MULTIDISCIPLINARY APPROACH IN TOOTH WEAR: BIOMECHANICAL ASPECTS AND COMPUTER VISION

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Abstract. *Bruxism is the habit of tooth-clenching or grinding. It leads to tooth wear, among other problems. It is a parafunctional habit, meaning an abnormal movement, leading to forces that are not compatible with the tooth geometry, and resulting in high stresses. Among the consequences of Bruxism one can list loss of dental structure, fracture of restorations, temporomandibular joint disorders, head aches, loss of implants, while the sounds derived from grinding teeth may affect the quality of sleep, for the individual or eventually other members of the family (LAVIGNE et al 2008, LOBEZZO, 2001). In this paper, the quantification of the wear produced in teeth enamel of bruxers is discussed. It can be monitored via a follow up by the clinical dentist, questionnaires, molding of teeth in different moments followed by analysis of the models (FAOT, 2008). In order to try to quantify Bruxism, specialists from the areas of Dentistry, Computer Science, Material Sciences and Engineering propose the following approach, which is described in the paper: Application of a questionnaire based on DAVIES (2002) to gather subjective information on the development of the topography of the tooth surface, based in visual observation and information from the patient; Development of a computer program for image treatment based on computational vision with the purpose to follow long term wear. The computational vision was designed based on the use of pictures taken over time. The analysis relates dental wear using the difference, in number of pixels, of each tooth between the pictures. The software was developed to be able to quantify and qualify the dental loss in cases of bruxism. Based on the work developed by BASTOS (2004), the global objective is to produce a methodology that, using profilometry, computer vision tools and follow up by the dentist, help to understand tooth wear mechanisms, monitor it and contribute to the development of new and effective clinical procedures to reduce it.*

Keywords*: dental wear; bruxism; computer vision; profilometry; biomechanics*

1. INTRODUCTION

Dental wear is a pathology that bothers a large number of patients and worries Dental Heath professionals, as the derived loss in tissue is permanent and commonly lead to pain. Dental wear is often associated to Bruxism, the parafunctional habit of tooth grinding or clenching. BADER & LAVIGNE (2000) stated that the majority of the population (85-90%) will occasionally grind or clench teeth some time in their lives, ad even though the topic has been subjected to extensive research, many of its aspects are not fully understood. Loss of dental material, fracture of restorations, worsening of temporomandibular disorders or induction of serious headaches and production of inconvenient nocturnal sounds are all possible consequences of Bruxism (LAVIGNE *et al.*, 2008), as well as loss of dental implants (LOBEZZO, 2006).

It is very important the follow-up of wear evolution in clinical cases by the dentist to plan and execute an intervention. (KOYANO, 2008) noted that there is no established norm to guide the dental control of wear progression. In BASTOS (2004), the author described a study were replicas of the affected teeth were produced in different times and used to characterize wear evolution along a given period. In order to validate the procedure, she suggested the statistical validation of the replicas as valid copies for the purpose of profilometry characterization of teeth surfaces.

Digital images also were used to extract some information of wear in several cases. In HAKETA *et al.* (2004), for example, the authors present an approach the estimate the wear area of teeth using image processing principles. The method is limited to use in replicas of teeth because it need manual interference in the scene (the wear area of each tooth is painted to became more easily targetable). This may incorporate a lot of noise in the final results and is not very practical. Other works such as (YAMANY *et al.*, 1998, LAURENDEAU *et al.*, 1991) use principles of three-dimensional reconstruction to estimate the tooth wear using images. These particular processes are very complicated and need a lot of time and computation power to be use. All methods cited need also very sophisticated equipments (expensive cameras, laser sensors) and a very controlled environment (illumination, calibrated camera supports) to be well used.

In the present article, the technique for producing the replicas is improved with the use and test of a different material. A Computer Vision algorithm is also produced by researchers of the Computer Vision and Robotics Laboratory (VeRLab) in the Department of Computer Science of UFMG, to semi-automatic detect changes in tooth outer surface level due to material loss using photographs, all this in a non-structured environment and with a simple digital camera.

2. PROPOSED METHODS

Profilometry measures in a nanometric scale a given surface profile, with the possibility to be a useful tool for wear characterization. The previously developed study (BASTOS, 2004) involved a reduced sample size and with a number of shortcomings. The material used for the replicas, epoxy (Araldite ®), often presented micro bubbles, which made it impossible to continue with the measurements. This implied in repeating the complete replica procedure. A search was then done for the choice of a more appropriate material, with the choice falling into a low viscosity composite resin. The description and validation of the obtained replicas is given below.

The most convenient method to follow wear progression should be simple and accessible. The complementary method to access wear was developed based in image processing, using photos that can be taken in the clinic. By following the progression of the loss of material when considering pictures taken in two different occasions, the profilometry data can be better interpreted with the consideration of the change in the position of the middle line of the tooth outer surface. With this purpose a computer program was developed at VeRLab with the necessary robustness to allow small changes in light and angles. The program is based on the superposition of images for a given tooth, and calculates the difference corresponding to material loss.

2.1. Profilometry

In contact profilometry a fine stylus displaces over a surface registering its irregularities; the vertical displacements are used as the basis for a two-dimensional graph representing its profile. To obtain a three dimensional plot, a large number of plane profiles are interpolated. The data is registered as a set of heights corresponding to peaks and valleys (Figure 1). A large number of parameters are calculated, each for describing a given aspect of the heights distribution, and a subset of appropriate parameters can then be selected to properly define the surface (MUMMERY, 1992).

For this study, the following parameters were chosen:

1) Sa (μm/μm): average roughness,
2) Sq (μm/μm): quadratic average roughness,
3) Sdq (μm/μm): quadratic average slope,
4) Ssc (1/μm): quadratic average curvature,
5) Ssk: asymmetry coefficient for the distribution height curve,
6) Sku: curtosis coefficient.

The first and second parameters provide an insight on the heights dispersion in relation to the medium surface of the surface, while the next two help in characterizing their shapes. Asymmetry and curtosis coefficients measure the departure of the obtained surface from a standard normal distribution.

2.1.1 Replicas

As direct *in vivo* application of profilometry is not possible, the use of replicas was proposed (BASTOS, 2004). In the present study, 8 extracted teeth were used, after donation from volunteers under the proceedings approved by the Bioethics Committee.

To improve the procedure, teeth were sectioned along their long axis and then in a place parallel to the surface containing the area of interest (wear facet). The tooth fragment was then stabilized in acrylic resin. The tooth fragment was then molded with addition-curing silicone and the obtained models filled with two materials that are not usually used in Dentistry for similar applications: epoxy resin and low viscosity dental resin (Figure 2). The choice of these materials was due to the fact that they have the required fluidity to copy details of the geometry and provide specimen with sufficient hardness to support the profilometry procedure.

Profilometry tests (Hommel Tester T4000 from Hommelwerke Gmbh) were performed over selected surfaces of the eight teeth and their replicas. The selection of the sample areas was made so that they had similar areas. Filtering was then applied, using a 0.05 mm filter as proposed by BASTOS (2008). After filtering, a threshold was applied to remove very high and low height amplitudes. Comparison between the original tooth and its replica was made using 2-

tailed Student t test for paired samples, with an alpha of 0,05, described by Fisher (SAMPAIO, 2007). The comparison was done using average values of the parameters, both for tooth/epoxy replica and tooth/resin replica.

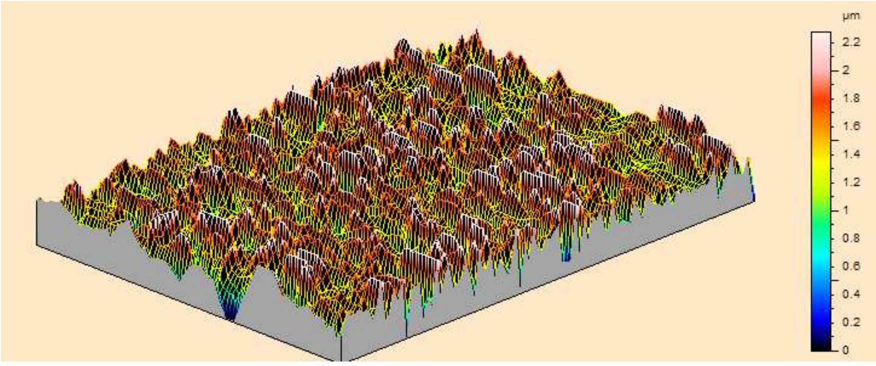


Figure 1. Wear surface as obtained by profilometry.

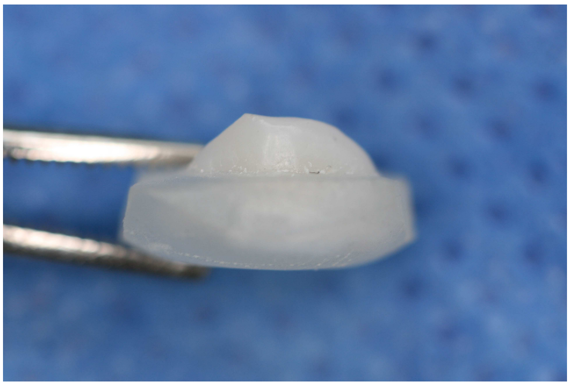


Figure 2. Sample of a copy teeth in Flow low-viscosity resin.

2.2. Computer Vision Approach

Computer Vision is the area of Science dedicated to obtaining models of the world based on digital images. We define our problem as a necessity of monitoring the tooth wear in a large time interval using just images of the mount of a patient. This is a very complicated problem, and can not be resolved by simple techniques. First, we need a very sophisticated camera with a high resolution CCD (or CMOS) sensor, because the wear we intend to measure may be very small (less than millimeters). Another problem is the illumination in the instant of the image capture, which constitute an important feature in some computer vision problems. As the tooth wear occur in large interval of time (in general, months or even years), it became impossible to keep the illumination conditions invariable in a common clinical dentist.

In order to facilitate the image processing in the computer vision algorithms, it is desirable also to keep the camera (and the patient) static between the acquisition of these images, but it is also a very problematic issue, once the time between images is very large. Even if the dentist trying to frame the image in order to match with images taken months later, the final result will be a variance of the original one, because camera parameters such as focal distance and lens distortion. The camera can also change in this time.

The methodology presented in this part of the paper was developed with the requirements of to be robust to all problems discussed above. We try to estimate the tooth wear of a patient comparing images taken in different instant times and with different illumination and camera view conditions. With this, it is possible to estimate the tooth wear from images taken by a non-calibrated camera in a non-calibrated environment, which represents a common clinical dentist.

The proposed method is divided in three steps: (I) a re-projection of the images using projective geometry, (II) segmentation of each tooth and (III) the estimation of the tooth wear using the profile. This profile is represented by a function that describes the shape of the tooth when the image was taken. The method uses optimization techniques to compare tooth wear in different intervals reducing the error arising from image processing. The method uses as input photographic images and provides a qualitative estimation of dental wear in a given period.

2.1.1 Projective Transformation

In this first step, we have two images taken from the same patient (but not necessarily with same camera). These images may present different illumination conditions and perspective views, but they represent the information of the same patient. We can call *I* the image taken before the teeth wear (without wear), and *I'* the image taken after the teeth wear (some months after). As we comment before, the image planes define by the camera in different instant times may have a different position in space, as can be seen in Figure 3. If we taken a image form a scene with distinct views, the information of the image (represented by the points *x* and *x'* correspondent to the *X* point on the scene) will certainly be different. This must be treated before compare the differences in the image relative only to the tooth wear.

In order to be able to compare directly the images *I* and *I'*, we must first align the image plane on the space. This will permit to correct the effects of scale between the images (due to the distance or zoom variation of the camera), and the rotation in relation to the scene. This alignment can be made by estimating the function that represents the geometric variation between these two images in the space. This function is generally called projective transformation.

The projective transformation is widely used in computer vision as it is able to describe different views of the same scene in the 3D space (GRACIAS, 2000). This transformation is modulated by the homographic function (2D projective transformation), defined as a function H (FORSYTH & PONCE, 2002). It needs correlated points in the same plane in 3D space in different images, as shown in Figure 3.

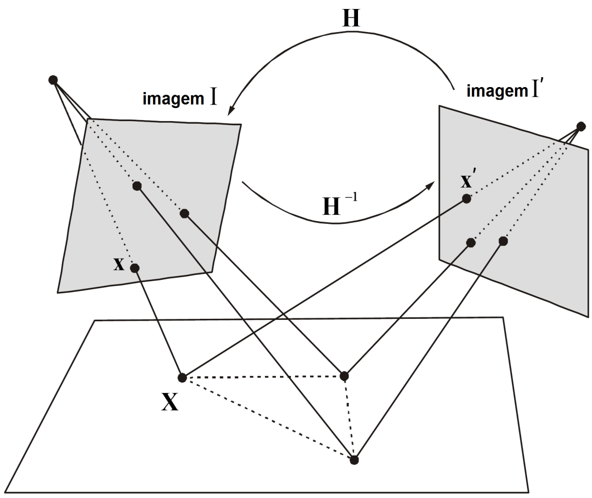


Figure 3. Projective transformation between two different view of the same scene.
Source: NEVES (2006).

The projective transformation is able to describe several types of movements. The most simple is the rigid model that may model rotation and translation. The similarity model represents scale, rotation and translation. The projective model represents all distortion in images: rotation, translation, scale, shear and projective distortion. In this work a projective model is used since tooth images are difficult to be acquired in general.

In order to be able to estimate the projective transformation between two images, we need to find some correspondent points among them that describe the same points in the three-dimensional scene, as seen in Figure 3. To do so, we must employ a technique that is robust to the illumination problem mentioned before. Then, we use the SIFT as a methodology to determinate such points.

2.2.2. SIFT (Scale Invariant Feature Transform)

The Scale Invariant Feature Transform (SIFT) (LOWE, 2004), is an efficient filter to extract and describe key points of images. It is robust method to treatment of noise, bad illumination, occlusion and minor changes in viewpoint, diminishing mismatches in points matching. Figure 4 shows an application example.

The algorithm has four major steps:

- **Scale-space extreme detection** - The first stage searches over scale space using a Difference of Gaussian function to identify potential interest points.

- **Key point localization** - The localization and scale of each candidate point is determined and key points are selected based on stability measures.

- **Orientation assignment** - One or more orientations are assigned to each keypoint localization based on local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned orientation, scale, and location for each feature, thereby providing invariance to these transformations.

- **Key point descriptor** The local image gradients are measured at the selected scale in the neighborhood of each key point. These are transformed into a representation that allows for significant levels of local shape. The description vector is divided by the square root of the sum of squared components to obtain partially illumination invariance.

Figure 4. Application Example of SIFT.
Source: LOWE (1999)

In this work, SIFT is used to match points of the same tooth in different images, and with this information it is possible to retrieve the homography matrix and adjust the point of view for each image. However SIFT is not perfect, since it will not automatically discard outliers, i.e., pair of points that are incorrectly matched. In this work, we use the epipolar geometry along with robust estimators were used to to tackle this problem. This geometry is described in a lot of works (HARTLEY & ZISSERMAN, 2003; ZHANG, 1998; TRUCCO & VERRI, 1998).

The RANSAC algorithm (RANdom SAmple Consensus) (FISCHLER & BOLLES, 1981) is used to robustly estimate the epipolar geometry. It consists of an iterative method to estimate parameters of a mathematical model from a set of observed data which contains outliers. It is a non-deterministic algorithm in the sense that the result is provided up to a probability, which increases with the number of iterations. Finally, after the outliers are removed, the transformation to adjust the point of view for all images is estimated. After this step, the tooth profile is determined using segmentation in the images.

2.2.3. Image Segmentation

Image segmentation is one of the key problems in computer vision area, and it can be described as labeling every pixel according to an equivalence class. Ideally the classes correspond to distinct objects in the scene. In other words, the result of image segmentation is a set of regions or a set of contours extracted from the image. The equivalence class may be defined based on characteristics such as pixel color, intensity, and gradient. Typically, segmentation is used as one of the steps for object recognition from images.

After correct the images in the previous step, we will apply a segmentation algorithm to identify the tooth in the images. To do so, we use a very simple approach based on the assignment of a threshold to binarize the image. This image is use to estimate the profile of the tooth.

2.2.4 Estimation of Tooth Profile

A profile in the image can be considered as a representation of data where each vector index represents the higher (or lower) intensity in the image corresponding to a pixel classified as Tooth for each column of this image. So, the profile represents the outline of the tooth in the image as a function of its lines and columns. In order to obtain this profile an edge detector was used. A few examples of edge detectors are Canny, Sobel, Prewitt. Once the profile has been obtained for each image that will be used in the comparison, the next step is to estimate the wear across time intervals. This is basically performed by estimating the difference between these profiles.

2.2.5 Estimation of Tooth Wear

At least, all profiles estimated previously could be used to generate some kind of estimation of tooth wear in the given time intervals. The homography matrix can include error which difficults the perfect equivalence between two profiles. To minimize those differences it can be used an optimization method: the Levenberg–Marquardt Method. This method have been demonstrated a very robust tool to optimize non-linear functions. In this case specifically, the considered functions are the profiles of the chosen tooth (d). The chosen transformations are affine in nature like translation, rotation, so that the geometry would not be changed, in order to not introduce error in the system. In general, the Levenberg–Marquardt Method, minimizes the differences making it possible the comparison without noise.

3. RESULTS AND DISCUSSION

3.1. Results of Replicas

The values of t were calculated for each parameter according SAMPAIO (2007), using an Excel spreadsheet. After the calculus of t of Student a table that expresses the difference level of significance. In this level, and with 7 degrees of freedom, the value given by the table is 2.365. In these conditions, the value of t calculated for each parameter must be within the interval of -2.365 and +2.365 (2-tailed alpha) for no difference. Tab. 1 shows the founded values and indicate that the copies in resin as well the copies in epoxy are not statistically different from the original tooth at 95% significance. That means that it is possible to use models both in epoxy and in Flow resin to study superficial texture. In this case, the study *in vivo* is possible and superficial changes that are not detected by other methods in a short period of time, could be used. The use of copies in Flow resin allows an improve for replica achievement. In, this paper only the steps of validation and materials tests were made, but in the future, this methodology will be connected to the Computer Vision methodology to try to evaluate the dental loss in a single population aiming the prediction of dental wear.

Table 1. Means and *t* for *Sa* and *Sq Sdq Ssc Ssk* and *Sku* for surfaces in the tooth and in epoxy and in flow resin replies

Parameters	Tooth	epóxi		flow resin	
	Value	mean	t	mean	t
Sa	0,27[a]	0,26[a]	1,33	0,28[a]	-0,36
Sq	0,35 [a]	0,33 [a]	0,94	0,30 [a]	1,60
Sdq	0,10 [a]	0,17 [a]	-1,10	0,10 [a]	-0,22
Ssc	0,10 [a]	0,16 [a]	-1,62	0,14 [a]	-1,46
Ssk	-0,17 [a]	-0,09 [a]	-1,45	-0,06 [a]	-2,02
Sku	3,34 [a]	3,31 [a]	0,21	3,29 [a]	0,46

Same letters in same line indicates that there is not significant difference among parameters means on the tooth, epoxy and flow resin replies surfaces. ($t_{7DF,\ 2\text{-tailed alfa } 5\%}$ = 2,365)

3.2. Computer Vision

To test the method, images taken from a model in plaster of a human arcade were used. This model was used to simulate wear without having to wait for long periods of time. Afterwards, the same method was used for images of real tooth. Later, the program was tested with photographs taken from a patient for a period of 18 months.

3.2.1. Test with Models

A model in plaster that was grinded in the canine was used in this phase. In order to determine the transformation matrix between those two images, the SIFT algorithm was used producing corresponding points in both images, as described before. Correspondences can be seen in Figure 5, where blue lines connect matched points in both two images.

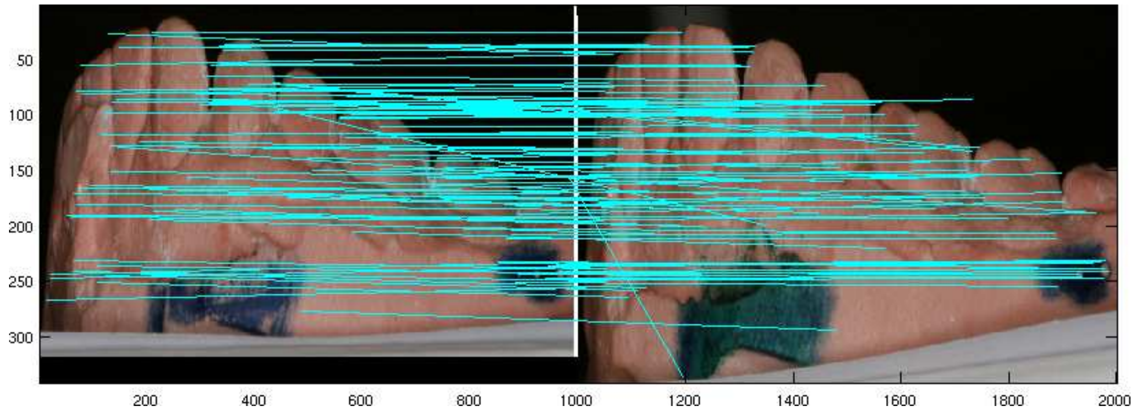
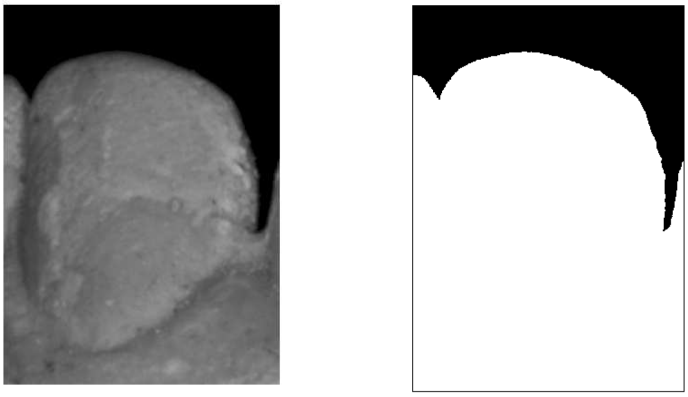


Figure 5**.** Corresponding points in both images using SIFT.

In order to register both images, the homographic transformation that was determined from the correspondence step using SIFT was applied to the second image (tooth with wear). This registration step enables viewing the second image as if it was taken from the same camera pose as the first one.

The next step is the identification of the tooth profile. In this case, primer is done a manual selection of a section from the images of this singular tooth. The Figure 6 (a) presents the cut on the original image of the canine without wear. From this section of the image, is done the segmentation to determinate the correspondents pixels. The process generates binary images like those shown in Figure 6 (b) in relation to Figure 6 (a).



(a) (b)

Figure 6 (a) section of the original image (Figure 5) and (b) its binary image.

The threshold value chosen for the segmentation of this image was estimated from the intensity histogram. In this particular case, a intensity pixel value of 40 (in 255) was chosen. All the pixels with intensity values above this threshold were classified as *Teeth*. From image 6 (b) it is simple to determine the tooth's profile by the simply applying an edge detection step using one of the several methods in the literature, such as Canny, Sobel, etc.

The final step consists of comparing the profile of the tooth as registered by the time spanned images. Now, the profiles of the same tooth taken at different times can be compared directly in the same scale (number of pixels) of the image. For example, Figure 7 is the result of applying the transformation to the second image profile.

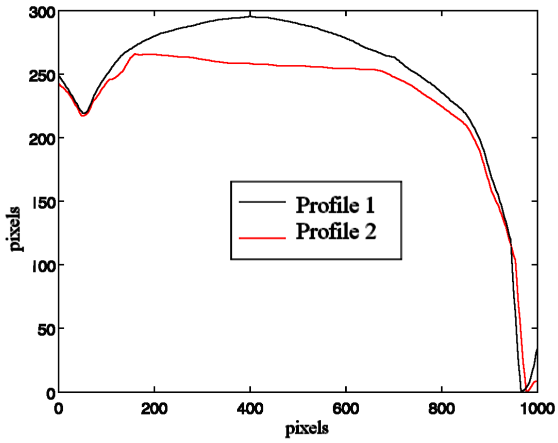


Figure 7. Comparison between two profiles after the process of optimization.

Finally, as we can see, it is necessary to convert pixel values into real metric values, in order to know the tooth wear in terms of a millimetric area. To do so, we need to know the relationship (constant K_p) between pixels in the image and distance in the real world. In other words, we desire discover how many millimeters a pixels can represent on the image plane. This is easily accomplished with a simple calibration step using a precise target (a millimetric ruler, for example) whose image is acquired and computed as pixels/ millimeters (pixel/mm). We can directly convert the different area between the profiles of the Figure 7 multiplying this value by K_p.

3.2.2 Tests with Real Tooth

In the sequence, images taken directly from the patient's mouth were used to test each step of the method. All the steps of the procedure described above were followed but with images taken at three distinct time intervals. Figure 8 presents the final result of the comparison among profiles. Tooth wear, which corresponds the difference of areas, which is estimated by computing the area under the curves, was found to be: 0.1 mm^2 for the second image in relation to the first, and 0.18mm^2, from the third image with respect to the first one. As it is the case of any real system, the presented method is affected by noise, which at this moment in the study, it has not been estimated. However, the results show that the both the proposed technique and method are applicable.

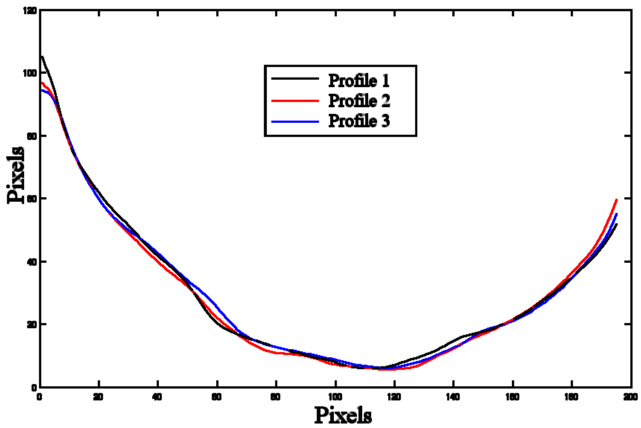


Figure 8. Final result to the application of the methodology with images of real teeth.

3.2.3. Tests with Volunteers Replica

Finally, tests with volunteers models based on profilometry replicas (Figure 2) were made to verify the applicability of the method. In this case, the tooth is also a canine of a different patient. The time difference between images was of approximately six months.

The final result, comparing among profiles (in difference of pixels) is presented in Figure 9. The determined value was 1.2. Again, it is possible to notice a significant difference between the two profiles that possibly correspond to teeth loss due to dental grinding.

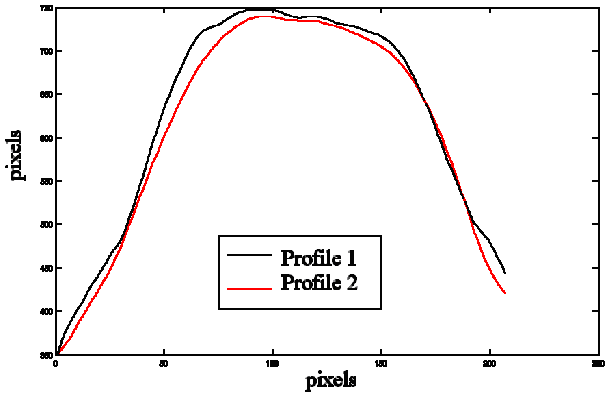


Figure 9. Final result using pictures of replicas.

It still remains to be determined how to estimate tooth wear from the obtained results. One possible solution is to estimate quantitatively or qualitatively. This study is under way and one of the priorities is to define a quality metric from the noise free estimative. Statistical validation of the results was not possible yet due to the small sample size. Nevertheless, preliminary results indicate very promising applications and it motivates the continuation of the study. One very important issue to be considered is noise. There are a several methods of noise reduction on images, and applying more precise segmentation methods and improving image resolution may also help in obtained better quality images with better signal to noise ratios.

The biggest advantage of this method is that it establishes a foundation for automatic wear estimation using images acquired in a very simple way. As it is, the method does not require any special lighting calibration or specific camera angles and positions, which means that it could be easily used at any dental office where typically these conditions are not controlled and even if they were, it would be very difficult to guarantee they would remain the same for long time intervals. In the future, we understand that it will be possible to apply this method to estimate the volume of dental loss, by taken and processing several pictures from the same teeth from different views.

4. CONCLUSIONS

Profilometry seems to be a very sophisticated research method and replicas have shown to be adequate to reproduce superficial texture which makes it practical to perform *in vivo* study. The detection of the initial wear without the dental structure loss in macro scale is an advantage, another one would be the study of texture parameters and their relationship to wear mechanisms. The use of replicas in studies was successfully tested. The improvement in model's technique, including the use of Flow resin, made it easier to use profilometry.

As the digital image technology and the use of computer vision algorithms increases in several areas, the use of photographs and Computation Vision seems to be an accessible solution and viable way to obtain precise data. The main problem is that these processes are very affected by external factors such as illumination, perspective views and camera parameters, which makes the problem very complex. In this study, a method that can effectively help clinicians to measure dental loss due to dental wear in a very simple and less dependent of external factors was presented and tested. These studies could contribute to the research and development of biomaterials.

Both methods present here still are under development and presented very promising results. As future works, the application of both methodologies to one single group is intended to evaluate the process of dental wear. We also intend to analyze the error in the image processing methodology in order to reduce the noise in each step of the process. We desire to make all these steps as automatic as possible to facilitate the use by dentists. This method still may be extend to estimate the volume loss of teeth, as mentioned before, which constitute a more complicated problem from the Computer Vision point of view.

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6. REFERENCES

Armangue, X., Salvi, J., “Overall view regarding fundamental matrix estimation”. Image and Vision Computing, p 205-220, 2003.

Bader, G., Lavigne, G., “Sleep Bruxism; an overview of an oromandibular sleep movement disorder”, Sleep Medicine Reviews. vol 04, p 27-43, 2000.

Bastos,F.S., “Avaliação da Textura Superficial e Comportamento ao Desgaste ao Esmalte Dentário”. 2004. 94p. School of Engeneering, Universidade Federal de Minas Gerais, Belo Horizonte.

Bastos,F.S. “Análise Numérica do Contato Oclusal, Atrito e Desgaste Dentário Humano”. 2008. 162p. School of Engeneering, Universidade Federal de Minas Gerais, Belo Horizonte.

Fischler,M., Bolles,R., “Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography”, Communications of the ACM, v 24, p381-395, NY, USA, 1981.

Gracias, N., Santos, V.J., “Underwater Video Mosaics as Visual Navigation Maps”,Computer Vision and Image Understanding, v 79, p 66-91, 2000.

Haketa, T., Baba, K., Akishige, S., Fueki, K., Kino, K., Ohyama, T., “Accuracy and precision of a system for assessing severity of tooth wear”. International Journal of Prosthodontics, v 17, p 581-584, 2004.

Hartley, R., Zisserman, A., “Multiple View Geometry in Computer Vision”, ed.2, Cambridge University Press, 2003. 672p.

Koyano,K., Tsukiyama,Y., Ichiki,R., Kuwata,T., “Review Article: Assessment of Bruxism in the clinic”. Journal of Oral Reahabilitation. 35, p 495-508. 2008.

Laurendeau, D., , Guimond, L., Poussart, D., “A Computer-Vision Technique for the Acquisition and Processing of 3-D Profiles of Dental Imprints: An Application in Orthodontics”. IEEE Transactions on Medical Imaging. Vol 10. No. 3. Septermber, 1991.

Lavigne,G.J., Khoury, S., Abe,S., Yamaguchi,T., Raphael,K., “Review Article: Bruxism Physiology and Patology: an overview for clinicians”. Journal of Oral Reabilitation. 35, p 476-494. 2008.

Lobezoo,F., Zaag,J.V.D., Naeije, M., “Bruxism: its multiples causes and its effects on dental implants -an updated review”. Journal of Oral Reabilitation. 33, p 293-300. 2006.

Lowe,D., “Object Recognition From Local Scale-Invariant Features”. International Conference on Computer Vision, p 1150-1157, 1999.

Lowe,D., “Distinctive Image Features From Scale-Invariant Keypoints”. International Journal of Computer Vision,v 60, p 91-110, 2004.

Mummery,L., “Surface Texture Anaslysis: The Handbook”.West Germany:Hommelwerke GmbH, 1992.105p.

Neves,R., “Localização e Navegação de Robôs Móveis a Partir de Mapas Visuais”. Rio Grande – RS, Brazil, 2006.

Forsyth D. A., Ponce, J., “Computer Vision: a Modern Approch”, ed.1, Prentice Hall, 1998. 693p.

Rousseeuw,P., “Least Median of Squares Regression”, Journal of the American Statistics Association, v 79, p 871-880, 1984.

Salvi,J., Armangue,X., Pages,J., “A Survey Addressing the Fundamental Matrix Estimation Problem”, International Conference on Image Processing, v 2, p 209-212, 2001.

Sampaio,I.B.M., “Estatística Aplicada á Experimentação Animal”. 3° ed. Belo Horizonte.FEPMVZ Editora, 2007.264p.

Stewart,C.V., “Robust Parameter Estimation in Computer Vision”, Society for Industrial and Applied Mathematics Review, v 41, p513-537, Philadelphia, PA, USA, 1999.

Torr, P., “Bayesian Model Estimation and Selection for Epipolar Geometry and Generic Manifold Fitting”, Microsoft Research, 2002, MSR-TR-2002-29.

Trucco, E., Verri, A., “Introductory Techniques for 3-D Computer Vision”, ed. 2, Upper Saddle River, NJ: Prentice Hall, 1998. 343p.

Yamany, S. M., Farag, A. A., Mohamed, N. A., “Orthodontics Measurements using Computer Vision”. Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 20, No 2, 1998.

Zhang, Z., “Determining the Epipolar Geometry and its Uncertainty: a review”. International Journal of Computer Vision, v 27, p 161-195, 1998.

7. RESPONSIBILITY NOTICE

The author(s) is (are) the only responsible for the printed material included in this paper. The experiments in this work were approved by the Bioethics Committee of UFMG under process UFMG-ETIC 300/03.