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# A New Perceptual Approach to Noisy X—ray Image Segmentation

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Abstract—This paper proposes a new perceptual approach to noisy X—ray image segmentation. It consists of the five major steps: (1) Pre—segmentation, (2) Improved region growing, (3) Object detection. The heuristic knowledge about the biological struction of the human organs and simulation of human expert diagnosis is arranged by knowledge mechanism. And the knowledge driven interpretation is consistent with the human perception deduction. The method has been applied in medical ultrasonic image and X—ray stereoscope analysis. The experimental results show that it is a perspective approach to computer—aided diagnosis for medical imaging.

Keyworks: medical image processing, knowledge engineering, image segmentation, computer vision.

## 1. INTRODUCTION

The interpretation for the medical imaging is a complicated process. The increasing complexity of modern imaging makes the computational approaches to computer—aided interpretation more important and imperative. The clinician must observe the images and make deductions about their normality on the basis of one' s experience of the imaging diagnosis and other information about the patient. This is a complex process requiring years of training and experience and there is also some variation in interpretation between practitioners. The use of computers as an aid to interpretation of images has been paid more attention to by tne researchers and become popular in biomedical engineering applications. The accurancy of medical diagnosis depends much more on the image interpretation. For reservation and propagation of the experienced knowledge, the building of computer—aided interpretation system for medical images, as intelligent assistant for clinical personnel, is necessary and practical.

In non—medical fields, complete vision systems have been developed for some particular applications such as industrial vision object detection, robot navigation etc. [10] However, the field of medical image interpretation is more difficult, because of the nature of medical images. The difficulties could be listed as five points[3],[8][1]

(1) The images derived from all the existing medical imaging modalities are more or less noisy.

(2) In general, object surfaces in the images are not opaque owing to the use of illumination that penetrates them.

(3) The defects sought are often small and subtle, the range of variation in a normal image is great, but the allowed margin of error is small.

(4) Much knowledge not directly concerned with the image itself needs to be considered to provide a perfect interpretation.

(5) The ad hoc performance of existing algorithms in machine vision could be improved and unsupervised adaptive one developed.

Since 1960s, many techniques have been developed in the field. The early works focus on chest radiographs which is usual in hospital treatment. E. L. Hall et al.[6] analyzes the feature extraction techniques in radiograph processing. H. Wechsler and J. Sklansky[7] uses edge detectors and linking curves to find the rib cage in chest radiographs and form ribs from them. J. F. Brinkley[5] uses knowledge—driven mechanism to ultrasonic modeling process. N. Zheng[1] and J. Liu presents a flexible knowledge representation scheme and discusses its application to ultrasonic image segmentation. S. A. Stansfield[4] builds a practical expert system for digital subtracted angiograms. The system consists of two levels. In the low level stages, the segmented representation of the input image is created by the system routines. And in the high—level, the expert system performs the knowledge inference by the rule based mechanism. However, the optimal segmentation for medical objects and their exact description are two crucial factors in automatic interpretation. To perform the perfect representation and interpretation for medical imaging, a new perceptual approach to noisy X—ray image sepmentation is proposed as follows.

## 2. OUTLINE OF THE ALGORITHM

The new algorithm consists of five major steps: (1)pre—segmentation, (2)improved region growing, (3)object detection, (4)semantic assignment, and (5)recursive inference. The flow chart is expressed in Fig. 1.

Pre—segmentation constructs the atomic elements for description. The improved region growing algorithm is guided by the heuristic inference. Based on Gestalt psychological principle, object detection performs the recognition of the meaningful regions such as human organs, especially the ones with adenoma. According to the attribute description (average value, variance of the intensity, area, form of the regions), the semantics are assigned to correspondent regions. The knowledge inference guides the recursive region segmentation and semantics assignment so that all the objects could be detected. The heuristic knowledge about the biological structure of the human organs and simulating of human expert diagnosis is arranged by knowledge mechanism. The frame—like structure and production rule representation processes the object description and dynamic inference respectively. And the knowledge driven interpretation is consistent with the human perception deduction. The whole system is with the hierarchical architecture of visual information processing. And low level perceptual operation is combined with high level cognitive process. The performance of the corresponding functional mechanism is quite satisfactory.

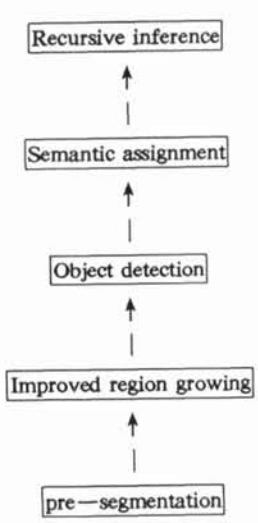


Fig. 1 flow chart of the algorithm

## 3. PRE—SEGMENTATION BY UNSUPERVISED ADAPTIVE NEURAL NET

Pre—segmentation performs the elemental feature extraction and region forming. It should be robust and adaptive. For the purpose, the unsupervised learning function is required. Fortunately, the promising artificial neural network technique could deal with these computational tasks efficiently. A new neural network model, which is proposed by J. Liu and N. Zhang[2], is applied in the procedure.

The neural net model consists of parallel subsystems:

(1) Local feature extraction: The local statistical features of original image are in moving window (e. g. of size as two—order neighbor or larger one). In the subsystem, the measurement vector expressing the statistical distribution is estimated by random field modeling. The gray level, statistical feature and quantitative description of textured structure could be taken into considered and the segmentation processing extended to texture image. If unsupervised statistical edge estimation is constructed, it could even be extended to noisy cases.

(2) Nonlinear measurement reflection: By the hypercube cell measurement, the multi — dimensional histogram is generated. The cell sizes are dependent on the cluster features in space distribution and usually are different for the corresponding cells. The non—linear measurement reflection is implemented to convert the original data space into the measurement space for pattern discrimination.

(3) Iterative parallel region merging: In the measurement space, the candidate regions represented by peaks and valleys are examined by local contrast. And the ones which satisfy the homogeneity and proximity, could be merged into a new region. The operation is parallizable and guided by AIC adaptive decision — making mechanism in the higher level.

(4) AIC based unsupervised adaptive clustering: Based on the AIC (Akaika Information Criteria), the adaptive decision—making is performed in the unsupervised mode. The AIC reflects the perfect quantitative measure of goodness in statistical clustering procedure. With the technique, a prior knowledge such as the number of classes isn't required. And the parameters concerned could be estimated by the optimal decision making mechanism. Both any thresholding and experienced parameters are not required. It is the significant difference from the traditional techniques. The result achieved in the layer guides the iterative region merging and the process doesn't stop untill the class number has reached the limit directed by the AIC mecha-

nism. So the optimal segmentation result has been obtained and its robustness is quite satisfactory.

The model is expressed in Fig. 2, and it has been applied in both medical image analysis and outdoor natural scene[2]

## 4. REGION REFINATION BY GRG ALGORITHM

Actually, the detected segmented results usually don' t correspond to the meaningful ones in semantics. The Generalized Region Growing (GRG) algorithm is presented to refine the region dextermination. It is defined as the concopt that the regions are merged into larger ones according to their semantic meanings and the exact contour determination is performed by AIC based edge location process.

On the basis of pre—segmentation, some isolated regions should be eliminated or merged into the meaningful regions. The uncontinuous edge should be linked and enough details preserved. These tasks could be dealed with by the GRG algorithm. The region merging is proceeded by the region analysar and the exact contours are located by the edge finder. In the local edge detection, the optimal estimation is constructed by the AIC process. The AIC mentioned here is refered to the local optimization identication for the statistical model. But the one dedicated in last section is used in global clustering work.

The region analysis consists of the geometical parameter computation for region, spatial location of different objects and semantic similarity judgement. The geometrical parameter includes the area center, radius, shape, etc. The relational matrix describes the mutual relations for different areas. And the similarity in semantic plays an important role in the judgement for the adjacent region merging process.

Based on the AIC[9], the stochastic model—fitting scheme is applied in cluster validation in unsupervised image segmentation. The model parameters such as the number of various classes in the observed image is estimated directly from the image under the condition that a prior knowledge isn' t known, The AIC formula is both brief and efficient:

$$AIC(K) = -2\log\{P_k(Y \mid \hat{a}(k)_{ML})\} + 2K' \quad (1)$$

where $\hat{a}(k)_{ML}$ is the maximum likelihood (ML) estimate of the model parameter vector $a^{(k)}$ and $K'$ is the number of independently adjustable parameters of the K—class data model. The AIC scheme will select the number of clusters to be $K_0$ if

$$K_0 = \arg \min_{1 \leq K \leq K_{max}} AIC(K) \quad (2)$$

where $K_{max}$ is a prespecified upper limit for K. So the optimal class number $K_0$ could be determined by the minimum AIC principle and the region clustering mechanism is proceeded iteratively to the optimal state of the dynamic classification.

Both an edge and a region analysis are performed, the two representations are then combined, with the edge analysis serving to verify and refine the region segmentation. This entails the creation of the segmented image containing both edges and regions and the construction of the geometric model of the objects it contains.

## 5. MODEL INTERPRETATION BY KNOWLEDGE DRIVEN MECHANISM

For the segmented representation of the image, the domain knowledge of anatomy and physiology are embodied in the high—level medical analysis. Applying this knowledge to the objects and relations determines the object recognition and description. It identifies those objects which are the organ with adenoma and gives the reasonable interpretation rule, and recursive inference for guidance to the low level region refination (Cf. Fig. 3). Among these parts, the key factor is the knowledge arrangement. Knowledge about objects is in the form of facts about their attributes. And corresponding rules contain knowledge about the shape and structure of organs. The inference engine generates the hypothese and then combines them to determine a final identification for the interested objects such as broken bone, inner organ with adenoma etc. And the general—purpose models which contain knowledge about images and their features perform the recursive operations for low level

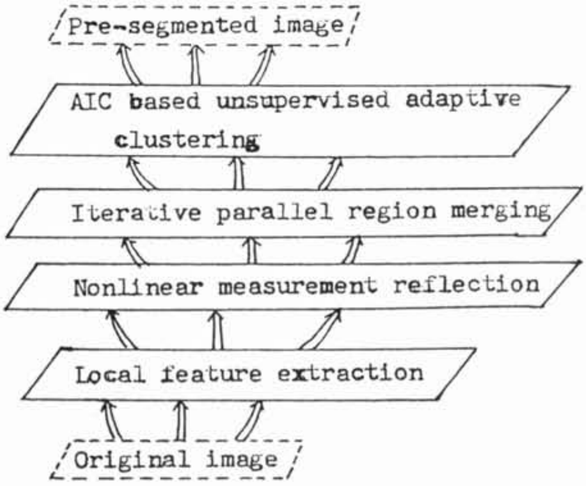


Fig.2 The neural net model

segmentation. Its purpose is domain—independent analysis and it works with both lines and regions, rules are divided into catagories dealing with object operations, control, and strategy. The rule—based data structure is efficient to identify organ segments in medical images.

The abnominal anatomy is represented by the integrated geometric model and the satisfied interpretation could be given by the modeling inference. Knowledge is in the form of the relational model of the biological structure include geometrical characteristics and procedural knowledge. The quantitative representation for physical objects, verification for hypothses, and geometric description are accessed by hierarchically related elements. Control via procedural knowledge is embedded in this model. So the knowledge—based image understanding is constructed by these mechanism to deal with the automatic inter pretation in specific domain. The semantic conflict is avoided by the priority selection. Based on the knowledge driven mechanism, the knowledg arrangement shell and support enviroment could be provided and the high flexibility and adaptability desired to be obtained.

## 6. DISCUSSION

The algorithm proposed in this paper has been complemented on a SUN—80386 computer system by Turbo—C language. It has been applied to radiographic images such as the hand brone, body skeleton etc. Permilinary experimental result is given in Fig. 4. Fig. 4(a) gives the original image which contains a hand bones with broken parts. The low quality of illumination could be found and the uniformity of gray level distribution is poor. Fig. 4(b) gives the result obtained by the new algorithm. In the image, the broken part is identified and represented by the enhanced window. To make the viewers see the contour more clearly, the region borders are thicken by the routines. Fig. 4(c) and Fig. 4(d) give the pre—segmentation result shown by region intensity and edge information respectively. They are achieved by two local features(gray level and predicate variance). The number of regions detected is larger than the meaningful region. In Fig. 4(a), only the local variance has been applied as clustering feature. But the uncontinuous edges exist near the region contours. So the pre—segmentation result should be used as input to the high level mechanism and refination is necessary. The final interpretation result expressed in Fig. 4(b) is the output of knowledge—driven image understanding process. From the satisfactory results, it is shown that the new computational approach is efficient and practical. And it has been applied in the X—ray stereoscope and medical ultrasonic image analysis.

## 7. CONCLUSION

A new perceptual approach is proposed in the paper to perform the noisy X—ray image segmentation The principal contributions of the research work are stated below:

1) The flexible knowledge driven strategy expresses the Gestalt psychonological concepts and knowledge based modeling. The guidance of geometric constraints could result in the near—optimal closed boundaries for meaningful regions and objects.

2) The segmentation procedure is constructed by unsupervised neural network which is adaptive non—parametric and parallizable hierarchical architecture. Any a prior parameters such as thresholding is not required. Automatic pre—segmentation is performed by the neural net to extract the enough details of the perceptual contour and region in medical images. The simulating process is consistent with the human preattentive vision perception.

As the knowledg rule base has been expanded and the parallel real—time hardware developed, the computer aided image interpretation technique could be perfected further so as to upgrade its efficiency largely. It could be expected that the computer—aided diagnosis for medical imaging will surely become a more promising and perspective field in biomedical engineering applications.

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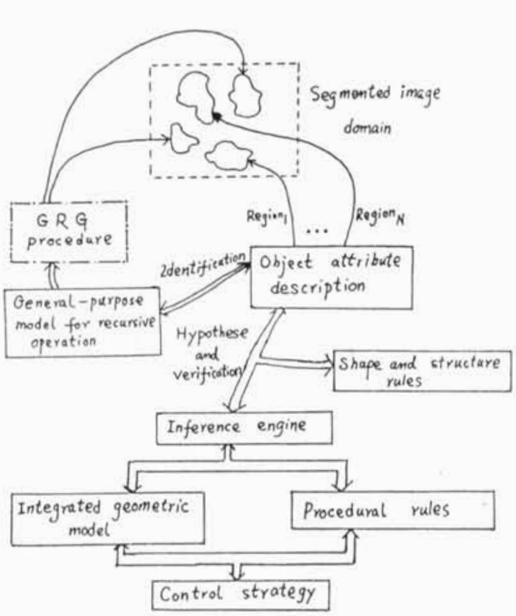
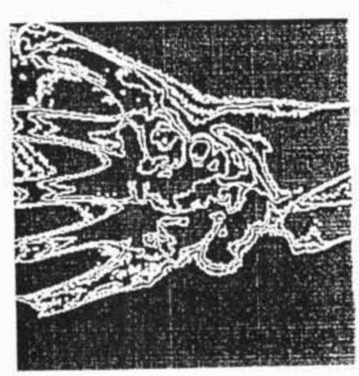



Fig. 3 Knowledge arrangement

(a)

(b)

(c)



(d)

Fig.4