Computer Aided Diagnosis of Bone Lesions in the Facial Skeleton

Wolfgang Sörgel[1,2], Sabine Girod[2], Martin Szummer[3] and Bernd Girod[1]

[1]Lehrstuhl für Nachrichtentechnik I, Universität Erlangen-Nürnberg, 91058 Erlangen
[2] Klinik und Poliklinik für Mund-,Kiefer-,Gesichtschirurgie, 91054 Erlangen
[3] M.I.T. Media Lab, Cambridge MA 02139, USA. **
{wsoergel,girod,szummer}@nt.e-technik.uni-erlangen.de

Abstract. We present a system for computer aided diagnosis of bone tumors in the facial skeleton. There are many different lesions with radiographic manifestation in the jaws. Our system helps performing the differential diagnosis of these. The input is a digitized orthopantomograph (OPG) in which the user marks the position of the lesion with a single mouse click. An active contour model then automatically finds the boundaries of the lesion. Gray-level histograms, MRSAR texture features and Gabor filter features are computed for the lesion region. These features are then combined and used to query a database containing expert-diagnosed reference cases. The result is a number of similar cases, with tumor position marked and with available expert annotations. We show good agreement between our results and differential diagnosis given by humans. The system is also a suitable tool for training and education.

Keywords: Computer aided diagnosis, content based image retrieval

1 Introduction

Bone tumors in the maxilla and mandible are relatively rare. The clinical symptoms are usually unspecific and therefore most of the tumors are discovered accidentally during routine radiological exams. The differential diagnosis of bone tumors in the jaws is difficult and can be based on the radiologic findings, e.g. the structure of the tumor region in the x-ray, defined or diffuse margins, presence or absence of teeth and localization of the lesion. Traditionally a printed tumor atlas [1] is used to compare the images and narrow down possible differential diagnoses. A system for computer-aided diagnosis of these lesions, based on characterization of the findings by the user and the use of Bayes rule to find a probability for each disease has also been devised [2]. In contrast to those approaches requiring the user to interpret the image, in our system the images are analyzed and features characterizing the lesions are computed. Based on these features a database containing expert diagnosed reference cases is queried for the cases most similar to the one presented. It is then the responsibility of the user to interpret the results and decide on necessary therapeutic measures, we do *not* attempt to classify a case or even give a computer diagnosis.

** M. Szummer contributed to this project as a visiting scientist supported by the Graduiertenkolleg 3-D Image Analysis and Synthesis.

2 Database

At the moment our database contains 236 cases from 20 different disease classes. Of these cases 161 were taken from the DOESAK (Deutsch-OEsterreichisch-Schweizerischer Arbeitskreis für Tumoren im Mund-Kiefer- und Gesichtsbereich) central registry of bone tumors in Basel, Switzerland, the rest are local cases from Erlangen. At least one OPG is stored for each case. The images were digitized at 150 dpi and normalized at 256 gray levels. Precomputed features for queries and tumor localization information are stored. Age and sex prevalence for the different diseases is also available in addition to the data of individual cases. Combination of databases, addition of new cases, manual browsing and restriction of the search is possible as well as remote access over the Internet.

3 Identification of Lesion Boundaries

After a new image is digitized the boundaries of a present lesion must be outlined. In our current implementation we rely on the user to find the lesion and point to it with the cursor. The subsequent outlining is automatic and usually requires no additional user interaction. Based on user input the contour boundaries are outlined using active contour models. Since lesion appearance is not uniform and the margins are often very diffuse, we use an energy formulation which is partly based on the image properties in a small circle around the initialization point to get a region based active contour model [3, 4]. While the contour converges, the region around each of its points is compared to the initial region, based on the result from filtering operations to indicate texture and gray-level properties. As long as there is similarity, given by a Mahalanobis measure, the contour expands rapidly, otherwise it stops.

We use three regions for image analysis: rectangular regions inscribed in and bounding the contour and the polygonally bounded region of the lesion itself.

4 Features for Database Query

Using this segmentation, features for database query are computed. The first, most important group of features is based on the image gray level. Further features are derived from the lesion contour and additional patient information.

The brightness of a lesion is a significant radiologic feature which we analyze using histograms to obtain a quantification of whether a lesion is radiopaque or radiolucent, and whether it is more uniformly colored or has flecks.

Different texture metrics are employed to assess the radiologic microstructure of the lesion bone tissue. Texture analysis is a powerful tool which has been successfully used in different content-based image query systems [5, 6] and has been proposed for identification and comparison of bone lesions in radiologic images [7]. It is also well-known that a single metric is not suitable for all queries, this was confirmed by early experiments. We thus apply several different metrics. The segmented image regions are first preprocessed by unsharp masking with a large median filter to remove low frequency disturbances and enhance the microstructure. The following algorithms have been chosen for feature computation:

- An autoregressive texture model (MRSAR) [8] with three resolution levels and four neighbors at each level. This metric is well suited to recover fine grainy structures and, applied to the lesion bounding region, indicates the presence of teeth around a lesion quite well.
- A texture description based on filtering with Gabor filters at different scales and orientations [9]. The metric derived from the energy of the filter output in the different bands identifies line-like structures especially well.

Each of these features is directly compared to the corresponding feature for each case in the database, using the Euclidean metric, Mahalanobis distance or undirected divergence.

Besides the above image derived features we also use the age and the sex of a patient to find similar images in a query. Since these features are only relevant for certain diseases, a probability density for each disease class has been estimated using 2744 cases from the DOESAK central registry as a statistical basis. The feature distance is then the joint conditional probability density function of the presented case and the database case under the hypothesis they are both from the same class as the database case.

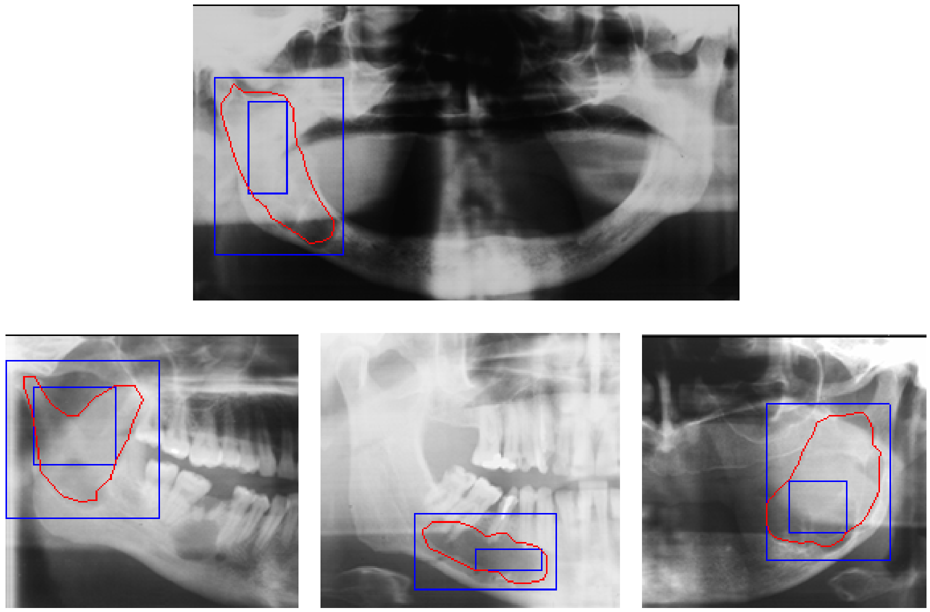
To finally query the database we must combine the multiple features into a single similarity measure for each case. We use a weighted rank-order combination of the features. Specifically, the database cases are sorted according to ascending distance for each feature. The rank numbers are then weighted by a feature weighting and summed up to give an overall measure of similarity for each database case. To gain robustness, the most poorly matching features for a given case are discarded.

The best matches are then presented to the user. Tumors are marked and all available annotations are displayed. The user can now view these images, retrieve more images which are similar to returned ones or perform a new query with changed parameters or a restricted database.

5 Example Queries

We show two example queries using our system. For case A we used an image of a 81-year-old female patient who was diagnosed with a kerato cyst of fairly typical appearance. The following features were used in the query: gray-level histogram (inscribed rectangle and polygonal region), MRSAR and Gabor filter based texture (inscribed and bounding rectangles), age and sex of the patient, contour aspect ratio and smoothness. Figure 1 shows the image and the best returned matches, Table 1 summarizes the results. All results returned for example case A, with exception of the fourth match, are either the correct diagnosis or relevant differential diagnoses. As a second example case B we used an osteogenic tumor,

Fig. 1. Example Results: Reference case A (Kerato Cyst) on top with the three best matches shown left to right below. The lesions are marked.



an osteoma, diagnosed in 28-year-old female as reference, results are also shown in Table 1. Again, all cases with exception of one (sixth match, a fairly atypical giant cell granuloma) are correct or relevant. More results, including images, can be found in the WWW at `http://www.nt.e-technik.uni-erlangen.de/~wsoergel/diagnosis/`. In general, we found that the system returns visually similar cases to the query case, and most of them are also diagnostically relevant.

6 Conclusions and Future Work

We have presented a system for computer aided diagnosis of bone lesions in the jaw, based on image analysis and content-based query of a database. A lesion in a digitized radiograph of the jaw is marked and then outlined by a region-based active contour model. Then gray level, texture and other features are computed for the suspicious region. Based on these features a database with expert diagnosed bone cancer cases is queried for similar cases. The returned matches have been found to be a valuable aid in giving a differential diagnosis. Currently we are evaluating additional features, e.g. considering form and location of the tumors. Clinical evaluation of the system also plays an important role in the project, as well as expanding our database.

Table 1. Results returned for example queries.

Case	Disease	Age	Sex	Case	Disease	Age	Sex
A	Kerato Cyst	81	female	B	Osteoma	28	female
1.	Pseudo Cyst	41	male	1.	Osteoma	36	female
2.	Kerato Cyst	46	male	2.	Osteoma	51	female
3.	Ameloblastoma	65	female	3.	Osteosarcoma	28	male
4.	Fibroma	17	female	4.	Compound Odontoma	12	female
5.	Kerato Cyst	25	female	5.	Compound Odontoma	54	male
6.	Kerato Cyst	54	male	6.	Giant Cell Granuloma	26	female

7 Acknowledgments

We acknowledge the support of Friatec AG, Mannheim for this project. We would also like to express our gratitude towards Dr. Jundt at Kantonshospital in Basel, Switzerland for providing us with images from the DOESAK central registry of bone tumors maintained at his institute.

References

1. J. Prein, W. Remagen, B. Speissl, and E. Uehlinger. *Atlas of Tumors of the Facial Skeleton.* Springer Verlag, 1996.
2. S.C. White. Computer-aided differential diagnosis of oral radiographic lesions. *Dentomaxillofacial Radiology*, 18(5):53 – 59, May 1989.
3. S. C. Zhu and A. L. Yuille. Region competition: Unifying snakes, region growing and Bayes/MDL for multi-band image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 18(9):884 – 901, September 1996.
4. J. Ivins and J. Porril. Active region models for segmenting medical images. In *Proc. ICIP'94*, volume 2, pages 377 – 386, 1994.
5. A. Pentland, R. Picard, and S. Sclaroff. Photobook: Tools for content-base manipulation of image databases. In *Proc. SPIE*, volume 2185, pages 34 – 47, San Jose, CA, February 1994.
6. J. R. Smith and S.-F. Chang. Local color and texture extraction and spatial query. In *Proc. International Conference on Image Processing*, Lausanne, Switzerland, September 1996.
7. F. Weiler, E. Pelikan, T. Nobis, T. Tolxdorff, and K. Bohndorf. Texturbasierte Extraktion medizinischer Merkmale aus Filmröntgenbildern. In S.J. Pöppl and H. Handels, editors, *Mustererkennung 1993*, Berlin, 1993. Springer.
8. J. Mao and A. K. Jain. Texture classification and segmentation using multiresolution simultaneous autoregressive models. *Pattern Recognition*, 25(2):173 – 188, 1992.
9. B. S. Manjunath and Y. W. Ma. Texture features for browsing and retrieval of image data. *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI)*, 18(8):837 – 841, August 1996.