

# Detection of Cancer Using Vector Quantization for Segmentation

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## ABSTRACT:

Breast cancer is one of the major causes of death among women. An improvement of early diagnostic techniques is critical for women's quality of life. Mammography is the main test used for screening and early diagnosis. Contrast-enhanced magnetic resonance of the breast is the most attractive alternative to standard mammography. This paper presents a vector quantization segmentation method to detect cancerous mass from mammogram images. In order to increase radiologist's diagnostic performance, several computer-aided diagnosis (CAD) schemes have been developed to improve the detection of primary signatures of this disease: masses and microcalcifications.

## Keywords:

Mammography, Segmentation, Vector Quantization, Clustering.

## 1. INTRODUCTION:

Breast cancer can be most effectively treated when it is detected at its early stage. Ultrasonography is widely used for the detection and evaluation of many diseases. In the case of breast cancer, it is a very useful complementary imaging technique to mammography. The most effective method for early detection and screening of breast cancers is X-ray mammography. However, reading mammography is a demanding job for radiologists, and cannot provide consistent results from time to time. The judgments depend on training, experience, and subjective criteria. In addition, mammography produces a high false positive rate, and only about 525 of 1800 lesions [1].

Segmentation will help in the computer-aided evaluation of the tumors and the distinction of benign and malignant nodules. Since screening mammography is currently the main test for early detection of breast cancer, a huge number of mammograms need to be examined by a limited number of radiologists. In order to improve the diagnostic efficiency, computer-aided diagnosis has been introduced into the screening process [2].

Mammography is the main test used for screening and early diagnosis. Early detection performed on X-ray mammography is the key to improve breast cancer prognosis. In order to increase radiologist's diagnostic performance, several computer-aided diagnosis (CAD) schemes have been developed to improve the detection of primary signatures of this disease: masses and microcalcifications [3].

A number of image processing methods have been proposed to perform this task. S. M. Lai et al [4] and W. Qian et al [5] have proposed using modified and weighted median filtering, respectively, to enhance the digitized image prior to object identification. D. Brzakovic et al [6] used thresholding and fuzzy pyramid linking for mass localization and classification. Other investigators have proposed using the asymmetry between the right and left breast images to determine possible mass locations. Yin *et al.* uses both linear and nonlinear bilateral subtraction [7] while the method by Lau *et al.* [8] relies on "structural asymmetry" between the two breast images. Recently Kegelmeyer [9] has reported promising results for detecting speculated lesions based on local edge characteristics and Laws texture features [10, 11]. The above methods produced a true positive detection rate of approximately 90%. The work we have done till now is to propose a segmentation process which identifies on a mammogram the opaque areas, suspect or not, present in the image using vector quantization [12-21].

Tumors or calcifications are embedded in an inhomogeneous background. In mammograms, background objects may even appear brighter. Therefore, global threshold methods suffer considerable drawback. The work we have done is to propose a segmentation process which identifies on a mammogram the opaque areas, suspect or not, present in the image using vector quantization which consumes moderate time but provide good accuracy with less complexity. Watershed algorithm has a drawback of over-segmenting the image making it obscure for identification of tumor. Segmentation using gray level co-occurrence matrix required huge time for tumor demarcation with less accuracy. Vector quantization segmentation algorithm attempts to overcome such drawbacks.

### 1.1 Vector Quantization:

Vector quantization is a classical quantization technique from signal processing which allows the modeling of probability density functions by the distribution of prototype vectors. It was originally used for data compression. It works by dividing a large set of points (vectors) into groups having approximately the same number of points closest to them. Each group is represented by its centroid point as in K-means some and other clustering algorithms.

The density matching property of vector quantization is powerful, especially for identifying the density of large and high-dimensional data. Since data points are represented by the index

of their closest centroid, commonly occurring data have low error, and rare data high error. This is why VQ is suitable for lossy data compression. It can also be used for lossy data correction and density estimation [6].

Vector Quantization (VQ) [22-30] is an efficient technique for data compression and has been successfully used in various applications such as index compression [31, 32]. VQ has been very popular in a variety of research fields such as speech recognition and face detection [33, 34]. VQ is also used in real time applications such as real time video-based event detection [35] and anomaly intrusion detection systems [36], image segmentation [37-40], speech data compression [41], content based image retrieval CBIR [42] and face recognition [43].

The rest of the paper is organized as follows. Section 2 describes Gray Level Co-occurrence Matrix (GLCM), Watershed algorithm and Kekre's Median Codebook Generation (KMCG) algorithm used for image segmentation of mammographic images. Followed by the experimental results for mammographic images for comparison in section 3 and section 4 concludes the work.

## 2. ALGORITHMS FOR SEGMENTATION

In this section we explain segmentation by Gray level co-occurrence matrix [44], basic watershed algorithm [45-49] and Kekre's Median Codebook Generation (KMCG) algorithm which are used for comparative performance of tumor detection.

### 2.1. Gray Level Co-occurrence Matrix

Haralick [50] suggested the use of gray level co-occurrence matrices (GLCM) for definition of texture features. The values of the co-occurrence matrix elements present relative frequencies with which two neighboring pixels separated by distance  $d$  appear on the image, where one of them has gray level  $i$  and other  $j$ . Such matrix is symmetric and also a function of the angular relationship between two neighboring pixels. The co-occurrences matrix can be calculated on the whole image, but by calculating it in a small window which scanning the image, the co-occurrence matrix can be associated with each pixel. By using gray level co-occurrence matrix we can extract different features like probability, entropy, energy, variance, inverse moment difference etc. Using co-occurrence matrix the major textural features are defined as:

$$\text{Maximum Probability: } \max(P_{ij}) \quad (2.1)$$

$$\text{Variance:} \quad (2.2)$$

$$(\sum (i - \mu_i)^2 \sum P_{ij}) (\sum (j - \mu_j)^2 \sum P_{ij})$$

$$\text{Correlation:} \quad (2.3)$$

$$\sum_i \sum_j (i - \mu_x)(j - \mu_y) P_{ij} / \sigma_x \sigma_y$$

where  $\mu_x$  and  $\mu_y$  are means and  $\sigma_x$ ,  $\sigma_y$  are standard deviation

$$\text{Entropy: } \sum_i \sum_j P_{ij} \log(P_{ij}) \quad (2.4)$$

Amongst all these features entropy has given us the best results. Hence in this paper we extracted entropy using gray level co-

occurrence matrix and the results are displayed in Fig.5 (b) along with that of watershed and KMCG algorithms for comparison.

### 2.2. Watershed Algorithm

Watershed segmentation [48] classifies pixels into regions using gradient descent on image features and analysis of weak points along region boundaries. The image feature space is treated, using a suitable mapping, as a topological surface where higher values indicate the presence of boundaries in the original image data. It uses analogy with water gradually filling low lying landscape basins. The size of the basins grows with increasing amount of water until they spill into one another. Small basins (regions) gradually merge together into larger basins. Regions are formed by using local geometric structure to associate the image domain features with local extremes measurement. Watershed techniques produce a hierarchy of segmentations, thus the resulting segmentation has to be selected using either some a priori knowledge or manually. These methods are well suited for different measurements fusion and they are less sensitive to user defined thresholds. We implemented watershed algorithm for mammographic images as mentioned in [2]. Results for mammographic images are displayed in Fig 5(c).

### 2.3 Proposed Algorithm

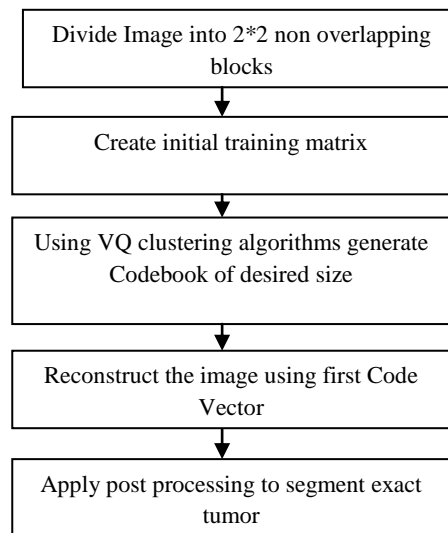


Fig. 1 Block Diagram of Proposed Algorithm

#### Steps for the algorithm

- Step1: Divide the image into non overlapping blocks.
- Step2: Convert each block into training vector. Entire Training matrix is considered as one cluster (X)
- Step3: Codebook of desired size is generated using KMCG.
- Step 4: Reconstruct image using first codevector
- Step 5: Post processing is applied on reconstructed image to segment exact tumor

#### 2.3.1 Kekre's Median Fast Codebook Generation (KMCG) Algorithm [26]:-

In this algorithm image is divided in to blocks and blocks are converted to the vectors of size k. The Fig. 2 below represents matrix T of size M x k consisting of M number of image training vectors of dimension k.

Each row of the matrix is the image training vector of dimension k.

$$T = \begin{bmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,k} \\ x_{2,1} & x_{2,2} & \dots & x_{2,k} \\ \vdots & \vdots & \vdots & \vdots \\ x_{M,1} & x_{M,2} & \dots & x_{M,k} \end{bmatrix}$$

**Fig.2 Matrix of image training vector**

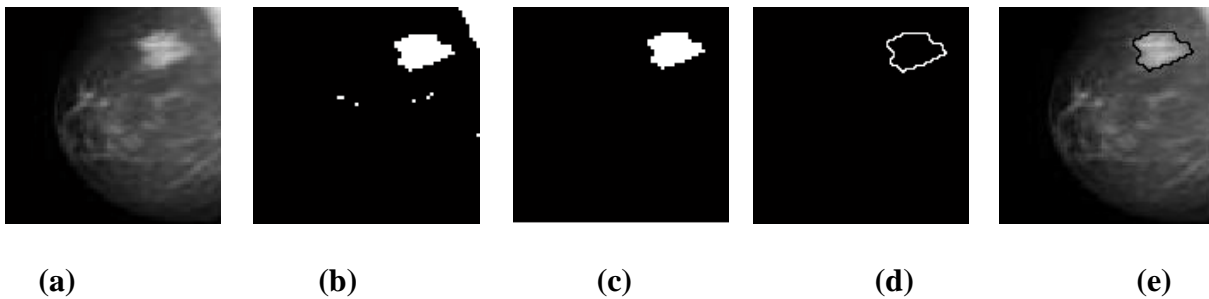
The training vectors are sorted with respect to the first member of all the vectors i.e with respect to the first column of the matrix T and the entire matrix is considered as one single cluster. The median of the matrix T is chosen (codevector) and is put into the codebook, and the size of the codebook is set to one. The matrix is then divided into two equal parts and the each of the part is then

again sorted with respect to the second member of all the training vectors i.e. with respect to the second column of the matrix T and we obtain two clusters both consisting of equal number of training vectors. The median of both the parts is the picked up and written to the codebook, now the size of the codebook is increased to two consisting of two codevectors and again each part is further divided to half. Each of the above four parts obtained are sorted with respect to the third column of the matrix T and four clusters are obtained and accordingly four codevectors are obtained. The above process is repeated till we obtain the codebook of desired size. Here quick sort algorithm is used.

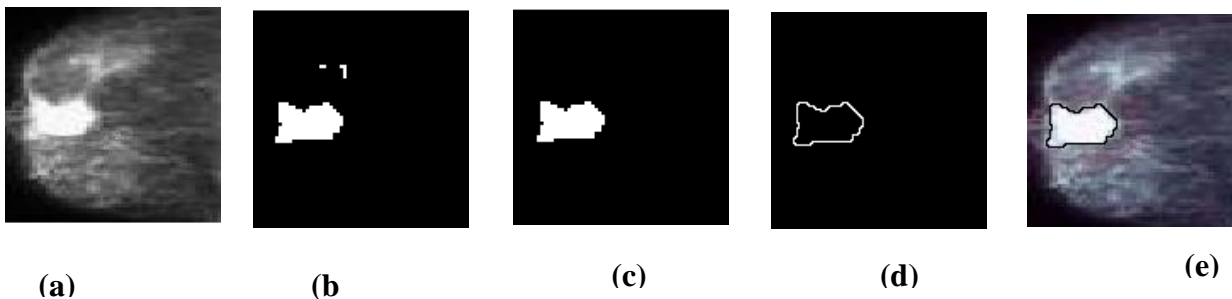
### 2.3.2. Post processing

In post processing step the image obtained after VQ segmentation is taken as input image. The VQ segmented image is labeled and area of each region is calculated. The region with larger area is extracted. The boundary of extracted region is superimposed on original image. Results for proposed method on mammographic images are displayed in Fig 3(a-e) and Fig.4 (a-e).

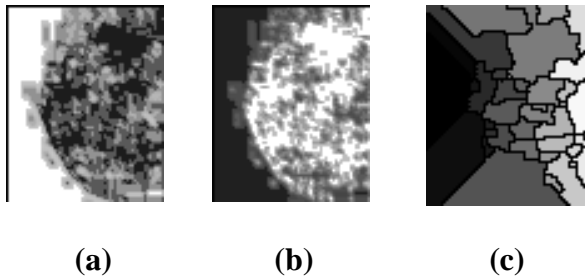
## RESULTS:



**Fig.3: (a) Original Breast tumor Mammogram Image,(b) Image after VQ segmentation, (c) ROI Extracted Image,(d)Boundary Extracted Image ,(e) Superimposed Image**



**Fig.4: (a) Original Breast tumor Mammogram Image,(b) Image after VQ segmentation, (c) ROI Extracted Image,(d)Boundary Extracted Image ,(e) Superimposed Image**



**Fig.5: (a) Probability image using GLCM, (b) Entropy image using GLCM, (c) Segmented image using Watershed algorithm**

#### 4. CONCLUSION:

Mammograms contain low signal to noise ratio (low contrast) and a complicated structured background. Breast tissue contrast and density vary with age, thus mammography produces varying image qualities. In addition, mammographic images are not bimodal. As a result, any segmentation method which utilizes an a-priori or single threshold value method is highly likely to generate serious segmentation errors. Moreover, tumors or calcifications are embedded in an inhomogeneous background. In mammograms, background objects may even appear brighter. Therefore, global threshold methods suffer considerable drawback.

Vector quantization segmentation algorithm attempts to overcome such drawbacks. Vector quantization is based on clustering algorithm. It is observed from the results that the KMCG algorithm takes least time to generate codebook, since it does not require Euclidean distance computation. The programs are tested on thirty five mammogram images. Identification rate for proposed method is 68.5%.

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