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Representation Learning for Dental Image Identification

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ABSTRACT

Forensic identification to victims of criminal acts or mass deaths due to disasters to determine the identity of victims using fingerprints, DNA, and teeth is very important for various reasons. In some cases, such as a fire disaster, DNA and fingerprints cannot be used. Identification using teeth is one of the alternatives that can be used because it is the most preserved part and the position, structure and shape of teeth are unique. Basic principle of dental identification is comparison of antemortem (AM) and postmortem (PM) dental images. For the current work only AM data is available, so it is necessary to manipulate dental x-ray images on AM data to produce PM image data using three methods, those are gamma correction, image rotation and image distortion using integral projection. From both datasets (AM and PM), important image features are extracted through representation learning by PCA, transfer learning using ResNet50's architecture methods. The results of representation learning namely the AM and PM datasets are compared using cosine similarity, which will give output the values of similarity each images. The best results of dental image identification have the best accuracy value using the transfer learning - ResNet50 method on all types of PM datasets.

Key words: representation learning, forensic dentistry, convolution neural network, transfer learning

1. INTRODUCTION

Forensic dentistry is very important to identify a deceased human when other approach of biometric identification such as finger print, and face identification are not available. This is the case when the deceased person is skeletonized, decomposed or burned. While other body tissues are normally damaged after death, the dental evidences are often still preserved. The fundamental principles of dental identification are comparison of postmortem (PM) dental records against specific antemortem (AM) records [1].

Dental identification of humans is needed for a number of different reasons, for instance, victims of violent crimes, fires, vehicle accidents, work place accidents, payment of pensions, life assurance and other benefits relies upon positive confirmation of death and many other reasons where only dental identifications have always played a key role in natural and manmade disaster situations. Persons who have been deceased for some time prior to discovery and those found in water also present unpleasant and difficult visual identifications [2]. A study has shown that the potential importance of dental evidence in a disaster with thousands of victim, 50 to 70% of the cases are identified using dental images, 20 to 35% using finger print, and ~3 to 20% of the cases with DNA evidence. Dental evidence is selected as the most suited biometric for casualty identification in the Indian Ocean earthquake, resultant tsunami of December 26, 2004, and Thailand tsunami attack in January 2005 [3].

A manual comparison between the AM and PM records is based on a systematic dental chart completed by some forensic experts. With the aid of advanced computing, automatic comparison has been widely studied using various approach. Many researches were focused on image segmentation and classification. Both traditional digital image progressing algorithms and deep learning methods had been applied in these fields. Some work using traditional digital image processing are found in [5]-[11]. Comprehensive studies were done by Jain and Chain used the contours of the teeth as the feature for dental matching. The proposed method involved three image processing phases, namely image segmentation, pixel classification and contour matching. Dental crown and root shape were extracted features [4]-[6].

Another excellent works was done by Abdol Mothaleb et al used traditional digital image processing for teeth or dental classification [8], [9]. Both works implemented iterative thresh-holding followed by adaptive thresh-holding for segmentation purpose [10], [11]. For teeth classification [9], a supervised Bayesian method classifier was invoked. For dental identification [8], shape matching was performed by evaluating distance between a PM image and an AM image based on the corresponding salient points on the teeth contour which obtained by applying a connected component analysis using 8-connectivity.

A recently comprehensive systematic review was performed using prominent publication databases to identify 25 articles using deep learning in the field of dentistry in the last three years [12]. The result has shown that Convolutional Neural network (CNN) was used as a main network component. The number of published paper and training datasets tended to increase, dealing with various field of dentistry. Objective of the researches are various such as identification of dental plague, osteoporosis, tooth classification and other dental disease analysis.

For instance, one of the reviewed publication has used CNN to train the model for automated clinical quality evaluation, namely a root canal treatment quality evaluation procedure based on dental radiograph image classification, which integrates medical experts experience. Their model achieves the F1 score of 0.749, which is comparable to the performance of expert dentists and radiologists [13].

Only few from the reviewed articles consider dental identification for forensic dentistry [14]-[16]. Teeth detection and classification of dental periapical radiographs for the medical curing and postmortem identification was performed using CNN in cooperation with label tree approach for each tooth and followed by a cascade network structure to do automatic identification on 32 teeth positions [14]. Other tooth labeling approaches for forensic dental identification purpose were carried out using deep learning technique [15], [16] where in both cases the fully convolutional network using AlexNet architecture was used for detecting each tooth.

In this work we will utilize deep learnings for representation of dental image for forensic dentistry. Due to lack of PM data, AM data images will be manipulated to simulate PM images by using gamma correction, image rotation and image distortion with aid of integral projection. Dental identification will be performed by comparing AM and PM data image using cosine similarity technique. This comparison will be analyzed based on extracted features from much higher dimensionality of original data image. The feature extraction will use the classical approach, namely principal component analysis and the state of the art method, namely transfer learning.

2. DENTAL IMAGE DETECTION

2.1 AM and PM Data Records

The purpose of forensic dentistry is to identify deceased person by comparing PM dental data against AM dental records. We have used AM data records from previous research [17]. The dataset consists of 343 dental image from 343 different persons with size of 1600x800 pixels with three RGB layers.

Since PM data set are not available, all 343 AM data set are manipulated in such way to obtain PM data set. According to White and Pharaoh [18] the difference between AM and PM image are only in scaling and small rotating image. Therefore, we used three image manipulation, i.e. a small rotation, gamma correction and image distortion using integral projection on region of interest as shown in Fig. 1.

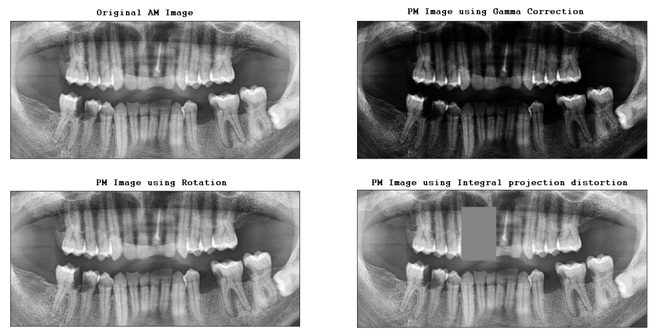

Figure 1: Original AM image is at top left, the manipulated PM images using gamma correction (top right), rotation (bottom left) and integral projection distortion (bottom right)

2.2 Representation Learning for Feature Extraction

References [14] used CNN followed by a cascade network structure for teeth labeling. The same approach was also used for face classification [19] where CNN invoked for feature extraction combined with PCA for dimensionality reduction followed by SVM for final recognition learning. In this work we also used deep learning CNN for feature extraction then followed by cosine similarity for dental image identification. However, a pre-trained CNN model was invoked as also known as transfer learning approach.

Transfer learning refers to the situation where what has been learned in one setting domain and distribution is exploited to improve generalization in another domain and distribution of the related problem. [20]. This approach is becoming very popular recently, especially in predictive modeling problem that use image data as input. Driven by ImageNet large scale visual recognition challenge a lot of pre-trained models are developed using deep learning methods [21]. The organization of ImageNet competition makes the final pre-trained model available for use under a permissive license. This pre-trained model would consume days or weeks if we trained on modern computer. This pre-trained model can be utilized by new problem that expect image data as input. Some popular model are Oxford VGG model [22], Google Inception Model [23] and Microsoft Residual Network model [24].

Comparison study between these three models [24], [25] has shown that in general Residual Network model, also known as ResNet, gives a better accuracy than others. The better results come from easier optimizing work by introducing a deep residual training framework Let ***H(x)*** is the original mapping of the stack layer with x as inputs then the residual function is introduced as $H(x) - x$. The original function thus becomes $F(x) + x$ as shown in Fig. 2. According to He et al. [24] it is easier to optimize the residual mapping than to optimize the original mapping.

In this work, ResNet50 from Keras library [26] will be used for feature extraction only. It means the top layer, i.e. the fully connected layers from deep learning is not used, while the convolution and pooling layer of ResNet50 model is transferred with AM and PM dental image data records as inputs. The output of transferred learning which is truncated at the bottle neck is a tensor or an array consisting significant features of the dental image data. The size of resulting array of ResNet50 is 2048.

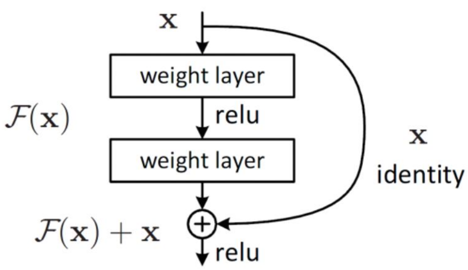

Figure 2: Residual learning framework [24]

2.3 PCA for Feature Extraction

A popular algorithm for feature extraction is the Principal Component Analysis (PCA). PCA seeks a new set of dimensions such that all the dimensions are orthogonal and ranked according to the variance data along them. It converts a set of correlated variables into a set of linearly uncorrelated variables. These new variables are called principal components. The number of principal component is less than or equal to the number of original variables.

Mathematically, the principal component is actually the eigenvectors obtained by decomposing the covariance matrix of the data. Solving eigenvalue problem of the covariance matrix yields eigenvectors and corresponding eigenvalues. The new features or variables are chosen from these principal components so the number of new features are less than the original feature dimension.

To choose the principal components, first the eigenvectors is sorted according to their eigenvalues in decreasing order. Evaluate its explained variance of each new variable which can be calculated from the eigenvalues. The explained variance indicates the extent of information can be contributed by each of the principal components. Cumulative explained variance curve from the highest value of explained variance provide a tools to make a cut off how much principal component will be taken into account as a new set features.

2.4 Cosine Similarity

Cosine similarity is a metric to determine how similar two images independent to the image size. Mathematically it evaluates the cosine of the angle between two vectors in the multi-dimensional space as follows

$$\cos(\theta) = \frac{\vec{a} \bullet \vec{b}}{\|\vec{a}\|\|\vec{b}\|} \tag{1}$$

Vector **a** and **b** are the array consisting image features. In the case of dental image identification these are vectors PM and AM features. The highest cosine similarity value predicts the match dental image between AM and PM.

3. DISCUSSION OF RESULTS

Using principal component analysis on 343 AM image data set, cumulative explained variance are plotted in Fig. 3. The picture has shown that 90% cumulative explained variance is achieved by using only 200 principal components and 95% explained variance with 250 components. Hence, for this work 250 new features extracted from PCA will be used in cosine similarity evaluation.

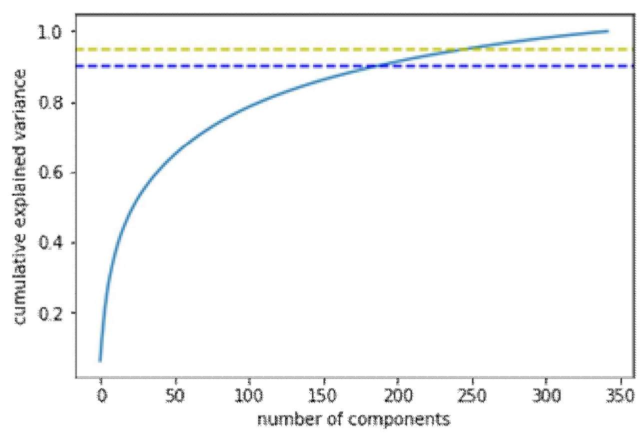

Figure 3: Cumulative explained variance from PCA using AM image data sets (343 image, 1600x800 size

Using these 250 features extracted from PCA inherent 95% of image information, the images are reconstructed as depicted in Fig. 4 where three images in the top row is the original data images and bellow each image is the corresponding reconstructed images using 250 features. The transformation matrix is composed of the selected 250 eigenvectors

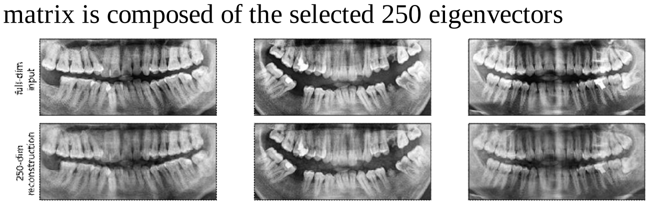

Figure 4: Reconstructed three images using PCA

Fig. 4 has shown that the reconstructed images using much less feature variable than the original images are not difference using human visual capability. Therefore, a successful face recognition was presented using PCA in [27] with accuracy more than 71% for all cases.

We compare each PM data image which is modified from an AM data image against all AM data sets using cosine similarity. The highest cosine value would be identified as a pair-match of AM-PM dental. Hypothetically, in the present study the match dental image should be the AM image with its modified PM image.

This comparison can be better visualized using heatmap, which depicts the two-dimensional data in a colored matrix form. This is a kind of correlation matrix where a darker color indicates higher correlation. The correlation is the cosine similarity, where vertical axis or row index is the PM image and horizontal axis or column index is the AM image on which the order of these two set are set accordingly to pair PM and corresponding original image AM. Therefore, a good correlation will be shown by the existence of a dark (black) color diagonal line.

Using transfer learning for representation of final image data for all type of PM modification shows a good correlation as an example shown in Fig. 5. While the heatmap produced by PCA representation characterizes with scattered black spots in the map which do not form a dark diagonal line.

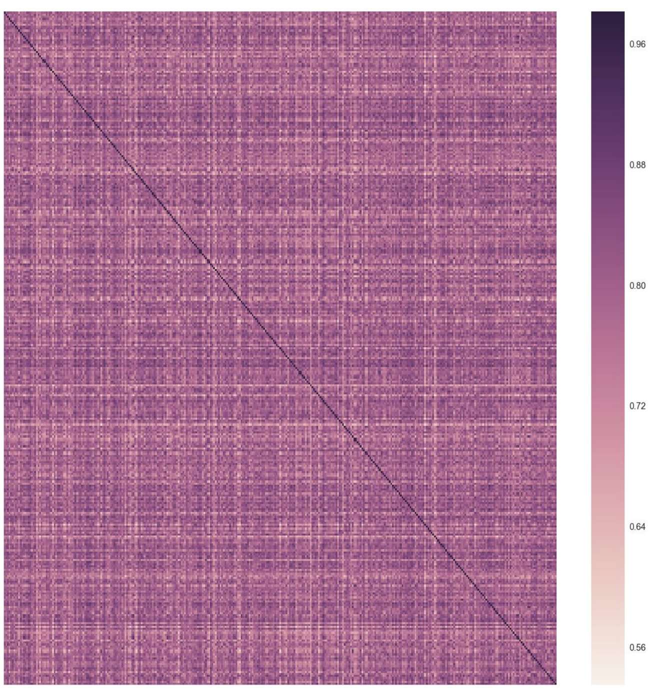

Figure 5: Heat map produced using ResNet representation

Performance metric that will be used is the accuracy. Accuracy is defined as the fraction of correct predictions compared to the total predictions. Using the parameters in confusion matrix, accuracy is formulated as follows

$$\text{accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \qquad (2)$$

Where TP is True Positives when PM image is predicted similar with the corresponding AM image, TN is True Negatives when PM image is predicted not similar with another AM image, FP is False Positives when PM image is predicted similar with another A image, and FN is False Negatives when PM image is predicted not similar with the corresponding AM image.

Table 1 shows the accuracy of PCA and transfer learning representation image for three different PM data sets. Transfer learning representation indicate a satisfying performance while it cannot be confirmed by PCA representation performance.

Table 1: Accuracy for different manipulated PM dataset using PCA and Transfer Learning representation

PM data set	Representation	
	PCA	**Transfer learning**
Gamma Correction	1%	90%
Rotation	1%	99%
Integral projection distortion	30%	98%

3. CONCLUDING REMARKS

This study has proven the great advantageous of deep learning method over the historical principal component analysis in representation dental image data. ResNet yields a satisfaction accuracy without any parameter tuning for this purpose

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