# **Intelligent Planning for Laser Refractive Surgeries**

Wei Wang<sup>1,2,4</sup>, Yong Yue<sup>1</sup>, Ahmed Elsheikh<sup>2</sup>, Fangjun Bao<sup>3</sup>

<sup>1</sup> Department of Computer Science and Software Engineering, Xi'an Jiaotong-

Liverpool University, Suzhou 215123, P.R. China

<sup>2</sup> School of Engineering, University of Liverpool, The Quadrangle, Brownlow Hill, Liverpool L69 3GH. UK

<sup>3</sup> School of Optometry and Ophthalmology and Eye Hospital, Wenzhou Medical University, Wenzhou 325027, P.R. China

<sup>4</sup> Institute of Complex Networks and Visualisations, Shijiazhuang Tiedao University, Shijiazhuang 050043, P. R. China

Abstract. Refractive error is one of leading ophthalmic diseases for both genders all over the world. Laser refractive correction surgery, e.g., laser in-situ keratomileusis (LASIK), has been commonly used worldwide. The prediction of surgical parameters, e.g., corneal ablation depth, depends on the doctor's experience, theoretical formula and surgery reference manual in the preoperative diagnosis. The error of prediction may present a potential surgical risk and complication. Being aware of the surgery parameters is important because these can be used to estimate a patient's post-operative visual quality and help the surgeon plan a suitable treatment. Therefore, in this paper we discuss data mining techniques that can be utilized for the prediction of laser refractive correction surgery parameters. It can provide the surgeon with a reference for possible surgical parameters and outcomes of the patient before the laser refractive correction surgery.

## 1. Introduction

In the last two decades, the globe prevalence of refractive errors has risen dramatically. In China, the prevalence of myopia and high myopia is more than the world average, and is associated with education [1~4]. This status will affect the Chinese population quality. Considerable research has been conducted on refractive surgeries and there are publications about the success of laser refractive correction surgery, e.g., LASIK [5~10]. While the patient satisfaction rate of LASIK surgery is more than 90%, it may not be recommended for everybody. There are two main reasons: (1) potentially no significant visual acuity improvement for certain types of patients, and (2) the complications after the surgery [5, 10]. At present, the surgeon performs the surgery prediction with patient's biological features, surgery parameters, theoretical formulas and hypotheses. This prediction is a theoretical result based on which, the surgeon can rely on their experience and surgical equipment manuals to roughly estimate the surgery outcomes [11, 12]. If there is a method to predict surgery parameters without theoretical formulas, hypotheses and the experience of the surgeon, it will provide another reference for the surgeon to adjust the surgery parameters for better surgery outcomes, and the patient could know the possible improvement of visual quality after the LASIK surgery.

The medical history of surgeries might hide the relationships between the pre- and post-operative parameters. This research explores ways to achieve accurate surgical parameters with data mining

techniques, and has obtained regression equations of surgical parameters with historical medical data. The goodness of fit, which is used to evaluate regression equations, is more than 0.8, indicating a high accuracy.

## 2. Related work

Data mining methods are divided into two types, predictive methods (e.g., classification, regression, time series analysis and prediction), and descriptive methods (e.g., clustering, association rule mining, and sequence analysis). Regression is widely used in medicine as a method of predicting, comparing, and evaluating medical procedures and outcomes.

Before laser refractive surgery, Jester *et al.* [13] and Salz *et al.* [14] used fresh human cadaver eyes to analyse the relationship among incision depth, corneal curvature, corneal thickness, corneal diameter and incision length with stepwise regression in radial keratotomy, and introduced a prediction equation of change in corneal curvature correlation after radial keratotomy. While impossible to track biological features and surgery outcomes for the cadaver eyes in the long term, they presented a way to predict refractive surgery outcomes with linear regression. Block and Block [15] used multiple regression to determine the surface of the cornea in radial keratotomy. They only introduced the algorithm and ellipsoid equation, and did not give any solution to the equation. Until 2011, Bao *et al.* [16] and partners solved the ellipsoid equation with multiple regression for 112 eyes. They also figured out that the axial length was the main morphological parameter related to myopia.

Since the laser refractive surgery was invented in early1990s, there has been research on the analysis of historical medical data and the discovery of relationship among patient biological features, surgical parameters and outcomes. For the analysis of patient biological features, Kohlhaas *et al.* [17] found that there were slight correlations among intraocular pressure (IOP), central corneal thickness (CCT) and corneal curvature with regression after corneal refractive surgery. With linear regression for 56 eyes, Bühren *et al.* [18] claimed that the postoperative wavefront error had limited influence on the subjective quality of vision. With linear regression for 706 eyes, Recep *et al.* [19] claimed that the decrease in IOP was related to the decrease in corneal stromal thickness after LASIK. Chen *et al.* [20] and Hamilton *et al.* [21] introduced the correlation between corneal biomechanical properties (e.g., corneal hysteresis and corneal resistance factor), and attempted refractive correction in LASIK. Chang and Stulting [22] presented a method to predict the change of IOP after LASIK with refractive change. Wangsupadilok *et al.* [23] presented a regression equation of IOP and CCT.

For the analysis of surgery parameters, Yi W-M and Joo C-K [24] introduced a linear regression method to evaluate the correlation between corneal flap thickness and preoperative corneal thickness with 69 eyes. Huang *et al.* [25] introduced a method to estimate the deviation in myopia and astigmatism mixed refractive surgery with multiple regression for 523 eyes. He found that the spherical ablation by LASIK had a refractive change 19% greater than by PRK. With linear regression for 102 eyes, Durairaj *et al.* [26] presented the regression equation of actual stromal ablation. Ogasawara and Onodera [27] analysed the correlation of residual stromal bed thickness and regression of myopia after LASIK with linear regression. Choudhri *et al.* [28] found that the corneal thickness was most significantly correlated with the corneal flap thickness with regression. Liyanage *et al.* [29] and Allan *et al.* [30] developed a systematic method for quantifying pre-treatment adjustments for LASIK patients with multiple linear regression.

For the analysis of surgery outcomes, Dutt *et al.* [31] used one-year results of excimer laser photorefractive keratectomy (PRK) to analyse the correlation between the attempted dioptric correction and the achieved correction with linear regression. With linear regression for 50 eyes, Lee [32] discovered that glare and halo symptoms were correlated with the attempted correction of spherical equivalent and astigmatism, but not with the pupil size. In contrast, with linear regression for 92 eyes, Helgesen *et al.* [33] claimed the large pupil size is associated with postoperative visual disturbances during scotopic conditions. For these small size datasets, the results may be disturbed by the outliers in the dataset. With linear regression for 20 eyes, Srivannaboon [34] claimed that the corneal power change was correlated highly with the manifest refractive change produced by LASIK. With linear regression

for 43 eyes, Lackerbauer *et al.* [35] claimed that there was limited correlation between the corneal ablation and refractive outcomes for LASIK. Alio *et al.* [36] evaluated PRK outcomes and introduced a predictive model for the refractive changes in the long term with linear regression for 33 eyes.

The related work provided an efficient way to plan and valuate the laser refractive surgery using data mining techniques. This research explores how to predict the corneal maximum ablation depth with data mining. In additional, more details of regression (e.g., standard error and correlation which have been neglected in previous research) will be used to evaluate the accuracy of model and results.

#### 3. Materials and Methods

In this research, the surgery data was collected from the Eye Hospital of Wenzhou Medical University (Zhejiang Eye Hospital). The dataset has 30 items for 1559 eyes of 786 patients in total. There are 4 items of patient demography, age, gender, preoperative examination date and surgery data. There are 6 items of preoperative examination, diopter of spherical power (SP) and cylindrical power (CP), astigmatism axial, best corrected visual acuity (BCVA), CCT and IOP with non-contact tonometer (NCT). There are 5 items of surgery parameters, optical zone dimeter (OpD, in mm), cutting zone diameter (in mm), corneal flap thickness (in  $\mu$ m), corneal residual thickness (in  $\mu$ m) and corneal maximum ablation depth (CMAD, in  $\mu$ m). The data is from three post-surgery examinations, diopter of spherical power and cylindrical, astigmatism axial, BCVA and IOP with NCT, 1 week, 1 month and 3 months, respectively. The data contains information for 786 patients in the age range of 16 to 51. 419 patients are females, and the rests are males. The histogram of preoperative SP is shown in Figure 1. 209 eyes are in the spherical power range of 0 D to -3.00 D. 825 eyes are in the spherical power range of -3.00 D to -6.00 D. 343 eyes are less than -6.00 D. 182 eyes are less than -8.00 D. The histogram of CMAD is shown in Figure 2. Both of these two parameters are with a similar distribution.



Figure 1. Histogram of preoperative SP



Figure 2. Histogram of CMAD

Parameter	Mean Difference±Standard Deviation		
Age (year)	23.85±5.90		
Preoperative SP (diopter)	-5.15±2.11		
Preoperative CP (diopter)	-0.81±0.69		
Preoperative astigmatism axis (degree)	86.93±73.63		
Preoperative CCT (µm)	540.81±30.24		
Preoperative NCT (mmHg)	$15.59 \pm 2.91$		
Preoperative BCVA	$1.06\pm0.12$		
OpD (mm)	6.58±0.42		
CMAD (µm)	93.38±24.15		
Postoperative SP (diopter)	$0.35 \pm 0.46$		
Postoperative CP (diopter)	-0.35±0.34		

For the prediction of CMAD, the biological features and optical zone diameter are considered as the known conditions of the regression equations. The mean values of these measures are shown in Table 1. The prediction model of CMAD is studied by correlation and regression analysis. The QR decomposition algorithm is used to complete the regression linear fit in R. A P-value of less than 0.05 is statistically significant.

# 4. Results

To judge whether the ablation depth and other parameters really have a high correlation, the correlation is calculated between ablation depth and other parameters with a Pearson correlation coefficient, as shown in Tables 2 and 3.

Table 2. Correlation between ablation depth and other parameters								
	Age	Gen	der Prec	operative SP	Preoperative CP	Preoperative axis		
Correlation	0.05	0.0	7.	-0.85	-0.35	0.03		
Table 3. Correlation between ablation depth and other parameters								
	Preoperative CCT	Preoperative NCT	Preoperative BCVA	OpD	Postoperative SP	Postoperative CP		
Correlation	0.05	0.07	-0.17	-0.53	0.19	-0.19		

According to the correlation among the parameters, preoperative spherical power, preoperative cylindrical power and optical zone diameter have high correlation with corneal maximum ablation depth. The three parameters are used in the multiple regression. The correlation of the ablation depth and the preoperative spherical power is the highest than others; therefore, the preoperative spherical power will be used in single regression, separately.



Figure 3. Linear regression between preoperative SP and CMAD

For the preoperative SP and CMAD regression, as shown in Figure 3, the regression equation is shown below. The residual standard error ( $\sigma$ ) is 12.36µm. The R-squared is 0.738. The P-value is less than 2.2e-16.

$$Y = 42.7577 - 9.8297x \tag{1}$$

where Y is expected ablation depth. x is preoperative SP.

For the multiple regression, the regression equation is shown below. The residual standard error ( $\sigma$ ) is 8.35µm. The R-squared is 0.8806. The P-value is less than 2.2e-16. The multiple regression is with less residual standard error and greater R-squared values than single linear regression.

 $Y = -146.0074 - 13.1426x_1 - 11.9439x_2 + 24.5865x_3$ (2) where *Y* is expected ablation depth. x<sub>1</sub> is preoperative SP. x<sub>2</sub> is preoperative CP. x<sub>3</sub> is OpD.

To evaluate the efficiency of the regression equation, the predictions are compared between the regression equation and Munnerlyn approximate formula [37].

Approximate Ablation Depth 
$$\cong \frac{OZ^2}{3}D$$
 (3)

where OZ is optical zone diameter. D is the correction in dioptres.

The mean-squared-error (MSE) is a measure of the quality of an estimator [38]. The root-meansquare-error (RMSE) is a measure of accuracy, to compare forecasting errors of different models for a particular dataset and not between datasets [39]. For the prediction model with regression, MSE and RMSE can be used to evaluate the accuracy. The comparison includes the mean difference, MSE and RMSE, and the results are shown in Table 4. The multiple regression equation with less MSE and RMSE means the accuracy is better than the accuracy of Munnerlyn approximate formula.

Table 4. Comparison of multiple regression and Munnerlyn approximate formula

	Mean Difference	MSE	RMSE
Multiple Regression Equation	0.01016±6.104959	69.49518	8.336161
Munnerlyn Approximate Formula	21.5491±8.148693	584.3581	24.1735

## 5. Conclusion

The research has achieved a data-driven model automated method to obtain a possible surgery parameter, the corneal maximum ablation depth. The regression equation is more accurate than the theoretical formula, and more convenient to use than the surgery system. It can also easily estimate the residual stromal depth, which is correlated with a series of postoperative complications.

In addition, more regression models (e.g., gradient boosting regression, Bayesian regression, ridge regression, lasso regression, neural network regression) will be used for the prediction of surgical parameters and outcomes. A comparison among these methods will also be made in the future.

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