TECHNICAL REPORT

Study of edge detection task in dental panoramic radiographs

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The purpose of this study is (1) to introduce a new approach for edge detection in orthopantograms (OPGs) and an improved automatic parameter selector for common edge detectors, (2) to present a comparison between our novel approach with common edge detectors and (3) to provide faster outputs without compromising quality. A new approach for edge detection based on statistical measures was introduced: (1) a set of N edge detection results is calculated from a given input image and a selected type of edge detector, (2) N correspondence maps are constructed from N edge detection results, (3) probabilities and average probabilities are computed, (4) an overall correspondence is evaluated for each correspondence map and (5) the correspondence map providing the best overall correspondence is taken as the result of edge detection procedure. A comparison with common edge detectors (the Roberts, Prewitt, Sobel, Laplacian of the Gaussian and Canny methods) with various parameter settings (304 combinations for each test image) was carried out. The methods were assessed objectively [edge mismatch error (EME), modified Hausdorff distance (MHD) and principal component analysis] and subjectively by experts in dentistry and based on time demands. The suitability of the new approach for edge detection in OPGs was confirmed by experts. The current conventional methods in edge detection in OPGs are inadequate (none of the tested methods reach an EME value or MHD value below 0.1). Our proposed approach for edge detection shows promising potential for its implementation in clinical dentistry. It enhances the accuracy of OPG interpretation and advances diagnosis and treatment planning.

Dentomaxillofacial Radiology (2013) **42**, 20120391. doi: 10.1259/dmfr.20120391

Cite this article as: Gráfová L, Kašparová M, Kakawand S, Procházka A, Dostálová T. Study of edge detection task in dental panoramic radiographs. *Dentomaxillofac Radiol* 2013; **42**: 20120391.

Keywords: panoramic radiography; medical imaging; computer-assisted image processing

Introduction

The edge detection procedure is a critical step in the analysis of medical images.¹ Conventional edge detectors are based on derivatives of the image intensity function.²⁻⁷ They have high performance speed and are widely implemented. However, they fail to detect edges in complex medical images and those with acquisition artefacts. Therefore, it necessitates a comprehensive modification to enhance their performance.⁸ Another drawback of these methods is their parameter setting,

which has to be determined prior to the edge detection and which has an impact on the quality of the whole-edge detection procedure. The process of parameter determination is often questionable owing to its subjective character (*e.g.* parameters are selected manually by a trial-and-error process). Many automatic parameter selectors have already been proposed,⁹⁻¹² which can potentially eliminate this issue. However, they are often time-consuming. The need to process and evaluate various aspects of orthopantograms (OPGs) led to the development of multiedge detectors based on diverse principles and approximations.^{13,14} However, a limitation of these detectors is their narrow spectrum of application and the inability to detect minute variations.

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Received 30 October 2012; revised 22 April 2013; accepted 29 April 2013

In dentistry, the OPG is an example of a complex image with acquisition artefacts. The OPG is one of the basic dental radiographs used in routine dental practice as well as in traumatology of the facial skeleton. It is an extraoral projection that produces images of the mandible including the temporomandibular joint, maxilla, all teeth in the upper and lower jaws, and impacted and supernumerary teeth. It can also partly image maxillary sinuses and nasal cavities.^{15,16} In dental practice, it can further be used for the diagnosis of temporomandibular joint abnormalities, impacted third molars and mesiodens. Moreover, it can be utilized to demonstrate periapical lesions as a result of acute or chronic inflammation. This method of imaging is an ideal modality for demonstration of lateral parts of both jaws. However, it often produces unclear images of upper and lower incisors because of the superimposition of the vertebral column, which casts a shadow on the frontal region.

On interpreting the OPG, one must exercise caution and bear in mind that this is a two-dimensional (2D) representation of a three-dimensional (3D) structure with many curves and angles. It can be particularly problematic when measuring the sizes of various structures (roots of molars, cysts, maxillary sinuses, etc.) as well as considering their position and the spatial relationship between various objects. This complication arises from the fact that a panoramic radiograph is a linear tomograph with intentional blurring of structures outside a desired focus. This results in superimposition of structures of various depths.¹⁷ The OPG usually magnifies and distorts all structures by 1.15–1.25 times their actual size depending on the structure position to the focal through radiographs.^{18–21} The utilization of edge detection procedures will facilitate the orientation in OPGs by reducing the amount of information processed. Moreover, there is the possibility for the most informative and important segments of the edge-detected image to be highlighted,

which will in turn facilitate image interpretation and possibly early diagnosis.^{22,23} The edge detection process in OPG images not only facilitates dealing with daily diagnostic tasks in dentistry but it also enables diagnosis of osteoporosis.^{9,13,24} It can also play a role in forensic science and aid human identification.^{14,25} The edge detectors currently used in OPGs are of satisfactory quality; however, they would benefit from various improvements. These improvements include simplification of procedures and implementation of their use in a broader spectrum.

The main aim of our study was to introduce a new approach for edge detection in OPGs based on statistical measures. This approach will enable edge detection in the majority of commonly used procedures in dentistry, such as teeth extraction, diagnosis and surgical treatment of cysts, mesiodens and dental caries. We further introduce an improved automatic parameter selector for common edge detectors. Finally, we provide a comparison between the efficiency of common edge detectors [Roberts, Prewitt, Sobel, Laplacian of the Gaussian (LoG) and Canny methods] with different parameter settings (304 combinations for each test image), in which our proposed new approach will be used as a reference for the evaluation.

Materials and methods

Test images

The capabilities of the new approach and conventional edge detectors (Roberts, Prewitt, Sobel, LoG and Canny methods) have been verified using a test set of four dental radiographs (jpeg image format, 1540×2815 pixels), designed with expert input to contain the most commonly used tasks in dentistry (teeth extraction, diagnosis of cyst and extirpation, mesiodens and dental caries); see Figure 1. All relevant consents were obtained prior to inclusion in the study.

Figure 1 The test set of dental radiographs: (a) teeth extraction, (b) cyst, (c) mesiodens and (d) dental caries

New approach performance

We have proposed a new approach for edge detection. The approach is based on part of a methodology used in parameter selection by Yitzhaky and Peli¹⁰ (see Appendix) but with a different aim. Our approach provides an edge detection result, whereas Yitzhaky and Peli provide a parameter set-up for conventional edge detection methods. The advantage of the new approach lies in its fully automatic running without the necessity for user intervention as well as its ability to provide a suitable edge detection output. It is also useful for complex medical images or for the images with acquisition artefacts. Its disadvantage is its high computational demand.

Principle of new approach

The method constructs a result based on statistical measures using a set of edge detection results. The set of results are produced by the selected conventional edge detectors and a set of parameter set-ups. The set of parameter set-ups is determined automatically. The process does not enforce any criteria regarding selection of a type of conventional edge detector and avoids the use of both human ratings and manual specification of parameters and, thus, it provides a general technique for an automatic edge detection procedure. The proposed approach can be summarised in the following steps. (1) User provides the input image for edge detection and chooses the type of conventional edge detector. (2) Based on the given input image, a set of N different parameter set-ups for the chosen edge detector is automatically determined. (3) N correspondence maps are constructed using N edge detection results that are carried out using the determined parameter set-ups. (4) The probabilities (true positive, false positive, true negative and false negative) are formed by matching each correspondence map to each result of the edge detection procedure. (5) For each correspondence map, the probabilities are averaged over all the results of the edge detection procedure. (6) For each correspondence map, the overall correspondence is evaluated using the χ^2 test. (7) The correspondence map that gives the best overall correspondence (*i.e.* the highest χ^2) is taken as the result of the edge detection procedure. A more detailed description of the procedure can be found in the Appendix.

This approach is principally applicable to any of the conventional edge detectors. In this study, we have employed the most sophisticated edge detector, the Canny approach.⁷

This new approach has been implemented in Matlab® [v. 7.11.0 (R2010b); The MathWorks Inc., Natick, MA]. Its ability to detect edges in OPGs has been demonstrated using the test set. The outputs of this new approach have been verified by experts in the field and have been used as references in method assessment.

Conventional method performance

We have provided a comparison between the efficiency of conventional edge detectors with different parameter

settings in which our new approach has been used as a reference for the evaluation. The Roberts,² Prewitt,³ Sobel,⁴ LoG⁶ and Canny⁷ methods have been employed as representatives of conventional edge detection methods in our comparison of edge detectors using the test set. Histogram equalization has been used in the pre-processing of the images produced by the conventional edge detectors (in the case of the new approach, no pre-processing is required).

Calculations have been carried out in Matlab (Image Processing Toolbox)^{26,27} with the method parameters as follows:

- parameters determined by Matlab (thresholds are chosen heuristically based on the input image; the value of standard deviation of the LoG filter and the gaussian filter is equal to 2 and 1, respectively)
- selected parameters using the new improved parameter selector (it forms 36 parameter set-ups and selects the best one); the parameter selector has been implemented in Matlab
- parameters taken from the parameter range that is formed using the newly improved parameter selector (36 parameters, see the previous point).

For more information about method parameter settings, see the Appendix.

The Roberts, Prewitt and Sobel methods return a value for the first derivative in the horizontal direction (G_x) and the vertical direction (G_y). From this, the edge gradient has been determined in two ways:

- $$G = \sqrt{G_x^2 + G_y^2} \quad (1)$$
- $$G = \max(G_x, G_y) \quad (2)$$

Method performance assessment

Output of the conventional edge detectors has been evaluated with respect to the output of the new approach based on:

- Objective assessment that relies on (i) edge mismatch error (EME) penalizing edge location discrepancies,^{28,29} (ii) modified Hausdorff distance (MHD) that penalizes the shape dissimilarity,³⁰ (iii) principal component analysis (PCA)³¹ that has been used for method similarity determination based on the Euclidean distance in 2D principal component space. The parameter set-ups for EME and MHD calculations are

$$\max \text{ dist} = 0.025N, \quad D_{\max} = 0.1N, \quad \omega = \frac{10}{N}, \quad \alpha = 2$$

where N is the image dimension. Note that, since the measurement of the Euclidean distance is in two dimensions, the PCA space represents a relative measurement of similarity, and it has to be evaluated with respect to the EME and MDH values. The EME and MHD criteria have been calculated for all methods and all images of the test set. The PCA has

been calculated for the methods with the best EME and MHD scores for a particular image of the test set. Our new approach has been used as a reference for the evaluation of the MHD, EME and PCA.

- (b) Subjective assessment: the outputs of the conventional edge detectors have been assessed by experts in the field who have affirmed the inaccuracy of conventional edge detectors in detecting the necessary landmarks on OPGs for the purpose of teeth extraction, cyst diagnosis and treatment, mesiodens and dental caries.
- (c) Computational demands: the total time required for the completion of all necessary tasks has been determined. All calculations have been carried out in Matlab using 64-bit Windows 7 on a PC with an Intel® Core™2 Duo Processor, 2.66 GHz and 4 GB RAM (Intel Corporation, Santa Clara, CA).

Results

The ability of this new approach to detect edges in OPGs has been demonstrated using the test set; see Figures 2 and 3. The use of this approach has been verified in clinical practice. This method provides the possibility of precisely locating the appropriate anatomical structures, which are required for reliable diagnosis and treatment in dentistry. Furthermore, this method can be used in both the lateral aspects of the jaw and the frontal aspects of the dental arch.

For the objective assessment of the conventional method performance, the EME, MHD and PCA have been used. The edge detection maps of the test images obtained using the new approach (Figure 2) have been employed as the reference for all calculations.

The EME, a metric penalizing edge location discrepancies, has been calculated for all methods and their

parameter settings (304 combinations) and for all images of the test set. Table 1 shows the performance of the best method. The EME value is less than 0.1 in only four cases (out of a total of 1216). None of the tested methods produce satisfactory results (*i.e.* for all test images, the EME value is less than 0.1). Table 2 summarises the EME calculations. The Canny family of methods achieve the best results and the LoG family of methods achieve the worst results. The parameter settings of the method determined by Matlab or using the parameter selector do not provide as good parameter settings as can be obtained using a scan through the parameter ranges formed by the parameter selector. The EME values show that the gradient calculation using Equation (2) gives worse results than the gradient calculation using Equation (1). The EME values show that the fourth test image (dental caries) is the most simple image for processing. On the other hand, the most demanding image for processing is the first image (teeth extraction).

The MHD, a distance measurement penalizing the shape dissimilarity, has been calculated for all methods and their parameter settings and for all images of the test set. Table 1 shows the results of the best performing methods. No method reaches an acceptable MHD value (MHD score less than 0.1). Table 2 summarises the MHD calculations. The trends in MHD results are similar to the trends in the EME result, except for the parameter settings. The best results are achieved by scanning through the parameter ranges that have been automatically selected (this is the same for EME), whereas the worst results are obtained by using the parameter setting determined by the parameter selector. There is a significant discrepancy between the imaged edges provided by our method and those provided by the conventional methods. This is evident from a high MDH value.

The PCA has been used for the determination of the relationship between the conventional methods and our

Figure 2 The edge detection results of the new approach in the test images: (a) extracted teeth, (b) cyst, (c) mesiodens and (d) dental caries

Table 1 Overview of the methods with the best performances with respect to the edge mismatch error (EME) and modified Hausdorff distance (MHD) values

Test image	Method	Parameter ^a	High threshold ^b	Low threshold ^b	Sigma ^c	Value
<i>Section 1</i>						
1	Canny	Scan	0.0391	0.0391	2	0.13
	Canny	Scan	0.0391	0.0391	2	0.76
2	Canny	Scan	0.0195	0.0195	3	0.13
	Sobel	Scan	0.0080	—	—	0.78
3	Canny	Scan	0.0371	0.0371	2	0.07
	Canny	Scan	0.0371	0.0371	2	0.66
4	Canny	Scan	0.0215	0.0215	3	0.09
	Canny	Scan	0.0215	0.0215	3	0.68
<i>Section 2</i>						
3	Canny	Scan	0.0371	0.0371	2	0.07
	Canny	Scan	0.0371	0.0371	3	0.09
	Canny	Scan	0.0371	0.0223	2	0.10
4	Canny	Scan	0.0215	0.0215	3	0.09

The first section of the table shows the performances of the best method for a particular test image; the first row of the subsection devoted to a particular test image corresponds to the performance of the best method as evaluated based on the EME, the second row corresponds to the performance of the best method as evaluated based on the MHD values. The second section contains the performances of the methods with an EME value of less than 0.5.

^aType of parameter determination.

^bTwo thresholds to the gradient: a high threshold for low edge sensitivity and a low threshold for high edge sensitivity.

^cThe standard deviation value of the filter.

approach based on their Euclidean distances in 2D principal component space. The PCA has been calculated for the methods with the best EME and MHD scores (*i.e.* for methods from Table 1); see Table 3. The distribution of the tested methods (with respect to the position of our new approach) in 2D principal component space is similar for all test images. A sample of a teeth extraction image is depicted in Figure 4. In all cases, the methods are divided into four groups: (i) our approach (denoted by “1”) is in the centre of the 2D space, (ii) the Sobel method (denoted by “2”) is on the left with respect to our approach, (iii) the Canny methods with a standard deviation of 2 (denoted by “3”, “5”, “8”) and (iv) the Canny methods with a standard

Table 2 Summary of edge mismatch error (EME) and modified Hausdorff distance (MHD) calculations

<i>(I) Test image</i>				
1	2	3	4	
0.57	0.46	0.53	0.44	
0.92	0.91	0.90	0.88	
<i>(II) Method family</i>				
Roberts	Prewitt	Sobel	LoG	Canny
1.97	1.97	1.97	2.90	1.00
3.59	3.59	3.59	3.78	3.49
<i>(III) Parameter</i>			<i>(IV) Edge gradient</i>	
Matlab ^a	Selector ^b	Scan ^c	Max ^d	Sqrt ^e
0.62	0.57	0.52	0.75	0.30
0.93	1.54	0.91	0.94	0.87

Max, maximum; Sqrt, square root.

The values in the first section of the table represent the mean values of the EME and MHD for processing of particular test images. The second section of the table contains the mean values of the EME and MHD for an individual family of methods. The third section of the table shows the mean values of the EME and MHD for a specific type of parameter. The last section of the table shows the mean values of the EME and MHD for a particular type of edge gradient determination. In all the sections of the table, the first row contains the results for the EME and the second row contains the results for the MHD.

^aDefault method parameters determined by Matlab.

^bMethod parameters chosen using the parameter selector.

^cMethod parameters from the parameter range formed by the parameter selector.

^dEdge gradient determination using Equation (1).

^eEdge gradient determination using Equation (2).

deviation of 3 (denoted by “4”, “6”, “7”). The Canny and Sobel methods have the most and least similarity, respectively, to our approach.

The distribution of the methods in 2D principal component space indicates the potential suitability of the Canny methods with a standard deviation value of the gaussian filter of 2.5. Therefore, we have carried out the Canny method with the parameters $t_L = 0.0371$, $t_H = 0.0371$, $\sigma = 2.5$ (the same parameters for t_L and t_H as in the case of methods 5 and 7) for all test images. The distribution of the methods with the added Canny method in 2D principal component space is very similar for all test images. Figure 5 depicts a sample of teeth

Table 3 A summary of principal component analysis (PCA) calculations

Method index	Method	Parameter ^a	High threshold ^b	Low threshold ^b	Sigma ^c	Test image			
						1	2	3	4
1			Our approach			0.00	0.00	0.00	0.00
2	Sobel	Scan	0.0080	—	—	2.75	2.62	2.75	2.60
3	Canny	Scan	0.0391	0.0391	2	1.05	0.67	0.85	0.86
4	Canny	Scan	0.0195	0.0195	3	1.14	1.64	1.37	1.45
5	Canny	Scan	0.0371	0.0371	2	1.09	0.70	0.89	0.89
6	Canny	Scan	0.0215	0.0215	3	1.12	1.60	1.34	1.42
7	Canny	Scan	0.0371	0.0371	3	0.91	1.21	1.04	1.03
8	Canny	Scan	0.0371	0.0223	2	1.18	0.76	0.98	0.96

Table shows the Euclidean distances between our approach and the methods in two-dimensional PCA space for particular test images. Rows of the table contain values calculated for a particular method.

^aType of parameter determination.

^bTwo thresholds to the gradient: a high threshold for low edge sensitivity and a low threshold for high edge sensitivity.

^cThe standard deviation value of the filter.

Figure 3 Edge detection of desired structures (the first row depicts the detection of teeth roots; the second row depicts the detection of a cyst lesion; the third row depicts the detection of mesiodens; and the fourth row depicts the detection of dental caries): (a) selected regions of interest from test images (Figure 1), (b) overlap of the edge detection outputs of our new approach and orthopantograms, (c) desired structures detected using our new approach. Desired structures detected using best conventional edge detectors: (d) the Sobel method with parameters from scan $t_L = 0.008$; (e) the Canny method with parameters from scan $t_L = 0.0391$, $t_H = 0.0391$, $\sigma = 2.0$; (f) the Canny method with parameters from scan $t_L = 0.0195$, $t_H = 0.0195$, $\sigma = 3.0$; (g) the Canny method with parameters from scan $t_L = 0.0371$, $t_H = 0.0371$, $\sigma = 2.0$; (h) the Canny method with parameters from scan $t_L = 0.0215$, $t_H = 0.0215$, $\sigma = 3.0$; (i) the Canny method with parameters from scan $t_L = 0.0371$, $t_H = 0.0371$, $\sigma = 3.0$; (j) the Canny method with parameters from scan $t_L = 0.0371$, $t_H = 0.0223$, $\sigma = 2.0$; and (k) the Canny method with parameters from scan $t_L = 0.0371$, $t_H = 0.0371$, $\sigma = 2.5$.

extraction. The Canny method with a standard deviation value of the gaussian filter of 2.5 is located near to our approach (consistent with our expectation).

As the assessment of the method performance has been performed with the purpose of finding the best

method for its implementation in clinical use, it is necessary to assess the method outputs based on subjective evaluation by expert dentists. Owing to a large number of method calculations (1216, taking into account different settings of methods and 4 test images), only the

Figure 4 The distribution of the best conventional methods and our approach in two-dimensional principal component space for the first test image, in which the methods are denoted according to the “method index” from Table 3. PCA, principal component analysis

Figure 5 The distribution of the best conventional methods with the added Canny method (parameters $t_L = 0.0371$, $t_H = 0.0371$, $\sigma = 3$) in two-dimensional principal component space for the first test image, in which the methods are denoted according to the “method index” from Table 3 and the added Canny method is denoted by “9”. PCA, principal component analysis

Figure 6 The best performances of tested methods: (a) detected test image 1 using the Sobel method with parameters from scan $t = 0.008$, (b) detected test image 2 using the Canny method with parameters from scan $t_L = 0.0391$, $t_H = 0.0391$, $\sigma = 2$, (c) detected test image 2 using the Canny method with parameters from scan $t_L = 0.0195$, $t_H = 0.0195$, $\sigma = 3$, (d) detected test image 3 using the Canny method with parameters from scan $t_L = 0.0371$, $t_H = 0.0371$, $\sigma = 2$, (e) detected test image 4 using the Canny method with parameters from scan $t_L = 0.0215$, $t_H = 0.0215$, $\sigma = 3$, (f) detected test image 3 using the Canny method with parameters from scan $t_L = 0.0371$, $t_H = 0.0371$, $\sigma = 3$, and (g) detected test image 3 using the Canny method with parameters from scan $t_L = 0.0371$, $t_H = 0.0223$, $\sigma = 2$

methods with the best performance (methods from Table 3 and the Canny method with the parameters $t_L = 0.0371$, $t_H = 0.0371$, $\sigma = 3$) have been subjectively evaluated. Figure 6 shows the best performances of the tested methods. Figure 3 shows the edge detection outputs of the desired structures (included in test OPGs) using the best methods.

The Sobel method (method 2 in Table 3) provides unsatisfactory edge detection results; see Figure 6a,b. Its edge detection outputs have not provided the desired information. The relatively small MHD value (in comparison with other tested methods) indicates the

shape similarity to edge detection output provided by our method, but the outputs are noisy owing to the overestimated number of pixels detected as edge (large EME value). The best method (the Canny method with parameters $t_H = 0.0371$, $t_L = 0.0371$, $\sigma = 2.5$) provides superior edge detection results to our method (it is closest to our approach in principal component space); see Figure 3k. The main drawback of all conventional methods is their inability to distinguish between important and less important edges. Because of this behaviour, the edge maps provided by this method are abstruse. Generally, the evaluated Canny methods

suffer from two main disadvantages: (i) inability to detect details of desirable structures or detection of noise and (ii) inability to distinguish between important and less important edges. Because of this reason, none of the tested methods satisfy our requirements.

The time required is an important criterion for the assessment of the method performance (Table 4). The fastest methods are those of Roberts, Prewitt and Sobel with determination of parameters before running the method or using the default Matlab parameter determination procedure. Their computational time is less than 1 s. The LoG and Canny methods with determination of parameters before running the method or using Matlab have a computational time of up to 5 s. The conventional methods in combination with the parameter selector generally have slower computational times than the Roberts, Prewitt and Sobel methods, which take up to 15 min; the LoG and Canny methods take approximately 30 min and 1 h, respectively. The computational time of our new approach is about 1 h, which is its drawback. For online pre-processing in clinical practice, the computational time has to be in the range of a few seconds.

Discussion

2D radiology is widely used in clinical practice for the evaluation of various pathological processes. Nowadays, 3D radiography could also be an option. Although 3D radiography, *i.e.* cone beam CT (CBCT) scans, can provide a detailed view of spatial relations, it is still not used extensively. Most experts believe that CBCT will not replace conventional radiographs, but will complement it.¹⁵ Some studies compared the accuracy of the use of conventional OPGs and CBCT in treatment, for example in implantology, and advised the use of CBCT only in the case of uncertainty or in special indications such as complicated root anatomy, trauma or computer-guided implantology.^{32,33} The main disadvantage in using 3D methods might be increased radiation.³³ Effective dose ranges of CBCT machines may easily vary from 10 µSv to 1200 µSv, being an equivalent of 2–240 dental panoramic radiographs. The same holds true for diagnostic image quality, which exhibits a huge variation among machines and parameter settings.³⁴

Table 4 An overview of method computational demands

	<i>I</i>	<i>II</i>
Roberts	0.2 s	14 min
Prewitt	0.2 s	13 min
Sobel	0.2 s	15 min
LoG	1.1 s	32 min
Canny	3.2 s	70 min
New approach	70 min	

Values represent the mean values of computational time for processing of a single test image. I, method parameters determined before the calculation or using the default Matlab parameter determination procedure; II, method parameters determined by the automatic parameter selector during the calculation.

This study has objectively demonstrated a clear advantage of the proposed method for edge detection on OPGs. One major aspect of our method is its ability to provide exact root positions in the cases of complicated extraction. It further provides spatial orientation of cystic structures in the bone and their relation to other structures. When detecting cavities, it is also important to know the depth of the caries or its proximity to the dental pulp. When detecting supernumerary teeth, usually mesiodens, this approach can provide clarification of their exact position and crown–root orientation. The method of edge detection does not necessarily have to be used for the whole panoramic radiograph; it can be used to highlight only the desired structures. Overall, it can be a good tool for achieving more successful treatment results and avoiding complications (Figures 2 and 3).

This study has shown for the first time the limitations of conventional methods for edge detection in OPGs. It is important to note that outputs of the methods could be improved using post-processing procedures such as eliminating redundant pixels labelled as edge, connection of edge parts, etc. However, these improvements are insufficient to make the conventional methods suitable for edge detection in OPGs. In addition, post-processing procedures are associated with the risk of deletion of important information. This study provides an attractive alternative approach to edge detection in clinical practice; however, it would benefit from a reduction in its computational load.

In conclusion, we have introduced an improved automatic parameter selector for conventional edge detectors. Based on the improved parameter selector, a new fully automatic approach for edge detection has been developed with the ability to detect the most common tasks in dentistry. The suitability of this approach has been confirmed by a team of experts in their respective fields of dentistry. Owing to the time-consuming nature of this approach, a comparison between the currently used conventional edge detectors has been performed with the aim of determining a suitable method that provides outputs with the same quality as our approach but in a shorter time. For this purpose, the test set of OPGs including the most commonly used tasks in dentistry was designed. The assessments included (in addition to measuring time) both objective evaluation using EME, MHD and PCA and a subjective evaluation based on verification of the method by experts in the field. Moreover, none of the conventional methods were able to appropriately detect the test images.

We are continually searching for new methods to decrease the computational demands of this novel approach and to ensure its place in routine clinical practice.

Funding

This work has been supported by the following grants: MSMT no. 20/2013, MSM 6046137306, IGA MZCR 13351-4 and MSM no. 6046137306.

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Appendix

Parameter selector

Yitzhaky and Peli¹⁰ presented a quasi-automatic parameter selector for an edge detector based on statistical measures. The method can be carried out using the following steps:

- (1) A user gives an input image for edge detection, chooses the type of conventional edge detector and gives a set of parameter set-ups for the selected edge detector.
- (2) N edge detection results D_j ($j = 1, \dots, N$) are obtained using N different parameter set-ups of the edge detector.

- (3) N correspondence maps, potential ground truths (PGTs), are constructed using N edge detection results and N correspondence levels i ($i = 1, \dots, N$). A correspondence level i indicates the pixel locations identified as edges in i edge detection results. Each PGT_i includes edge pixels with i th or higher correspondence.

- (4) Each PGT_i is matched to each edge detection result D_j forming the following probabilities (according to statistical decision theory terminology):

- (a) True-positive probability TP_{PGT_i, D_j} :

$$TP_{PGT_i, D_j} = \frac{1}{O \cdot P} \sum_{o=1}^O \sum_{p=1}^P PGT_{i1} \cap D_{j1} \quad (A1)$$

(b) False-positive probability $FP_{PGT_i;D_j}$:

$$FP_{PGT_i;D_j} = \frac{1}{O \cdot P} \sum_{o=1}^O \sum_{p=1}^P PGT_{i1} \cap D_{j0} \quad (A2)$$

(c) True-negative probability $TN_{PGT_i;D_j}$:

$$TN_{PGT_i;D_j} = \frac{1}{O \cdot P} \sum_{o=1}^O \sum_{p=1}^P PGT_{i0} \cap D_{j1} \quad (A3)$$

(d) False-negative probability $FN_{PGT_i;D_j}$:

$$FN_{PGT_i;D_j} = \frac{1}{O \cdot P} \sum_{o=1}^O \sum_{p=1}^P PGT_{i0} \cap D_{j0} \quad (A4)$$

where O and P are the dimensions of the input image; PGT_{i1} and PGT_{i0} are the pixels in the PGT_i detected as edges and non-edges, respectively; D_{j1} and D_{j0} are pixels detected as edges and non-edges in the edge detection result j , respectively.

(5) For each PGT_i , the probabilities are averaged over all edge detection results D_j , producing the following average probabilities:

$$(a) \quad \overline{TP}_{PGT_i} = \frac{1}{N} \sum_{j=1}^N TP_{PGT_i;D_j} \quad (A5)$$

$$(b) \quad \overline{FP}_{PGT_i} = \frac{1}{N} \sum_{j=1}^N FP_{PGT_i;D_j} \quad (A6)$$

$$(c) \quad \overline{TN}_{PGT_i} = \frac{1}{N} \sum_{j=1}^N TN_{PGT_i;D_j} \quad (A7)$$

$$(d) \quad \overline{FN}_{PGT_i} = \frac{1}{N} \sum_{j=1}^N FN_{PGT_i;D_j} \quad (A8)$$

(6) For each PGT_i the overall correspondence is evaluated using the χ^2 test:³⁵

$$\chi^2_{PGT_i} = \frac{(\overline{TP}_{PGT_i} - Q_{PGT_i})(Q_{PGT_i} - \overline{FPR}_{PGT_i})}{Q_{PGT_i}(1 - Q_{PGT_i})}, \quad (A9)$$

$$Q_{PGT_i} = \overline{TP}_{PGT_i} + \overline{FP}_{PGT_i}, \quad (A10)$$

$$\overline{TPR}_{PGT_i} = \frac{\overline{TP}_{PGT_i}}{P}, \quad (A11)$$

$$\overline{FPR}_{PGT_i} = \frac{\overline{FP}_{PGT_i}}{1 - P}, \quad (A12)$$

$$P = \overline{TP}_{PGT_i} + \overline{FN}_{PGT_i}, \quad (A13)$$

$$1 - P = \overline{FP}_{PGT_i} + \overline{TN}_{PGT_i}. \quad (A14)$$

- (7) The PGT_i that gives the best overall correspondence (*i.e.* the highest $\chi^2_{PGT_i}$) is denoted as the estimated ground truth (EGT).
- (8) The EGT is matched to each of the edge detection results D_j producing new probabilities: $TP_{D_j,EGT}$, $FP_{D_j,EGT}$, $TN_{D_j,EGT}$, $FN_{D_j,EGT}$ (calculated in the same way as described in Step 4).
- (9) The overall correspondence is evaluated for the EGT (calculated in the same way as described in Step 6).
- (10) The D_j that gives the best match with the EGT according to the χ^2 test represents the best edge detection result. The selected detector parameters are those that produce this best detection.

The drawbacks of the parameter selector are a requirement to determine a set of parameter set-ups prior to the method run and its high computational demand.

New approach for edge detection

The new approach for edge detection is based on part of a methodology used in parameter selection by Yitzhaky and Peli¹⁰ (see above) and can be summarised in the following steps:

- (1) A user gives an input image for edge detection and chooses the type of conventional edge detector that has to be used in the edge detection procedure.
- (2) A set of 36 parameter set-ups for a given edge detector is determined fully automatically:
 - (a) Edge detectors with one parameter (*e.g.* Roberts, Prewitt, Sobel methods)
A parameter that has to be set is the threshold t for the calculated gradient magnitude. A set of threshold t values is formed from the range T :

$$T = \{t | t_{\min} \leq t \leq t_{\max}\} \quad (A15)$$

where $t_{\min}$ and $t_{\max}$ are the lower and upper limits of the range for threshold t , respectively. The limit values are calculated using the following formulae (*e.g.* using the bisection method):

$$t_{\min} = \left\{ 0 \leq t \leq 1 \mid c(t) = \frac{c_{\max}}{10} \right\} \quad (A16)$$

$$t_{\max} = \left\{ 0 \leq t \leq 1 \mid c(t) = \frac{c_{\max}}{10} \right\} \quad (A17)$$

where $c(t)$ is number of pixels detected as an edge in a given input image using the edge detector with the threshold t ; $c_{\max}$ is the maximum number of pixels that can be detected as an edge in a given input image using the edge detector and it can be calculated using the following equation:

$$c_{\max} = c(t = 0) \quad (\text{A18})$$

A set of parameter set-ups S_t has 36 values and an equidistant step:

$$S_t = \left\{ t_k \in T, k = 1, \dots, K \mid t_k = t_{\min} + \frac{(k-1)(t_{\max} - t_{\min})}{K-1} \right\} \quad (\text{A19})$$

where t_k is the k th parameter set-up in the set and K (in this case $K = 36$) is the number of elements in the set.

(b) Edge detectors with two parameters (*e.g.* LoG method)

Parameters that have to be set are the threshold t for the zero-crossings and the standard deviation σ of the filter. First, the range S_t for the threshold t is formed according to Equations (A13)–(A17) using the edge detector with the standard deviation σ value of 2 and considering the parameter $K = 1$. Then the range S_σ for the standard deviation σ of the filter is formed:

$$S_\sigma = \{\sigma_l > 0, l = 1, \dots, L \mid \sigma_l = l\} \quad (\text{A20})$$

where σ_l is the l th element of the range and L (in this case $L = 4$) is a number of values in the range. The last step is the formation of a set $S_{t,\sigma}$ of parameter set-ups:

$$S_{t,\sigma} = \{t_k \in S_t, k = 1, \dots, K; \sigma_l \in S_\sigma, l = 1, \dots, L \mid (t_k, \sigma_l)\} \quad (\text{A21})$$

(c) Edge detectors with three parameters (*e.g.* Canny method)

Parameters that have to be set are the low threshold value t_l , high threshold value t_h and the standard deviation σ of the filter. First, the range S_t for the high threshold t_h is formed according to Equations (A13)–(A17) using the edge detector with the low threshold calculated according to the following equation:

$$t_l = 0.4t_h \quad (\text{A22})$$

with the standard deviation σ value of 1 and considering the parameter $K = 3$. Then the range S_σ for the standard deviation σ of the filter is formed according to Equation (A18), considering the parameter $L = 4$. The next step is the formation of the range S_{t_l} for the low threshold:

$$S_{t_l} = \left\{ t_{hk} \in S_t, k = 1, \dots, K; 0 \leq t_{lkm} \leq t_{hk}, m = 1, \dots, M \mid t_{lkm} = t_{hk} \left(0.2 + \frac{0.8(m-1)}{M-1} \right) \right\} \quad (\text{A23})$$

where t_{lm} is the m th element of the range and M (in this case $M = 3$) is a number of values of parameter m . The last step is the formation of a set $S_{t_h, t_l, \sigma}$ of parameter set-ups:

$$S_{t_h, t_l, \sigma} = \{t_{hk} \in S_t, k = 1, \dots, K; t_{lkm} \in S_{t_l}, m = 1, \dots, M; \sigma_l \in S_\sigma, l = 1, \dots, L \mid (t_{hk}, t_{lkm}, \sigma_l)\} \quad (\text{A24})$$

- (3) The EGT is produced using Steps 2–7 of the parameter selection procedure by Yitzhaky and Peli¹⁰ (see above).
- (4) The EGT is the edge detection result.

The approach is principally applicable to any of the conventional edge detectors.

Conventional edge detectors

Table A1 shows the parameter set-ups determined by Matlab, Table A2 shows the parameter set-ups determined by the parameter selection procedure proposed by Yitzhaky and Peli, and Table A3 presents the parameter set-ups determined by our method. In all tables, the threshold for the Roberts, Prewitt and Sobel methods means the threshold value for the calculated gradient magnitude. Threshold and σ for the LoG method mean the threshold value for the zero-crossings and the standard deviation value of the LoG filter, respectively. High/low thresholds and σ for the Canny method mean two thresholds to the gradient (a high threshold for low edge sensitivity and a low threshold for high edge sensitivity) and the standard deviation value of the gaussian filter, respectively.

Table A1 An overview of parameter values determined by Matlab

<i>Method</i>	<i>Roberts</i>	<i>Prewitt</i>	<i>Sobel</i>	<i>LoG</i>		<i>Canny</i>		
<i>Parameter</i>	<i>Threshold</i>			<i>Threshold</i>	<i>Sigma</i>	<i>High threshold</i>	<i>Low threshold</i>	<i>Sigma</i>
Test 1	0.0722	0.0519	0.0535	0.0017	2	0.0469	0.01876	1
Test 2	0.0442	0.0364	0.0370	0.0009	2	0.0313	0.01252	1
Test 3	0.0670	0.0491	0.0506	0.0015	2	0.0469	0.01876	1
Test 4	0.0446	0.0378	0.0383	0.0011	2	0.0313	0.01252	1

Table A2 An overview of parameter values determined by the parameter selector

<i>Method</i>	<i>Roberts</i>	<i>Prewitt</i>	<i>Sobel</i>	<i>LoG</i>		<i>Canny</i>		
<i>Parameter</i>	<i>Threshold</i>			<i>Threshold</i>	<i>Sigma</i>	<i>High threshold</i>	<i>Low threshold</i>	<i>Sigma</i>
Test 1	0.0375	0.0282	0.0301	0.0028	1	0.0703	0.0422	1
Test 2	0.0125	0.0119	0.0119	0.0012	1	0.0410	0.0246	2
Test 3	0.0321	0.0240	0.0254	0.0024	1	0.0615	0.0369	1
Test 4	0.0113	0.0125	0.0125	0.0014	1	0.0420	0.0252	2

Table A3 An overview of parameter ranges

<i>Method</i>	<i>Roberts</i>	<i>Prewitt</i>	<i>Sobel</i>	<i>LoG</i>		<i>Canny</i>		
<i>Parameter</i>	<i>Threshold</i>			<i>Threshold</i>	<i>Sigma</i>	<i>High threshold</i>	<i>Low threshold</i>	<i>Sigma</i>
Test 1	<0.0273:0.0008: 0.0547>	<0.0195:0.0007: 0.0430>	<0.0215:0.0006: 0.0430>	<0.0017:0.0003: 0.0039>	{1, 2, 3, 4}	{0.0391, 0.0703, 0.1016}	{0.2 t_H , 0.6 t_H , 1.0 t_H }	{1, 2, 3, 4}
Test 2	<0.0078:0.0003: 0.0195>	<0.0073:0.0003: 0.0195>	<0.0073:0.0003: 0.0195>	<0.0007:0.0001: 0.0017>	{1, 2, 3, 4}	{0.0195, 0.0410, 0.0625}	{0.2 t_H , 0.6 t_H , 1.0 t_H }	{1, 2, 3, 4}
Test 3	<0.0234:0.0007: 0.0469>	<0.0166:0.0006: 0.0352>	<0.0176:0.0005: 0.0371>	<0.0015:0.0002: 0.0034>	{1, 2, 3, 4}	{0.0371, 0.0615, 0.0859}	{0.2 t_H , 0.6 t_H , 1.0 t_H }	{1, 2, 3, 4}
Test 4	<0.0071:0.0003: 0.0176>	<0.0078:0.0003: 0.0195>	<0.0078:0.0003: 0.0195>	<0.0008:0.0002: 0.002>	{1, 2, 3, 4}	{0.0215, 0.0420, 0.0625}	{0.2 t_H , 0.6 t_H , 1.0 t_H }	{1, 2, 3, 4}

Numbers in curly brackets represent a list of values. Numbers in angle brackets separated by a colon represent the range of values in which the middle number is a step value.