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FPGA Based Real-Time Image Segmentation for Medical Systems and Data Processing

KEYWORDS

X-ray angiography (XRA), magnetic resonance angiography (MRA), magnetic resonance imaging (MRI), computed tomography (CT), Digital Infrared Imaging(DII), Orthopantomography (OPT or OPG), object-oriented programming (OOP), Just-In-Time (JIT), (Just-In-Time),Field Programmable Gate Array (FPGA).

L.Pattathurani	Rajat Kumar Dwibedi	Dr.P.Sivachidambaranathan
Assistant Professor/EEE, Jeppiaar Institute of Technology, Sriperumbudur, Chennai,India	Assistant Professor/ECE, SRR Engineering College, India	Professor& Head /EEE, Sathyabama university, India

ABSTRACT *Medical imaging often involves the injection of contrast agents and subsequent analysis of tissue enhancement patterns. X-ray angiograms are projections of 3D reality into 2D representations there is a fair amount of self occlusion among the vessels. Hence one cannot extract the vessels directly using the image intensities or gradients (edge) alone. Vessel extraction from angiogram images is useful for blood vessels measurement and computer visualizations of the coronary artery. This project describes the algorithm for automatic segmentation of coronary arteries in digital X-ray projections (coronary angiograms) .The pattern recognition technique used in this project is K-Means clustering. In this technique clusters are formed based on the minimum distance criteria with random seed point selection. As the dataset's scale increases rapidly, it is difficult to use K-means and deal with massive data, so an improved K-means algorithm is proposed.*

1. Introduction

1.1 Background

With the advances in imaging technology, diagnostic imaging has become an indispensable tool in medicine today. X-ray angiography (XRA), magnetic resonance angiography (MRA), magnetic resonance imaging (MRI), computed tomography (CT), and other imaging modalities are heavily used in clinical practice. Such images provide complementary information about the patient.

While increased size and volume in medical images required the automation of the diagnosis process, the latest advances in computer technology and reduced costs have made it possible to develop such systems. Blood vessel delineation on medical images forms an essential step in solving several practical applications such as diagnosis of the vessels (e.g. stenosis or malformations) and registration of patient images obtained at different times.

Segmentation algorithms form the essence of medical image applications such as radiological diagnostic systems, multimodal image registration, creating anatomical atlases, visualization, and computer-aided surgery Vessel segmentation algorithms are the key components of automated radiological diagnostic systems. Segmentation methods vary depending on the imaging modality, application domain, method being automatic or semi-automatic, and other specific factors.

There is no single segmentation method that can extract vasculature from every medical image modality. While some methods employ pure intensity-based pattern recognition techniques such as thresholding followed by connected component analysis, some other methods apply explicit vessel models to extract the vessel contours. Depending on the image quality and the general image artifacts such as noise, some segmentation methods may require image preprocessing prior to the segmentation algorithm.

On the other hand, some methods apply post-processing to overcome the problems arising from over segmentation. Vessel segmentation algorithms and techniques can be divided into six main categories, pattern recognition techniques, model-based approaches, tracking-based approaches, artificial intelligence-based approaches, neural network-based approaches, and miscellaneous tube-like object detection approaches. Pattern recognition techniques are further divided into seven categories, multiscale approaches, skeleton-based approaches, region growing approaches, ridge-based approaches, differential geometry-based approaches, matching filters approaches, and mathematical morphology schemes.

2. oveRVIEW

Segmentation problems are the bottleneck to achieve object extraction, object specific measurements, and fast object rendering from multi-dimensional image data. Simple segmentation techniques are based on local pixel-neighborhood classification. Such methods fail however to "see" global objects rather than local appearances and require often intensive operator assistance. The reason is that the "logic" of an object does not necessarily follow that of its local image representation. Local properties, such as textures, edginess, and ridgeness etc. do not always represent connected features of a given object.

2.1 Region Growing Approach

Region growing technique segments image pixels that are belong to an object into regions. Segmentation is performed based on some predefined criteria. Two pixels can be grouped together if they have the same intensity characteristics or if they are close to each other. It is assumed that pixels that are closed to each other and have similar intensity values are likely to belong to the same object. The simplest form of the segmentation can be achieved through thresholding and component labeling. Another method is to find region boundaries using edge detection. Segmentation process, then, uses region boundary information to extract the regions. The main disadvantage

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of region growing approach is that it often requires a seed point as the starting point of the segmentation process. This requires user interaction. Due to the variations in image intensities and noise, region growing can result in holes and over segmentation. Thus, it sometimes requires post-processing of the segmentation result.

2.2 Clustering
Clustering can be considered the most important unsupervised learning problem, so it deals with finding a structure in a collection of unlabeled data. A cluster is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters. Clustering algorithms may be classified as listed below.

- Exclusive Clustering
- Overlapping Clustering
- Hierarchical Clustering
- Probabilistic Clustering

In the first case data are grouped in an exclusive way, so that if a certain datum belongs to a definite cluster then it could not be included in another cluster. On the contrary the second type, the overlapping clustering, uses fuzzy sets to cluster data, so that each point may belong to two or more clusters with different degrees of membership. In this case, data will be associated to an appropriate membership value. A hierarchical clustering algorithm is based on the union between the two nearest clusters. The beginning condition is realized by setting every datum as a cluster.

2.3 GSC Segmentation
K-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate k new centroids as bar centers of the clusters resulting from the previous step.

After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done. In other words centroids do not move any more. Finally, this algorithm aims at minimizing an objective function, in this case a squared error function. The objective function where is a chosen distance measure between a data point and the cluster centre, is an indicator of the distance of the *n* data points from their respective cluster centers.

2.4 Hierarchical Segmentation
A hierarchical set of image segmentations is a set of several image segmentations of the same image at different levels of detail in which the segmentations at coarser levels of detail can be produced from simple merges of regions at finer levels of detail. A unique feature of hierarchical segmentation is that the segment or region boundaries are maintained at the full image spatial resolution for all segmentations. In a hierarchical segmentation, an object of interest may be represented by multiple image segments in finer levels of detail in the segmentation hierarchy, and may be merged into a surrounding region at coarser levels of detail in the segmentation hierarchy. If the segmentation hierarchy has sufficient resolution, the object of interest will be represented as a single region segment at some intermediate level of segmentation detail.

3. PROPOSED BLOCK DIAGRAM

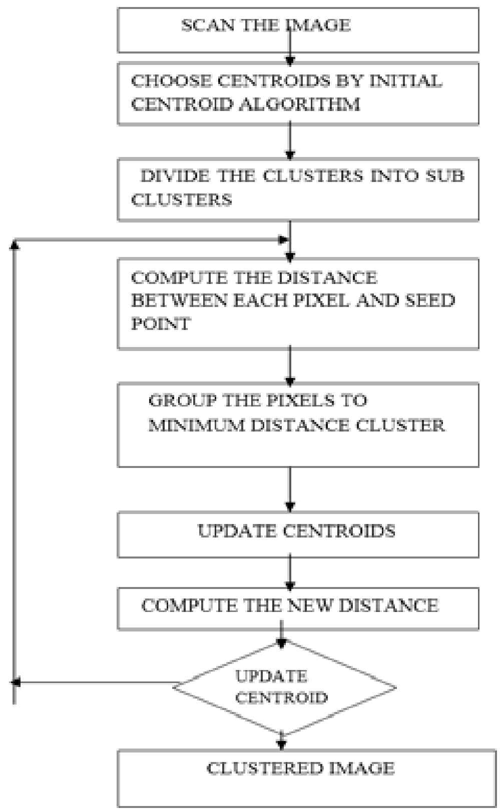

Fig.1.Proposed block diagram
The above fig. shows the block diagram of proposed method. Original K-means algorithm choose k points as initial clustering centers, different points may obtain different solutions. In order to diminish the sensitivity of initial point choice, we employ a median, which is the most centrally located object in a cluster, to obtain better initial centers. The demand of stochastic sampling is naturally bias the sample to nearly represent the original dataset, that is to say, samples drawn from dataset can't cause distortion and can reflect original data's distribution In order to lessen the influence of sample on choosing initial starting points, following procedures are employed.

First, drawing multiple sub-samples (say J) from original dataset (the size of each sub-sample is not more than the capability of the memory, and the sum for the size of J sub-samples is as close as possible to the size of original dataset) . Second, use K-means for each sub-sample and producing a group of medians respectively. Finally, comparing J solutions and choosing one group having minimal value of square-error function as the refined initial points.

To avoid dividing one big cluster into two or more ones for adopting square-error criterion, we assume the num-

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ber of clustering is *K'* (K > K, K' depends on the balance of clustering quality and time). In general, bigger K' can expand searching area of solution space, and reduce the situation that there are not any initial values near some extreme. Subsequently, re-clustering the dataset through K-means with the chosen initial conditions would produce K' medians, then merging K' clusters (which are nearest clusters) until the number of clusters reduced to k.

4. IMAGE SEGMENTATION

Segmentation is the process of identifying coherent regions in images that one hope corresponds to objects. Automated segmentation is probably the most difficult problem in computer vision. There are three major reasons why automated segmentation is so hard.

1.Lots of information is lost when 3-D scenes are projected to two dimensions. When objects cross in front of other objects (which we call "occlusion"), it's hard to keep the pieces together.

2.Segmentation attempts to produce primitive object regions. The notion, however, of what constitutes a primitive object is nebulous.

We use our brains extensively in our perceptual processes. We easily recognize that certain parts belong or don't belong together not because of similar properties of the regions, but because we know that they form parts of the same known and recognizable object. Endowing computers with such cognitive ability is currently beyond our possibilities. It is my personal opinion that until we can build computers that think like people us won't be able to build computers that *see* like people.

Image segmentation is one of the most important steps leading to the analysis of processed image data. Its main goal is to divide an image into parts that have a strong correlation with objects or areas of the real world contained in the image. There are two kinds of segmentation:

1) Complete segmentation
2) Partial segmentation

4.1 Complete Segmentation

Complete segmentation which results in set of disjoint regions uniquely corresponding with objects in the input image, Cooperation with higher processing levels which use specific knowledge of the problem domain is necessary.

4.2 Partial Segmentation

Partial segmentation in which regions do not correspond directly with image objects. Image is divided into separate regions that are homogeneous with respect to a chosen property such as brightness, color, reflectivity, texture, etc. In a complex scene, a set of possibly overlapping homogeneous regions may result. The partially segmented image must then be subjected to further processing, and the final image segmentation may be found with the help of higher level information.

However, there is a whole class of segmentation problems that can be solved successfully using low-level processing only. In this case, the image commonly consists of contrasted objects on a uniform background simple assembly tasks, blood cells, printed characters, etc.

Here, a simple global approach can be used and the complete segmentation of an image into objects and background can be obtained. Such processing is context independent -- no object-related model is used and no knowledge about expected segmentation results contributes to the final segmentation. Totally correct and complete segmentation of complex scenes usually cannot be achieved in this (low-level) processing phase. A reasonable aim is to use partial segmentation as an input to higher level processing.

5. THRESHOLDING

Gray-level thresholding is the simplest segmentation process. Many objects or image regions are characterized by constant reflectivity or light absorption of their surface a brightness constant or threshold can be determined to segment objects and background. It is computationally inexpensive and fast. It is the oldest segmentation method and is still widely used in simple applications. It can easily be done in real time using specialized hardware. The different types in thresholding are:

1. Basic thresholding
2. Band thresholding
3. Multi thresholding
4. Semi thresholding

5.1 Basic Thresholding

If we consider an image R, The complete segmentation is a finite set of regions $R_{1,} \dots, R_s$.

If i! = j

$R = {}_{i=1}\cup^{s} R_i, \qquad R_i \cap R_j = \Phi$

From this we can say complete segmentation can result from thresholding in simple scenes. Thresholding is the transformation of an input image ***f*** to an output (segmented) binary image *g* as follows

g(i, j) = 1 for f(i, j) >= T

= 0 for f(i, j) < T

where *T* is the threshold, *g(i , j) = 1* for image elements of objects and *g(i,j)=0* for image elements of the background (or vice versa).

5.2 Band-Thresholding

In band thresholding we segment an image into regions of pixels with gray levels from a set D and into background otherwise

g(i, j) = 1 for f(i, j) >= T

= 0 otherwise

This thresholding definition can serve as a border detector as well. If the gray-level set *D* is chosen to contain just these object-border gray-levels, and if thresholding according to above equation is used, object borders can be found. Isolines of gray can be found using this appropriate gray-level set *D*.

5.3 Multi Thresholding

There are many modifications that use multi-thresholding, after which the resulting image is no longer binary, but rather an image consisting of a very limited set of gray-levels

g(i, j) = 1 for $f(i, j) \in D_1$

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= 2 for f(i, j) ∈ D_2 ....
= n for f(i, j) ∈ D_n
= 0 otherwise.

Where each D_i is a specified subset of gray-levels.

5.4 Semi Thresholding

Another special method of thresholding defines semi-thresholding. It is sometimes used to make human-assisted analysis easier.

g(i, j) = f(i, j) for f(i, j) >= T
= 0 otherwise

This process aims to mask out the image background, leaving gray level information present in the objects. Thresholding has been presented relying only on gray-level image properties. Thresholding can also be applied if the values *f(i, j)* do not represent gray-levels, but instead represent gradient, a local texture property or the value of any other image decomposition criterion.

5.5 Threshold Detection Methods

If some property of an image after segmentation is known a priori, the task of threshold selection is simplified. A printed text sheet may be an example if we know that characters of the text cover *1/ p* of the sheet area. Using this prior information about the ratio between the sheet area and character area, it is very easy to choose a threshold *T* (based on the image histogram), such that *1/p* of the image area has gray values less than T and the rest has gray values larger than T. This method is called p-tile-thresholding.

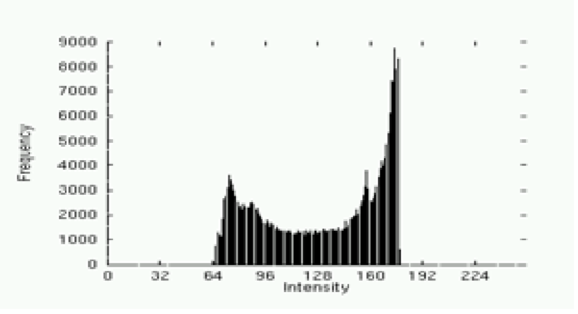

Fig.2. bi-model histogram of image

Pixels of objects form one of its peaks, while pixels of the background form the second peak. The histogram shape illustrates the fact that the gray values between the two peaks are not common in the image, and *probably* result from border pixels between objects and background. The chosen threshold must meet minimum segmentation error requirements. It makes intuitive sense to determine the threshold as the gray-level that has a minimum histogram value between the two mentioned maxima.

If the histogram is multi-modal, more thresholds may be determined at minima between any two peaks. Each threshold gives different segmentation results, of course. Multi-thresholding is another option. To decide if a histogram is bimodal or multi-modal may not be so simple in reality. It is often impossible to interpret the significance of local histogram maxima.

Bi-modal histogram threshold detection algorithms usually find the highest local maxima first and detect the threshold as a minimum between them. This technique is called the mode method. To avoid detection of two local maxima belonging to the same global maximum, a minimum distance in gray levels between these maxima is usually required or techniques to smooth histograms are applied.

Note that histogram bi-modality itself does not guarantee correct threshold segmentation even if the histogram is bi-modal, correct segmentation may not occur with objects located on a background of different gray-levels. Thresholding is a very popular tool in image segmentation, and a large variety of thresholding detection techniques exist in addition to the main techniques discussed above. Real-time threshold detection is a current research effort.

6. IMAGING TECHNOLOGY

6.1 Radiography

Two forms of radiographic images are in use in medical imaging; projection radiography and fluoroscopy, with the latter being useful for intra operative and catheter guidance. These 2D techniques are still in wide use despite the advance of 3D tomography due to the low cost, high resolution, and depending on application, lower radiation dosages. This imaging modality utilizes a wide beam of x rays for image acquisition and is the first imaging technique available in modern medicine.

- Fluoroscopy produces real-time images of internal structures of the body in a similar fashion to radiography, but employs a constant input of x-rays, at a lower dose rate. Contrast media, such as barium, iodine, and air are used to visualize internal organs as they work. Fluoroscopy is also used in image-guided procedures when constant feedback during a procedure is required. An image receptor is required to convert the radiation into an image after it has passed through the area of interest. Early on this was a fluorescing screen, which gave way to an Image Amplifier (IA) which was a large vacuum tube that had the receiving end coated with cesium iodide, and a mirror at the opposite end. Eventually the mirror was replaced with a TV camera.
- Projection radiographs, more commonly known as x-rays, are often used to determine the type and extent of a fracture as well as for detecting pathological changes in the lungs. With the use of radio-opaque contrast media, such as barium, they can also be used to visualize the structure of the stomach and intestines - this can help diagnose ulcers or certain types of colon cancer.

6.2 Photo acoustic Imaging

Photo acoustic imaging is a recently developed hybrid biomedical imaging modality based on the photo acoustic effect. It combines the advantages of optical absorption contrast with ultrasonic spatial resolution for deep imaging in (optical) diffusive or quasi-diffusive regime. Recent studies have shown that photo acoustic imaging can be used in vivo for tumor angiogenesis monitoring, blood oxygenation mapping, functional brain imaging, and skin melanoma detection, etc.

6.3 Breast Thermography

Digital Infrared Imaging Thermography is based on the principle that metabolic activity and vascular circulation in both pre-cancerous tissue and the area surrounding a developing breast cancer is almost always higher than in normal breast tissue. Cancerous tumors require an ever-increasing supply of nutrients and therefore increase circulation to their cells by holding open existing blood vessels, opening dormant vessels, and creating new ones (neoangiogenesis). This process frequently results in an increase in regional surface temperatures of the breast. Digital Infrared Imaging uses extremely sensitive medical infrared cameras and sophisticated computers to detect, analyze, and produce high-resolution diagnostic images of these temperature variations. Because of DII's sensitivity, these temperature variations may be among the earliest signs of breast cancer and/or a pre-cancerous state of the breast.

6.4 Tomography

Tomography is the method of imaging a single plane, or slice, of an object resulting in a tomogram. There are several forms of tomography:

- Linear tomography: This is the most basic form of tomography. The X-ray tube moved from point "A" to point "B" above the patient, while the cassette holder (or "bucky") moves simultaneously under the patient from point "B" to point "A." The fulcrum, or pivot point, is set to the area of interest. In this manner, the points above and below the focal plane are blurred out, just as the background is blurred when panning a camera during exposure. No longer carried out and replaced by computed tomography.
- Poly tomography: This was a complex form of tomography. With this technique, a number of geometrical movements were programmed, such as hypocycloidal, circular, figure 8, and elliptical. Philips Medical Systems [1] produced one such device called the 'Polytome.' This unit was still in use into the 1990s, as its resulting images for small or difficult physiology, such as the inner ear, was still difficult to image with CTs at that time. As the resolution of CTs got better, this procedure was taken over by the CT.
- Zoography: This is a variant of linear tomography, where a limited arc of movement is used. It is still used in some centers for visualizing the kidney during an intravenous urogram (IVU).
- Orthopantomography (OPT or OPG): The only common tomographic examination in use. This makes use of a complex movement to allow the radiographic examination of the mandible, as if it were a flat bone. It is often referred to as a "Panorex", but this is incorrect, as it is a trademark of a specific company.
- Computed Tomography (CT), or Computed Axial Tomography (CAT: A CT scan, also known as a CAT scan, is a helical tomography (latest generation), which traditionally produces a 2D image of the structures in a thin section of the body. It uses X-rays. It has a greater ionizing radiation dose burden than projection radiography; repeated scans must be limited to avoid health effects.

6. DESIGN SPECIFICATIONS OF PROPOSED ALGORITHM

Cluster analysis, an important technology in data mining, is an effective method of analyzing and discovering useful information from numerous data. Cluster algorithm groups the data into classes or clusters so that objects within a cluster have high similarity in comparison to one another, but are very dissimilar to objects in other clusters.

Dissimilarities are assessed based on the attribute values describing the objects. Often, distance measures are used. As a branch of statistics and an example of unsupervised learning, clustering provides us an exact and subtle analysis tool from the mathematic view K-means algorithm belongs to a popular partition method in cluster analysis. The most widely used clustering error criterion is squared-error criterion, it can be defined as

$$J_c = \sum_{j=1}^{c} \sum_{k=1}^{n_j} \left\| x_k^{(j)} - m_j \right\|^2$$

Where J_c is the sum of square-error for all objects in the database, x_i is the point in space representing **a** given object, and m_j is the mean of cluster C_j. Adopting the squared-error criterion, K-means works well when the clusters are compact clouds that are rather well separated from one another and are not suitable for discovering clusters with no convex shapes or clusters of very different size.

For attempting to minimize the square-error criterion, it will divide the objects in one cluster into two or more clusters. In addition to that, when applying this square-error criterion to evaluate the clustering results, the optimal cluster corresponds to the extreme. Since the objective function has many local minimal values**,** if the results of initialization are exactly near the local minimal point, the algorithm will terminate at a local optimum. So, random selecting initial cluster center is easy to get in the local optimum not the entire optimal. For overcoming that square-error criterion is hard to distinguish the big difference among the clusters, one technique has been developed which is based on representative point-based technique**.**

Besides, there are various approaches to solving the problem that the permanence of algorithm heavily depends on the initial starting conditions: the simplest one is repetition with different random selections .some algorithms also employ simulation anneal technique to avoid getting into local optimal**.** The idea is that multiple sub-samples are drawn from the dataset clustered independently, and then these solutions are clustered again respectively, the refined initial center is then chosen as the solution having minimal distortion over all solutions.

Aiming at the dependency to initial conditions and the limitation of K-means algorithm that applies the square-error criterion to measure the quality of clustering, this paper presents a new improved K-means algorithm that is based on effective techniques of multi-sampling and once-clustering to search the optimal initial values of cluster centers. Our experimental results demonstrate the new algorithm can obtain better stability and excel the original K-means in clustering results.

6.1 Matlab Coding

The MATLAB language supports the vector and matrix operations that are fundamental to engineering and scientific problems. It enables fast development and execution. With the MATLAB language, you can program and develop algorithms faster than with traditional languages because you do not need to perform low-level administrative tasks, such as declaring variables, specifying data types, and allocating memory. In many cases, MATLAB eliminates the need for 'for' loops. As a result, one line of MATLAB code can often replace several lines of C or C++ code. At the same time, MATLAB provides all the features of a traditional programming language, including arithmetic operators, flow control, data structures, data types, object-oriented programming (OOP), and debugging features. MATLAB lets you execute commands or groups of commands one at a time, without compiling and linking, enabling you to quickly iterate to the optimal solution.

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For fast execution of heavy matrix and vector computations, MATLAB uses processor-optimized libraries. For general-purpose scalar computations, MATLAB generates machine-code instructions using its JIT (Just-In-Time) compilation technology. This technology, which is available on most platforms, provides execution speeds that rival those of traditional programming languages.

6.2 Matlab Conversion Unit

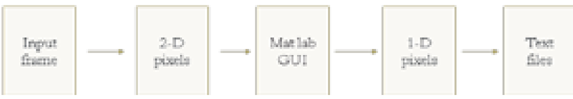


Fig.3 MATLAB conversion unit

6.2 Proposed Plan

1. Conversion of the image into a text file format
2. Convert text file into integer value ,then find centroids using 2 D-GSC algorithm
3. Implementation in FPGA

6.3 Algorithm For Getting Initial Centroids

Now let's review the standard k-means algorithm,

Input : The number of clusters K

Output : K number of clustered images.

The process of the algorithm is as follows.

(1) Give the input number of cluster value.

(2) Find the initial centroid by using the formula

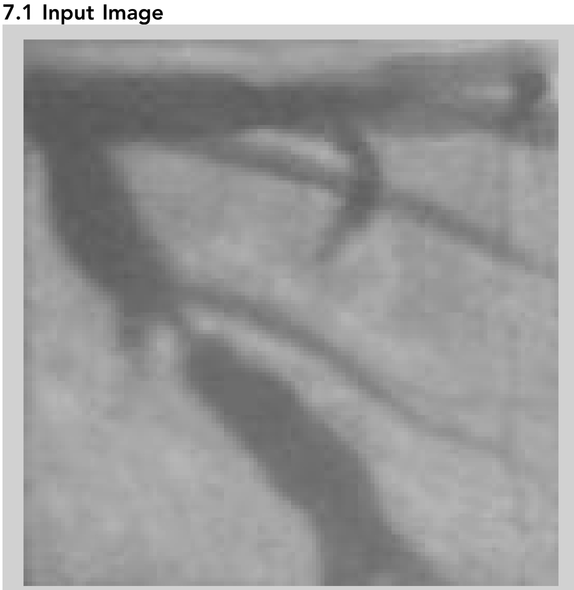
Centroid = [upper pixel value –lower pixel value]/ no. of clusters k

(3) Find the shortest distance pixels to the centroid

(4) Form the clusters.

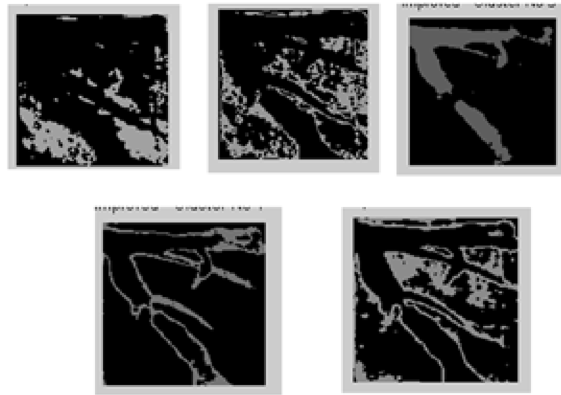
7. SIMULATION RESULTS

7.1 Input Image



th1=10;

7.2 Segmentation By Using Initial Centroids



8. HARDWARE IMPLEMENTATION

For an efficient implementation of the algorithm on FPGA based platform several modifications had to be performed. A main aspect here is to reduce memory accesses with respect to the not very fast FPGA-DRAM connection (compared to current PC arch.). The modifications comprise as follows. The indirect database scheme using a key table for database access to registered regions (code elements) has been dropped in favor of regular-sized database entries.

Of course, this wastes a fair amount of memory but the number of memory accesses is significantly reduced. The regular-sized database entry format allows for replacing absolute region coding addresses by relative ones which can be calculated by the FPGA concurrently without performance penalty. The coding phase has been optimized for minimal hardware resource consumption and maximum speed but still giving the same results as the software reference implementation.

To avoid time-consuming neighborhood searches by looking up position indices before database access, we developed a new linking scheme using overlapping lists which are generated during the registration of code elements. The nondeterministic recursive splitting phases had to be replaced by a regular root-to-level-0 label propagation scheme including additional merging capabilities during the generation of the segmentation result (label dataset and segments' list).The overall algorithmic dataflow then has been laid out to keep all implemented modules mostly busy over time.

The much more simpler 2-D case is depicted and shows that the best module utilization can be achieved by using two independent memory devices for database storage and two additional independent fast memory blocks for inter module data exchange or caching purposes. Likewise, this shows that three layers of the hierarchical structure are processed in parallel covered by the coding array (20 coding modules) and the two linking arrays between the two memory banks proposed (first processing line from top).

Additional a second processing line with two linking arrays can also start to work if the memory contains sufficient data for the modules. For larger images the two linking modules of the first processing lines will be reused. Please note, the arrows shows the data flow from the input image via different data base levels up to the resulting label image, and see the attached timing diagram that shows the process utilization of the processing.

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An FPGA-based digital signal processing board optimized for applications needing large memory with high bandwidth has been developed and successfully used for the parallelization of a modern image segmentation algorithm for medical and industrial real-time applications. Although the GSC algorithm is optimized for gray scaled images, this can be easily extended to multidimensional data when an appropriate distance function is given. Use of this 128-bit coprocessor board is not limited to image segmentation but might also comprise applications such as FPGA-based project development and prototyping, simulation, reconstruction, FEM, etc. Future developments will comprise a hardware upgrade by the Xilinx Virtex-4 family, a PCI-Express interface, and a Gigabit Ethernet link.

To broaden the applicability for no experienced users it is intended to expand the programmability of the system by a common DSP library especially exploiting user configurable parallelism and featuring an easy-to-use interface on a high abstraction level.

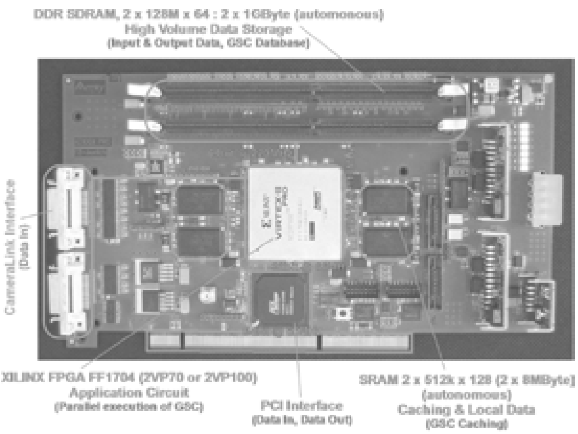

Fig.4. Flow diagram of the hardware algorithm

To broaden the applicability for no experienced users it is intended to expand the programmability of the system by a common DSP library especially exploiting user configurable parallelism and featuring an easy-to-use interface on a high abstraction level.

Before the advent of programmable logic, custom logic circuits were built at the board level using standard components, or at the gate level in expensive application-specific (custom) integrated circuits. The FPGA is an integrated circuit that contains many (64 to over 10,000) identical logic cells that can be viewed as standard components. Each logic cell can independently take on any one of a limited set of personalities. The individual cells are interconnected by a matrix of wires and programmable switches. A user's design is implemented by specifying the simple logic function for each cell and selectively closing the switches in the interconnect matrix. The array of logic cells and interconnect form a fabric of basic building blocks for logic circuits. Complex designs are created by combining these basic blocks to create the desired circuit.

9. CONCLUSION

Vessel segmentation methods have been a heavily researched area in recent years. Even though many promising techniques and algorithms have been developed, it is still an open area for more research. This algorithm does not require any user interaction, not even to identify a start point. Here seed points are selected randomly which determines the main branches of the vessel structure. Random selection of seed points does not yield accurate segmentation. Accuracy of the segmentation process is essential to achieve more precise and repeatable radiological diagnostic systems. Accuracy can be improved by incorporating a priori information on vessel anatomy and let high level knowledge guide the segmentation algorithm. K-means algorithm is a popular clustering algorithm applied widely, but the standard algorithm which selects k objects randomly from population as initial centroids cannot always give a good and stable clustering. Experimental results show that selecting centroids by our algorithm can lead to a better clustering.

REFERENCE [1].Cemil Kirbas and Francis K.H. Quek, "A Review of Vessel Extraction Techniques and Algorithms". Technical report. Vision Interfaces and Systems Laboratory (VISLab), Department of Computer Science and Engineering, WrightState University, Dayton, Ohio, Nov. 2002. [2].Yu-Fang Zhang; Jia-Li Mao; Zhong-Yang Xiong," An efficient clustering algorithm" International Conference on Machine Learning and Cybernetics, 2003 Volume 1, 2-5 Nov. 2003 Page(s):261 - 265 Vol.1 [3].Fang Yuan; Zeng-Hui Meng; Hong-Xia Zhang; Chun-Ru Dong; "A new algorithm to get the initial centroids". Proceedings of 2004 International Conference on" Machine Learning and Cybernetics, 2004 Volume 2, 2004 Page(s):1191 - 1193 vol.2 [4].Usama Fayyad, Cory Reina, P. S. Bradley Initialization of Iterative Refinement Clustering Algorithms. Microsoft Research Technical Report MSR-TR-98-38, June 1998 [5].Kanungo, T.; Mount, D.M.; Netanyahu, N.S.; Piatko, C.D.; Silverman, R.; Wu, A.Y." An efficient k-means clustering algorithm: analysis and implementation", IEEE Transactions on Pattern Analysis and Machine Intelligence Volume 24, Issue 7, July 2002 Page(s):881 – 892 [6].D. Guo and P. Richardson, ``Automatic vessel extraction from angiogram images'', IEEE Computers in Cardiology, vol. 25, pp. 441-444, 1998. [7].P.J. Yim, P.L. Choyke, and R.M. Summers, ``Gray-scale skeletonization of small vessels in magnetic resonance angiography'', IEEE Trans. on Med. Img., vol. 19, pp. 568-576, June 2000. [8].F. Zana and J.C. Klein, ``Robust segmentation of vessels from retinal angiography'', in IEEE International Conference on Digital Signal Processing, vol. 2, pp. 1087-1090, 1997. [9].R.T. Ritchings and A.C.F. Colchester, ``Detection of abnormalities on carotid angiograms'', Pattern Rec. Let., vol. 4, pp. 367-374, October 1986. [10].N. Otsu, ``A threshold selection method from gray-level histograms'', IEEE Trans. on Sys. Man, and Cybernetics, vol. 9, pp. 62-66, 1979. [11].Singh, M.; Patel, P.; Khosla, D.; Kim, T." Segmentation of functional MRI by K-means clustering" Nuclear Science, IEEE Transactions on Volume 43,Issue 3,Part 2,June 1996 Pages(s):2030-2036. [12].Rui Xu; Wunsch, D "Survey of clustering algorithms" IEEE Transactions on Neural Networks Volume 16, Issue 3, May 2005 Page(s):645 – 678. [13].http://www.elet.polimi.it/upload/matteucc/Clustering/tutorial_html/index.html. [14].http://turing.iimas.unam.mx/~elena/Projects/segmenta/IEEEMI00 R2/node6.html.