

Teeth Classification Based on Haar Wavelet Transform and Support Vector Machine

Fangyuan Liu^{1,*}, Zhi Li² and Wagner Quinn³

¹Jiangsu Key Laboratory of 3D Printing Equipment and Manufacturing, Nanjing, Jiangsu 210042, China

²Department of Stomatology, Jinling Hospital, School of Medicine, Nanjing University, 210002, Nanjing, Jiangsu, China

³Department of Computer Science, University College Cork, Ireland

*Corresponding author

Abstract—To improve the efficiency of stomatology practitioners, this paper proposed a novel teeth type classification method. Our method was based on three successful components: Haar wavelet transform, principal component analysis, and support vector machine. We create a 120-image dataset, with 30 images for incisor, canine, premolar, and molar. The results showed our method achieved an overall classification accuracy of $81.83 \pm 1.79\%$, better than decision tree and multilayer perceptron methods.

Keyword—Haar wavelet transform; support vector machine; principal component analysis

I. INTRODUCTION

It is well known that teeth are one of the most important organs in the human body, which help chew food, control pronunciation and keep healthy. Learning and acquiring dental information is closely watched by researchers from the medical and academic fields. At present, dental information is collected and recorded by the staff through the oral head imaging equipment. In practical application, CT technique is most beneficial to identify, diagnose, and treat teeth. CT has the advantages of low ray volume, short scan time, high image clarity and simple operation, so as to provide accurate data recording and reduce the experimental cost.

In recent years, researchers have proposed various methods for tooth recognition and classification. Yoke-San, Xin [1] introduced a classification system based on the iterative closest point algorithm(ICP) to handle four types of teeth. The system used PCA extracted eigentooth feature, projected datasets into the tooth geometric space and then classify tooth type by KNN. Ghodsi and Faez [2] created an automated dental identification system (AIDS) which applied Zernike moment(ZM) to extract feature and calculate Euclidian distance in the match phase. The method reduced search space, increased matching certainty by voting mechanism and ZM ensured the stability of experimental results. Al-sharif, Guo [3] established a method contains two stages for identifying bitewing dental images: (i) Orthogonal Locality Preserving Projection(OLPP) projected Laplaciantooth spaces to complete the initial classification; (ii) validate class and assign number based on teeth neighborhood rules, the classification accuracy reached 89%. Hosntalab, Zoroofi [4] combined the traditional segmentation techniques with wavelet-Fourier descriptors(WFDs) to select the most effective eigenvector, and then used feed-forward neural network to classify tooth images. Pushparaj, Gurunathan [5] utilized

support vector machine and universal numbering system to recognize teeth and number of teeth respectively. The key part of this approach is feature extraction which is aimed at individual teeth identification. PPED vectors, geometric features and regional descriptors are used in the process of feature extraction. The results show that the method is feasible and effective, and the average accuracy rate is 92.65%. Yeasarapat, Auephanwiriyaikul [6] adapted fuzzy C-means clustering algorithm(FCM) based on multiple features(the pixel values of RGB and HIS) to classify dental fluorosis. FCM determines tooth status by cyclic updating membership values and prototypes until stable. Tangel, Fatichah [7] presented a fuzzy inference system to achieve four categories of dental images. This system used Mamdani type FIS with centroid defuzzification method which employed multiple fuzzy attributes and the selected threshold is 0.15. This approach can deal with blurred tooth images and guaranteed the robustness of the classification, the overall classification accuracy reaches 82.51%. Karthick and Harikumar [8] analyzed the performance of Naïve Bayes and SVM in the classification of five dental diseases. Before classifying the tooth images, they preprocessed through Median filter, segmented and extracted GLCM features by FCM algorithm. Veeraprasit and Phimoltare [9] described a model to recognize the tooth images by using the mixed feature. The researchers fused global features (singular values and color histogram) and local features (teeth width), and then applied MLP with Levenberg-Marquardt algorithm to determine the type of tooth effectively. Finally, the accuracy rate of the experiment is about 93.6%, which is superior to Naïve Bayes and k-Nearest Neighbor methods.

Based on the above studies on classification methods, the potential for various learning is getting better in various fields at the same time. In this paper, support vector machine is proposed to classify four kinds of dental images: central incisor, lateral incisor, canine and premolar. The methodology adopted in this study is described in Section 2. The material used in the experiment is shown in Section 3. In Section 4, we analyzed the experiments and results in detail, which is compared with the current methods. The last part is Section 5 which includes conclusion and the prospects we expect.

II. METHOD

Firstly, we utilize histogram equalization technique [10] to enhance the data of dental images. Histogram equalization method has the following advantages: (i) increased the contrast; (ii) improved the changes of gray tone; (iii) enhanced the

sharpness of the image, so that we can obtain high-quality sample data.

Next, Haar wavelet transform is one of the most popular wavelet transform in the field of wavelet analysis [11-14]. It can guarantee the integrity of image information because it gets the global information while recording the local information. The basic Haar wavelet function [15] is defined as Formula (1) and the scaling function is defined as Formula (2). In Formula (2), j is a scaling factor and i is a translation parameter. In the future, we shall test the performance of biorthogonal wavelet [16, 17].

After extracting the four-level wavelet features, we used PCA to decrease the feature dimension. This way can reduce the number of features, noise and redundancy, and the likelihood of excessive fitting.

$$x(a) = \begin{cases} 1, & 0 \leq a \leq 1/2 \\ -1, & 1/2 \leq a \leq 1 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$x^j(a) = x(2^j a - i), i = 0, \dots, (2^j - 1) \quad (2)$$

Finally, we employ an effective classification learning model, support vector machine (SVM), to classify four types of dental images.

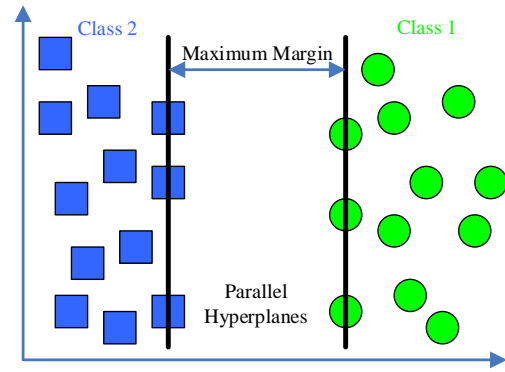


FIGURE 1. ILLUSTRATION OF SVM

As far, SVM has been widely used in medical detection, text processing [18], speech recognition [19], and so on. SVM has been reported to be superior to the traditional classification method, such as BPNN [20], RBF network [21], k-Nearest Neighbors algorithm. Figure 1 gives an illustration of SVM, which finds several samples called “support vectors” [22-24] and created hyper-planes based on them [25-30].

III. DATASET

We used the ISO standard dental notation. Take upper right as an example, 11 and 12 are incisors; 13 is canine; 14 and 15 are premolars; 16, 17, and 18 are molars. Some samples of the dataset are listed in Figure 1. The images were obtained by participating hospitals. In total, we have a 120-image dataset, which contains 30 incisors, 30 canines, 30 premolars, and 30 molars. Figure 2 gives an example of each teeth type.

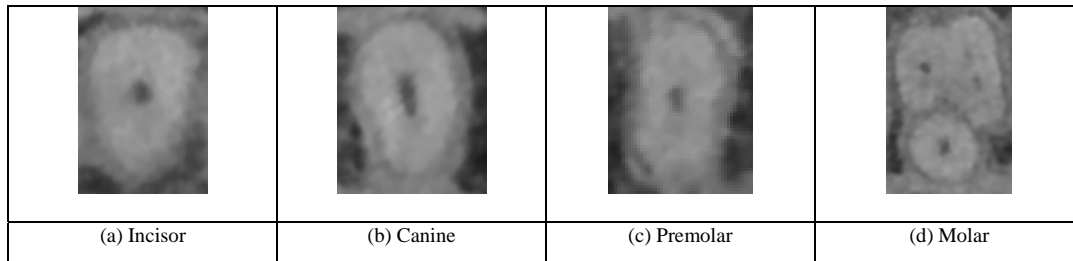


FIGURE 2. SAMPLES OF DATASET

IV. EXPERIMENTS AND RESULTS

This proposed “HWT_PCA_SVM” method was implemented 10 times. Within each time, a 5-fold cross validation was used. That means there are 6 image for each tooth type within each fold. The classification results in terms of sensitivity were given in Tables 1. The whole accuracy of all four classes were given in Table 2.

TABLE I. SENSITIVITY OF EACH CLASS

	Incisor	Canine	Premolar	Molar
R1	76.67	86.67	73.33	90.00
R2	86.67	86.67	76.67	86.67
R3	83.33	76.67	90.00	86.67
R4	76.67	76.67	86.67	83.33
R5	83.33	83.33	80.00	83.33
R6	86.67	80.00	83.33	76.67
R7	80.00	80.00	86.67	86.67
R8	86.67	83.33	83.33	70.00
R9	80.00	80.00	80.00	83.33
R10	86.67	76.67	73.33	76.67
Average	82.67± 4.10	81.00± 3.87	81.33± 5.71	82.33± 6.10

TABLE II. ACCURACY OF ALL FOUR CLASSES

	F1	F2	F3	F4	F5	Total
R1	70.83	87.50	91.67	83.33	75.00	81.67
R2	87.50	83.33	87.50	83.33	79.17	84.17
R3	79.17	87.50	79.17	91.67	83.33	84.17
R4	75.00	66.67	91.67	75.00	95.83	80.83
R5	75.00	83.33	83.33	87.50	83.33	82.50
R6	79.17	79.17	83.33	79.17	87.50	81.67
R7	79.17	87.50	95.83	62.50	91.67	83.33
R8	75.00	66.67	95.83	75.00	91.67	80.83
R9	79.17	75.00	87.50	83.33	79.17	80.83
R10	70.83	70.83	91.67	83.33	75.00	78.33
Average						81.83± 1.79

We observe that the sensitivities of incisor, canine, premolar, and molar are $82.67 \pm 4.10\%$, $81.00 \pm 3.87\%$, $81.33 \pm 5.71\%$, and $82.33 \pm 6.10\%$, respectively. The whole accuracy was $81.83 \pm 1.79\%$. This demonstrates the effectiveness of HWT, PCA, and SVM. Except HWT, there are many other excellent feature descriptors, such as fractional Fourier transform [31], etc.

In addition, we compared our method with traditional decision tree (DT) [32], and multilayer perceptron (MLP) [33]. All the methods were implemented by 10 runs, and the results are shown in Table 3.

TABLE III. ALGORITHM COMPARISON

Method	Accuracy
DT [32]	73.83± 2.05
MLP [33]	76.25± 3.54
SVM (Proposed)	81.83± 1.79

The DT [32] obtained an overall accuracy of $73.83 \pm 2.05\%$. MLP [33] obtained an overall accuracy of $76.25 \pm 3.54\%$. The details of two basis algorithms were show in Table 4. Finally, the proposed SVM method could yield the greatest accuracy of $81.83 \pm 1.79\%$.

TABLE IV. ACCURACY OF DT [32] AND MLP [33]

DT [32]	F1	F2	F3	F4	F5	Total
R1	75.00	75.00	75.00	62.50	83.33	74.17
R2	66.67	70.83	70.83	83.33	66.67	71.67
R3	79.17	79.17	62.50	79.17	79.17	75.83
R4	83.33	70.83	70.83	83.33	70.83	75.83
R5	75.00	62.50	66.67	66.67	79.17	70.00
R6	66.67	70.83	70.83	79.17	79.17	73.33
R7	83.33	62.50	79.17	79.17	75.00	75.83
R8	58.33	91.67	75.00	87.50	66.67	75.83
R9	75.00	75.00	62.50	75.00	79.17	73.33
R10	75.00	66.67	79.17	83.33	58.33	72.50
Average						73.83± 2.05
MLP [33]	F1	F2	F3	F4	F5	Total
R1	91.67	95.83	75.00	70.83	62.50	79.17
R2	62.50	75.00	91.67	75.00	83.33	77.50
R3	70.83	79.17	87.50	79.17	75.00	78.33
R4	79.17	83.33	95.83	83.33	66.67	81.67
R5	70.83	75.00	75.00	62.50	62.50	69.17
R6	75.00	62.50	75.00	87.50	83.33	76.67
R7	87.50	62.50	83.33	62.50	66.67	72.50
R8	83.33	58.33	83.33	70.83	79.17	75.00
R9	79.17	79.17	75.00	79.17	75.00	77.50
R10	83.33	66.67	70.83	79.17	75.00	75.00
Average						76.25± 3.54

Although SVM obtained good results, we shall try to collect

more data than used in this study, and tested the effect of deep learning, such as convolutional neural network [34-36], deep belief network [37], and autoencoder [38, 39].

V. CONCLUSIONS

In this study, we proposed a novel method based on Haar wavelet transform, principal component analysis, and support vector machine. The simulation experiments validated the effectiveness of our method.

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