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Localization of Certain Cephalometric Landmarks Using HOG and KNN

Oğuz Sözkesen[1](ORCİD ID: 0000-0002-4441-1675), Asst Prof. Adem Özyavaş[2]

[1]*Master Thesis Student, ISTANBUL AYDIN University Department of Computer Engineering, Florya, Istanbul, Turkey*

[2]*Assistant Prof,ISTANBUL AYDIN University Department of Computer Engineering,Florya, Istanbul, Turkey.*

Corresponding Author: Oğuz Sözkesen

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ABSTRACT: Cephalometric tracing is a standard technique used by orthodontistsfor analysis and treatment planning. Important landmarks in cephalometric X-ray images are marked by experts. Measurements based on these landmark locations are used for diagnosis.Performing this process manually is tedious and hence error-prone even for experts. Therefore, fully automatic landmark localization (FALL) software has been developed. The aim of this study to help reduce the search area for landmarks to be detected by FALL software to speed up the process of localization. This study focuses on the Prn landmark detection. The potion of the image that is sure to contain the Prn landmark is divided into 16x16 pixels size windows. For each window, its histogram of oriented gradient is computed. These histograms are compared to the histograms created manually before that form the positive and negative dataset of histograms for Prn. K-nearest neighbors (KNN) algorithm is utilized for classification of the window whether it contains Prn or not. Search results are promising in that no true positives are missed and the number of false positives are minimized. The window that contains the Prn landmark is found with 100 % accuracy. A computationally more demanding algorithm could then be used to pinpoint the landmark.

KEYWORDS:HOG algorithm, KNN, cephalometric images, classification.

I. INTRODUCTION

Cephalometry is a clinical method used to measure the morphometric parameters of the human head region, usually performed from lateral head-and-neck X-ray images. Morphometric parameters are essentially specified by the distances and angles between the points of interest anatomically, ie landmarks. Manual placement of landmarks by a qualified clinician takes approximately 20 minutes [1]. That makes the procedure time consuming and prone to human error. These problems can be overcome with the help of various software used in computer vision. These problems can be solved with the help of various software used in computer vision. Therefore, computerized cephalometry can be used for orthodontic treatments planning or for statistical analysis of large image data. In the early stages of computerized cephalometry, density and gradient-based methods were used to detect landmarks [2-3], but also anchor structures and lines around landmarks [4]. On the other hand, these methods often produce outlier landmark values because they rely heavily on the quality of cephalometric X-ray images. Therefore, the results are affected by image artifacts, shadows, and differences in projective displacement of image structures. Detection robustness is increased by developing more complex display features, restricting search fields for each landmark, or taking into account the shape of observed structures between landmarks.

Classification of images has an important place in many areas such as monitoring, diagnosis and medical image acquisition. Many problems encountered in computer vision can be redefined as an image classification [5]. Therefore, image classification is the most important step in multimedia content analysis. Nowadays, many advanced multimedia content analysis algorithms such as clustering, decision tree method, histogram of gradients method according to computer vision are generally preferred.

Histogram of Gradient (HOG) algorithm, which is one of those image processing algorithms is an effective way of extracting features from pixel colors to create a classifier object recognition. The HOG algorithm generally consists of 4 steps:processing, calculating the gradient images, calculating histogram of gradients in 8x8 cells and 16x16 Block Normalization [6].

In the first step, the HOG feature descriptor is calculated on a 64×128 patch of an image. An image can be of any size. Typically, patches at multiple scales are analyzed at multiple image locations. The only restriction is that it has a fixed aspect ratio of the analyzed patches. In the next step, to calculate a HOG discriptor firstly horizontal and vertical gradients must be calculated. For horizontal and vertical gradients, the same results can be achieved by applying sobel filter. Then, magnitude and direction of gradients needs to be calculated. Then, the image is divided into 8×8 cells and a gradient histogram is calculated for each 8×8 cells, thus providing a compact representation. The reason for using 8x8 cell patch is a design selection arranged according to the scales of the desired features. In the final step, gradients of an image are sensitive to overall lighting. Therefore, the discriptor is required to be independent of lighting variations. After all these steps histogram of gradient algorithm can produce results as histograms [7].

The K-Nearest Neighbor algorithm is one of the Machine Learning algorithms based on the Supervised Learning technique. The KNN algorithm finds the similarity between the data in a data set and the newly added data to this data set, based on selected “K” neighbors and places the new data in whichever of the existing categories is appropriate. The KNN algorithm is mostly used for the solution of classification problems [8].

II. LITERATURE REVİEW

Vishad D. Bharate et al., In their study in the literature, they obtained the data of the emotion changes on human faces as a result of the reactions of people under various situations using HOG and GobarFilter and applied the KNN algorithm to these data and obtained the best result with 80% correction [9]. GökhanŞengül and Tariq Khalifa used Local Binary Pattern (LBP) and Directed Gradient Histogram (HOG) algorithms for feature extraction in their study on gender estimation from facial images. They use KNN and Support Vector Machine (SVM) algorithms for classification. In the results, they observed that the accuracy rate of the KNN classification algorithm was calculated for K=11 with an accuracy of 98.60% in the grey scale version and 98.30% in the color version of the image after the HOG algorithm was applied to the image [10]. MohdNorhisham bin Razali et al. Compared the SURF and SIFT algorithms in their study to recognize food products from photographs and show that SURF detects fewer key points than SIFT and performs better than SIFT in terms of processing time [11]. Xiqi Yang et al. have worked on a new edge detection algorithm based on the Extreme Learning Machine that they developed in their research on edge detection in Cassini Astronomy images [12]. They have shown that currently used edge detection algorithms such as Sobel, Canny, Roberts contain a lot of detail and noise, and according to the experimental results of their edge detection algorithms, they work with an accuracy of 93% on Cassini astronomy images. Firnanda Al IslamaAchyunda Putra et al. Proposed a combination of HOG and KNN algorithms to ensure autonomous vehicle driving safety [13]. In their study, they used the HOG algorithm to detect whether there is a car in front of the vehicle, and they used the KNN algorithm to classify this data they obtained with HOG. In the same way, they also used SVM to classify and compared the results. In this way, they observed that the best algorithm for safe autonomous driving is HOG and KNN algorithms with an accuracy rate of 84%. S. Yu et al., in their study to automatically find landmarks on cephalometric images using deep learning methods, create a region of interest (ROI) to determine landmarks on cephalometric orthodontic images used as test data from 2 different data sets. They then used ResNet50, a convolutional neural network, to find the landmarks and observed that the neural network gave the coordinates of the landmarks [14]. Sung Min Lee et al., in their study on automatic interpretation of 3D cephalometric images using shaded 2D image-based machine learning methods, is a machine learning technique that uses 2D images with various lighting and shadows using VGG net to capture 3D geometric clues by addressing the size difference between 2D images and 3D images.This proposed method shows an average point-to-point error of 1.5pointmm for the 7 major landmarks [15].Claudia Lindner et al. developed a fully automatic landmark annotation system (FALA) to accurately detect landmarks on cephalometric images. The system they developed achieved an average point-to-point error of 1.2 millimeters and 84.7% of the landmarks[16].C. Chu and colleagues proposed a fully automated method of landmark detection using a random forest algorithm for landmark detection on X-ray images. This algorithm works by combining the bookmark correction based on the sparse shape composition model and can detect landmarks with an accuracy rate of 77.79%[17].Claudia Lindner and Tim F. Cootes developed a random forest regression voting application to fully automatically locate landmarks in cephalometric images and perform automatic cephalometric evaluation. The developed application shows an accuracy between 77% and 79% for automatic cephalometric evaluation[18].

III. THE PROPOSED METHOD

The proposed method locates a window of size 16x16 pixels that contains the landmark of interest. The landmarks that are selected in this study enclose most of the other landmarks. Locating the outer landmarks ensures that the search area for the remaining landmarks are reduced so that search for them should be faster.

As an example, the-tip-of-the-nose landmark (Prn) is discussed in the rest of the text. Figure 1 shows a sample cephalometric x-ray image. In this case, almost one third of the right-hand side of the image is selected as the area that contains Prn. This region is divided into blocks where each block consists of 2x2 cells of each 8x8 pixels. Therefore, each block is 16x16 pixels size. There are approximately 300 windows in the region selected.

Fig. 1.A sample cephalometric image

The first step of the proposed method is to rescale the cephalometric image to fixed of 400 pixels with and its corresponding height so that no distortion results in after the rescaling. Bilinear scaling is utilized for the rescaling. Since the same size blocks are used in histogram creation, Rescaling is required to have similar HOG for similar shape and texture. Also, for illumination invariance, histogram values are normalized as well.

The next step is to create the dataset for each landmark of interest. This is performed manually by selecting the blocks (windows) for positive and negative datapoints. As a ratio for every positive window around 5 negative windows are selected. Specifically, the dataset for each landmark contains 96 positive datapoints and 476 negative ones. A positive window is one that contains the landmark, and a negative window is one that does not contain the landmark point from the region that contains the landmark. For each positive and negative window, its HOG is computed together with its class and stored in a file. Around 100 cephalometric images are used to create the dataset for each landmark of interest.

Searching for a landmark is performed by extraction of the region that contains the landmark. The size of this region is generally one fourth of the whole cephalometric image. The search window is moved from left to right and top to bottom in this region. To reduce the number of both false and true positives and negatives each search window is separated by 8 pixels (a cell size). For most images more than one true positive is located. Figure 2(a) shows the false and true positives for the Prn landmark. As it can be seen there are three true positives and two false positives (around the lips area). Reducing the number of windows from around three hundred to less than ten could be very useful for a more computationally demanding method that can locate the landmark with more accuracy. 100% accuracy is obtained for the Prn landmark using the Euclidean distance as the similarity measure between two histograms. The second-best results are achieved using the Manhattan distance which is 87.5% correct detection for the same Prn landmark.

For histogram similarity measure Euclidean distance proved to produce the best results in terms of not missing any true positives and minimum number of false positives.

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Fig.2 (a). False and true positives using Euclidean distance as measure of similarity between histograms

Figure 2(b) shows the same cephalometric image that uses Chi-squared for similarity between two histograms. As it can be seen it performs much worse than the Euclidean distance in terms of including too many false positives. In the case of Manhattan distance, there are 210 false positives which is the vast majority of the windows in the selected region that contains the Prn landmark.

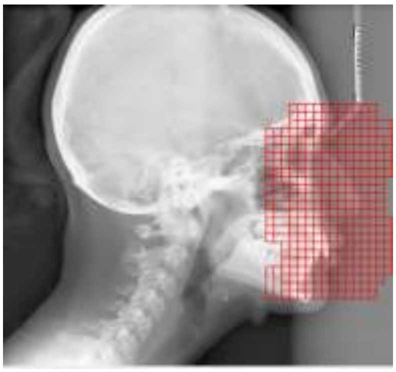

Fig. 2 (b) Positive windows using Chi-squared similarity measure with too many false positives

The implementation of KNN algorithm uses the 5 nearest neighbors and majority of the neighbors' class determines the class of the window under consideration. The histograms of both true and false positive windows are shown in Figure 3 (a-d).

Fig. 3 (a, b). Histograms of false positives for the Prn landmark

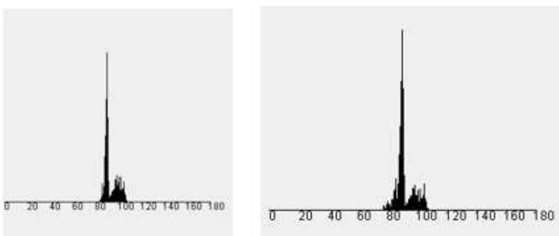

Fig.3 (c-d). Histograms of true positives for the Prn landmark

Figure4 shows the histogram with the minimum distance to the actual Prn landmark histogram shown also in Figure 3 (d).

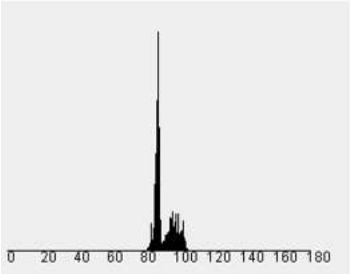

Fig. 4. Histogram with minimum Euclidean distance to actual Prn landmark histogram

The smallest distance histogram is shown in Figure 5 whose histogram is shown in Figure 4.

Fig. 5. The minimum Euclidean distance histogram's window

IV. CONCLUSION

This study aims to extract features from cephalometric images using HOG and the use of KNN classification algorithm to detect certain landmarks in an efficient way. Only a few enclosing landmarks are selected for detection and locating them will confine the search to a minimum area in cephalometric images. If this process if fast enough, then more time demanding algorithms can be used to pinpoint the landmarks' exact location. In this study the Prn landmark is used as an example. After the dataset is produced manually, the window containing the Prn landmark is located with 100% accuracy within 1044 millisecond. The implementation of the algorithms is done in Java and the code is executed on a platform with Intel i7 second generation CPU with 8GB memory 2.67 GHz. The cephalometric images used in this study are freely available for research purposes at www-o.ntust.edu.tw/~cweiwang/ISBI2015/challenge1/

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