A Multibiometric Approach in a Semi Automatic Dental Recognition Using DIFT Technique and Dental Shape Features*

Elizabeth Bonsaglia Barboza
São Paulo State University - UNESP
School of Sciences
Bauru, São Paulo, Brazil
elizabeth@fc.unesp.br

Aparecido Nilceu Marana
São Paulo State University - UNESP
School of Sciences
Bauru, São Paulo, Brazil
nilceu@fc.unesp.br

***Abstract*—Teeth are one of the most important and popular biometric characteristic used in Forensic Dentistry. The development of automatic or semiautomatic, robust and precise forensic human identification systems are crucial for forensic, principally in mass disasters, like tsunamis and airplanes crashes. In this work we propose the use of the Differential Image Foresting Transform (DIFT) to extract the teeth and dental work contours from panoramic dental radiographs that are used as dental features. The shape descriptors based on the Shape Context method and Beam Angle Statistics (BAS) were implemented and evaluated for the teeth recognition. The Dental Code technique was used to evaluate all dental works, including the restorations. The experiments were carry out using a database of 1126 teeth images, obtained from 40 panoramic dental radiograph images from 20 individuals. The multibiometric approach improved the system performance generating, in the best case, an EER of 9%.**

Keywords- Multibiometrics; Forensic Dentistry; Dental Recognition; Image Forest Transform; Shape Context, Beam Angle Statistics, Edit Distance.

I. INTRODUCTION

The dental appearance is one of the most important and popular biometric characteristic, particularly used in the field of Forensic Dentistry [1].

The great difficulty in using dental characteristics in forensic identification, in comparison to other biometrics, is that the teeth appearance can change significantly throughout life.

In Forensic Dentistry, the human experts perform manual comparisons between ante-mortem (AM) and post-mortem (PM) dental records, searching for differences among the teeth, noting down all the differences found in each tooth [2]. This task requires much time and practice and is very susceptible to errors [2, 3], hence the importance of developing robust automatic or semiautomatic techniques for dental segmentation.

In this work it is proposed a semiautomatic dental recognition method, completely described in [4], composed by the DIFT (Differential Image Forest Transform) [5] method to teeth and dental work segmentation and Shape Context [6], Beam Angle Statistics (BAS) [7] and Dental Code [8] as shape descriptors, using multi-biometrics techniques.

On a database composed of 2 panoramic radiograph images of 20 individuals, the experiments showed that the adopted segmentation algorithm can accurately delineate the 1126 teeth contours, as confirmed by a human expert.

The dental recognition accuracy can be considered promising since the fusion of the teeth's and dental works' characteristics, performed by BAS and Shape Context methods and Dental Code (Edit Distance), respectively, showed better results than each individual technique. With the fusion, it was possible to obtain an EER (Equal Error Rate) of 9% and 65% of correct identification using rank equal to 1. This corresponds to a decrease of 4%, comparing with the best individual results. These results were achieved even with some poor quality of the radiograph images.

This paper is structured as follows. Section 2 describes the DIFT segmentation algorithm. Section 3 describes the shape description methods (Shape Context, BAS and Dental Code). Section 4 presents the semiautomatic dental recognition approach proposed in our work, as well as the multibiometric experiments. Section 5 presents the experimental results and, finally, Section 6 presents the conclusion of our work.

II. DIFFERENTIAL IMAGE FORESTING TRANSFORM

In this work, we have adopted a semiautomatic image segmentation algorithm based on Differential Image Foresting Transform (DIFT) in order to segment the teeth in the ROI of panoramic dental radiographs images.

The DIFT is based on the IFT method, which is a general tool, proposed by Falcão et al. [9], for the design, implementation, and evaluation of image processing operators based on connectivity.

The IFT defines a robust and efficient minimum-cost path forest in a graph given a set of seed pixels which are the roots of a forest in which the region grown must begin [9].

In the IFT approach, the image is considered a graph where the nodes are the image pixels, and the arcs are defined by an adjacency relation between the pixels. A simple path p in this graph is a distinct and adjacent nodes sequence. Every path p has an associated value cost $c(p)$ determined by a path-cost function, which usually depends on local image properties, such as color, gradient, and the

* Article related on Master's thesis (WTD)

node position along the path. A path p is called optimum if $c(p) \leq c(t)$ for any other path t with the same fate as p. In typical applications of IFT, normally, the search is restricted to paths starting in a predefined set S of seed pixels.

The IFT assigns a minimum cost path starting from the set of seeds to each graph node, so that the union of these paths forms an oriented forest, spanning the entire image, producing three attributes for each pixel: its predecessor node in the optimal path, the path cost, and the corresponding root node [9].

Fig. 1(a) shows an example of an image graph with 4-connected adjacency, the numbers are the pixels intensities, and the seeds are represented by the two bigger black dots. The Fig. 1(b) is the optimum path forest for the path cost function f_{max}, with the pixels costs and predecessors [10].

The IFT-based image segmentation can be used in an interactive way, in which the user has to select some internal and some external points (seeds). After the image segmentation, the user can do some corrections in the leaking regions. The segmentation with interactive corrections (changes on the IFT seeds sets) depends on the optimum-cost path update, based on the new set of seeds. In the original IFT approach, after the seed set updating, it is necessary to recalculate the forest.

The Differential Image Foresting Transform method (DIFT), proposed by Falcão and Bergo [5], solve this problem efficiently by updating the segmentation result with processing time proportional to the number of vertices in the modified forest regions. The DIFT key idea is to allow seed addition and removal of optimum-path trees in a differential way. When a pixel is added to the seed set, it may define a new optimum-path tree by invading the influence zones of other roots. When an optimum-path tree is removed from the forest, its pixels become available for a new dispute among the remaining roots.

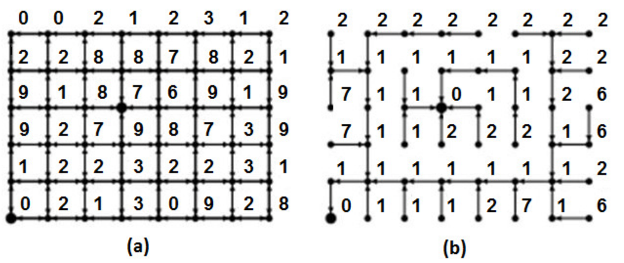

Figure 1. IFT – Minimum-cost path. (a) Image graph with 4-connected adjacency. (b) Optimum-path forest. The internal and external seeds are represented by the two bigger dots. Source: [10].

III. TEETH SHAPE DESCRIPTORS

In the proposed method for human identification by means of its dental characteristics, the teeth and all dental work are used as biometric features. Therefore, the performance of two very popular and efficient shape descriptor methods were applied and assessed for teeth shape recognition: Shape Context [6] and Beam Angle Statistics (BAS) [7] for teeth shapes and Dental Code [8] for dental works information.

A. Shape Context

Shape Context is a descriptor that measures the similarity between two shapes in digital images [6]. In order to calculate the descriptor, for each shape point p it is necessary to compute a log-polar histogram, regarding the distances and angles from p to all other shape points q. The angle is measured in relation to the abscissa axis of the image space.

Fig. 2 presents examples of shape context descriptors for three shape points. Fig. 2(a) and 2(b) present two distinct shape contours of the same tooth. Fig. 2(c) presents the log-polar histogram composed by 60 bins (six distance values and 12 angles). Fig. 2(d) shows the displacements existing between the two shapes. Fig. 2(e), 2(f), and 2(g) show the histograms calculated for shape points 1, 2 and 3, respectively. It is possible to observe the greater similarity between the shape points 1 and 2, compared with the shape points 1 and 3.

After calculating the alignment costs of all points of both shapes, it is verified what is the minimum global cost. This minimum cost is used to measure the similarity between both shapes (the cost is normalized by using the total number of points) [6].

The Shape Context is a descriptor that expresses the configuration of the entire object shape relative to a reference point. To have a reliable description it is important that the segmented object has many border points [6].

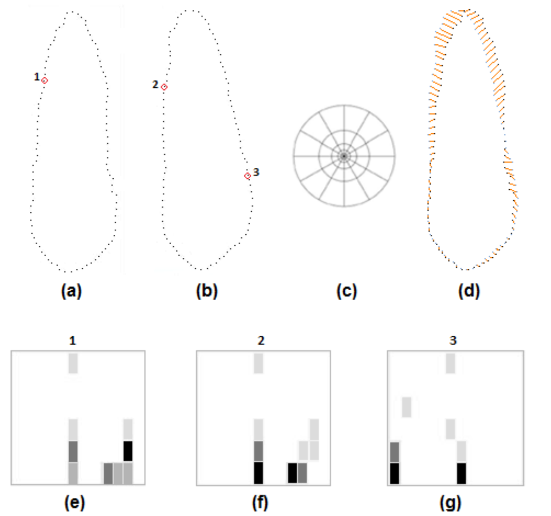

Figure 2. Shape Context descriptor. (a) and (b) Shape contours of the same tooth. (c) Log-polar histogram. (d) Displacement existing between the two shapes. (e), (f) and (g) Histograms calculated for shape points 1, 2 and 3, respectively. Source: [11]. Adapted from [4].

B. Beam Angle Statistics

The Beam Angle Statistics (BAS) shape descriptor method is based on beams, which are the lines connecting the reference shape point p with all other shape points q.

The characteristics of each shape point are extracted by using the angles between each pair of beams [7]. From these angles, taken as random variables at each point on the shape, the moment theorem is applied to provide statistical information. In the functions expressing the moments the valleys and hills corresponds, respectively, to concave and convex parts of the object shape.

The moments describe the statistical behavior of the beam angles at the shape points and are stored in a vector. In practice, to represent a shape, it is taken usually only the first two moments (mean and variance).

In Fig. 3 are presented the first two moments calculated from the shape of the same tooth, extracted from two different radiograph images.

One of the advantages of BAS method is that it is naturally invariant to rotation and scale transformations, since it is based on beam angles. Likewise Shape Context, BAS is invariant to translation [7].

The similarity measure between two shapes is determined by the best alignment cost between them, obtained from the features of the first two moments [7].

C. *Dental Code*

The method used for dental work description was proposed by Hofer & Marana [8] and consider the position and the distance between segmented objects in the image to form a code that represents de image: the dental code (DC).

After the segmentation step, which is performed by means of a grayscale thresholding, it is necessary to know whether the tooth belongs to the maxilla (upper jaw) or to the mandible (lower jaw). For this, a border between the maxillary and the mandibular teeth is detected. So, the location of the DW (Dental Work) is represented in the DC (Dental Code) with the letters "L" (Lower) or "U" (Upper).

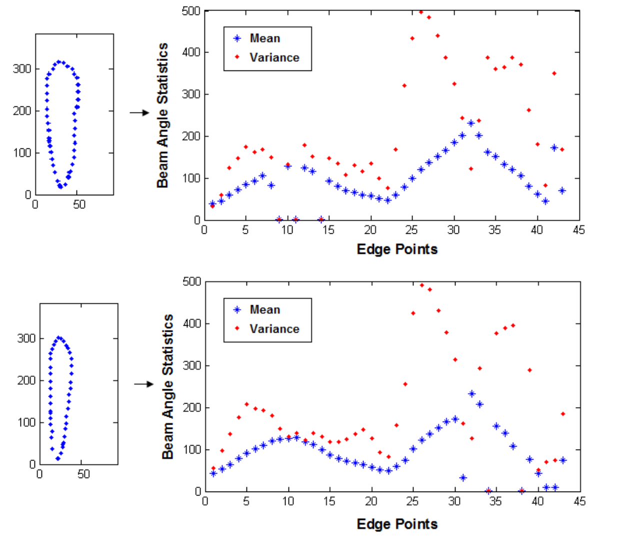

Figure 3. BAS descriptor. Top: First two moments of a tooth shape. Bottom: First two moments of the same tooth, extracted from a different radiograph image. Source: [11]. Adapted from [4].

The segmented objects in the image are enumerated, from left to right, considering their centers of mass. Then, the distance between two neighboring DWs is included into the DC, in order to make it more discriminative. The areas (amount of pixels) of each object are also calculated and included into de DC. [8].

Therefore, the DC composed by the letters L or U, followed by the area of the DW and, finally, by the distance between the centers of mass of the current DW and its predecessor, as shown in Fig. 4.

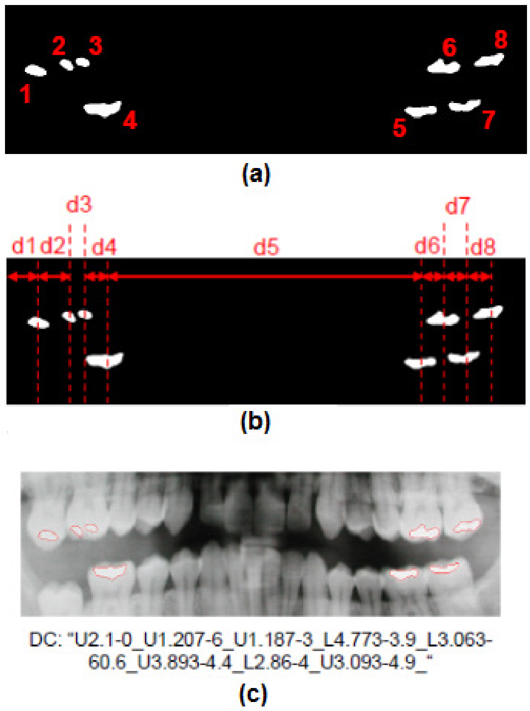

Figure 4. Dental Code descriptor. (a) Dental work enumeration. (b) Centers of mass distance. (c) Final dental code of a dental panoramic radiograph. Source: Adapted from [8].

With the DC created, they are compared through an algorithm which works with the "Edit distance" (Levenshtein distance) [8].

IV. MULTIBIOMETRIC METHOD

This work proposes a semiautomatic dental recognition method that uses a graph-based segmentation algorithm (DIFT) and teeth shapes (Shape Context or BAS) and dental work information (Dental Code) as biometric features, applied on panoramic dental radiograph images.

After the segmentation using the DIFT-based algorithm, the teeth contours and dental works information are used as biometric descriptors. In the matching step, the PM panoramic radiographs descriptors are compared with the AM panoramic radiographs descriptors, previously stored in the database, and a decision about the identity of the PM query image is obtained.

The teeth shape-based recognition method consists in selecting manually, by the user, a region of interest (ROI).

The ROI is a rectangle that completely encloses the tooth's crown and root and from where each tooth is segmented. Fig. 5 presents a diagram of this method.

For both teeth descriptor methods (BAS and Shape Context), the shapes of each particular tooth i of an individual in the AM and PM images are compared, generating a local cost value, c_i. The global cost S between the AM and PM radiograph images is defined by (1), in which Q_A and Q_B are the number of teeth present in the two compared radiographs and n is the number of teeth compared between them.

$$S = \left[1 + \frac{(Q_A - Q_B)^2}{32^2}\right] \frac{1}{n} \sum_{i=1}^{n} c_i \qquad (1)$$

For the dental work-based recognition method, the dental codes are compared. The cost of the dental work similarity is calculated based on Edit Distance method proposed by Hofer and Marana and descript in [8].

To improve correct recognition rates, this work proposes a multibiometric system that fuses the semiautomatic dental features obtained by the teeth and dental work information through DIFT [5] and BAS [6], Shape Context [7] and Dental Codes [8] methods.

The goal is to apply fusion techniques, especially in the levels of Rank and Score, like Highest Rank Fusion, Borda Count Rank Fusion, Lowest Score and Score Sum Fusion, linking information obtained from the segmentation of the teeth contours with dental work. In Fig. 6 it is shown a simplified diagram of the proposed approach for the multibiometric human forensic recognition.

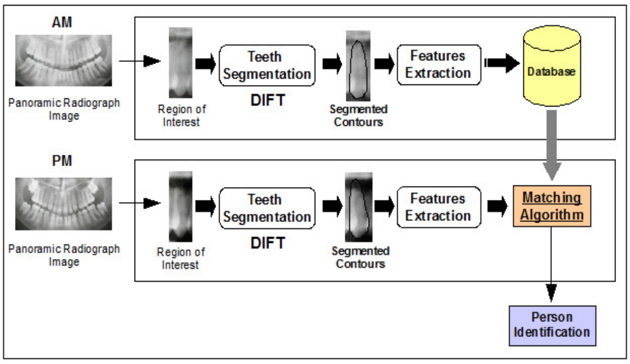

Figure 5. Diagram of the method for semiautomatic teeth recognition from panoramic radiograph images. Source: [4, 11] .

V. EXPERIMENTAL RESULTS

The proposed method was evaluated on a set of 40 panoramic dental radiographs images of 20 individuals (adults and children). For all individuals, there were two radiographs images. In our experiments, for a given individual the oldest radiograph was taken as the antemortem (AM) image, while the newest as the postmortem (PM) image.

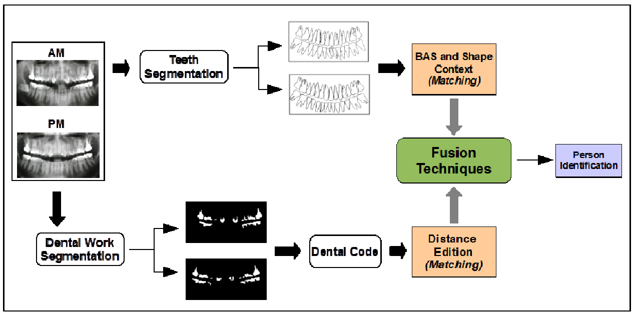

Figure 6. Diagram of the multibiometric method proposed for semiautomatic dental recognition from panoramic radiograph images. Source: [4].

A. *Teeth-Based Method*

The semiautomatic tooth segmentation was carried out using the DIFT-based algorithm on pre-processed images with Sobel operator, which was used to enhance the teeth contours. In our database there are 1126 teeth, whose ROI were manually defined by the user before the segmentation.

After the teeth segmentation, in order to enhance the teeth contours, the segmented images were post-processed by using two Mathematics Morphology operators, opening and closing, achieving thus, smoother contours.

Fig. 7 shows some pairs of AM and PM samples of teeth contours obtained semi-automatically using the DIFT-based algorithm.

It is important to emphasize that the DIFT segmentation quality and accuracy depend on the correct use of the system and on proper training of the user who will operate it. In our experiments, this task was performed by an inexperienced user in the field of Radiology, but expert in the system usage.

For qualitative analysis, the teeth contours were divided into two parts: teeth crowns and roots. The obtained contours were assessed by a human expert of the Dentistry field, who scored them as excellent (4), good (3), regular (2), or poor (1). The mean, mode, and variance values of the scores assigned by the human expert to each teeth part (crown and root) were calculated.

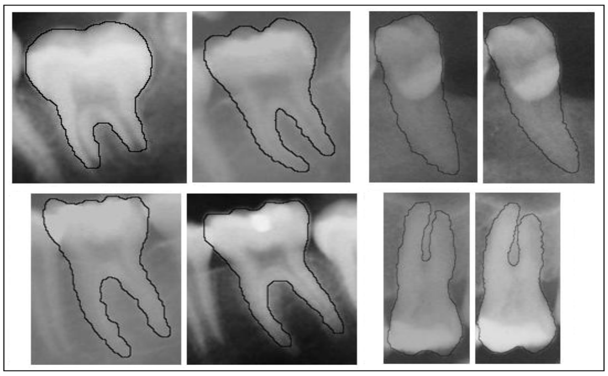

Figure 7. Diagram of the method for semiautomatic teeth recognition from panoramic radiograph images. Source: Adapted from [4, 11].

In Table 1 it is possible to observe the results. The teeth crowns and roots contours were classified as good (mode = 3) by the human expert.

TABLE I. RESULTS OF THE DIFT TEETH SEGMENTATION EVALUATED BY THE HUMAN EXPERT.

DIFT Teeth Segmentation Qualitative Analysis				
	MODE	MEAN	VARIANCE	CLASSIFICATION
Crowns	3	3.25	0.65	Good
Roots	3	2.57	0.90	Good

To evaluate the effectiveness of teeth shape matching techniques for a test case with the database of AM and PM radiographs of twenty individuals it was plotted the ROC curves. The equal error rate (EER) of the Shape Context method was 17%, with 55% of correct identification for rank 1. With the BAS method, the EER was 13%, with 60% of correct identification for rank 1. The obtained ROC curves are shown in Fig. 8.

In general, the results of these assessments indicate low impostors acceptance and low rejection of genuine, validating the results.

B. Dental Work-Based Method

The dental work evaluation was under the same conditions of the teeth evaluation, using a database of 20 individuals. After the segmentation, the AM and PM dental codes were generated and compared. With this method, the EER was 13% with 75% of correct identification for rank 1 and a 100% of correct retrievals for rank 8. The obtained ROC curve is shown in Fig. 9.

C. Multibiometric Evaluation

The biometric features of teeth shapes and dental work information, extracted from panoramic radiographs, were fused in order to make the dental-based identification method more robust and with better performance.

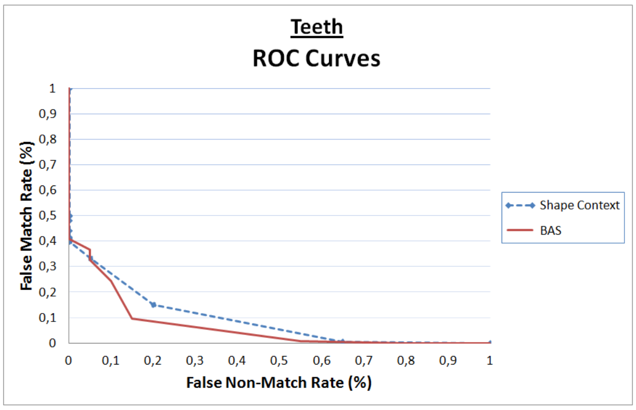

Figure 8. Teeth ROC Curves. The BAS EER is 13% and Shape Context EER is 17%. Source: [4].

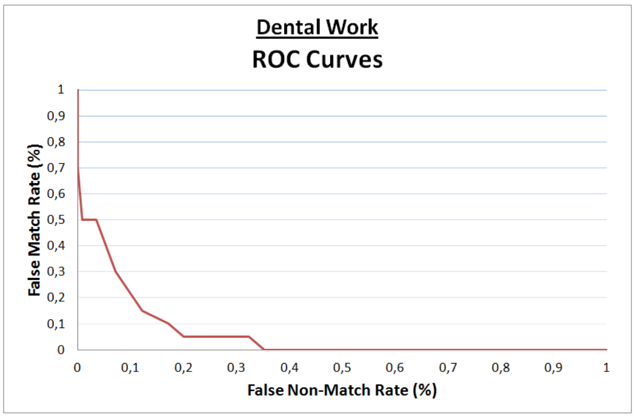

Figure 9. Dental works ROC Curve. The EER is 13%. Source: [4].

In Table 2 are presented the fusion results for all fusion cases, in Rank and Score levels. In this table, it is possible to observe the lowest EER reached, 9%. This result was obtained by the BAS–Dental Works case on the Lowest Score level fusion, with a 50% on Top 1. The better result for Top 1 is 65% also on Minimum Score level fusion for the Shape Context-Dental Works and triple fusion case.

TABLE II. RESULTS OF THE DIFT TEETH SEGMENTATION EVALUATED BY THE HUMAN EXPERT.

Features Fusion			
	Fusion	**EER**	**TOP1**
BAS Shape Context	Highest Rank	15%	50%
	Borda Count	14%	55%
	Minimum Score	16%	50%
	Score Sum	14%	55%
BAS Dental Works	Highest Rank	10%	60%
	Borda Count	10%	55%
	Minimum Score	9%	50%
	Score Sum	10%	50%
Shape Context Dental Works	Highest Rank	13%	60%
	Borda Count	12%	55%
	Minimum Score	10%	65%
	Score Sum	10%	55%
BAS Shape Context Dental Works	Highest Rank	10%	60%
	Borda Count	10%	50%
	Minimum Score	10%	65%
	Score Sum	10%	60%

In Fig. 10 it is shown the ROC curve of the best EER case, 9 %, for Lowest Score Rate with BAS-Dental Works in comparison with the individual techniques results.

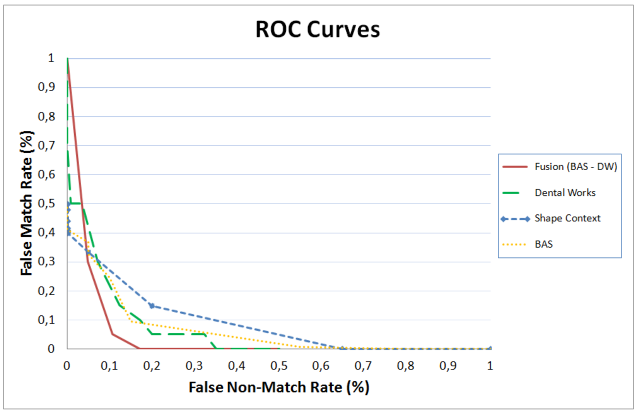

Figure 10. ROC curves. The continuous red line represents the ROC curve of BAS-Dental Works fusion with Minimum Score rate. It's possible to observe that the EER is reduced from 13% to 9%.

VI. CONCLUSION

The results obtained in this work showed that the DIFT-based image segmentation algorithm can perform very well in a semiautomatic biometric system, designed for deceased person identification by using panoramic dental radiographs. According to the human expert who have assessed the 1126 segmented teeth obtained in our experiments, both, crowns and roots contours, were classified as good. This can be considered a very good result, since, in general, the image quality of panoramic radiographs are poor, presenting low contrast, mainly in the teeth root area.

Besides providing accurate results, DIFT segmentation approach requires little human intervention during the segmentation process, since it executes in a differential way when it is necessary to redefine the set of internal and external seeds. This means that it is not necessary to recalculate all the optimum path forest every time a new seed is inserted in the set.

Regarding the teeth shape matching, the BAS descriptor was slightly superior to the Shape Context method (BAS - EER: 13%; Shape Context - EER: 17%). This better result can be partially explained since BAS uses the angles between neighboring boundary points, making it naturally invariant to scale and rotation, in contrast to Shape Context.

It is also essential to point out that during the experiments, the comparisons failures, for both shape description methods were derived mainly by radiographs whose segmentations were classified as poor by the human expert.

The dental work segmentation has also a positive evaluation, because of the high contrast of these structures. The use of dental codes show us that dental work can be a reliable biometric feature and deserves great attention in people identification systems, since it can result in promising performance. The disadvantage of this biometric feature is its short persistence, whereas are common dental interventions during all an individual's life.

From our experiments, we have concluded that the proposed methods can be useful in forensic identification systems through panoramic dental radiograph images.

Applying fusion techniques in the proposed system is highly recommended, since the information of the dental works and the teeth shapes are derived from the same source (radiographic). The best fusion result was observed for the teeth BAS descriptor method with dental work (Dental Code), which reduced the best EER of 13%, reached individually by these two techniques, to 9%.

Finally, we would like to observe that our work is the first one that has proposed the use of DIFT-based segmentation algorithm for this kind of application (forensic human identification based on dental radiographs).

REFERENCES

[1] G. O. Arbens, "Introdução à Odontologia Legal," São Paulo, 1959.

[2] American Board of Forensic Odontology, "Body Identification Guidelines", J. Am. Dent. Assoc., vol.125: pp. 1244-1254, 1994.

[3] A. K. Jain, and H. Chen, "Tooth Contour Extraction for Matching Dental Radiographs," Proc. 17th ICPR, vol. III, pp. 522-525, August, Cambridge, UK. 2004.

[4] E. B. Barboza, "Reconhecimento Semi-Automático de Dentes para a Identificação Humana Forense," Master Thesis. IBILCE – Universidade Estadual Paulista (Unesp), 2012.

[5] A. X. Falcão, and F. P. G. Bergo, "Interactive Volume Segmentation Differential Image Foresting Transforms," IEEE Transactions on Medical Imaging, vol. 23 (9), pp. 1100-1108, 2004.

[6] S. Belongie, J. Malik, and J. Puzicha, "Shape Matching and Object Recognition Using Shape Contexts," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 24, no. 4, pp. 509-522, Apr. 2002.

[7] N. Arica, and F. T. Y. Vural, "BAS: a perceptual shape descriptor based on the beam angle statistics," Pattern Recognition Letters. Vol. 24. Number 9. p. 1627-1639(13). Elsevier. 2003.

[8] M. Hofer, A. N. Marana, "Dental Biometrics: Human Identification Based on Dental Work Information". In: SIBGRAPI 2007 - XX Brazilian Symposium on Computer Graphics and Image Processing, 2007, Belo Horizonte. IEEE Proceedings of the SIBGRAPI 2007.

[9] A. X. Falcão, J. Stolfi, and R. A. Lotufo, "The Image Foresting Transform: Theory, Algorithms, and Applications," IEEE Trans. on Pattern Analysis and Machine Intelligence, 26(1):19-29, 2004.

[10] P. A. V. Miranda, "Segmentação de Imagens pela Transformada Imagem-Floresta," Master Thesis. IC-UNICAMP, 2006.

[11] E. B. Barboza, A. N. Marana, and D. T. Oliveira, "Semiautomatic Dental Recognition Using a Graph-Based Segmentation Algorithm and Teeth Shapes Features," IAPR International Conference on Biometrics (ICB), 2012, New Delli. Proceedings of the ICB 2012, 2012.