New Embedded Denotes Fuzzy C-Mean Application for Breast Cancer Density Segmentation in Digital Mammograms

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Abstract. In this research we explore the application of normalize denoted new techniques in advance fast c-mean in to the problem of finding the segment of different breast tissue regions in mammograms. The goal of the segmentation algorithm is to see if new denotes fuzzy c-mean algorithm could separate different densities for the different breast patterns. The new density segmentation is applied with multi-selection of seeds label to provide the hard constraint, whereas the seeds labels are selected based on user defined. New denotes fuzzy c-mean have been explored on images of various imaging modalities but not on huge format digital mammograms just yet. Therefore, this project is mainly focused on using normalize denoted new techniques employed in fuzzy c-mean to perform segmentation to increase visibility of different breast densities in mammography images. Segmentation of the mammogram into different mammographic densities is useful for risk assessment and quantitative evaluation of density changes. Our proposed methodology for the segmentation of mammograms on the basis of their region into different densities based categories has been tested on MIAS database and Trueta Database.

1. Introduction
Cancer is the leading cause of death in humans. One of the causes of death was cancer breast cancer. Breast cancer is cancer that occurs in the breast due to uncontrolled growth of cells of glands and ducts, thus damaging surrounding organs or tissues and spread to other body gets. To help the radiology and radiologist doctor expert in detecting cancer, patients can perform mammography. Mammography is an examination using X-rays to provide a picture of soft tissues in the breast. In the field of medicine, radiologists often have difficulty in observing the raw image of mammography, because the image produced has a degree of gray so it is difficult to see clear recognition of the cancer area. To overcome this necessary image processing operations one such image processing segmentation. Mammography image segmentation is a process to clarify and sharpen up the image of a feature or features segmented by division Cluster.
Breasts have a complex structure and compact with glands, and fat layer is thick and fibrous tissues affected by changes in female hormones estrogen and progesterone. Challenges in the compact segment image which is to be preferred, time-consuming and rather subjective. Development approach for segmenting each pixel in a cluster of its own into the impact of the information clear spatial give it a good medium for the interpreting prevail. The study found that the potential possibility of automatic algorithm to segmentation breast density in the evolution of longitudinal studies. A longitudinal study showed segmentation trend decline in the ratio depends on the number of early breast density.

Mammography containing quantities pixel density has been found to be a strong risk factor for breast cancer. Helping with spatial data available in highlight form and structure of the cancer helps doctors to interpret. A method of storing, accessing, organizing, and comparing spatial data spatial invitation to override data to support the process of analysis takes a too long time to process. This method is based on the classification of pixels in which a different approach known in the literature for breast density segments are integrated and expanded. In addition, the method that combines knowledge of trained observers, using segmentation obtained by user-assisted Fuzzy C-Mean (FCM) as training data. Remarkable novel ingredient (matrix normalization) purr into the FCM algorithm to enhance their routine (denote) whilst increase speed. This approach straightforward absorb in highly flexible fine-grained parallelism computing model.

Digital mammography nowadays generated in the database already been digitized to the edge pixel 50 micron scan microdensitometer Joyce-Loebl, linear devices in optical density range 0 - 3.2 and represent each pixel with 8-bit. Although the database is so great detail still cannot help personalize medical radiologist to interpret early breast cancer properly

2. Classification of the breast according density
In clinical practice regularly check your breasts through breast self examination did not identifying the density of the mammary gland because does not felt. X-ray is a test used to detect changes in the breast tissue to penetrate various types of breast tissue relative to the amount of fat, connective tissue and epithelial to determine the radiographic appearance of the breast on a mammogram. Light (not radiolucent) areas on a mammogram representing fibrous and glandular tissue in the breast, while, dark (radiolucent) mostly fat regions [1], [2]. The difference density pattern classification methods are needed, Wolfe classification has been traditionally used in clinical practice and research. classification has four patterns of breast parenchyma or six category classification system based on a visual estimate of the density per cent. Breast imaging reporting and data system (BIRADS) classification. The density of the four categories are: BIRADS-1 shows the breast, especially fat; BIRADS-2 density scattered fibro-glandular; BIRADS-3 breast heterogeneous solid and BIRADS-4, the highest level, which is very dense breasts that can obscure the wound [3], [2]. Examples of the types of breast are shown in Figure 1.

Other measure that is related with density is sensitivity, because with high mammographic density have a reduced ability of detecting an existing cancer. It is very difficult locate ill-defined cancers within an opaque uniform background. Thus, as mammographic breast density is a strong predictor of breast cancer the first step of image and processing analysis of mammogram is the density classification. In first two stage BI-RADS 1 and 2, the accumulation of cancer is unexpected and need screening to identify density uprising. Here focused research to improve quantification of medical practice for formation and existence of abnormality.
2.1 Lesion Detection
There are a number of lesions that can be present in a breast. Develop algorithms that detection micro-calcifications and masses, the two most common abnormalities in breast cancer. The detection of masses can be divided in two main blocks, the detection of suspicious regions and a posterior step of classification of those regions, which is typically called false positive reduction.

2.2 Micro-Calcifications Detection
Breast calcifications are deposits of calcium inside breast tissue. They appear widespread in the breast and most women will have a few on their mammograms at some point in time. Most calcifications will not be detected during clinical exams or breast self-examination. However, mammography allows to find them long prior to they could move forward into an actual lump. This fact helps explaining why developed countries are adopting the so-called screening programs, which mainly consist in promoting regular women examinations using mammography.

Develop a new approach for the detection of micro-calcifications and clusters. The individual micro-calcification detection is based on learning the variation in morphology of the micro-calcifications using local image features. Afterwards, this set of features is used to train a pixel-based boosting classifier which at each round automatically selects the most salient micro-calcification feature. Therefore, when a new mammogram is tested, only the salient features are computed and used to
classify each pixel of the mammogram as being part of a micro-calcification or actually being normal tissue as show in Figure 2. Afterwards, the micro-calcification clusters are found by inspecting the local neighbourhood of each micro-calcification.

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3. Fuzzy C-Mean With Normalize Denotes Approach

To an image with size, the supposition is as follows: \( f(s,t) \) is the pixel gray level of the image array in the object \( (s,t) \), \( f(s,t) \in \{0,1,2, \ldots, L-1\} \); \( L \) is the gray level of the image; \( H(l) \) means the one-dimensional gray statistic mapping function of the image. Namely, the definition is:

\[
H(l) = \sum_{s=0}^{S} \sum_{t=0}^{T} \delta[f(s,t) - l]
\]

\( l \in \{0,1,2, \ldots, L-1\} \)

\[
\delta[f(s,t) - l] = \begin{cases} 
1 & f(s,t) = l \\
0 & f(s,t) \neq l 
\end{cases}
\]

\( H(l) \) is the pixels number of the gray level \( l \). The statistic normalized mapping \( H(l) \) supersedes the FCM data item \( f(s,t) \). So the FCM algorithm is developed to solve the minimization of new objective function.

\[
J_m(U,V:l) = \sum_{i=0}^{L-1} \sum_{c=1}^{C} (u_{il})^m H(l)d^2(l,v_i)
\]

If the above narration objective function follow our work in [4] is minimized, then the new F-FCM iteration functions are obtained.

\[
u_{il}^{(b)} = \frac{1}{\sum_{j=1}^{c} (d_{ij}^b / d_{jj}^b)^{2(m-1)}}
\]

\[
v_{ij}^{(b+1)} = \frac{\sum_{l=1}^{L-1} (u_{il}^{(b)})^m H(l)d}{\sum_{l=1}^{L-1} (u_{il}^{(b)})^m H(l)}
\]

Obviously, the speed of the F-FCM algorithm is enhanced greatly, and the result of sort is same with the FCM algorithm. Based on Equation (1), we proposed architecture implemented in a circuit fashion.
4. Software Interface Between LabVIEW and FPGA’s

The goal of clustering is to partition data samples into different classes according to the samples’ mutual similarity. First, a distance metric is defined to measure similarity. Next, by minimizing the overall cost, you can determine the centroids and partition scheme. This process is often iterative and the cluster centroids will converge after several iterations. Possible applications of clustering include pattern recognition, data mapping, image segmentation, and clustering.

Structures with multiple sub-diagrams, such as Case structures and Flat Sequence structures, have a separate VHDL entity for each case or frame as shown in Figure 3. These VHDL entities have names ending with diagram to indicate that they represent a sub-diagram. Re-entrant subVIs appears in the VHDL code in the same manner as structures appear. Re-entrant subVIs has multiple instances in the VHDL code hierarchy. These instances correspond to calls to the subVIs from the block diagram. Non-re-entrant subVIs includes special VHDL logic to manage the data flow to and from re-entrant subVIs.

For sake of brevity, the images considered in this section are gray-level images. Each data point \( x_k \) represents a pixel with gray level values in the range between 0 and 255. For colour images, each pixel \( x_k \) becomes a vector consisting of three colour components: red, green and blue. In the proposed architecture, each data point \( x_k \) can be a scalar or a vector. Therefore, the proposed architecture can be directly applied to colour image segmentation by implementing \( x_k \) as a 3-dimension vector. The performance of the image segmentation is measured by segmentation error rate, which intensity information using structural similarity index measure (SSIM) and Peak signal to noise ratio (PSNR). Experiment data segmentation error rate still ongoing.

The choice was made to use an FPGA, not only for its speed advantages but also for the ability to create functional logic blocks. This allowed many areas of the controller to function independently, without requiring complex threading or interrupts on the micro-controller. FPGAs can support large internal shift registers, which is important as thousands of bits need to be shifted out at a rapid rate. Figure 4 show Hardware / Software Code-sign Platform.

![Figure 3. F-FCM in LabVIEW complete block diagrams.](image-url)
Figure 4. Hardware / Software Code-sign Platform.

Figure 5 show graphical user interface window, reform all function need for user interface. Designing the visual composition and temporal behaviour of a GUI is an important part of software application programming in the area of human-computer interaction. Its goal is to enhance the efficiency and ease of use for the underlying logical design of a stored program, a design discipline known as usability.

In this application graphical user interface or GUI is the type of interface that allows users to interact with electronic devices through graphical icons and visual indicators such as secondary notation use to employ number of cluster, as opposed to text-based interfaces, typed command labels whereby use to select mammogram image or text navigation. GUIs were introduced in reaction to the perceived steep learning curve of command-line interfaces which require commands to be typed on the keyboard. Meanwhile, the mammogram image applied and clustered result shown in window display panel 540 x 540 sizes as initial visual template, conclusive big data image (1024 x 1024) can be retrieved from designated folder database. All reconstructed image accumulated for medical image standard diagnosis. Images containing suspicious areas have associated pixel-level "ground truth" information about the locations and types of suspicious regions. Finally, execution time displayer window put on place for performance and evaluation purpose.

Figure 5. F-FCM Design Graphical User Interface.
5. Experimental and Result
The medical image segmentation is implementing using FCM whilst objective test means is produced. Objective test is the repetition of a unit amount that maintains its size, within an allowable range of error, no matter which instrument, intended to measure the variable of interest, is used and no matter who or what relevant person or mammogram is measured. Both quantitative and qualitative characterization digital image in this research bonded on objective test. Illustration on Figure 6 indicates quantitative-(objective test) analysis of task for test meanwhile qualitative-(objective test) trend in test is the research outline.

Subjective test is a form of expression in the form of image to test medical personal knowledge, experience, skills and levels of cognitive abilities of personal by the response. They require medical personal to create their own responses, rather than selecting a response from a list of options. The objective measurements are an evaluation of detector performance alone, while the observer threshold contrast results include effects of observer detects ability, observer visual response, display magnification and processing, ambient viewing conditions including display reflection and scattered radiation and grid performance [5].

The objective analysis began with the generation of variance images from flat field images. These images were useful in obtaining a visual impression of the variance across the entire process of calcification [6]. Eventually, hope to perform objective test of the mammogram using measured image pixel data process automatically segmentation to identify regions of interest. The accuracy of Fuzzy C-Mean (FCM) is due to the employment of fuzziness for the clustering of each image pixel.

Propose of finding cluster centres by iteratively adjusting their position and minimizing an objective function. This approach to testing image processing remains objective. It is proven objective test using FCM approach for diagnostic purposes namely in assisting radiologist in interpreting the mammogram that they have to scrutinize. In this research objective test more suitable with proper process and method. Subjective test more manually depend on human experience (medical specialists). Factor influence depend on age, high, eye side vision and experience.

![Figure 6. Research area.](image-url)
6. Qualitative Experiment and Result

In order to show the benefits of this research approach, a qualitative analysis is performed using the entire MIAS database (322 images in total) using previous researcher breast density segmentation (thresholding approaches). Figure 7 shows the results obtained for the MIAS database when using both excess entropy thresholding in [7] and the second one based on the multiclass Fuzzy C-Means clustering algorithm in [8] approaches for breast density quantification. Note that the performance of both algorithms for class BIRADS I is not the expected one, obtaining a large dispersion in the dense percentage ratio. The reason for this behaviour is that there is a set of mammograms correctly segmented (without dense cluster or being small), while there is another set incorrectly segmented.

![Boxplot of breast dense percentage using the MIAS database and two well-known thresholding approaches. First row shows the results using the excess entropy thresholding, while second one using the multiclass Fuzzy C-Means clustering algorithm.](image)

In these cases, the thresholding approaches segmented the outer part of the breast from the inner part due to the fact that pixels near the skin-line (those with less breast tissue) are darker than the other ones. Hence, in homogeneous fatty mammograms, this tends to produce an incorrect estimation of the threshold. In contrast, the rest of BIRADS classes show more compact results, increasing the median of the class according to the increasing density. This approach is based on the conjecture that the optimal thresholding corresponds to the segmentation with maximum structure.
Introduce the excess entropy as a measure of the spatial structure of an image. There an adaptive thresholding method based on the maximization of excess entropy. It also use of uniformly distributed random lines to overcome the main drawbacks of the excess entropy computation. Performance of the segmentation bulky spatial in such a way but surface structure not allocated.

The fully-automated algorithm (multiclass Fuzzy C-Means clustering) was successful in identifying the fibroglandular tissue of the breast in digital mammographic images. These findings indicate that the proposed algorithm can provide some clinically relevant information from digital mammography for the assessment of breast density.

One surprising result was the relatively poor performance of the multiclass Fuzzy C-Means paradigm, previously used for density assessment in digitized film mammograms, in identifying the dense tissue region. Although BIRADS classification and quantification has often been the primary focus [10], this finding is in apparent contrast to findings by [7], who reported good visual agreement between FCM and expert markings [9]. Further investigation showed that one possible explanation for the poor performance of the 2-class FCM algorithm is the fact that majority gray-level intensity profiles of breast tissue as extracted from digital mammograms tend to be multi-modal, such as in the BIRADS-IV case illustrated in Figure 4. Given that appropriate selection of the number of clusters, k, is critical for proper clustering, the intensity profile of digital mammograms are complex enough that multi-class techniques, such as the one described in this work, may be required to appropriately analyze digital mammography images.

As breast tissue seen mammographically is a 2D superimposition of different tissue types with different image properties, future studies should seek to expand density based risk-stratification analysis beyond the dichotomous, fatty vs. dense tissue paradigm. Furthermore, as mammography is essentially limited by the effect of projection/tissue superimposition, volumetric analysis of fibroglandular tissue through emerging tomography breast imaging modalities, such as breast tomosynthesis and magnetic resonance imaging, has been suggested as necessary to advance breast cancer risk modeling [10] and the approach described in this work could become the foundation for fully-automated density quantification from three-dimensional images.

6.1 Qualitative Performance and Evaluation Breast Density Segmentation (F-FCM) on MIAS Database

In order to show the benefits of our approach compared the obtained results with a new F-FCM method of normalized spatial density approach as mention in section 3.1 and 4.3.2. This new normalized with mapping and mesh technique portray aggregately to accelerate the matrix transform arithmetic and improve overall FCM algorithm to become F-FCM. The method is trained and tested using 322 digitized film mammographic images acquired with a variety of systems. A combination of segmentation strategies outperforms the application of single segmentation techniques. The value of $\rho$ is set using data collected from experiment on mammogram digital images is set 0.0001. This is important for start performing experiment using $\rho$ value setting for consistent application outcome result. The value of $\rho$ is computed first time load mammogram image, there is possibility the value change as the source of mammogram came from different apparatus type.

A qualitative analysis is performed using MIAS database (322 images in total). Figure 8 show some selected MIAS image before and after segmentation whilst fatty and dense areas can clearly perceive. After segmenting the breast in both fatty and dense tissues, computed the percentage of segmented dense area relative to the overall breast area (fatty and dense areas). Afterwards, the constructed a boxplot analysis detailing this percentage according to each density class provided in the MIAS annotations (fatty, glandular and dense). This is shown in Figure 9. Observe that the percentage of dense area increases according to the class density. Note also that mammograms belonging to fatty class do almost not show any dense area, while dense mammograms have large percentage dispersion. Notice that a obtained several outliers in the fatty and glandular classes. This is due to the fact that
there is a small set of mammograms brighter than the rest, and in these cases, the algorithm is not able to correctly recognize the fatty tissue. In these cases, a previous grey-level normalization of the image should be necessary.

Figure 8 shows the mammogram samples of MIAS sample after applying our segmentation approach using our Fuzzy C-Mean (FCM) clustering. The lighter cluster shows the dense area, while the darker one shows the fatty tissue. Note that the dense area of the mammograms is segmented in a multiple and homogeneous region, except for the mammogram belonging to BIRADS I, BIRADS II, BIRADS III and BIRADS IV which has a small or bigger dense cluster. Moreover, observe that the size of the dense cluster increases as the density of the breast also increases. The performance of the presented algorithm is evaluated and shown it catch every micro-calcifications in form density mean.
Figure 8. MIAS image before and after segmentation.
Repeated the same analysis but using the annotations provided by the radiologists, who classified the MIAS database according to the BIRADS standard. The results are shown in Figure 10. Note that the dense area of mammograms belonging to BIRADS I is significant increase, while mammograms belonging to BIRADS II have a small part of dense tissue. The dispersion in dense classes is now reduced, and the outliers have also been reduced. Moreover, according to the notches, the difference in the median of all classes is clearly significant.

However, comparing these results with those shown in Figure 7, the median is higher. This is also a consequence of bad threshold estimation. However, in this case, the bias is smaller due to the fact the tissue of the mammograms is more heterogeneous, and therefore, the estimated threshold is greater than the obtained when segmenting mammograms belonging to BIRADS I. The target intensity loosens whereby it over taken on pixel tabulated. Furthermore, structural dimension flatten on stand which not added value from previous medical machine CAD (DICOM) analysis.
6.2 Qualitative Performance and Evaluation Breast Density Segmentation (F-FCM) on Trueta Database

In this section, we repeat the same qualitative analysis but using the Trueta database and now analyzing 125 MLO (Mediolateral) and 125 CC (Craniocaudal) views independently. The preprocessing step of CC mammograms did not include the pectoral muscle removal since the muscle was not present in this view.

Figure 11 shows the boxplots of the dense percentage obtained. The first row analyses the CC mammograms, while the second one analyses the MLO. Note that, in both cases, the percentage increases according to the BIRADS classes. However, we found two outliers using the CC set and two more when using the MLO. Note that the trend is similar when comparing both datasets, showing that our approach is able to correctly segment both MLO and CC mammograms.

Comparing the obtained results using the MIAS and the ones using the Trueta database, we observe that the BIRADS I distribution is better defined when using the former database. This is due to the different nature of the databases. Remember that the MIAS is a digitized database, while the Trueta one is fully digital. In the Trueta database, almost all fatty mammograms have a small region segmented due to the fact that the digital database has more contrast than the digitized. Hence, some
ducts and linear structures that are brighter than the fatty breast tissue are incorrectly segmented. In contrast, the performance for the other classes is similar.

The approach was validated by comparing manual expert annotations with automatically obtained estimations. Transversal analysis of the breast density analysis of CC and MLO views of both breasts acquired in the same study showed a correlation coefficient of \( r = 0.96 \) between the mammographic density percentage for left and right breasts, whereas a comparison of both mammographic views showed a correlation of \( r = 0.95 \).

7. Conclusion
The performance of the initial pre-processing (thresholding approaches) step explained in “Initial Pre-processing Step”, which was performed in order to remove background, annotations and pectoral muscle of the images briefly discussed. In general, the performance of these algorithms is good enough in most of the cases. However, for the MIAS database, there is a large set of images where the breast segmentation algorithm decreases its accuracy, incorrectly segmenting a small border of the breast. In contrast, regarding the Trueta database, the pectoral muscle is incorrectly segmented in few cases, having the problem of segmenting a small portion of fatty tissue besides the pectoral muscle. However, in both cases, the segmentation algorithm segments correctly the dense tissue due to the fact that the algorithm does not depend on the fatty tissue. Note that, for these special situations, as a small area of the fatty tissue has been suppressed, the ratio of dense area is slightly biased to higher values.

Compare between database --with the advent of confocal microscopy and other advanced imaging techniques-- Furthermore, the spatial agreement between automated-algorithm segmentations and radiologic ground-truth \( J=0.62\pm0.22 \) was found to be similar to the human-observer inter-reader variability of \( 0.65\pm0.18 \) previously reported by [11].

In F-FCM outcome, the classifications of cluster cover the spatial relationships within the cluster (i.e. between groups of micro-calcification that form a cluster). In additional, the F-FCM segmentation breast density highlighted the value of spatial aggregation into a level where densities mimic 3-D surface structure without brittle image structure (fringe 3-D image). Consensually, it helps medical prentices observe the structure also with other anatomical structures /tissue (i.e. linear structure, such as vessels and ducts). This contribution and expand the ontology especially their work on interpret micro-calcifications and masses. Strong agreement with radiologist-provided ground truth was obtained, both in terms of the quantitative estimate and the spatial agreement of the segmented dense tissue.

Acknowledgment
The authors would like to thank my supervisor and anonymous reviewers for their constructive comments.
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