

Detection of Caries in Panoramic Dental X-ray Images



Calles Delection in randianile Dental Ariay intages

OCIA Lab. – Soft Computing and Image Analysis Grou

ounded in September 2006, we accommodate 18 members, both faculty and students

Ve develop and apply soft computing methods (neural networks, support vector machi etic algorithms, fuzzy logic) for data analysis, and in particular, image analysis.

Medical Image Analysis, Object Detection, Video Annotation, ...

Biometrics: iris recognition in non-cooperative environments.





Cooperative Scenario



Non-Cooperative Scenario









SOCIA Lab. – Soft Computing and Image Analysis Group M.Sc. Work: Detection of Caries in Panoramic Dental X-Ray Images >Student: João Oliveira, Computer Science Engineer. Supervisor: Hugo Proença, IT – Instituto de Telecomunicaçã Department of Computer Science, University of Beira Interior. Valuable biological advices from Dr. Rui Conceição.



0 - Input Image



Outline





3 – Teeth Gap Valley Detection

th Division







4 – Tooth Segmentation



5- Feature Extraction

1 – ROI Definition



2 – Jaws Partition





input images

- nensions $-2816W \times 1540H$;
- Properties:
- Grayscale images [0; 255];
- Variable dental structure, mouth size and number of teeth per image;
- Complex morphologic and topologic properties:
- \succ Low contrast images;
- \succ Blur that difficults the proper detection of edges;
- Chinal column that covers the control nort of come images



Lamples of mput mayes





- Region of Interest 1

- ere, Image acquisition is a constrained process.
- Human morphology dictates that some regions
- ever have usefull information.
- xtraction of four distances from the image center:
- $(x_c, y_c) = (w/2 = 1408, h/2 = 770);$
- Asumed a normal distribution, (μ, σ) ;
- Crop images with 95% certainty:

 $R_1 \approx 897.77$; $R_2 \approx 863.36$; $R_3 \approx 406.31$; $R_4 \approx 471.27$;

R1 Number of Images 800 R_2 Number of Images 100 ⁷⁰⁰ Lengths 800 **R**3 000 08 09 12 09 12 00 12 300 Longthe 200 400 Number of Images **R**4 300 Lengths

Calles Delection in randianile Dental A-lay inages

Roi Definition Examples:



Calles Delection in a anotamic Dental A-lay images – Partition of the Image Into Jaws Extraction of T points (experimentally, T = 20) between the jaws: Based on the horizontal projection – $v(u) = \sum_{i=0}^{i=0} I(x,i)$ Initial point is defined – $p_0(x_0, w - 1) = \arg \min_x(v(u))$ Remaining points p_i are regularly spaced $- \frac{p_0 : p_i(x_i, (w-1) - W/2)}{p_0 : p_i(x_i, (w-1) - W/2)}$ itting process:

The division of jaws is given by the 10th order polynomial, defined $(x) = a_0 + \ldots + a_{10} x^{10};$

- Jaws Partition (examples):



alure examples, (Due to missing teeth)



- Delection of the rectined by valley

Morphologic pre-processing methods applied to the images:

The Top-hat and Bottom-hat filtering; (computes the morpholog

pening of the image and then subtracts the result from the original ima







Crop unusefull data (jaws)



Canes Delection in a anotamic Dental Ariay images — Detection of the Teeth Gap Valley

- The next stage was problematic. The goal was to localize every va ween teeth.
- > Even assuming that lines can appropriately divide teeth, the oriental and position of each line revealed one of the hardest stages of this wo
- >Initial observation was that regions between teeth are darker.



3 – Detection of the Teeth Gap Valley : he chosen solution translates the original image represented in tesian space into polar coordinates;

The image center was used as the reference point.

The key insight is that lines that divide theeth are mostly radial.

>Considerably reduces the dimension of the search space.



Example of an upper jaw in polar coordinates

3 – Detection of the Teeth Gap Valley :

- For each tooth, search for the radial lines with mimimal average ensities.
- Remapping these lines into cartesian coordinates gives the teeth divisic







4 – IUUII UEginentation

- Having a corsely defined region that contains each tooth, the goal is form its segmentation
- ome of the operations applied in this stage are similar to the previous es (morphological pre-processing)
- The contour of each tooth is obtained with active contour techniques
- >Tested classical snakes variant, geodesic active contours and chosen
- Chan and Vese; Active Contours Without Edges, IEEE Transactions
- Image Processing;

xamples:







5 – Dental Caries Features Extraction:

- Having each tooth segmented, the problem is regarded as a class
- tern classification task (with two classes).
- Input: Segmented region that contains a tooth.
- Output: Either the tooth has a carie (Class 1) or not (Class 0)
- ased in the statistical pattern recognition paradigm.
- Each tooth is regarded as a set of features in a high dimensional spac
- Hopefully, features have discriminating cappacity.
- Contour and regions descriptors.

1.32; 34.76; 67.42 -0.928 12.645 23.454 34.746 12. 4.5 4.854 0.012 0.001 12.



5 – Dental Caries Features Extraction:

A large number of features was extracted:

- Region-based (entropy, median, intensity statistics, moments,...)
- Contour-based (SIFT, chain codes,...)

Mean	Median	Entropy (3x3)	Min
49.4690	50.0	0.69	78



Calles Delection in randianile Dental Allay intages Dental Caries Features Extraction:

Region-based features (area, hu moments, etc.);

Hμı	Ηµ₃	Ηµ₃	Ηµ₄	Hμ₅	Ηµ₀	Ηµ7	Area	Euler Number
6.6236	13.9931	23.4765	26.2996	52.1814	33.7726	51.3743	21906	2
6.8630	15.2387	23.0212	24.3041	47.9695	31.9239	50.6677	27512	1

Calles Delection in randianile Dental Allay intages **Dental Caries Features Extraction:**

exture-based features (energy, third moment, etc.);

Contour-based features (fourier descriptors, MMP);







J – Dental Galles I catule Normanzation and Selection

- Feature Normalization. Tested two normalization strategies:
- \succ Linear mapping to the unit interval.
- > Zero mean and unit variance: $\frac{x-\mu}{x-\mu}$



- Feature Selection.
- > The high dimensionality of the feature space was a problem (over 50
- >It is known that such high dimensional feature spaces will deman
- huge number of instances to be proper populated.

J – Dental Galles i catule Normanzation and Selection

- PCA: Principal Components Analysis
- >Transforms a number of possibly correlated features into a sma
- number of uncorrelated ones, called principal components.
- ➢Based in the eigenvalues / eigenvectors and covariance ma concepts, its operation can be thought of as revealing the inter structure of the data in a way which best explains the variance in data.

eature 1, Feature 2, ... Feature N



ed features into a sma components.

> Feature 1'; 75% Feature 2'; 12% ... Feature N'; 0.01%

J – Dental Galles Glassification (Ongoing)

- Having a learning set:
- >Half divided between positive and negative examples.
- Performed feature extraction for each example.
- \rightarrow Reduce the dimensionality of the feature space (PCA).
- Experimented several types of classification methods:
- Bayesian Classifiers, Neural Networks, Nearest Neighbors a Support Vector Machine;

Results:



e 3 – Teeth Gap Valley Detection

- e 3.1 Teeth Division
- ge 4 Tooth Segmentation

ge 5 – Dental Caries Classification

Results (% of correct)

95.7

92.6

87.5

98,7

In Progress

Further Work

- e improvement of the teeth segmentation stage by using active contour
- he all process (undone due to computation concerns);
- dd knowledge-rules to the feature extraction process:
- Examples:
- > The size of the dark area of the tooth in contact with the outer parts the crown;
- Template matching of the tooth border, for cases where the dental ca artially or totally, damaged the tooth crown;