
UNL-F	86.2%	94.0%	83.9%
variant	15×15	9	2
PDH	76.0%	92.4%	92.5%
variant	50 bins	2	2
ZM	94.0%	94.5%	94.5%
variant	8th order	4	2

Table 5: Summary results for single-rooted class.

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