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Review Paper on Validation of Medical Image Devices for Detection and Diagnosis of Various Diseases by Using Soft Computing Tools.

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ABSTRACT: *The imagining technologies employ conventional projection radiography, computed tomography, MRI, Ultrasonography etc. Image processing techniques play a crucial role in clinical studies of different diseases. Current manual methods of measurement are laborious and subjective. Our purpose is to expedite clinical research with an accurate, reliable and intelligent digital image processing method. Medical imagining research will investigates new modalities and improvements to existing ones for clinical diagnosis. The objective of the present research work is to develop intelligent interpretation using different approach for Improving the quality of imaging device and quantative image analysis to provide a guide for clinicians to improve the quality of diagnosis and increase therapy success by early detection of diseases.It is very essential to hv good quality of images in this regard this work will make attempt to develop various techniques.*

KEYWORDS: Imagining, Technology Interpretation, Imaging Device and Quality

INTRODUCTION

By the increasing use of direct digital imaging systems for medical diagnostics, digital image processing becomes more and more important in health care. In addition to originally digital methods, such as Computed Tomography (CT) or Magnetic Resonance Imaging (MRI), initially analogue imaging modalities such as endoscopy or radiography are nowadays equipped with digital sensors.

Digital images are composed of individual pixels(this acronym is formed fromthe words “picture” and “element”), to which discrete brightness or color valuesare assigned. They can be efficiently processed, objectively evaluated, and made available at many places at the same time by means of appropriatecommunication networks and protocols, such as Picture Archiving and Communication

Systems (PACS) and the Digital Imaging and Communications in Medicine (DICOM) protocol, respectively. Based on digital imaging techniques, the entire spectrum of digital image processing is now applicable in medicine.

The development of medical imaging over the past years has been truly revolutionary. For example, wireless capsule endoscopy and telemedicine systems have provided some of the most effective diagnostic tools in the field of health science. These systems involve X-ray images, CT scan images, and endoscopic images that require large volume of storage, as well as bandwidth for data transmission, which in turns increase the cost and transmission time. The need is then to have an effective and efficient compression and decompression algorithm that is capable of achieving higher compression ratio while preserving the critical image/video information for better data reconstruction.

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Image data is a combination of information and redundancy, the information is maintained. Image processing, low-level processing denotes manual or automatic techniques, which can be realized without a priori knowledge on the specific content of images. This type of algorithms has similar effects regardless ofthe content of the images. For example, histogram stretching of a radiograph improves the contrast as it does on any holiday photograph. Therefore, low-level processing methods are usually available with programs for image enhancement.

Even if captured with the same modality and following a standardized acquisition protocol, shape, size, and internal structures of theseobjects may vary remarkably not only from patient to patient (inter-subject variation) but also among different views of a patient and similar viewsof the same patients at different times (intra-subject variation). In other words, biological structures are subject to both inter- and intra-individualalterability. Thus, universal formulation of a priori knowledge is impossible.

Unknown delineation of objects: Frequently, biological structures cannot be separated from the background because the diagnostically or therapeutically relevant object is represented by the entire image. Even if definable objects are observed in biomedical images, their segmentation is problematic because the shape or borderline itself is represented fuzzily or only partly. Hence, medically related items often can be abstracted at most onthe texture level.

Robustness of algorithms*:* In addition to these inherent properties of medical images, which complicate their high-level processing, special requirements of reliability and robustness of medical procedures and, when applied in routine, image processing algorithms are also demanded in the medical area. As a rule, automatic analysis of images in medicine should not provide wrong measurements. That means that images, which cannot be processed correctly, must be automatically classified as such, rejected and withdrawn from further processing. Consequently, all images that have not been rejected must be evaluated correctly. Furthermore, the number of rejected images is not allowed to become large, since most medical imaging procedures are harmful and cannot be repeated just because of image processing errors.

Artificial Neural Networks (ANNs) are mathematical analogues of biological neural systems, in the sense that they are made up of a parallel interconnected system of nodes, called neurons. The parallel action is a difference between von Neumann computers and ANNs. Combining ANN architectures with different learning schemes, results in a variety of ANN systems. The proper ANN is obtained by taking into consideration the requirements of the specific application, as each ANN topology does not yield satisfactory results in all practical cases. The evolution of digital computers as well as the development of modern theories for learning and information processing led to the emergence of Computational Intelligence (CI) engineering. Artificial Neural Networks (ANNs) and Fuzzy Logic are CI non-symbolic learning approaches for solving problems. The huge mass of applications, which ANNs have been used with satisfactory results, has supported their rapid growth.

Image processing techniques play a crucial role in clinical studies of tumor. Current manual methods of measurement are laborious and subjective. Our purpose is to expedite clinical research with an accurate, reliable and intelligent digital image processing method. Semi-automated, supervised computer aided interpretation may be done reproducibly and

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accurately with adaptations of commercial software. This technique for image analysis has potential for use in clinical research.

Color photographs have been routinely employed for diagnostic purposes for many years, and are central to clinical studies of tumor detection. There has been continued interest in the use of digital techniques for quantification of biomedical decisions. However, despite progress, none of the previous methods have gained widespread use. A major obstacle has been that the reflectance of the normal background, on which the pathology is superimposed, is inherently non-uniform. The human eye with training makes allowances for this variability, but a computer applying a threshold does not.Prior methods have so far been unable to deal with this non-uniform background reflectance as a whole. Despite the use of a wide range of general image analysis tools, their methods, as those in the other references, take no account of the intrinsic background variability, and accordingly can produce errors in a systematic and predictable fashion: inadequate segmentation centrally. On the other hand, a potential advantage of using simpler techniques in less specialized software, with expert oversight of the final segmentations, is portability and use at other institutions for research.

A BRIEF REVIEW OF THE WORK ALREADY DONE IN THE FIELD

The concept of CAD was introduced with mammography CAD as its first application. Over the last few years, a huge number of mammography procedures have been performed with CAD as a second reader. The role of CAD is to alert the radiologist to "regions of interest" that might have been overlooked in the initial read.

The CAD market is developing at a rapid pace and new CAD applications have emerged, such as detection of lung cancer with chest radiography and detection of lung nodules with chest CT. In addition to lung CAD applications, there is increasing interest in the use of CAD technologies for the detection of colon polyps. This can be characterized by the following interrelated needs.

Population-wide: to meet the large demand and to enable effective management of the diseases.

1. Clinical: owing to the nature of the colon's anatomy subject to deformation, variability of the preparation, distension, insufflations and cleanliness and the difficulty of detecting of polyps even when examining both prone and supine, since polyps may be visible in only one of the two volumes.

2. Information and data management new powerful CT systems have increased spatial resolution (up to 0.4 mm with Siemens Sensation 64) for better diagnostic evaluations but have also increased the number of slices acquired (up to 1200 per volume for a routine abdominal scan).

Therefore, a CAD system must be able to handle the evolving technology, provide better means to visualize and analyze data, and improve physician's sensitivity in the detection of clinically relevant lesions. Whilst visualization and analysis are keys to enabling a physician to deliberate on the nature of lesions, the ability to automatically detect lesions (polyps) is where CAD's impact can be most significant. Two types of study designs can be used to determine the sensitivity of a CAD system.

- Comparative: a CAD system is run on a set of cases, and its sensitivity is computed and compared with the performance of physicians on (a) the same set cases or (b) other study with similar population characteristics.

- Additive: a CAD system functions as a second reader. In this type of study a reader reviews the case first and then evaluates the CAD findings. Any new true positive findings accepted by the reader constitute the added sensitivity. Okamura et al [16] report a first study in which CAD was demonstrated to add value to all physicians participating in the study, regardless of the level of expertise, when used as a second reader.

The performance of the Colon CAD prototype was developed as part of a study involving data sets obtained from two sites, New York University Medical Center (NYU) and the Cleveland Clinic Foundation (CCF). Both sites granted Independent Review Board approvals and all cases were de-identified (all patient identification information was removed) prior to their transfer to Siemens.

NOTEWORTHY CONTRIBUTION IN THE FIELD OF PROPOSED WORK

Chung-Ming Wu, et al. [3] proposed a texture feature called Multiresolution Fractal (MF) feature to distinguish normal, hepatoma and cirrhosis liver using ultrasonic liver images with an accuracy of 90%.

Yasser M. Kadah, et al. [4] extracted first order gray level parameters like mean and first percentile and second order gray level parameters like Contrast, Angular Second Moment, Entropy and Correlation, and trained the Functional Link Neural Network for automatic diagnosis of diffused liver diseases like fatty and cirrhosis using ultrasonic images and showed that very good diagnostic rates can be obtained using unconventional classifiers trained on actual patient data.

Aleksandra Mojsilovic, et al. [5] investigated the application and advantages of the non separable wavelet transform features for diffused liver tissue characterization using B-Scan liver images and compared the approach with other texture measures like SGLDM (Spatial Gray Level Dependence Matrices), Fractal texture measures and Fourier measures. The classification accuracy was 87% for the SGLDM, 82% for Fourier measures and 69% for Fractal texture measures and 90% for wavelet approach.

E-Liang Chen, et al. [6] used Modified Probabilistic Neural Network (MPNN) on CT abdominal images in conjuction with feature descriptors generated by fractal feature information and the gray level co occurrence matrix and classified liver tumors into hepatoma and hemangeoma with an accuracy of 83%. Pavlopoulos, et al. [7] proposed a CAD system based on texture features estimated from Gray Level Difference Statistics (GLDS), SGLDM, Fractal Dimension (FD) and a novel fuzzy neural network classifier to classify a liver ultrasound images into normal, fatty and cirrhosis with accuracy in the order of 82.7%.

Jae-Sung Hong, et al. [8] proposed a CAD system based on Fuzzy C Means Clustering for liver tumor extraction with an accuracy of 91% using features like area, circularity and minimum distance from liver boundary to tumor and Bayes classifier for classifying normal and abnormal slice.

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The CAD system proposed by Gletsos Miltiades, et al. [9] consists of two basic modules: the feature extraction and the classifier modules. In their work, region of interest (liver tumor) were identified manually from the CT liver images and then fed to the feature extraction module. The total performance of the system was 97% for validation set and 100% for testing set. Haralick transform and Hopfield Neural Network were used to segment 90% of the liver pixels correctly from the CT abdominal image by John. E. Koss, et al. [10]. However, texture based segmentation results in coarse and blockwise contour leading to poor boundary accuracy. Chien-Cheng Lee, et al. [11] identified liver region by using the fuzzy descriptors and fuzzy rules constructed using the features like location, distance, intensity, area, compactness and elongated-ness from CT abdominal images. Wen-Li Lee et al. [12] proposed a feature selection algorithm based on fractal geometry and M-band wavelet transform for the classification of normal, cirrhosis and hepatoma ultrasonic liver images. A hierarchial classifier which is based on the proposed feature extraction algorithm is at least 96.7% accurate in distinguishing between **normal and abnormal liver images and is** at least 93.6% accurate in distinguishing between cirrhosis and hepatoma liver images. Maroulis, D.E. Savelonas, M.A. [48] 2005 have proposed Computer-aided thyroid nodule detection in ultrasound images. In this paper, they propose a novel method for computer-aided detection of thyroid nodules in ultrasound (US) images. The proposed method is based on a level-set image segmentation approach that takes into account the inhomogeneity of the US images. **Xiaowei Chen, Xiaobo Zhou and Wong, S.T.C. 2006 [47] has proposed Automated segmentation, classification, and tracking of cancer cell nuclei in time-lapse microscopy.** Existing computational imaging methods are rather limited in analyzing and tracking such time-lapse datasets, and manual analysis is unreasonably time-consuming and subject to observer variances. An automated system that integrates a series of advanced analysis methods to fill this gap. The cellular image analysis methods can be used to segment, classify, and track individual cells in a living cell population over a few days. Experimental results show that the proposed method is efficient and effective in cell tracking and phase identification Yu-Len Huang, et al. [13] used autocorrelation features and Multilayer Perception (MLP) Neural Network for predicting malignancies in the order of 80.5% from unenhanced CT images. This reduced the need for iodinated contrast agent injection in CT examinations.

SUMMARY AND CONCLUSION

In this survey paper various automatic detection methods of brain diseases through MRI has been studied and compared for the period of more than two decades. The literature survey shows that the tumor region is classified without identifying tumor region from brain and Liver region. Also, they don’t classify the subcategories of benign and malignant tumor.

The methods reviewed fall roughly into four model groups: c-means, maximum likelihood, neural networks, and k-nearest neighbor rules. Both supervised and unsupervised schemes require human intervention to obtain clinically useful results in MR segmentation. Unsupervised techniques require somewhat less interaction on a per patient/image basis. Maximum likelihood techniques have had some success, but are very susceptible to the choice of training region, which may need to be chosen slice by slice for even one patient. Generally, techniques that must assume an underlying statistical distribution of the data (such as LML and UML) do not appear promising, since tissue regions of interest do not usually obey the distributional tendencies of probability density functions. The most promising

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supervised techniques reviewed seem to be FF/NN methods that allow hidden layers to be configured as examples are presented to the system. An example of a self-configuring network, FF/CC, was also discussed. The relatively simple k-nearest neighbor rule algorithms (hard and fuzzy) have also shown promise in the supervised category. Unsupervised techniques based upon fuzzy c-means clustering algorithms have also shown great promise in MR image segmentation. Several unsupervised connectionist techniques have recently been experimented with on MR images of the brain and have provided promising initial results. A pixel-intensity-based edge detection algorithm has recently been used to provide promising segmentations of the brain. This is also an unsupervised technique, older versions of which have been susceptible to over segmenting the image because of the lack of clear boundaries between tissue types or finding uninteresting boundaries between slightly different types of the same tissue. To conclude, we offer some remarks about improving MR segmentation techniques. The better unsupervised techniques are too slow. Improving speed via parallelization and optimization will improve their competitiveness with, e.g., the k-nn rule, which is the fastest technique covered in this review. Another area for development is dynamic cluster validity. Unsupervised methods need better ways to specify and adjust c, the number of tissue classes found by the algorithm. Initialization is a third important area of research. Many of the schemes listed in Table II are sensitive to good initialization, both in terms of the parameters of the design, as well as operator selection of training data.

In this regard, this study focused on the design and the development of a CAD system for classifying the liver and brain tumors using wavelet based texture analysis and neural network.

PROPOSED METHODOLOGY AND SCOPE OF WORK

Segmentation is an important process to extract information from complex medical images. Segmentation has wide application in medical field [3-4]. The main objective of the image segmentation is to partition an image into mutually exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogeneous with respect to a predefined criterion. Widely used homogeneity criteria include values of intensity, texture, color, range, surface normal and surface curvatures. During the past many researchers in the field of medical imaging and soft computing have made significant survey in the field of image segmentation. Expert knowledge can be used to formulate human rules for interpretation and accordingly fuzzy aspects of segmentation can be utilized effectively for localization of image.

In this research work, it is proposed to develop fuzzy model of interpretation of image. Statistical aspects of several images will be taken into consideration. Statistical aspects include similar age group features of tumor, pattern of variation and correlation for different case of patients will be given due consideration.

The past, present, and future paradigms of medical image processing are composed the pragmatic issues of image generation, processing, presentation, and archiving stood in the focus of research in biomedical image processing, because available computers at that time had by far not the necessary capacity to hold and modify large image data in memory. The former computation speed of image processing allowed only offline calculations. Until today, the automatic interpretation of biomedical images still is a major goal. Segmentation,

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classification, and measurements of biomedical images is continuously improved and validated more accurately, since validation is based on larger studies with high volumes of data. Hence, we focused this on image analysis and the processingsteps associated with it.The future development is seen in the increasing integration of algorithms and applications in the medical routine. Procedures in support of diagnosis, treatment planning, and therapy must be easily usable for physicians.

It is proposed to develop separate expert system for interpretation of diff medical images. With the suggested approach, two objectives will be fulfilled: 1) a more accurate handling of severe case and 2) any unusual case can be used as a new case for training the software to avoid future failure of interpretation.

EXPECTED OUTCOME OF THE PROPOSED WORK

The objective of the present research work is to develop

1) Imagining devices reliability.

2) More efficient tests.

3) New modalities and improvements to existing one. for clinical diagnosis intelligent interpretation using computer aided approach of detection and its severity. The proposed method is to design and implement a satisfactory interpreter of statistical aspects ofdise. Lot of data cooperation has been expected from biomedical experts, which will make our research to achieve its perspective. This imaging research aims to developed new metods and software for clinical diagnosis.Real data with expert decisions of eminent doctors is going to yield inclusion of health investigation as image processing focus**.** Our result in this research will very clear for physician to distinguish the area for surgical planning as well save the time of patient and delay in decision of Doctors will be avoided.

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