TOOTH MATERIALS MONITORING SCHEME FOR DENTAL OPERATIONS USING CUTTING SOUNDS

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ABSTRACT

This paper introduces a monitoring scheme for discerning the boundary of the tooth in dental operations. In this scheme, tooth structures and dental fillings were discriminated based on their cutting sounds. Support vector machines were employed for classification; and averaged short time Fourier transform coefficients were selected as the features. The results confirmed capability and feasibility of the proposed scheme.

Index Terms— Tooth materials monitoring scheme, Sound classification, Support vector machine.

1. INTRODUCTION

Tooth is an inhomogeneous structure, which is composed of different layered tissues, including enamel, dentin, cementum, and pulp. The mechanical characteristics and hardness of these layered tissues varies depending on the mineral contents. Tooth decay which is the most prevalent dental disorders, also alters dental tissue hardness. Dental restoration is a process that begins with removing carries and affected tissues to retain the functionality of tooth structures. Air-turbine dental handpieces (ATDH) are high-speed rotary cutting tools that are widely used by dentists during this operation. The next stage in the process is filling the cavity with appropriate restorative materials.

There are different dental restorative materials that are commercially available such as gold, silver amalgam, composite polymers, glass ionomers, etc [1]. Among these materials, silver amalgam and composites are extensively used by dentists. Amalgam is a low cost, easy to handle filling material. The use of amalgam fillings has recently declined due to adverse health concerns of mercury and this has created a shift towards composite polymers. The main advantage of composites over amalgam is the aesthetical characteristics. Composites can be produced in a variety of tooth colors, which can blend and mimic real tooth structures.

Typical dental filling procedure is not just limited to the removal of the infected parts of a tooth. In fact, most old fillings eventually fail and need to be removed along with the new decay. A Common reason of dental filling degradation is the external forces of clenching or grinding which may result in fatigue, microcracks and ultimate failure. The performance of dental restorations is subject to several factors, including restorative materials [2-4], type and position of a tooth [5, 6], restoration's shape, size and number of restored surfaces [7, 8], as well as the patient's habits and age [2, 8]. Replacing old filling is one of the most frequent performed procedures in dental practices [9-11], and the rate has not declined despite the advancements in dental materials and restoration techniques.

To conduct restorative operations, dentists receive training to become experts of interpretations of their tactile and visual senses [12]. They transfer such sensory information to the actual practice through their perception. This perceptual procedure is highly subjective, and is dependent on the individual abilities and experience of dentists [13]. The main problem with these approaches is that human senses have limited functionality, and sometimes are insufficient for dentists to rely on.

One of the difficulties in replacing failing dental restorations is discerning the boundary of the filling materials. Dentists may remove healthy tooth structures while replacing tooth-colored composite materials [13-16]. Although, in the case of silver amalgam filling material, the visibility issue is less challenging, replacing it also results in healthy tooth structure losses [11]. This is of great concerns considering that tooth is one of the few human tissues that has very limited healing ability and almost all structure losses will be irreversible.

Developing an objective and sensor-based method for dental restorative operations is a promising approach to overcome the limited functionality of human tactile and visual senses. In this approach, restorative materials and tooth structures can be accurately distinguished during the cutting and removal procedures. To satisfy this monitoring goal, the cutting sounds of an ATDH were recorded; and support vector machine (SVM) was used for classifying them. SVM is a powerful tool for classification which is explained in section 2. Section 3 describes in detail the data collection and preprocessing stages. Section 4 presents the results and relevant discussions. Section 5 reviews the prior works, and finally section 6 concludes with the objectives of this paper.

2. SUPPORT VECTOR MACHINE

Support vector machine (SVM) is a popular method for classification and regression, and has been employed in various fields of science and engineering [20, 21]. SVM is originally a binary classifier. It tries to find a decision surface (DS) by maximizing the margin which is defined as the minimum distance of any sample in the feature space to the DS (Fig. 1):

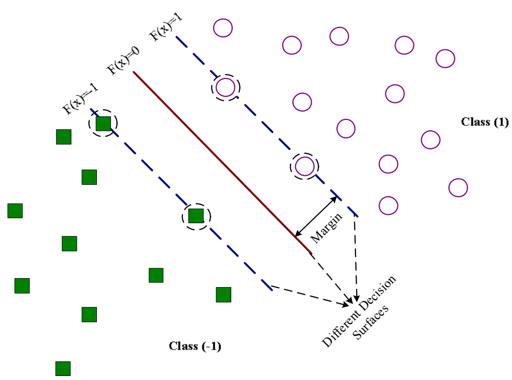

Fig. 1: Support vector machine classifier

The decision surface, depicted in Fig. 1, is assumed to have the format of:

$$f(x) = w^T \phi(x) + b \tag{1}$$

where, w and b are the weight vector and the bias term (w^Tdenotes the transpose of w), $\phi(x)$ is the feature space, and (x_i, y_i) indicates a pair of input-class label ($i = 1, \ldots, m$, $x_i \in R^n$, $y_i \in \{1, -1\}^m$).
The DS described in Eq. 1 can be followed by a threshold function (i.e. sign) to assign a class label y_i to each input x_i. As Fig. 1 displays, there are many decision surfaces with different margins; however SVM is looking for the one with the maximum margin. After several manipulations [21], it can be shown that maximizing the margin is equivalent to minimizing ${}^1\!/_2\, w^T w$ subject to $y_i(w^T \phi(x_i) + b) \geq 1$. In the case that $y_i(w^T \phi(x_i) + b) = 1$, x_i is called a support vector. In addition if the data in the feature space are not linearly separable, a slack variable ϵ can be introduced, which allows the violations of the constraints. Therefore, the following optimization problem will arise for SVM:

$$\min_{w,b,\epsilon} \frac{1}{2} w^T w + C \sum_{i=1}^{m} \epsilon_i \tag{2}$$

$$\text{subject to} \quad \begin{aligned} & y_i(w^T \phi(x_i) + b) \geq 1 - \epsilon_i \\ & \epsilon_i \geq 0 \end{aligned}$$

C is a regularization parameter, and higher values for it corresponds to stronger penalties for constraints violations. To solve the above problem, Lagrange multipliers (a_i) should be employed which yields the following dual representation [21]:

$$\min_{a_i} \quad L = \sum_{i=1}^{m} a_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} a_i a_j y_i y_j k(x_i, x_j) \tag{3}$$

$$\text{subject to} \quad 0 \leq a_i \leq C \quad \text{and} \quad \sum_{i=1}^{m} a_i y_i = 0$$

The solution to Eq. 3 is:

$$w = \sum_{i}^{m_S} a_i y_i \phi(x_i) \tag{4}$$

$$b = \frac{1}{m_m} \sum_{i}^{m_m} \left\{ y_i - \sum_{j}^{m_S} a_j y_j k(x_i, x_j) \right\}$$

where m_S denotes the set of support vectors; and m_m indicates the set of data points having $0 < a_i < C$. Eq. (3) is a convex optimization problem and so any local minimum is global. In addition, $k(x_i, x_j)$ is called Kernel function; and in case it is a symmetric and positive definite matrix, it equals to $k(x_i, x_j) = \phi(x_i)^T \phi(x_j)$. Therefore, SVM is a kernel-based algorithm; and predictions for new inputs depend on the evaluations of w and b (Eq. 4) on the some subsets of data points (no need to store all x_i).

3. DATA COLLECTION AND PREPROCESSING

In order to collect data, we conducted several tests in a dental clinic to have similar condition to the cutting procedures performed by dentists. All tests were performed in-vitro, and were undertaken on cubic samples ($1 \times 1 \times 1$ cm) of amalgam and composite, as well as two intact extracted human third molars. The samples were fixed in a chuck (clamp). A “W & H Toplight 898le” ATDH and a “330 Diamond” bur were used for cutting, which are among common choices for dentists during restorative procedures. A microphone (GRAS 40be) was attached to the handpiece with an adhesive tape (Fig. 2) to record the cutting sounds. This arrangement ensured the relative position of the handpiece and the microphone is fixed for all the tests. The sampling frequency was chosen 48k Hz; high enough to capture the maximum speed of the handpiece (~ 4900 rps) based on Nyquist–Shannon sampling theorem. A high-speed data acquisition card (LDS Dactron Photon II); and a signal processing software for FFT analysis (RT Pro Photon) were employed to sample and collect the data on a personal computer.

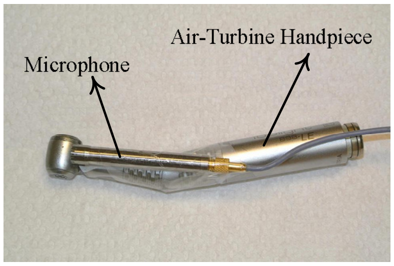

Fig. 2: The microphone and air-turbine handpiece

All cuttings were conducted three times in a parallel plane to the sample's surface by an experienced dentist. The cutting procedure was comprised of three parts. In the first part (NonCon 1), the handpiece ran freely for $2-3$ s; followed by the second part (Con) in which the cutting was undertaken for $2-3$ s. In the last part (NonCon 2), again the handpiece ran freely for $1-2$ s (Fig. 3).

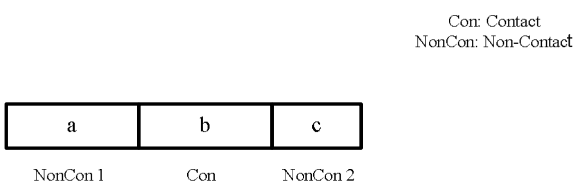

Fig. 3: The format of each test

The recorded data were filtered using a high-pass filter at 4k Hz to remove the effect of noises and disturbances (i.e. the compressor sound) at lower frequencies. In each test, the cutting part (part b in Fig. 3) was identified, and labeled appropriately (i.e. tooth, composite, or amalgam).
Short time Fourier transform (STFT) coefficients were selected as the features. Hamming windowing with 50% of overlapping was used; and in each window 2100 data points were considered (window length ~ 44ms). The first 2048 Fourier coefficients were selected, and then divided to 64 equal-sized groups (32 coefficients in each group). The data of each group were averaged mathematically to obtain 64 coefficients as the features.
Two of the three repeated experiments were used for training the SVM, and the third one was employed for testing and validation. Table 1 indicates different groups of training and testing sets.

TABLE 1
DIFFERENT GROUPS FOR TRAINING AND TESTING

Group Name	Training Set	Testing Set
G1	1 and 2	3
G2	1 and 3	2
G3	2 and 3	1

4. RESULTS

Two cases of classification were studied in this paper considering the fact that in each dental filling only one restorative material is used (i.e. composite or amalgam). In the Case I, classification was applied to tooth, composite, and noncontact classes (TCN). In the Case II, tooth, amalgam, and noncontact classes were classified (TAN). It should be noted that noncontact was considered as a "class", because the classifier should be able to differentiate it from the contact classes (tooth or composite/amalgam).
SVM is basically designed for binary classifications. However, our problem was a 3-class problem. Hsu and Lin compared different methods for multiclass SVM, and concluded that a "one-against-one" approach was more suitable considering practical aspects [22]. In this approach, $k(k-1)/2$ binary classifiers were trained (k is the number of classes), and the class that received maximum "votes" was assigned to a test data.
Considering the above method, 3 binary classes were trained for each case of the problem (TCN or TAN). To apply SVM, the software LIBSVM was used [23]. For training, the radial basis function (RBF) was selected as the kernel [21]:

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right) \qquad (5)$$
$$\gamma > 0$$

C and γ were the "hyper-parameters" of the classifying model described by Equations 2, and 5. A "grid search" approach was employed; in which the values of these parameters were changed exponentially. The hyper-parameters were varied from $2^{-15}, 2^{-13}$, ... to $2^{1}, 2^{3}$; and the optimal values were found based on cross validation. In a ν-fold cross validation, the training data is divided to ν equal-sized subsets. Then, $\nu-1$ subsets are used for training, and the one remained subset is utilized for testing. The entire procedure is performed ν times, and the total classification error is obtained [24].
A 5-fold cross validation was employed in our tests, and those values of C and γ were selected that resulted the least error (Table 2).

TABLE 2
THE HYPER-PARAMETER VALUES FROM 5-FOLD CROSS VALIDATION

Classes[i]	C_{G1}[ii]	γ_{G1}	C_{G2}	γ_{G2}	C_{G3}	γ_{G3}
T/A	32	0.032	100	0.032	32	0.032
T/N	2048	2	2048	2	2048	2
A/N	4096	0.002	512	0.5	256	0.25
T/C	32	0.032	256	0.25	64	0.062
C/N	256	0.25	1	1	512	0.5

[i] T:Tooth, A:Amalgam, N:Noncontact, C:Composite
[ii] G1, G2, and G3 corresponds to data sets specified in Table 1

All the values of the Table 2 resulted in 98-100% cross validation accuracy, and therefore it was not needed to look for other values of C and γ. After employing the hyper-parameters of Table 2 for training, 3 bi-class classifiers were obtained for TCN and TAN cases. A "one-against-one" approach was employed for testing, and the results are shown in the following Tables:

TABLE 3
THE CLASSIFICATION ACCURACY OF CASE I (%)

Classes [i]	**Groups** [ii] G1	G2	G3
T	95 (579) [iii]	70 (608)	93 (567)
C	87 (225)	97 (338)	90 (283)
N	55 (1021)	96 (1047)	87 (1055)

[i] Similar to Table 2
[ii] Groups are based on Table 1
[iii] The accuracy is represented by percentage. The numbers in parentheses indicate the total number of test samples for the specified class.

TABLE 4
THE CLASSIFICATION ACCURACY OF CASE II (%)

Classes [i]	**Groups** [ii] G1	G2	G3
T	100 (579) [iii]	94 (608)	98 (576)
A	74 (368)	94 (284)	99 (293)
N	53 (922)	90 (911)	70 (1003)

[i] Similar to Table 2
[ii] Groups are based on Table 1
[iii] The accuracy is represented by percentage. The numbers in parentheses indicate the total number of test samples for the specified class.

The classification accuracy for cases I and II are displayed in Tables 3 and 4 respectively. The worst accuracy for case I was 55% which was obtained in classifying of 1021 test-samples of noncontact data (G1). The best accuracy for this case was for composite (G1) with 97% correct classification. For case II, the worst and best accuracy were for noncontact (G1) and tooth (G1) in which 53% and 100% classification were acquired respectively.
Considering both cases, the accuracy range was 70%-100% for tooth, 87%-97% for composite, 74%-99% for amalgam, and 53%-96% for noncontact data.

5. RELATION TO PRIOR WORKS

Thus far, no prior works has been found on discrimination of tooth and restorative materials based on the cutting sounds. The work presented here was in the area of tooth materials monitoring using audio signals. A SVM classifier and averaged STFT features were used in our work. Audio signals are rich sources of information, and they have been utilized in similar problems in other fields.
Yadav, *et al.*, [17], used audio signals for condition monitoring of internal combustion engine. They used FFT as the features, and utilized a classifying scheme based on the cross- and autocorrelation coefficient values. Quran, *et al.*, [18] developed a security monitoring instrument based on audio classification. They employed a hierarchical structure using a threshold classifier and a time delay neural network. Their feature vector consisted of mel-frequency cepstral coefficients (MFCC), delta mel-filtered cepstral coefficients, and pitch ratio value. In another work, Wan, *et al.*, [19] developed an automatic pipeline monitoring system using sound information of road cutters. They utilized MFCC for the features, and employed a threshold classifier.
Amft, *et al.*, [25] presented an automatic dietary monitoring to predict food weight based on acoustic recognition of chewing. In their study, features included log-band spectral energy, cepstral coefficients, and linear predictive coefficients. They trained a nearest centroid classifier based on a Fisher's linear discriminant feature transformation. In another study, Istrate, *et al.*, [26] investigated the detection and classification of alarming sounds in a noisy environment for medical tele-monitoring. They used discrete wavelet transform coefficients as the features, and employed the Gaussian mixture model for classification.

6. CONCLUSIONS

In this paper, the cutting sounds of an air-turbine handpiece were employed to discriminate between tooth structures and amalgam/composite fillings. The features were selected from averaged STFT (64 coefficients), and the support vector machine was used for classification (one against one approach).
The accuracy range was 70%-100% for tooth, 87%-97% for composite, 74%-99% for amalgam, and 53%-96% for noncontact data. These results indicated the capability and feasibility of the proposed tooth materials monitoring scheme based on the cutting sounds.

7. REFERENCES

[1] R. G. Craig, J. M. Powers, "Restorative Dental Materials," Mosby Inc., Eleventh edition, 2002.

[2] I. A. Mjor, A. Jokstad, "Five-Year Study of Class II Restorations In Permanent Teeth Using Amalgam, Glass Polyalkenoate (Ionomer) Cement and Resin-Based Composite Materials", Journal of Dentistry, vol. 21, pp. 338-343, 1993.

[3] C. J. Collins, R. W. Bryant, K. L. Hodge, "A Clinical Evaluation of Posterior Composite Resin Restorations: 8-Year Findings", Journal of Dentistry, vol. 26, pp. 311-317, 1998.

[4] J. A. Soncini, N. N. Maserejian, F. Trachtenberg, M. Tavares, C. Hayes, "The Longevity of Amalgam versus Compomer/Composite Restorations in Posterior Primary and

Permanent Teeth", Journal of the American Dental Association, vol. No. 18, 138, pp. 763-772, 2007.

[5] G. H. Johnson, D. J. Bales, G. E. Gordon, L. V. Powell, "Clinical Performance of Posterior Composite Resin Restorations", Quintessence International, vol. 23, no. 10, pp. 705-711, 1992.

[6] C. W. Drake, "A Comparison of Restoration Longevity in Maxillary and Mandibular Teeth", Journal of the American Dental Association, vol. 116, no. 6, pp. 651-654, 1988.

[7] A. Jokstad A, I. A. Mjör, "Replacement Reasons and Service Time of Class- II Amalgam Restorations in Relation to Cavity Design", Acta Odontologica Scandinavica, vol. 49, no. 2, pp. 109-126, 1991.

[8] M. J. Wahl, M. M. Schmitt, D. A. Overton, M. K. Gordon, "Prevalence of Cusp Fractures in Teeth Restored with Amalgam and with Resin-Based Composite", Journal of the American Dental Association, vol. 135, no. 8, pp. 1127-1132, 2004.

[9] A. O. Adegbembo, P. A. Watson, "Removal, Replacement and Placement of Amalgam Restorations by Ontario Dentists in 2002", Journal of the Canadian Dental Association, vol. 71, no. 8, p. 565, 2005.

[10] J. C. Setcos, R. Khosravi, N. H. Wilson, C. Shen, M. Yang, I. A. Mjor, "Repair or Replacement of Amalgam Restorations: Decisions at a USA and a UK Dental School", Operative Dentistry, vol. 29, no. 4, pp. 392-397, 2004.

[11] F. Sardenberg, C. C. Bonifácio, M. M. Braga, J. C. P. Imparato, F. M. Mendes FM, "Evaluation of the Dental Structure Loss Produced During Maintenance and Replacement of Occlusal Amalgam Restorations", Brazilian Journal of Oral Sciences, vol. 22, no. 3, pp. 242-246, 2008.

[12] J. D. Bader, D. A. Shugars, "What Do We Know About How Dentists Make Caries-Related Treatment Decisions?" Community Dentistry and Oral Epidemiology, vol. 25, no. 1, pp. 97-103, 1997.

[13] V. V. Gordan, C. W. Garvan, J. S. Richman, J. L. Fellows, D. B. Rindal, V. Qvist, M. W. Heft, O. D. Williams, G. H. Gilbert; DPBRN Collaborative Group, "How Dentists Diagnose and Treat Defective Restorations: Evidence From the Dental Practice-Based Research Network," Operational Dentistry, vol. 34, no. 6, pp. 664-673, 2010.

[14] V. V. Gordan, "In Vitro Evaluation of Margins of Replaced Resin-Based Composite Restorations", Journal of Esthetic Dentistry, vol. 12, no. 4, pp. 209-215, 2000.

[15] V. V. Gordan, "Clinical Evaluation of Replacement of Class V Resin Based Composite Restorations," Journal of Dentistry, vol. 29, no. 7, pp. 485-488, 2001.

[16] V. V. Gordan, E. Mondragon, C. Shen, "Evaluation of the Cavity Design, Cavity Depth, and Shade Matching in the Replacement of Resin Based Composite Restorations" Quintessence International, vol. 32, no. 3, pp. 273–278, 2002.

[17] S. K. Yadav, K. Tyagi, B. Shah, P. K. Kalra, "Audio Signature-Based Condition Monitoring of Internal Combustion Engine Using FFT and Correlation Approach", IEEE Transactions on Instrumentation and Measurement, vol. 60, no. 4, pp. 1217-1226, 2011.

[18] A. R. Abu-El-Quran, R. A. Goubran, "Security Monitoring Using Microphone Arrays and Audio Classification", IEEE Transactions on Instrumentation and Measurement, vol. 55, no. 4, pp. 1025-1032, 2006.

[19] C. Wan, A. Mita1, T. Kume, "An Automatic Pipeline Monitoring System Using Sound Information," Structural Control and Health Monitoring, vol. 17, pp. 83–97, 2010.

[20] C. J. C. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition", Data Mining Knowledge Discovery, vol. 2, pp. 121–167, 1998.

[21] C. M. Bishop, "Pattern Recognition and Machine Learning", Springer Science, 2006.

[22] C. W. Hsu, C. J. Lin, "A Comparison of Methods for Multiclass Support Vector Machines", IEEE Transactions on Neural Networks, vol. 13, no. 2, pp. 415-425, 2002.

[23] C. C. Chang, C. J. Lin, "LIBSVM: A Library for Support Vector Machines", ACM Transactions on Intelligent Systems and Technology, vol. 2, no. 3, pp. 27:1--27:27, 2011.

[24] T. Hastie, R. Tibshirani, J. Friedman, "The Elements of Statistical Learning", Springer-Verlag, 2001

[25] O. Amft, M. Kusserow, G. Troster, "Bite Weight Prediction From Acoustic Recognition of Chewing", IEEE Transactions on Biomedical Engineering, Vol. 56, No. 6, pp. 1663-1672, 2009.

[26] D. Istrate, E. Castelli, M. Vacher, L. Besacier, J. F. Serignat, "Information Extraction From Sound for Medical Telemonitoring", IEEE Transactions on Information Technology in Biomedicine, Vol. 10, No. 2, pp. 264-274, 2006.