Apnoea-hypopnoea Index Estimation using Craniofacial Photographic Measurements

Hadis Nosrati, Nadi Sadr, Philip de Chazal

Charles Perkins Centre, School of Electrical and Information Engineering,
Faculty of Engineering and Information Technologies
The University of Sydney, Sydney, Australia

Abstract

This paper presents a novel way of estimating the apnoea-hypopnoea index (AHI) using craniofacial photographs. We compared the correlation and classification performance of the photograph-determined AHI against expert-determined AHI for a number of selected measurement sets. Our best performing system used five craniofacial measurements selected from 71 manual craniofacial phenotype features, which had been determined from frontal and profile photographs of a patient's head and neck. The measurements were processed with a Support Vector Machine Regression algorithm to estimate AHI. The best features included face width, mandibular length, binocular width, cranial base area, and criocomental space distance. A database of 114 subjects with OSA (AHI≥10/h) and 66 controls (AHI <10/h) was used for algorithm development and testing. Leave-one-record-out cross-validation was used to estimate performance. The Pearson correlation was 0.52 for the AHI estimation. Classification performed using an AHI threshold of 10 events per hour, resulted in an estimated accuracy of the algorithm of 73.3% with an area under the ROC of 0.78.

1. Introduction

Obstructive Sleep Apnoea (OSA) is a widespread sleep related respiratory disorder involving consecutive blockage of the upper airway. Although, it can lead to serious health issues such as cardiovascular disorders, about 80% of OSA cases are undiagnosed [1]. The current OSA diagnosis tools are invasive and expensive. Thus, there is a trend toward developing reliable non-invasive OSA detection methods.

It has been reported in the previous imaging studies that anatomical and functional abnormalities of the upper airway and craniofacial morphology could be significant factors in OSA detection. It has been shown that craniofacial abnormalities can lead to upper airway collapsibility which can result in OSA. Hence, in majority of patients, a combination of imaging methods illustrating craniofacial abnormalities and measures of obesity could be utilized as a tool for OSA recognition and measuring the OSA severity. The current available craniofacial evaluation tests and imaging including cephalometry, computed tomography (CT) and magnetic resonance filtering (MRI) are expensive and invasive. Therefore, photogrammetry has been widely used as an interesting OSA diagnosis tool due to its non-invasive, accessible and quantifiable nature. Recent studies investigated quantitative photographic analysis of the craniofacial morphological phenotype of OSA patients and normal subjects [2]–[4]. A few craniofacial photographic measurements have been discovered with the ability of detecting OSA [3].

This study looks at the craniofacial photographic measurements, as a powerful and non-invasive tool to predict OSA severity. It uses the estimated apnoea-hypopnoea index (AHI) as a surrogate measure to classify subjects with and without OSA. The benefits of photogrammetry for OSA diagnosis over the standard in-lab overnight polysomnogram test include: independence of time of day for the administering of the test, labour inexpensive, cost effective and minimally invasive. These benefits could also lead to its application in developing countries where expensive diagnostic tools may not be readily available.

2. Database

The landmark features used in our study are selected from manual photographic measurements representing the dimension of various craniofacial regions including face, head, neck, eyes, nose, mandible and maxilla as described in Table 1 and Fig. 1. Measurements are derived from the study conducted by Lee et.al [2] where subjects were referred for polysomnography to a university teaching hospital for the initial investigation of OSA. A total of 180 subjects were included in the analysis where 114 subjects

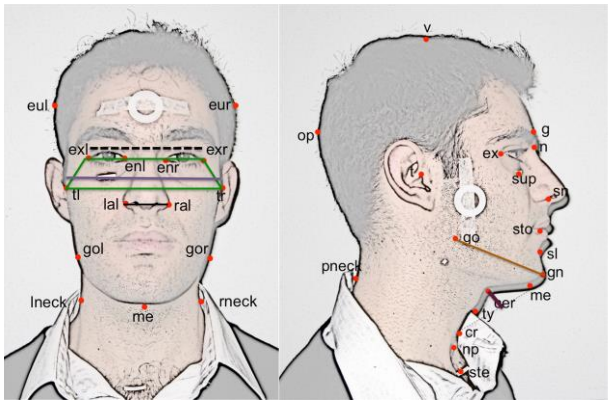

Figure 1. Photographic Landmarks – Profile and Frontal View

Table 1. Examples of 71 Craniofacial photogrammetry features [2]

Feature	Landmarks
Biocular width	exl-exr
Cervicomental angle	np-cer-me
Cranial base area 1(ax)	tl-exl-exr-tr
Cricomental space distance	cer-cr-me
Eye width	exl-enl
Face width	tl-tr
Mandibular length 2	gn-go
Mandibular nasion angle 2	go-n-me

had OSA (AHI >=10/h) and 66 were selected as controls (AHI <10/h) [2].

Before the photographs were taken, certain landmarks were identified on the subjects and indicated with a white tape. A calibration washer of known size was taped to the forehead and to the cheek. It was used to calibrate measurements determined from the photograph. Frontal and profile photographs of the head and neck were then obtained with a single-lens reflex digital camera (D70 with 18-70mm lens and external flash unit SB-29s; Nikon Corp., Japan) using a standardised setup. The subjects then underwent a diagnostic polysomnography (PSG) overnight test. Following the study, PSG scoring was performed by experienced accredited sleep technologists Sleep staging was performed using standard definitions. Apnoea was defined as complete airflow cessation for greater than 10 seconds with oxygen desaturation of at least 3% and/or associated with arousal. Hypopnoea was defined as a reduction in amplitude of airflow or chest/abdominal wall movement greater than 50% of the baseline measurement for more than 10 seconds with an accompanying oxygen desaturation of at least 3%, and/or associated with arousals. AHI was calculated as the total number of apnoeas and hypopnoeas per hour of sleep.

3. Signal Processing

Seventy one features for each of the 180 photographs had previously been manually determined by an expert to support the studies described in [2,3,4].

Our first step was to normalize the features into the interval 0 to 1 by scaling the mean and the variance. The features were then ranked using a Support Vector Machine Reverse Elimination Feature (SVM-REF) algorithm [5] and the optimal number of ranked features selected. The result of this algorithm was five selected features. The support vector regression (SVR) algorithm was then used to map the input features to an estimated AHI. We describe SVR in the section 3.2.

Sections 4 and 5 provide the details of the experiments, the results, and the conclusions.

3.1. Craniofacial Photographic Features

Three systems were considered as the photographic features for AHI estimation.

The first system uses the five most discriminative features from 71 craniofacial based on the SVM-REF technique [5]. These features are face width, mandibular length 2, binocular width, cranial base area (ax), and criocomental space distance.

The second and third systems use the selected calibrated and uncalibrated features from the study by Lee.et.al [3].

Lee's calibrated system used a logistic regression model processing the following calibrated photographic measurements: face width, eye width, cervicomental angle, and mandibular length. It obtained 76.1% of accuracy, sensitivity of 86%, specificity of 59.1% and area under curve of ROC of 0.82 for discriminanting sleep apnoea using an AHI threshold of 10. This system resulted in the highest rate of true classification with the lowest number of variables [3].

Lee's uncalibrated system also used a logistic regression model processing the following uncalibrated photographic measurements: face width-eye width ratio, cervicomental angle and mandibular-nasion angle 2. This model achieved an accuracy of 71.1% with sensitivity of 80.7%, specificity of 54.5% and area under ROC curve of 0.80 [3].

The measurements used in Lee's and our system are illustrated in Table 1 and Figure 1.

Table 2. AHI estimation using craniofacial measures and clinical variables using RBF kernel.

Feature set	MAE	CC
Lee's uncalibrated features	13.3	0.54
Lee's calibrated features	13.5	0.53
5 SVM-REF selected features	13.4	0.52
5 clinical features	14.6	0.42

Table 3. Classification Results of OSA detection using radial basis function kernel SVM

Feature/ Performance	Accuracy	Sensitivity	Specificity	ROC AUC
Uncalibrated	68.3	87.7	34.8	0.75
Calibrated	72.22	89.47	42.42	0.77
Selected	73.3	90.4	43.9	0.78
Clinical	71.67	89.47	40.91	0.78

Notes: Calibrated: Lee's 4 calibrated features [3]; 5 Selected: SVM-REF 5 selected features; Uncalibrated: Lee's 3 uncalibrated features [3]; Clinical: 5 clinical features

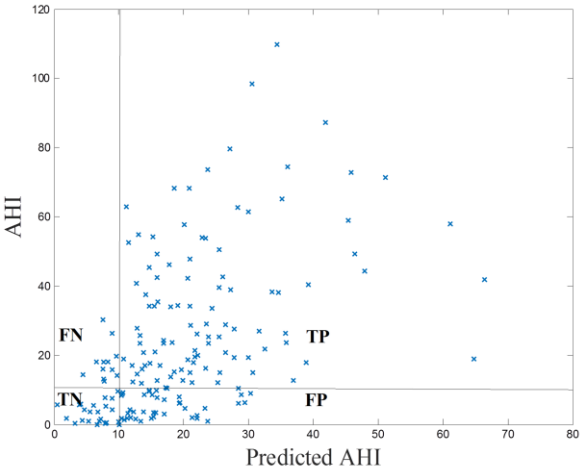

Figure 2. Scatter plot of predicted AHI versus true AHI for 5 SVM-REF selected features.

A fourth system using clinical features was also considered. The clinical features were age, BMI, neck circumference, abdominal girth, and hip girth.

3.2. Support Vector Regression

SVM uses an ϵ-insensitive loss function to solve regression problems. Support Vector Regression (SVR) attempts to find a continuous function where training points lie within ϵ distance of the target values. The ϵ factor is chosen to balance the margin of error and generalisibility of the prediction function to unseen data [6, 7]. LibSVM has been used to calculate the regression measurement via support vectors [7]. The SVR models the regression directly. Similar to support vector classifiers [8], a key part of SVRs is producing a measurement of similarity using a kernel function. The basic concept of SVR is to discover a function $f(x)$ which map the input training data closest to the targets y_i in a way to obtain the most flat function [6,7]. A simple linear function $f(x)$ is illustrated as follows,

$$f(x) = w.x + b \ , w \in X \ , b \in R, \qquad (1)$$

where the y_k are the ideal outputs, b is a learned constant and the weight vector w is a linear combination of training points. In order to obtain flatness, smaller weights, w, are found through minimizing its norm, $\|w\|^2 = w.w$, through a convex optimization problem,

$$minimize \quad \frac{1}{2}\|w\|^2$$
$$subject\ to \begin{cases} y_i - w.x_i - b \le \varepsilon \\ w.x_i + b - y_i \le \varepsilon. \end{cases} \qquad (2)$$

Equation 2 is augmented by introducing a region for the support vectors. This is created by using the negligent variables, ξ_i , ξ_i^* with a constant cost function $C > 0$, which represents the cost between the flatness of function $f(x)$ and the deviation tolerance over ε,

$$minimize \ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*),$$
$$subject\ to \begin{cases} y_i - w.x_i - b \le \varepsilon + \xi_i \\ w.x_i + b - y_i \le \varepsilon \ + \xi_i^* \\ \xi_i \ , \xi_i^* \qquad 0. \end{cases} \qquad (3)$$

Using Lagrange multipliers in solving the dual problem leads to the following function

$$L := \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) - \sum_{i=1}^{l}(\mathfrak{y}_i\xi_i + \mathfrak{y}_i^*\xi_i^*)$$
$$- \sum_{i=1}^{l}\alpha_i(\varepsilon + \xi_i - y_i + w.x_i + b)$$
$$- \sum_{i=1}^{l}\alpha_i^*(\varepsilon + \xi_i^* + y_i - w.x_i - b), \quad (4)$$

$where\ \alpha_i, \alpha_i^*, \mathfrak{y}_{i,\mathfrak{y}_i^*}$ 0. The approximation function is obtained by solving (4) using

$w = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)x_i,$

$$F(x) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)(x_i.x) + b. \qquad (5)$$

The support vector regression is estimated as above in (3) [6].

3.3. Parameter Optimisation

LibSVM was used for training and testing of the proposed model [7]. A grid search was utilized for optimizing the SVR and RBF parameters [9]. It employed a 5-fold cross validation of comprehensive searching of the subset of hyperplanes and hyper-parameters to optimize regression performance [9].

3.4. Performance Measures

Two measures were used to evaluate the performance of the model including Mean Absolute Error (MAE) of the estimated AHI measures and Pearson linear correlation coefficient (CC) between the predicted AHI and the expert determined AHI [7].

Accuracy, sensitivity, specificity, and area under the curve for the receiver operator characteristic (AUC-ROC) were used to quantify classification performance.

4. Results and Discussion

The results of AHI estimation using craniofacial measure and clinical variables using the RBF kernel are shown in Table 2 for the three sets of craniofacial photograph features and the clinical features. A scatter plot for the SVM-REF selected features is shown in Figure 2. The classification results are shown in Table 3.

The results in Table 2 show that the three craniofacial feature sets achieved around 0.5 correlation with the expert determined AHI. The scatter plot for the SVM-REF features shows while the AHI trend is correct there is a high degree of variability on an individual determined AHI point. Encouragingly, the system had low level of false negatives (see Fig. 2) indicating that the system may have potential utility as a screening device. This result was also seen in the high level of specificity 90.4% in Table 3. The clinical features resulted in a lower correlation of 0.42, demonstrating that the craniofacial photograph features had greater predicting power.

Our classification results using a regression model are comparable to Lee's result of 76.1% [4] but with the added ability of estimating the severity of sleep apnoea.

While our system has a way to go before it is a clinically useful system, we've shown that a highly convenient, low cost, day-time test can be used to predict the severity of sleep apnoea. With further development, our system has potential as primary diagnostic tool to tackle the societal burden of undiagnosed sleep apnoea.

Future work will look at restricting the feature pool to the set of measurements not requiring calibration (e.g. angles and relative distances) and choosing an optimal subset. This would remove the need to use the calibration washers used on the forehead and the cheek shown in Fig. 1. Our selected landmarks can also serve as a baseline for a fully automatic photographic analysis system for OSA detection, where the key craniofacial indicators are to be identified automatically using image processing algorithms. This could create the opportunity of using low cost, ubiquitous technology such as smart camera phones to perform the apnoea screening.

5. Conclusion

This paper has presented a novel way of estimating the apnoea-hypopnoea index using craniofacial photographs. Five craniofacial measurements were selected from 71 manual craniofacial phenotype features determined from frontal and profile photographs of a subject's head. The measurements were processed with a Support Vector Machine Regression algorithm to estimate AHI. Using leave-one-record-out cross-validation the estimated accuracy of the algorithm was 73.3% with an area under ROC of 0.78. The correlation coefficient of the estimated AHI against the expert AHI was 0.52.

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Address of correspondence:
Philip de Chazal
School of Electrical and Information Engineering, Building J03, The University of Sydney, NSW, 2006, Australia.
philip.dechazal@sydney.edu.au