Real Time Surface Angle Measurement of Dental Implants**

Uğurhan Kutbay[1]

[1] Gazi University, Faculty of Engineering, Departmant of Electrical & Electronics Engineering, Ankara, Türkiye (ORCID: 0000-0003-2167-9107)

Abstract

Dental implants and related product family are very important for jaw health. Dental implants are generally produced by titanium materials. Since titanium based alloys have high mechanical strength, quality control of these products is important to prevent possible defective products that may arise during CNC based biomaterial production processes. In addition, these parts are produced by a high number which are almost impossible to control visually. Machine vision prevents of human based errors in automated production. Presented system detects length and angle defects for dental products using image processing methods. The state of art of this work is developing machine vision based real time dental implant defection system design. Gaussian blur filtering and Otsu thresholding were used for detecting the titanium dental product in gray scaled images. Root mean squared linear regression model is applied to preprocessed images to detect the line of the product. The angle between the two lines is also calculated by trigonometric methods. As the result of the presented algorithm, maximum 0.0015 mm and 0.013° absolute deviations are observed for length and angle measurements, respectively. Presented measurement algorithms for dental implants show that these fast algorithms give feasible results for mass production lines.

Keywords: Dental Implant, Quality Control, Image Processing, Auto-Thresholding, Linear Regression Model.

Diş İmplantların Gerçek Zamanlı Yüzey Açısı Ölçümü

Özet

Diş implantları ve ilgili ürün ailesi çene sağlığı için çok önemlidir. Dental implantlar genellikle titanyum malzemelerden üretilir. Titanyum esaslı alaşımlar yüksek mekanik mukavemete sahip olduklarından, bu ürünlerin kalite kontrolü, CNC bazlı biyomateryal üretim süreçlerinde ortaya çıkabilecek olası kusurlu ürünleri önlemek için önemlidir. Ek olarak, bu parçalar görsel olarak kontrol edilmesi neredeyse imkansız olan yüksek sayıda üretilir. Yapay görme, otomatik üretimdeki insan kaynaklı hataları önler. Sunulan sistem, görüntü işleme yöntemlerini kullanarak dental ürünler için uzunluk ve açı kusurlarını tespit etmektedir. Bu çalışmanın özgün yönü, makine görmesine dayalı gerçek zamanlı dental implant hatalı ürün tespiti sistemi tasarımı geliştirilmesidir. Gri ölçekli görüntülerde titanyum dental ürünün saptanması için Gauss bulanıklaştırma filtresi ve Otsu eşiği kullanılmıştır. Ürün hattını tespit etmek için önceden işlenmiş görüntülere ortalama hataların karesini içeren doğrusal regresyon modeli uygulanmıştır. İki çizgi arasındaki açı ise, trigonometrik yöntemlerle hesaplanır. Sunulan algoritmanın sonucu olarak uzunluk ve açı ölçümleri için sırasıyla maksimum 0.0015 mm ve 0.013° mutlak sapmalar gözlenmiştir. Dental implantlar için sunulan ölçüm algoritmaları, bu hızlı algoritmaların seri üretim hatları için uygun sonuçlar verdiğini göstermektedir.

Anahtar Kelimeler: Diş İmplantı, Kalite Kontrol, Görüntü İşleme, Otomatik Eşikleme, Doğrusal Regresyon Modeli.

1. Introduction

Biocompatible materials such as 316L stainless steel, cobalt-chromium(CoCr) and titanium-6aluminium-4vanadium(Ti6Al4V) are used in medical products [1]. Dental implant products are generally made by titanium based alloys such as Ti6AlV4 because of MRI compatible and which can be integrated to bone [2]. Ti6AL4V is also superior corrosion resistance and high mechanical strength [3,4]. Since the mechanical strength of the Ti6Al4V, CNC based biomaterial manufacturing is a big challenge. The material's mechanical strength damages CNC's end mills and drills. When end mills and drills are damaged, unqualified products are produced which situation is unacceptable for dental surgeons.

In addition to challenging processes, hundreds of different shaped products are produced in mass production, such as: implants, screws, abutments etc.

Quality control in classical production lines for dental implants include human-based consideration processes. Considering all challenges about production and quality control of products, human based quality control processes are error-prone and time consuming.

Avoiding the unqualified dental implant production, machine vision based quality control process is crucial. Serial production fault detection systems have been widely used in recent studies [5–8]. Recent studies have been examined in quality control processes such as: detection of microscopic cracks [9], microscopic analysis of fractured dental implant surface [10], image guided implantology [11] in dental implant industry.

Quality control systems are generally used in the mass production lines for serial production. In order to work faster on the serial production line, algorithms must include time-saving processes. This paper represents lengths and angles measurement processes for dental implants by using low cost algorithms.

Presented dental implant angle measurement process uses surface detection by using Gaussian bluring [12], Otsu thresholding [13], root mean squared linear regression model [14] and angle measurement between two linear regression lines, respectively.

This paper is organized as follows. In the part "Materials & Methods" represents used algorithms and detailed explanations about presented methodology. Research findings are described in the "Results" part. In the fourth part, related discussions take place and the last part of the paper concludes the present study.

2. Materials and Method

This study aims to measure dental implant family products' angles and lengths measurement with time-saving processes for mass production lines. Measurement methodology and algorithms are mathematically explained in this section in details.

This study also aims to help quality controllers for specifying the surface lines and measure the angles for critical part of the figures. Algorithm of the process is given in Fig. 1 which shows the stages for the angle measurement process.

Presented research was performed at Gazi University, Engineering Faculty, Electrical & Electronics Engineering Department. Python language was used and performed in a computer with 16 GB RAM, Intel i7-7500U processor at 2.7 Ghz. In addition, images were captured by industrial type 8Mp CMOS detector with 5-50mm optical lens. Images include Bilimplant abutments for different angled products.
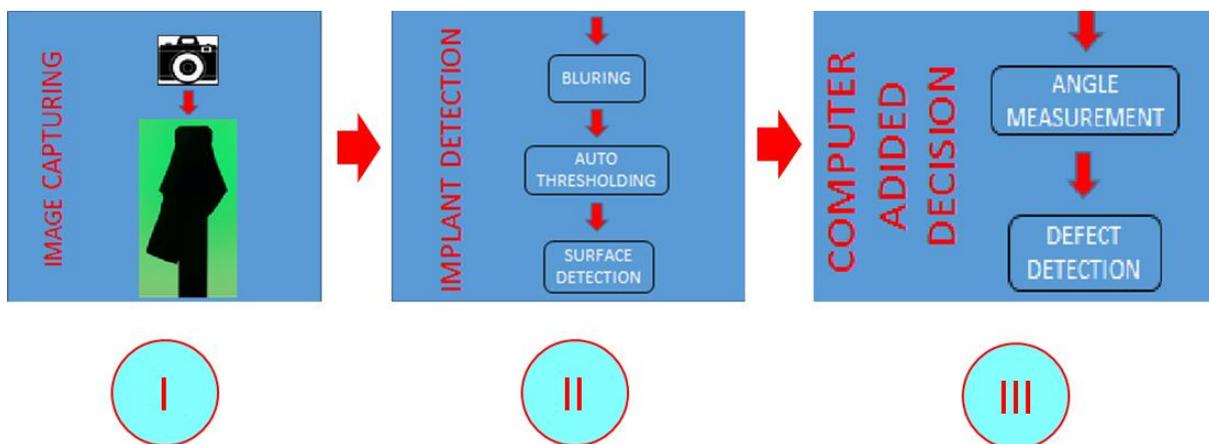

Fig. 1. Algorithm of the presented methodology

Gaussian blurring uses Gaussian function which reduces image noises. Output of the smoothing blur is enhancing image structures at different scales. Gaussian blur is two dimensional convolving the image with a Gaussian function. Gaussian blurring is a low pass filter which reduces the image's high frequency components.

The Gaussian blurring uses a Gaussian function normal distribution by using calculation of convolution for each pixel in the image. Gaussian blurring could be represented as [15];

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

where x and y is the Euclidean distance from the origin, σ is the standard deviation of the Gaussian distribution.

Otsu is a regional based automatic thresholding method which is used into image analysis in many works [16–18] for object detection. Otsu thresholding is unsupervised and nonparametric process and this methodology is applied to grayscaled images. Otsu minimizes intra-class variances and which classifies into two classes [19]. Weighted sums of variances are shown as;

$$\sigma_w^2 = \omega_0\sigma_0^2 + \omega_1\sigma_1^2$$
$$\sigma_b^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 = \omega_0\omega_1(\mu_1 - \mu_0)^2 \tag{2}$$
$$\sigma_T^2 = \sigma_b^2 + \sigma_w^2$$

where, ω_0 and ω_1 represent weights of histograms; μ shows the mean of classes and σ is variance of classes. Class weights could be given by;

$$\omega_0(t) = \sum_{i=0}^{t-1} p(i)$$
$$\omega_1(t) = \sum_{i=t}^{L} p(i) \tag{3}$$

where, $p(i)$ is the pixel value, t represents the threshold and L shows bins of the histograms. Means of classes could be represented as,

$$\mu_o(t) = \sum_{i=0}^{t-1} ip(i) \Big/ w_0(t)$$
$$\mu_1(t) = \sum_{t=0}^{L} ip(i) \Big/ w_1(t) \tag{4}$$
$$\mu_t(t) = \sum_{t=0}^{L} ip(i)$$

After the detection of the surface by using Gaussian blurring and Otsu binarization, surface detection could be done by using least squared linear regression lines. Least squared based detection is widely used in recent works for surface detection [20,21]. Linear regression line could be represented as,

$$y = mx + b \tag{5}$$

Least squared regression aims to minimizes errors by using partial derivative of determined loss function. The loss function could be determined as squares of errors between measured values and predicted values. When the partial derivatives of loss function for both m and b equal zero, errors will be minimized. Least squared linear regression could be defined as,

$$m = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{6}$$
$$c = \bar{y} - m\bar{x}$$

where $\bar{x}$ and $\bar{y}$ are means of all values, x_i and y_i are actual values. The angle between two lines also can be represented as,

$$\theta = \tan^{-1}(\frac{m_1 - m_2}{1 - m_1 m_2}) \tag{7}$$

Presented methodology is applied to dental implant abutments for Bilimplant bone level abutments. Next section presents all results for different bone level implants in details.

Presented methodology uses image capturing; implant detection by using, Gaussian bluring, Otsu thresholding and surface detection for measurement processes; line detection and angle detections, respectively.

Mean Square Error (MSE) assessment criteria is used for measured values and catalogue values for both lengths and angles. MSE could be defined as,

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{P}_i - P_i)^2 \qquad (8)$$

3. Results

Measurement of the length and angle of the abutment is critical for quality control process. Since the defect detection is crucial process, computer aided defect detection could help the quality control departments. This process is time sufficient and presented system eliminates error-prone human based quality control processes.

Presented methodology results are shown in this section in details. Bilimplant bone level wide abutments are performed for angle measurement. Gaussian blurring, otsu based thresholding, least mean square regression lines and angle measurement results are shown in this part, respectively.

Fig. 2 represents the optical measurement system for dental implants. The system has conical mandrel for fixing the abutment. Pinning on to the mandrel, dental implant abutment picture can be captured via 8Mp camera including 5-50mm optical lens.

Cmos detector based optical quality control system includes two cameras. Top camera provides correct placement for the measurement and side camera measures lengths for defined both row and column, distance between two lines and angles between two lines.
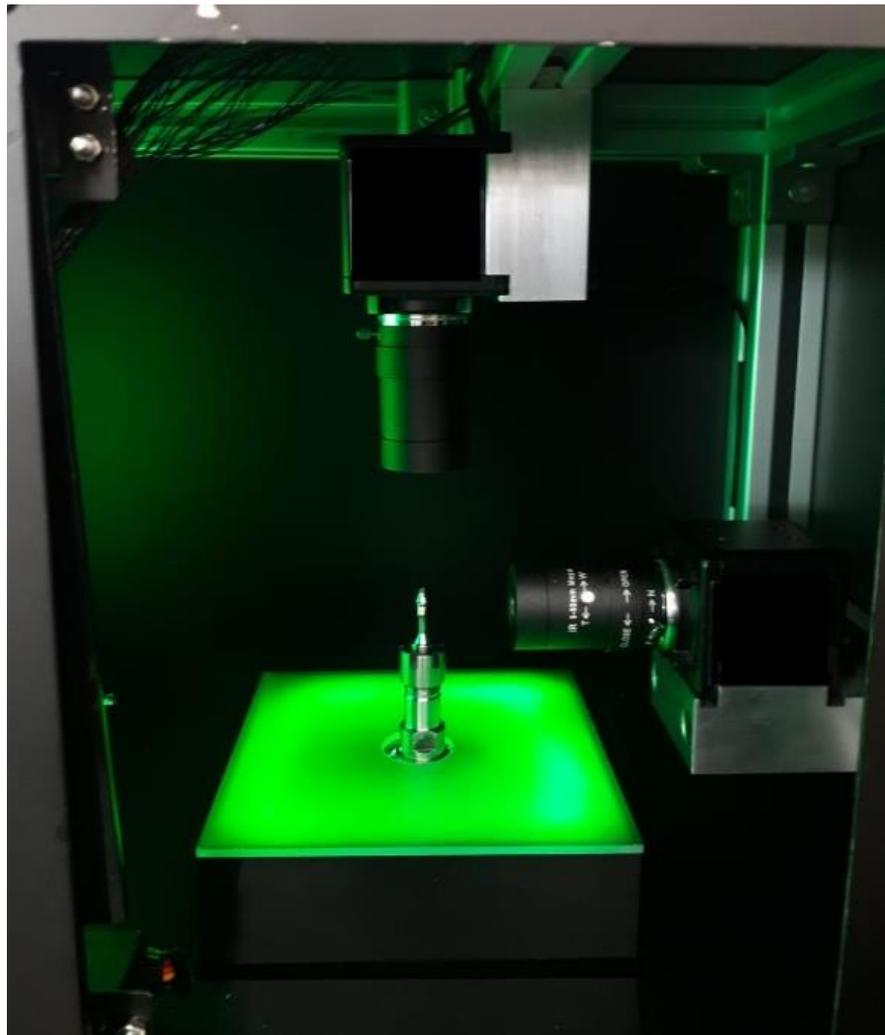

Fig. 2 Dental implant abutment measurement system

Side camera captures frames via USB by using Python based interface. Fig. 3 shows the 25° angled, 4mm, bone level wide abutment, the abutment's Gaussian blured and binarized images, respectively.
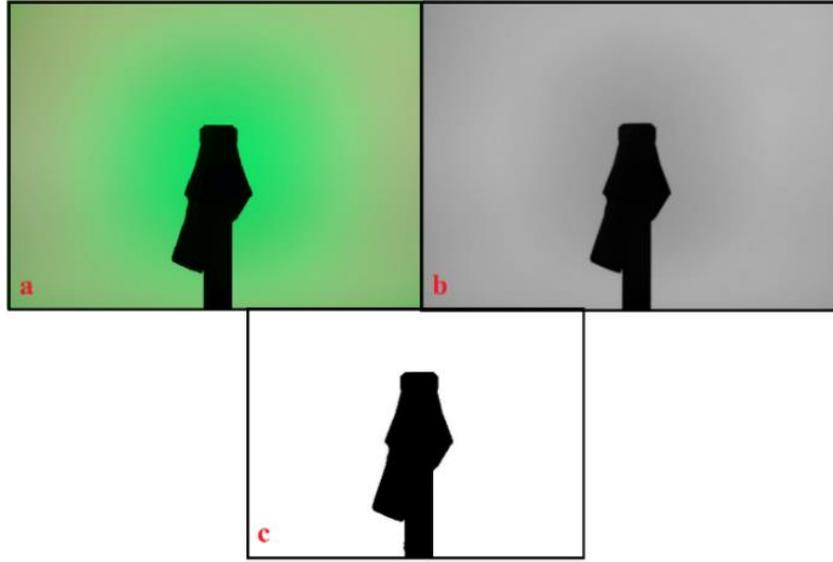

Fig. 3 a. 25° Angled, 4mm, bone level wide abutment b. Gaussian blurred image c. Binarized image

After binarization process, least square regression is applied for surface detection in the obtained binarized image. After surface selection points from the interface, least squared line is generated. Line could be generated in the defined squared error percentage which can be selected in the range of [0,1]. When two-line selection process is done, the angle between two surfaces could be measured. Fig. 4. shows the interface of the surface selection and measurement outputs.
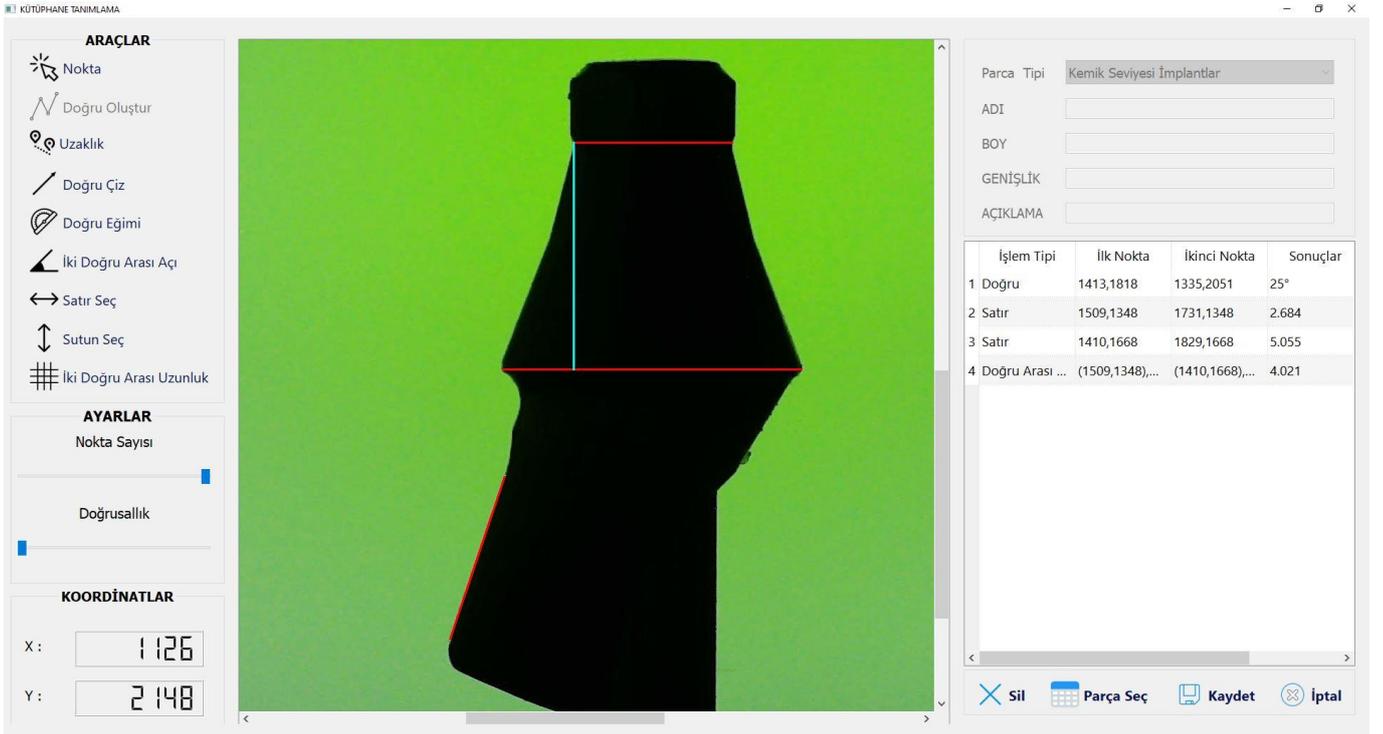
Fig. 4 Interface of the angle measurement

Presented methodology is applied to all bone level angled wide abutments produced by Bilimplant. In the production line, angled wide abutments are produced 15° and 25° angled and four different lengths to the tissue. Table 1 represents the catalogue value and measured values, respectively.

Table 1. Comparison of measurement and catalogue

Catalogue Value		Measured Value		Catalogue Value		Measured Value	
L (mm)	Angle (°)	L (mm)	Angle (°)	L (mm)	Angle (°)	L (mm)	Angle (°)
1	15	1.010	15.13	1	25	1.015	25.10
2	15	1.915	15.11	2	25	2.005	25.11
3	15	3.015	14.95	3	25	2.990	24.92
4	15	4.005	14.89	4	25	4.010	25.08

Maximum 0.0015 and 0.013° absolute deviations are observed for length and angle measurements, respectively. Presented results can be evaluated by using MSE assessment criteria. As the results of the comparison with catalogue values and measured values by using MSE, 0.001003 and 0.009812 are calculated.

3. Discussions

Presented methodology proves that surface detection could be done by using auto-thresholded images. Adjustment of the squared error percentage provides surface smoothness selection. Computer-based examinations of the obtained dental implant abutment images were also performed in the present research, and it was found that green lighted titanium (Ti6Al4V) surfaces could be detected by using CMOS detectors easily, as shown in Fig. 4.

Machine vision quality control procedure provides ease of use for detection of titanium surfaces. In addition, presented methodology represents that machine vision is time-saving method at least twenty seconds rather than human based quality control procedure.

5-50mm optical lens could be used for maximum 40mm products to measure 5µm resolutions. Repeatable success of the angle measurement is in the range of the ±0.05°. It was observed that repeatable errors are as the results of cumulating of mechanical placement error, binarization procedure, linear regression etc.

Presented results reveal that length measurement is more precise than angle measurement. It depends on the regression model uncertainty and thresholding loses.

Despite these uncertainties and losses, it has been determined that the proposed model can measure length and angle with very low deviation. Low MSE results show that represented methodology can be used for automated quality control processes.

Lightning source should be adjustable because of camera aperture selection for achieving the best performance. Experimental research shows that the light source should be given not only from a single point but also from the back of the camera homogeneously.

4. Conclusion

In the paper we found that computer-based image processing methods could help the quality control decision-making process in mass production lines. Presented hybrid methodology results show that this method is suitable for measurement of Ti6Al4V dental implants. In the view of the results, we found that the optical machine vision procedure is time-saving and dependable method. Presented results prove that quality control staff could use this system easily. In the light of this study, future works could be organized based on improving full automated procedures.

Acknowledgments

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