Detecticav(ity): A Dental Caries Detection System Using Acoustic Echodentography

Christopher Elliott
Cornell University
cne27@cornell.edu

Grace Song
Cornell University
gs488@cornell.edu

Colton Zuvich
Cornell University
cjz36@cornell.edu

ABSTRACT

The proliferation of low-cost ubiquitous detecting systems has permeated many facets of quantified self-tracking in various medical applications. In this paper, we develop Detecticav(ity) a system which uses a combination of Spectral Chirp Analysis on a Teensy 3.6 micro-controller and an SVM machine learning algorithm to generate a binary classifier to determine if a tooth has a cavity or not. Our method employs a new technique we call "acoustic echodentography" which uses acoustic sound waves at varying frequencies to measure the changes in the density of the tooth. Initial results of our lab testing suggest this technique is still in its infancy with a range of 42 - 68% success rate of classification. We argue this result is due to low-quality instruments and a small sample size of teeth used to train our ML classifier. We discuss future iterations of how acoustic echodentrography can be improved as well as implications if our classification system reaches figures closer to an 80% success rate.

Author Keywords

Dental Caries Detection, Spectral Chirp Analysis, Pattern Recognition

ACM Classification Keywords

H.5.5. [Sound and music computing]: Signal analysis, synthesis, and processing

INTRODUCTION

In today's society, we consume excessive amounts of artificial sugars,coffee, and carbonated drinks which contribute to cavities and poor oral hygiene. A cavity is the result of dental caries lesion or the decay of the tooth from an environment saturated with acidic and sucrose compounds [1]. The increased presence of these substances both lower the PH levels in the mouth and buildup dental plague which cause the enamel surrounding the crown of the tooth to decay. This is especially pronounced if individuals do not adhere to an oral self-care routine which involves brushing one's teeth twice a day and flossing regularly. In the early stages of the formation of dental caries, with proper oral hygiene dental cavities can be repaired by using the minerals generated naturally in saliva and fluoride from toothpaste and mouthwashes. However, once bacteria infect the inner-wall of the tooth's enamel, called infected dentin, this requires a dental filling. If the caries lesion continues to extend to the inner pulp this could result in the need for a new dental crown or root canal which requires a medical treatment from a dentist or maxillofacial surgeon. If left untreated cavities can become a critical issue as they substantially increase the risk of developing an infection.

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A recent report from the Centers for Disease Control found that among children aged 5-19 there was an 18.6% rate of untreated dental cavities and a 31.6% rate among 20-44 year-old's [4]. These rates, however, differ across racial demographics. For instance, 27.1% of white Americans aged 20-44 have untreated dental caries, whereas the rate jumps to 46.1% for African-Americans and 37.8% for Hispanic and LatinX Americans. Similar rates can be found between races for regularly scheduled medical visits. Patrick et al. (2006) posits that disparities in obtaining dental care for low-income and minority communities are likely due to socioeconomic stratification and barriers to accessing affordable healthcare [11]. Another theory, posited by Brayne (2014) argues one reason minority communities do not seek medical treatment is due to "system avoidance," or the avoiding of public institutions where they might be surveilled due to radicalized criminal surveillance [2]. Thus, whatever the reason it's clear that gaps in medical care persist and, presumably, the development of medical devices which provide detailed information to these communities would seek to bridge this gap.

Currently, diagnosis of a cavity requires seeing a medical professional to either visually examine the tooth or to utilize x-ray radiography. While it is possible for an individual to sense a cavity due to tooth pain and sensitivity, by this point the cavity has extended into the pulp and will require a filling, crown, or root canal. All of these procedures and costly and retroactive procedures. Thus, we designed Detecticav(ity) to be a low-cost, effective alternative to monitoring one's teeth for cavities in-between dental check-ups. Studies have found a positive correlation between oral health literacy and oral-health self-efficacy [7]. Thus, we intend for Detectivac(ity) to provide individuals, especially for those without access to medical care, with a system that can improve their oral self-efficacy via access to their current dental caries status.

RECENT WORK

Current exploration by other researchers into the oral hygiene space in ubicomp has focused on persuasive computing and tracking behaviors as part of the quantified-self movement. Two examples of current consumer-facing retail products include the Colgate Connect E1 Smart Toothbrush and the Philips Sonicare FlexCare Platinum Toothbrush [6] [12]. These ubiquitous systems were designed to provide targeted behavioral modification as well as behavioral data tracking so users can be nudged into improving their self-efficacy. However, these products focus solely on proper brushing skills and habit tracking rather than detection of oral hygiene issues (e.g. dental caries, gingivitis). Ubicomp work in this area has been done by Chang et al. which proposed a ”playful toothbrush” which combines a multimedia experience with an interactive toothbrush to improve the brushing habits of kindergarten students [5]. The students were presented with an interactive visual guide showing them which tooth to clean in a predefined order, while the brush sensed the number of strokes and the duration of brushing. Similar work done by Kyeong-Seop Kim et al. prosed a system which would map a real-time 3D visual image based on the built-in accelerometer and magnetic sensor of the toothbrush to correct incorrect brushing styles [9].

Beyond merely correcting improper brush strokes, researchers Caraban et al. devise a persuasive computing system which relies on lateral surveillance in families to ensure members brush frequently and properly [3]. The system builds on the previous work of Chang et al. in that the smart toothbrush apparatus can detect the frequency, duration, and performance of individuals brushing patterns. However, the work then uses social transparency to nudge users into better brushing behaviors by allowing all family members to see others brushing habits. The researchers posit that if members are socially coerced into brushing they will adopt proper habits early, presumably preventing dental caries before they begin.

Alternative systems focus not on persuasive computing but rather on providing users with real-time information about their oral hygiene. For instance, Lumio, a system developed by Yoshitani et al. takes a different approach to caries prevention - plague detection [13]. The researchers embedded a small camera into an electric toothbrush and performed a method called Quantitative Light-induced Fluorescence (QLF), a well-documented method for detecting a build-up of plague. QFL works by shining a blue-violet ray onto the plague while the camera utilizes computer vision to detect the biofilm. Qualitative assessments from users found improved self-efficacy in regards to plague eradication and toothbrushing more-generally. Taking a more direct role in identifying existing dental caries, a U.S. patent from 1983 proposed a mouth guard-like device which would use liquid crystals to indicate differences in temperature between adjacent teeth [10]. In theory, healthy teeth exposed to the surface of the device should display a uniform color, while decaying teeth will produce a color-change on the device so the user can visually see where the decay is occurring. To our knowledge, this patent never became a full-fledged product or tested empirically.

Finally, researchers Ghorayeb and Valle demonstrate a new testing technique entitled ”echodentrography” which utilizes ultrasound to detect anomalies in teeth. In the tooth tested with a machine-drilled artificial ”cavity”, the ultrasound propagated through the tooth showed a change in frequency due to the varying density of the tooth [8]. The author’s preliminary experimental findings demonstrated the potential to use ultrasound in detecting dental caries and cavities. However, the complex structure of the tooth makes it difficult to understand how waves move through the tooth. Moreover, ultrasound is quite expensive and draws a ton of power, limiting its use-cases to medical professionals, not ubiquitous computing solutions.

EXPERIMENTAL METHODOLOGY

Theory of Operation

We intend to extend on the work of Ghorayeb Valle’s echodentography, but instead develop a system based on acoustic frequencies to pass through the teeth rather than using ultrasound. Thus, the goal of Detecticav(ity) is to perform a spectral chirp analysis on a tooth to determine if changes in the density (i.e. cavity or no cavity) will correlate with distortions in how the frequency passes through the tooth. We hypothesize that among the artificial teeth we have to sample - teeth without a cavity will elicit similar frequencies, while teeth with drilled holes will elicit distortions due to the pockets of less dense matter. After collecting data from the frequency signal receiver we intend to train a machine learning model to see if it can accurately classify teeth based on our existing dataset.

The benefit of this approach is that if ”acoustic echnodentography” proves successful our system would be a relatively affordable system compared to alternatives in dental caries diagnosis. How successful our method proves, of course, is predicated on the precision of the instruments used to collect this signal data as well as the overall size of the dataset.

Acoustic Chirp Generator and Frequency Signal Receiver

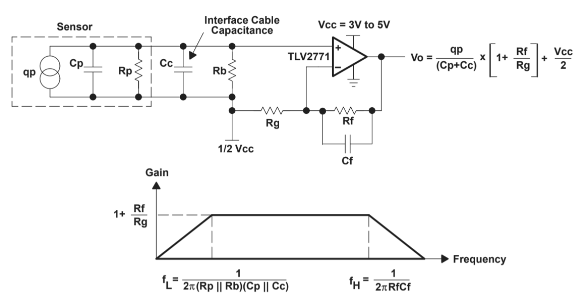

Figure 1. The voltage mode amp allows us to configure the Piezoelectric buzzer to input frequency signal data. In the voltage mode amplifier the output depends on the amount of capacitance seen by the sensor.

Our team utilized a Teensy 3.6 micro-controller wired with a voltage amp (Figure 1), a Piezoelectric buzzer, and a Piezoelectric signal receiver to generate the chirp (frequency sweep) and eventually collect the data. We programmed these components onto our micro-controller using the Teensydrino support library in the Arduino platform. To generate the frequency sweep we programmed the Piezoelectric speaker to up the frequency of the sine wave after completing each period from a range of 1000Hz to 3000Hz. This allowed us to test varying frequencies to determine which frequency in the range resonated best with the tooth density. To read the frequency signals we attached a Piezoelectric signal receiver through the DAC pin. Our experimental design is shown in Figure 2, the buzzer was placed on the left side of the tooth to transmit the frequency sweep while the signal receiver was placed on the right side to read the frequency signal.

Data Collection

Figure 2. Left, the Piezoelectric speaker which played the frequency sweep. Middle, the artificial tooth being tested. Right, the Piezoelectric Signal Receiver reading the frequency signal.

We had a sample size of n=40 teeth which we performed the spectral chirp analysis on as shown in Figure 3. To perform the analysis on teeth with cavities we artificially drilled holes into random areas of the crown in 20 teeth using a 1.6mm drill bit. We chose to drill on the top and the sides of the tooth to simulate the different types of lesions that can occur due to tooth decay [8]. For each tooth we conducted 5 frequency sweeps per trial, generating a total of 40 trials. The reason we include five separate chirps per trial is to capture not only the sine wave sweep but also the resulting reverberation afterward. This could help to better train the ML model because teeth of differing densities might elicit different reverberation. Our team used a serial monitoring system, RealTerm, to read the information sent to the USB bus. To note, the data was saved in 100000 bits to ensure its dimensionality to train our ML classifier.

Support Vector Machine Classifier

Since our data collection process allowed our team to label each trial with its ground truth classification, i.e. cavity or no cavity. We were able to use a supervised, soft-margin, Support Vector Machine (SVM) algorithm on our dataset using a radial basis function (RBF) kernel, which is represented by this formula:

$$\left[\frac{1}{n}\sum_{i=1}^{n}\max\left(0,1-y_i(w\cdot x_i-b)\right)\right]+\lambda\|w\|^2$$

The SVM classifies data by drawing a decision boundary (i.e. hyperplane) between the extreme data points for each of the binary clusters. The support vectors are represented as these extreme vectors and set the margins of where to draw the hyperplane are based on these outlier points. Ultimately, the model will construct a hyperplane with the widest distance separating the two categories, which in this case is cavity vs. no cavity. Thus, once the SVM has identified the hyperplane it can classify new teeth to determine what cluster it belongs to. To note, SVM does not predict the probability of a vector being in a given cluster it only specifies what cluster the data falls in. To test our findings we conducted a train-test split on 33% of our dataset.

We decided on using an SVM algorithm because it is good practice to use a model with the least amount of interpretability and a high level of accuracy when undergoing exploratory data analysis. SVM's are particularly useful for binary classification on linearly separable data. Moreover, SVM's are particularly useful when there is a low number of data to features ratio. This is because typically ML models experience overfitting when this ratio is low, however, because SVM is only looking at a few extreme points to create the hyperplane it doesn't matter as much that there is a smaller sample size.

RESULTS

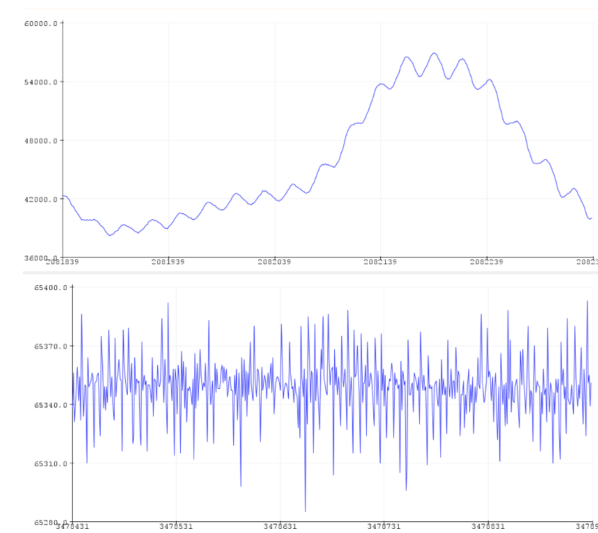

Figure 3. Shown above, the reverberation measured from a tooth without a cavity. Below is the reverberation from a tooth with a cavity.

Based on our train-test split for 33%, the SVM we constructed on our n=40 sample data yielded a range of 42-68% success rates. The range is due to re-running the model for multiple trials with different training/testing data each time its initialized. In short, the model did not effectively work to classify our data since the model predicts the binary classification only around 55% of the time (essentially a coin toss). However, as we hypothesize below we believe this was due to the lack of sensitivity in the hardware and a relatively small sample size. Thus, our initial results suggest the current design of Detecticav(ity) isn't sensitive enough to generate meaningful data, however, future iterations can improve upon its sensitivity. Thus, researchers should not discount the potential of acoustic echodentography due to the current findings.

DISCUSSION

Given the time and scope of this project, we outline the myriad ways in which future iterations of Detecticav(ity) can be improved.

Better Precision Instrumentation

While our current system utilized the Piezoelectric sensors, we would be interested in finding alternative, more precise instruments to transmit and read our frequency sweeps. Regarding the Piezoelectric transmitter, we posit that a system which can better localize the sound from the frequency chirp into the tooth would reduce the Signal to Noise ratio (SNR) by reducing ambient sounds in the environment and allowing less of the chirp to escape. Pertaining to the Piezoelectric signal receiver, we are interested in employing an instrument which could receive frequency signals at a higher resolution (i.e. 24-bit, modern HD format). The concern with using more precise instrumentation is that the cost of the device would scale alongside the sensors. The original goal of this project was to build a low-cost, ubiquitous cavity detection system, so any increased costs would need to be justified by significantly improved data collection.

Improving Data Collection

Our current sample size, of which we build and classified our SVM model, included only n=40 teeth (i.e. 20 with cavities, and 20 without cavities). Increasing the sample size will increase the variability within the total dataset, helping to ensure that we don't over-train or under-train the ML model. The more data fed into the model the easier it is to classify outliers and understand the underlying distribution. Another concern is that we tested our data with artificial teeth, due to ease of access, but these synthetic alternatives might not be a fair proxy for the model to work on real teeth. Furthermore, artificial teeth might also contain air bubbles in their construction, leading to inaccuracies in classifying the teeth based on their densities. One final improvement to data collection might include developing a purpose-built apparatus to hold each tooth in place during data collection. Our current method involved laying each tooth atop the Piezoelectric receiver. However, a system in which all of the instruments remained fixed in space, while the tooth stayed still would reduce potential noise caused by holding the transmitter.

Classifying the Severity of Tooth Decay

One final improvement to Detecticav(ity) involves classifying teeth not on a binary scale of 'cavity' or 'no cavity,' but rather in terms of the severity of a cavity. For instance, some dental caries lesions are still repairable my improved dental hygiene, more significant incisions in the dentin can require fillings, while significant cavities in the crown may require a root canal procedure. Thus, it would be even more insightful for users to know the severity and level of treatment required to repair their cavities. We propose that using a K-means ML algorithm will allow us to classify based on severity. K-means will label the data based on the density and the euclidean distances of points. Thus, it is possible to classify the changes in wave distortions by differing cavity seventies. In addition, a large dataset would naturally help to get a more representative population.

CONCLUSION

In this paper, we developed and tested a new technique of detecting dental caries called acoustic echodentography as an alternative to x-ray radiography. The resulting system, Detecticav(ity), performed spectral chirp analysis on artificial teeth to ultimately train a machine learning SVM model to predict whether a tooth had a cavity. While initial results suggest our current apparatus isn't capable of accurately predicting yet, we believe that future iterations of this work, described above, can yield success in classifying teeth. We discuss where limitations in our project exist and how to migrate them in our future work in this space. The potential to build a low-cost, ubiquitous cavity detection system can have enormous outsize public health benefits. Specifically, in improving access to medical information and improved self-efficacy of oral hygiene in low-income and marginalized communities.

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