Contrast enhancement and detection of microcalcifications mammary using hidden Markov chains

A. Mehidi, M. Mimi, M. Bentoumi and A. Taleb Ahmed

***Abstract*—** Breast cancer is continually one of the mean causes of female mortality. Mammography is the most widely used imaging technique for detecting tumors at a premature stage. This investigation is currently the best for breast cancer screening. The presence of microcalcifications in mammography images is particularly interesting for the early detection of breast cancer. The objective of our work is the automation of microcalcifications' detection by mammographic images' processing. This helps the experts in their work because the number of images to be inspected and evaluated is very large. For this purpose, an automated algorithm is proposed for the detection of microcalcification clusters following a specific methodology. First, mammography is preprocessed using a technique that involves improving the quality of mammography (improvement of local contrast). Then, the clusters are identified using a stochastic analysis based on hidden Markov chains, together with a Hilbert-Peano analysis of the medical images. This may allow detecting nodular components such as microcalcifications with precision by introducing size information. The obtained results are visually very clear, precise and show that the proposed approach permits to successfully extract the microcalcifications from the referential mammographic images of the MIAS database. Furthermore, we have showed that the use of hidden Markov chains (HMM) is more efficient for the detection of microcalcifications because HMMs rely mainly on the spatial regularity constraint for image processing. On the other hand, based on objective performance measures namely true positive rate (TPR) and false positive rate (FPR), the comparative study carried out on the three breast densities has shown the efficiency of our method whatever the type of the breast density.

***Keywords*—**Mammography, Microcalcification, contrast enhancement, Hidden Markov Chains (HMCs), Iterative Conditional Estimation (ICE) algorithm, Mode Marginal's Posteriori (MPM) algorithm, unsupervised segmentation.

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I. INTRODUCTION

MICROCALCIFICATIONS in mammography are considered as the most important reliable first sign of breast cancer and their early detection is essential to improve its prediction. Microcalcifications are fine calcareous deposits only visible in mammography, which may correspond to benign or malignant lesions. In a primary way, the clinical diagnosis of breast cancer is made by a palpation of the breast, the aim being to spot an abnormal mass, but also to search for lymph nodes. The doctor will then perform a bilateral mammogram (radiography of both breasts) [22]. Early diagnosis by detection of microcalcification requires this radiography. This allows obtaining 2D images from inside the breast using X-rays. The examination of the obtained images by a radiologist allows to detect, in the first place, the cancer and to distinguish the type of detected lesions. Then, the images are examined by a specialist doctor who gives its opinion about the subject.

The objective of our work is to automate the detection of microcalcifications by processing of mammographic images. This helps the experts in their work since the number of images to be valued is very large.

The microcalcifications appear on the radiographic image as a grouping of few pixels brighter than the neighboring pixels [40]. This means that they correspond to pixels of stronger intensity and their detection is obtained by extracting features from analysis of the radiographic image. The attributes of pixel groupings representing microcalcifications remain a fundamental problem for the detection of these calcium salt deposits. These attributes (size, shape, density, distribution model, and number of microcalcifications) are examined in order to differentiate between benign and malignant microcalcifications [19]. The size of the microcalcifications is within the range [0.1-1mm], and the average is about 0.3 mm. As a result, it is difficult to detect them by the examining radiologist. Microcalcifications are represented on a radiographic image by a number of less than 5 pixels per group [13], [29]. They may be of low contrast, so the difference in intensity between the suspicious areas and their surrounding tissues may be quite low [9], [18]. Consequently, microcalcifications can be closely related to surrounding tissues, and simple segmentation algorithms cannot work properly [11], [35]. On the other hand, in some cases where the tissues are dense or the skin is thick, in particular for younger women, the suspicious areas are almost

invisible and hence they may not be detected as microcalcifications. Fig.1. shows four mammograms of the MIAS database containing a group of microcalcifications [1]. The four examples have been selected for a good visualization of the problem, although in general, microcalcifications are subtler and difficult to appreciate, even for experts in radiology.

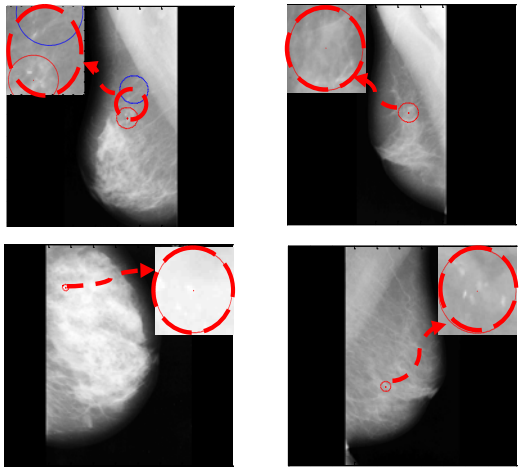


Fig. 1 four mammograms containing microcalcifications (extracted from the MIAS database).

In the following, we briefly describe several approaches for microcalcifications' detection. We define each method and provide an overview on its implementation and discuss its advantages and drawbacks.

In the literature, the most methods are based on the analysis of digital radiographic images. These methods are based on simple morphological operations such as filtering and image subtraction [3]. Such approaches can be effective but they usually require determining manually the thresholds under visual control. Thus, the threshold does not take into account the spatial characteristics of the image. This makes them sensitive to the noise and intensity of the homogeneities that can occur in the mammographic images [2]. In this context, the related works are often difficult to compare due to the fact that some methods use the whole mammographic images whereas some others use only the regions of interest. However, the objective is always the same: detection of benign and/or malignant microcalcifications.

The methods of coalescence, for example, are numerous and very often used for their simplicity and fast calculation. These cluster algorithms do not directly incorporate spatial modeling and then can be sensitive to intensity inhomogeneities and noise. However, this lack of spatial modeling can provide significant benefits for fast calculation [28]. The LBG (Linde Buzo Gray) algorithm consists of successively cutting the observation using the K-means algorithm (with metric d). The main difference with the previous method is the construction of groupings in the image. Indeed, the number of classes increases progressively in the LBG algorithm (via a sequence of division of the already established groupings) while it is maintained constant for the K-means. On the other hand, as for the K-means, the LBG algorithm does not introduce any spatial constraint between the current element and its neighbors in the image [31].

Another approach consists of performing thresholding. A thresholding procedure attempts to determine an intensity value, called a threshold, which separates the desired classes. The process that serves to determinate more than one threshold value is called multi-thresholding [4], [20]. Note that thresholding is one of the simplest and strongest commonly used ways to perform image segmentation [5]. Its main limitations are: i) in its simplest form, only two classes are produced and ii) it cannot be applied to multiple-channel images. Furthermore, the thresholding does not introduce any spatial constraint between the current element and its neighbors in the image. This makes it sensitive to noise and intensity inhomogeneities that can occur in mammographic images [6], [7].

Other methods are based on the classification tools. These methods are composed of two steps. The first one consists of a pre-preprocessing that serves to extract a vector of attributes representing the relevant characteristics of the image. The second one is the classification that consists of two stages: learning and use of the classifier [19], [28]. The major drawback of these tools is the need for a complete and relevant pre-preprocessing phase. Among the most used classification methods we cite: the statistical methods [8], the spatial distribution of grayscale level values by calculating the local indices in the image and then deducing a set of parameters and the discriminant factorial analysis. The latter, for example, separates linearly the data by projecting them into a space minimizing the intra-class variance while maximizing the interclass variance. This method is particularly fast and the obtained decisions' boundaries linearly discriminate the points' clouds. The major limitation here is the need to have a complete and relevant learning set in order to determine the decision boundaries between the classes.

Some research teams have focused on the of Support Vector Machine (SVM) method which is an elegant nonlinear approach [14]. In fact, SVMs use a kernel (simple analytic function), or a combination of kernels, in order to linearize the data and obtain a hyperplane separating the classes. The SVM method is fast and flexible to use, especially thanks to the construction of specific kernels to a given problematic but remains supervised [33], [48].

More recently, some researchers have focused on the use of multiresolution techniques [12] and multifractal analysis in the detection of microcalcifications [10]. The combination of wavelet transforms and grouping was also used by many authors [14], [15]. The deformable models delimit the boundaries of regions by using closed parametric curves or surfaces that are deformed under the influence of internal and external forces. To delimit an object boundary in an image, a closed curve or surface must first be placed near the desired boundary and then an iterative relaxation process is effectuated. The Internal forces are calculated inside the curve or surface to keep it smooth throughout the deformation. External forces are usually determined from the image to guide the curve or surface to some desired characteristics of interest [16]. The main advantage of deformable models is their ability to directly produce closed parametric curves or

surfaces in images. This provides robustness to noise and false contours. A drawback is that they require manual interaction in order to place an initial model and choose appropriate parameters [24], [26].

Another approach consists of the use of a geometric form, also called a template, which we will try to locate on the image. The principle is to know exactly (or almost) the shape of the object we are looking for and then browse the whole image to place the template in the most likely place. This is much more constraining than needing to know how many elements are present in the image. In this case, it is necessary to know the precise form of what we are searching. There are works on deformable templates that approximate snakes. We locate the best place to put the template in the image and then let it be deformed in order to best match the image. The template is subjected to energy of the same kind as the external energy of a snake (energy imposed by the image). An advantage of these approaches is that labels are transferred as well as segmentation. They also provide a standard system for the morphometric study of properties [26], [34].

Several authors have developed techniques based on the concept of texture to analyze mammographies and detect microcalcifications [36], [45], [49]. This is motivated by the fact that information in the textures of an image can bring variations of luminous intensity in the neighborhood, which can reflect the object's properties. Furthermore, the choice of an analysis window remains problematic. The analysis of the texture based on the cooccurrence matrix is the most common method for analyzing textured images in general and mammographies in particular [30]. However, the major disadvantage is the computational time: knowing that the cooccurrence matrix is an $N \times N$ matrix, where N is the number of grayscale levels contained in the image; the texture analysis applied to the size of the mammography image implies a matrix of cooccurrence of dimension 256x256 with 80% of its components set to zero.

In our work, we propose to use Hidden Markov **C**hains (HMCs) for the detection of microcalcifications in a mammogram image. HMCs are frequently used to model stochastic interactions between classes and to enable overall bayesian optimization of the segmentation result. The Markov chains are probabilistic tools quite widely used in image processing. Their major benefit is to be able to provide modeling of the spatial dependencies of the random variables, whose realizations model the observed or wanted quantities, in a relatively simple and suitable way for various processing. Several models based on Markov chains have been proposed, including HMCs, largely used in image segmentation. It is important first of all to clarify that the modeling by HMCs is not in itself a segmentation method, but a statistical model that can be used in segmentation methods. It may also be noted that the hidden variables do not have, a priori, physical existence in the observed phenomenon; but, they are primarily used to create flexible models. However, after analyzing the data with respect to the model, they often find a concrete interpretation a posteriori [17], [23].

The HMCs allow, thanks to their structure, to take into account the spatial dependencies between the different pixels of the image and to incorporate priori information on the segmentation [32]. A difficulty associated with these models is the appropriate choice of parameters that control the force of spatial interactions. In addition, they usually require intensive computing time algorithms.

II. The Proposed Method

The main objective of the proposed method is to improve the pixel groupings' contrast representing microcalcifications by highlighting the spatial information present in the mammographic images. Another objective is to show that that use of hidden Markov chains is more efficient for microcalcification detection. This is due to the fact that the HMC is mainly based on the spatial regularity constraint for image processing [23]. Fig.2 shows the flowchart of the proposed method.

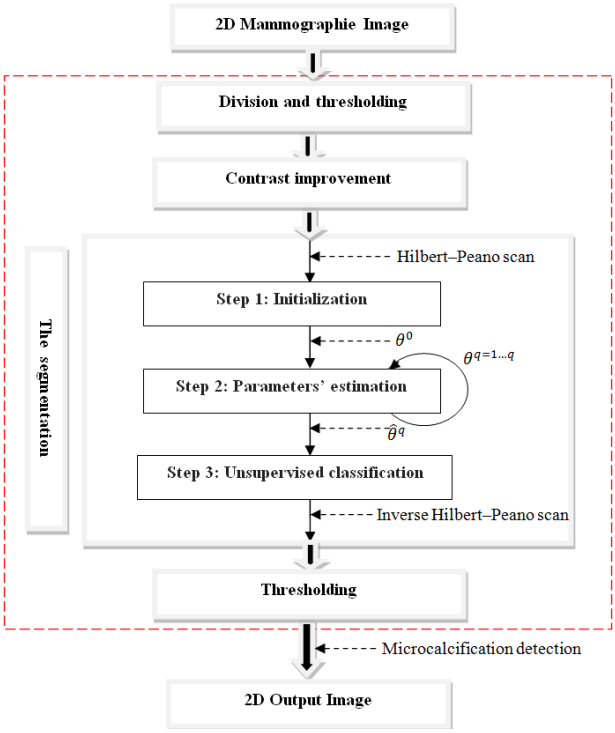
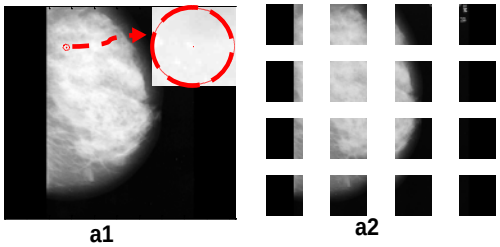
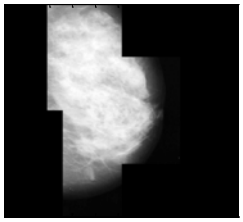


Fig. 2 flowchart of the proposed detection method

A. Division and thresholding

In the vast majority of mammographic images, the size is very large and almost 50% of the entire image composed of background (black). In this stage, we apply an automatic image division by dividing the analyzed image into a set of sub-images of size (256x256). For each sub-image, the intensity average is calculated. Then, using the thresholding method, we eliminate all sub-images that have only background information. The sub-images with more intensity (information) are kept for the subsequent processing.



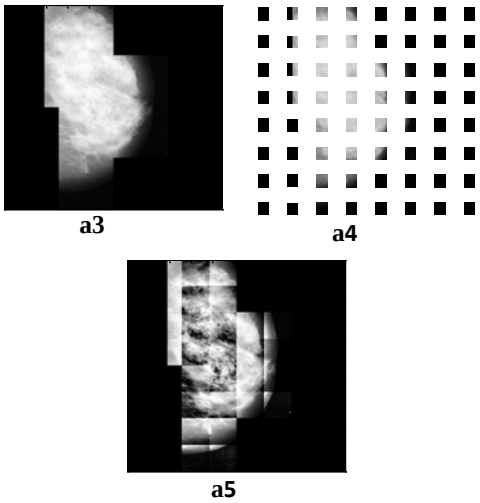


a3

Fig. 3 division and thresholding
(a1) Image of original malignant mammogram (1024 × 1024 pixels), (a2) sub-images (256×256 pixels) obtained after division of «a1», (a3) reconstruction of «a2» after thresholding operation (1024 × 1024 pixels).

B. Contrast improvement

The objective of contrast enhancement is to highlight the regions of interest by attenuating the others in order to simplify the detection process. In fact, the groupings of pixels representing microcalcifications are characterized by a low contrast. On this other hand, the difference in intensity between the suspicious areas and their surrounding tissues can be quite slim. This problem is resolved in two steps: 1) subdividing the sub-images retained after the thresholding operation into sub-images of size (128x128) and 2) carrying out the histogram dilatation of local intensity on each sub-image. This results on increasing the intensity dynamics of the sub-images and thus increasing the contrast of the pixels representing microcalcifications compared to the surrounding tissues' contrast.



a3 a4

a5

Fig. 4 division, thresholding and improvement of local contrast (a3) reconstruction of "a2" after thresholding operation (1024 × 1024) pixels, (a4) sub-images (128 × 128 pixels) obtained after "a3" division, (a5) reconstruction of « a4 » after improving the local contrast.

C. The segmentation

The segmentation of a two-dimensional image is the technique permitting to divide this image into a finite number of homogeneous areas, called classes. Statistical segmentation consists of searching for these areas from the observed image. The problem is to estimate the components of a hidden random process from an observed process [42], [43], [44]. In fact, segmentation constitutes a complex problem. The calculation of the posterior law is not always possible; in particular, it may be very complex [46], [51]. The difficulties occur when the sample size increases. In such cases, a solution, which has often proved to be efficient, consists of using the hidden Markov **c**hains which take into account the dependencies between components and allow the exact calculation of posteriori laws.

The entire segmentation algorithm is divided into three steps (see Fig.2):

Step 1: Initialization: the objective is to perform a preliminary estimation of the model's parameters. The output parameter θ^0 (the mean value and the variance for a scalar Gaussian distribution) is obtained using an initial classification algorithm (K-means algorithm).

Step 2: Parameters' estimation: this step is performed by Iterative Conditional Estimation (ICE) algorithm. Each iteration q gives an estimation of the parameters θ^q. When the final estimate is obtained, ordinary segmentation with known parameters is effectuated. Since the number q of iterations cannot be defined a priori, the algorithm is stopped when the values of the output parameters do not change under a given limit or when the maximum number of iterations is reached.

Step 3: Unsupervised classification: this last step allows segmenting the original image from the estimated parameters θ^q (at the output of ICE). In a Bayesian context, the Mode Marginal's Posteriori (MPM) algorithm is used.

*C.1. Hidden Markov **C**hain*

A hidden Markov Chain is a stochastic discrete time process composed of two processes X and Y. The term "hidden" means that the realizations of X are unobservable. We consider two random processes $X = (X_s)_{s\in S}$ and $Y = (Y_s)_{s\in S}$ where X is the unknown class image and Y represents the observed image. Let S be a finite set corresponding to the N pixels of an image. Each random variable X_s takes its values from the finite set of classes $\Omega = \{\omega_1,...,\omega_K\}$, whereas each Y_s takes its values in the set of real numbers. We denote realizations of X and Y by $x = (x_s)_{s\in S}$ and $y = (y_s)_{s\in S}$, respectively [25], [37].

Hereafter we suppose that the random variables $Y = (Y_s)_{s\in S}$ are conditionally independent with respect to X and that the distribution of each Y_s conditional on X is equal to its distribution conditional on X_s. All the distributions of Y conditional on X are then determined by the K distributions of Y_s with respect to $X_1 = \omega_1,..., X_S = \omega_K$, which will be denoted $f_1,..., f_K$:

$$P(Y = y|X = x) = \prod_{s\in S} P(Y_s = y_s|X_s = x_s) = \prod_{s\in S} f_{xs}(y_s) \quad (1)$$

A Markov chain is a sequence of random variables $X=(X_n),\quad 1\le n\le N$ with values in Ω such that:

$$\forall n>1,\quad P\left(X_n=x_n\middle|X_1=x_1,\ldots,X_{n-1}=x_{n-1}\right)=$$
$$=P\left(X_n=x_n\middle|X_{n-1}=x_{n-1}\right) \qquad (2)$$

The elements of a Markov chain will therefore be entirely determined by the data of its initial probability $P(X_1=\omega_i)$, denoted by π_i, and the probabilities of transitions $a_{ij}=P\left(X_{n+1}=\omega_j\middle|X_n=\omega_i\right)$.

As indicated above, we will model the interactions among the random variables X_s by considering that the prior distribution of X can be modeled by a Markov process [38]. We refer to as hidden Markov chains, as X is not directly observable. The segmentation problem consists in estimating $X=x$ from the observation $Y=y$.

As required by the Markov chains, the 2D image must be converted into a one-dimensional vector. The simplest idea is to sweep the image line by line or column by column. The problem of this method is that the past and the future of a pixel do not always correspond to its spatial context. Thus, when one considers the method line by line, two neighboring pixels and belonging to the same column are near spatially and distant in sense of Markov chain. To avoid the problem of the temporal and spatial contexts, a lot of authors uses the Hilbert Peano scan [25], [37] as illustrated in Fig.5.

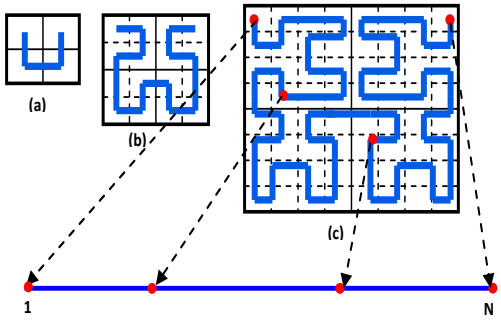


Fig. 5 construction of a Hilbert Peano scans for an 8 × 8 image (a) Initialization. (b) Intermediate stage. (c) Result.

C.2. Initialization

The objective of this step is to provide an initial estimation of the models' parameters θ^0. For this propose, the K-means algorithm is implemented. The later is an iterative method for classifying the pixels of an image into K classes ($K\in\Omega$) according to their grayscale level. The pixel is assigned into the class for which the distance from the pixel to the class's center is minimal. It should be noted that this method can only be used to initiate classes with different mean values [28]. For example, the algorithm is not adapted to classes that have the same mean value but different variances. However, one drawback is that the K-means is basically a thresholding method. Hence, if there is much overlap between the true classes' distributions, the resulting class vector will be quite irregular and the initial classes' statistics will not be very representative. Figs.6-7 shows some examples illustrating these limits.

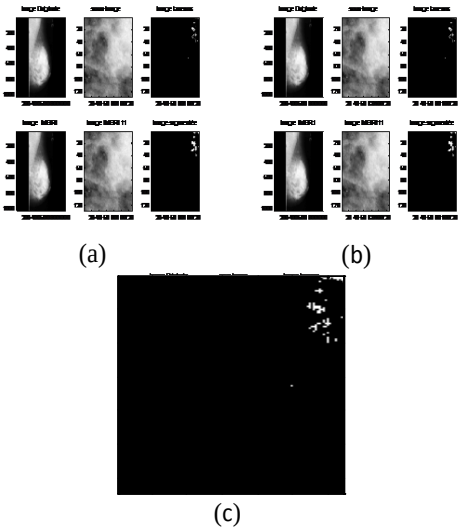


Fig. 6 limits of K-means detection without local contrast enhancement: (a) original mammography image (1024 × 1024 pixels), (b) sub-image (128× 128 pixels) without local contrast enhancement and (c) result of K-means algorithm.

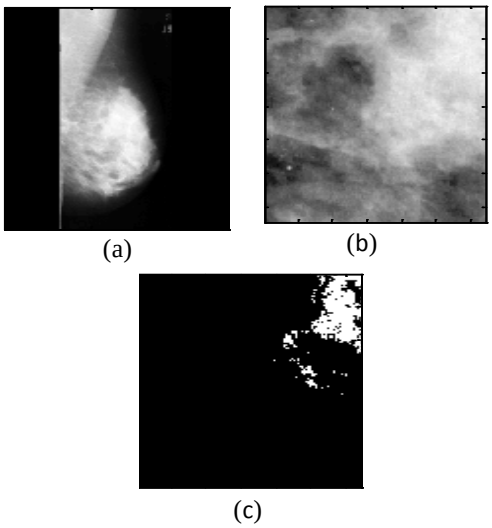


Fig. 7 limits of K-means detection with local contrast enhancement: (a) original mammography image (1024 × 1024 pixels), (b) sub-image (128× 128 pixels) with local contrast enhancement and (c) result of K-means algorithm.

C.3. Parameters' estimation

In practice, the regularity parameters and those of classes' distributions are often unknown and must be estimated from the observation $Y=y$. On the other hand, as the distribution of Y can be written as a weighted mixture of probability densities $f_Y(y)=\sum_x P(X=x)f_x(y)$, the estimation problem is double: we do not know neither the classes' characteristics nor which pixels are representative for each class [23], [25]. In this context, there are several iterative methods for mixture

estimation, including EM (for Expectation Maximization) SEM (for Stochastic Expectation Maximization) and ICE [38], [41]. The latter is used in this paper.

In what follows, we consider classic mixture estimation, where all classes are supposed to be Gaussian [37], [39]. The ICE algorithm is initialized using K-means in order to define the class parameters θ_i^0 and thus the marginal conditional distributions f_i^0. Furthermore, the uniformly distributed a priori probabilities π_i^0 and the generic transition matrix $A^0 = \{a_{ij}^0\}$ are also determined. Each ICE iteration q is based on two assumptions:

1. There exists at least one estimator $\hat{\theta}$ defined for the complete data θ.
2. The possibility of simulating the hidden process according to its a posteriori law.

C.4. Unsupervised classification

Let us first assume that we know the distribution f_i and the associated parameter vector θ_i of each class ω_i (in the case of a scalar Gaussian distribution, for example $\theta_i = (\mu_i, \sigma_i^2)$, where μ_i is the mean value and σ_i^2 the variance), as well as the regularity parameters c_{ij}. In a bayesian framework, the aim of the segmentation is to determine the realization $X = x$ that best explains the observation $Y = y$, in the sense that it minimizes a given cost function [35], [41], [50]. Hence, the choice of the cost function determines which kind of estimator we will use, namely the MAP (for maximum a posteriori), that maximizes the global a posteriori probability $P = (X|Y)$, and the MPM, which consists in maximizing the posterior marginal distribution $P = (X_S|Y)$ for each pixel. In this work, we use MPM classification.

C.5.Thresholding

The aim of thresholding at the output of HMC is to eliminate all groupings of pixels having a number greater than (5x5) pixels by group. This is because the size of microcalcifications is within the range [0.1-1mm]. If the cancer affects several regions and if the size of the tumor is large (greater than 5mm), the mastectomy is performed: It is too late for the patient. Our method allows to detect the presence or not of the anomaly without being able to determine the type of this anomaly.

III. EXPERIMENTAL RESULTS

We present here results of application of our algorithm on real database of mammographic images. In order to highlight the performance of microcalcifications' detection, we have used some evaluation criteria of the obtained results namely sensitivity and specificity. First, we describe the database used for the test and validation of the proposed method. Then, we present some experimental results involving several tests on real mammographic images including pre-processing and microcalcifications' detection according to the development described in Section II. Discussions are provided in Section III.D followed by conclusions.

A. The used database

In order to evaluate and validate the performance of our approach, the MIAS [1] (Mammography Image Analysis Society) database has been used. The latter is as a result of the work of a group of British scientists interested in mammography. The MIAS database contains a set of 322 digitalized mammographic images of MLO (Medio-Lateral Oblique) type that explore the left and right breast of 161 women. These images belong to three categories: normal, benign and malignant, which are considered abnormal. Furthermore, abnormal cases are divided into six classes namely: calcification (CALC), well-defined/circumscribed masses (CIRC), spiculated masses (SPIC), other, ill-defined masses (MISC), architectural distortion (ARCH) and asymmetry (ASYM). The original MIAS database (digitised at 50 micron pixel edge) has been reduced to 200 micron pixel edge and clipped/padded so that every image is 1024 × 1024 pixels [1] with a gray level ranging from 0 to 255.The base also contains the location of various abnormalities present in a mammography given by expert radiologists. Only images with microcalcifications' were considered.

B. Evaluation criteria

For detection problems in medicine, the a priori of each decision is not absolute but based on the judgment of the expert. More concretely, in our application, it is a question of making the compromise between the risk of not detecting a cancer and the inconvenience of having additional examinations on a large number of patients. We propose here an evaluation method of the quality of a detection result that does not require any a priori knowledge on the investigated images. The sensitivity that is, in fact, the true positive rate (TPR), represents the ability of a diagnostic test to provide a positive result in the presence of the disease. The specificity represents the ability of an examination to provide a negative result in the absence of the disease [21], [27], [47]:

$$TPR = Sensitivity = \frac{TP}{TP + FN} \quad (3)$$

$$FPR = 1 - Specificity = \frac{FP}{FP + TN} \quad (4)$$

where TP means the true positive number, TN the true negative number, FP denotes the number of false positive or type I error (in decision theory terminology), FN denotes the number of false negative or type II error and FPR is the false positive rate.

C. Results

In order to evaluate the performance of the proposed method, several tests were performed on the MIAS database mammographic images of different characteristics. These microcalcifications belonging to three categories: normal, benign and malignant. The appropriate number of classes can be obtained either from the opinion of an expert depending on

the context or using the histogram. In order to provide a comparative study, Figs. 8-9 show the results experiments concern real images containing of application of the proposed contrast enhancement approaches (local and global) to one of the mammographies presented in Fig.1. The same procedure is applied to the other remaining three images.

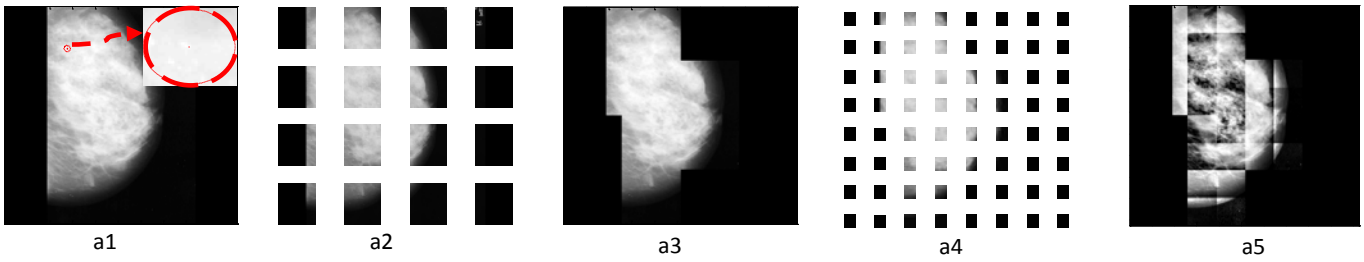


Fig. 8 result of application of local contrast enhancement
(a1) Malignant original mammography image (1024 × 1024 pixels), (a2) sub-images (256 × 256 pixels) of (a1) after division, (a3) reconstruction of (a2) after thresholding (1024 × 1024) pixels, (a4) sub-images (128 × 128 pixels) of (a3) after division and (a5) reconstruction of (a4) after enhancement of local contrast.

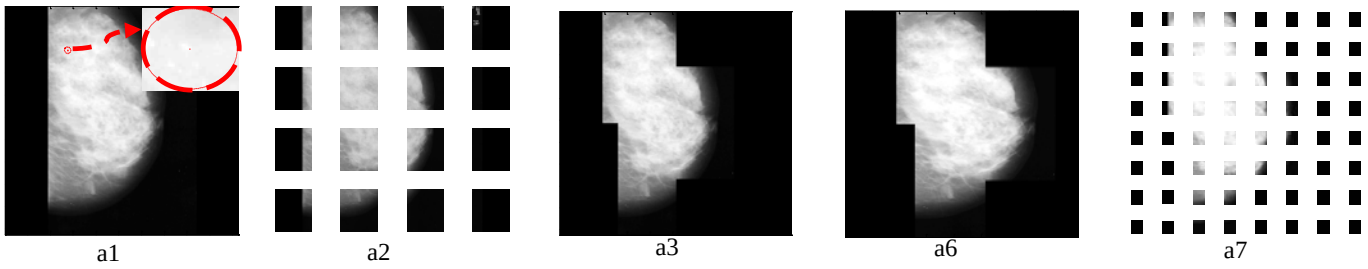
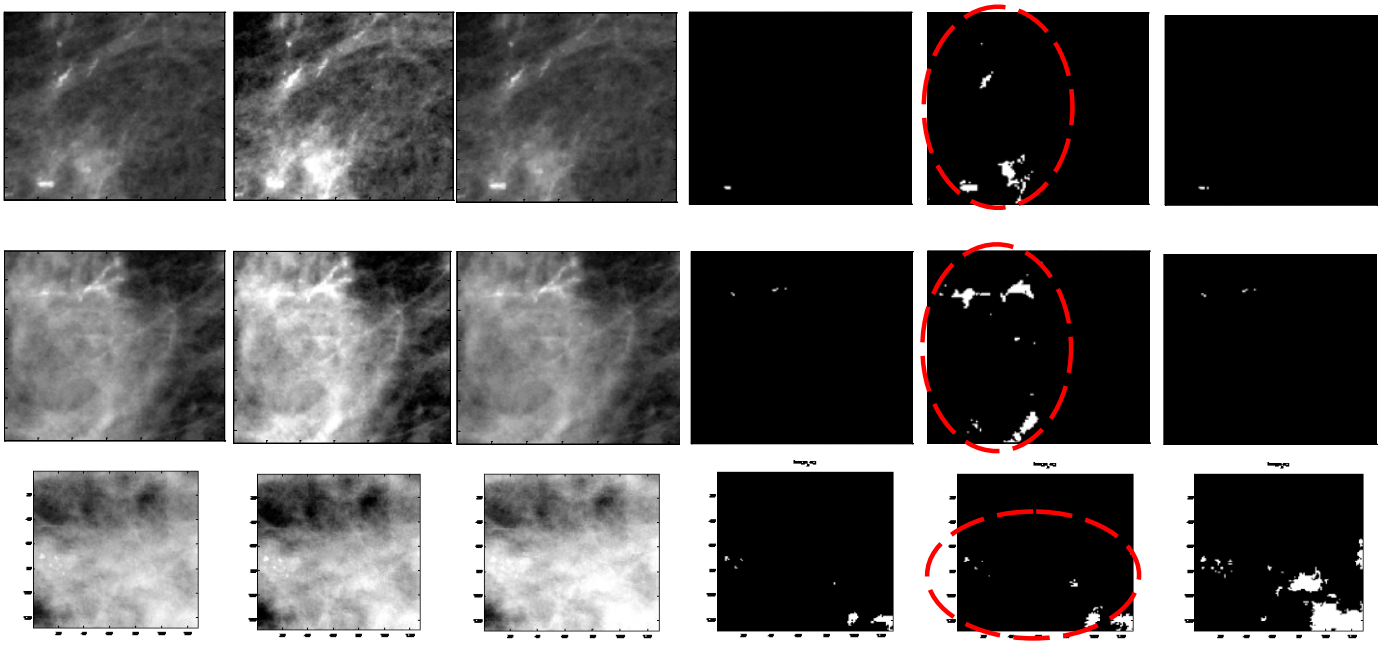


Fig. 9 result of application of global contrast enhancement
(a1) Malignant original mammography image (1024 × 1024 pixels), (a2) sub-images (256 × 256 pixels) of (a1) after division, (a3) reconstruction of (a2) after thresholding (1024 × 1024) pixels, (a6) (a3) after enhancement of the global contrast (1024 × 1024) pixels and (a7) sub-images (128 × 128 pixels) of (a6) after division.

The obtained results confirm the performance of contrast enhancement in highlighting the regions of interest for the proposed microcalcifications' detection (see Fig.10). At that moment, the latter becomes quite simple due to the following: i) only sub-images with most intensity (i.e. information) are kept for subsequent processing and ii) intensity dynamics of the sub-images is increased which increases the contrast of pixels representing microcalcifications with respect to the surrounding tissues. From Fig.10, we see that microcalcifications have been successfully detected. Note that our method allows detecting the presence of the anomaly or not without being able to determine the type of the anomaly.



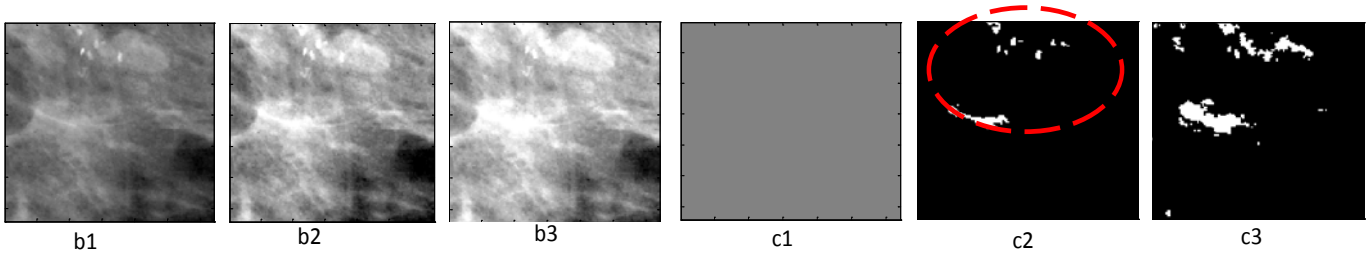


Fig.10 results of the propose microcalcifications' detection method applied to the four mammographic images of Fig.1 (b1) (a4) after thresholding without contrast enhancement, (b2) (a5) after thresholding, (b3) (a7) after thresholding, (c1) microcalcifications' detection by proposed algorithm without contrast enhancement, (c2) microcalcifications' detection using the proposed algorithm with local contrast enhancement, and (c3) microcalcifications' detection using the proposed algorithm with global contrast enhancement.

The presented results are comparable to those found in the literature. However, the study of the different approaches show that the theory of probabilities based on hidden Markov chains is the most appropriate to model information extracted from images. These stochastic models introduce contextual information with a spatial regularization while the other segmentation methods do not respect the spatial coherence of the classes in the image. Furthermore, the main advantages of our approach are : 1) possibility of detecting the presence of microcalcifications of sizes smaller than 1mm (3 to 5 pixels), 2) consideration of spatial information in the classification of the image's pixels as it is evident from the various investigated examples, 3) better preservation of boundaries of regions of excellent structures and robust estimation of regularity parameters and 4) the choice of a Gaussian model leads to satisfactory segmentation results with notable improvement in the homogeneity of the performed segmentation with improved contrast.

D. Analysis and discussion

In general, the obtained results are very satisfactory and suitable for estimation of the segmentation model parameters and detection of microcalcifications. If we analyze the obtained results from visual point of view and in the sense of objective evaluation criterion, we see that they are coherent. However, we note the following remarks:

The efficiency of applying hidden Markov chains on microcalcification detection is proved through several tests applied to real mammographic images. Estimation of regularity parameters, which are the elements of a stationary transition matrix, is much more robust. The area boundaries are often slightly irregular, but fine structures are generally better detected. The obtained results confirm that microcalcification can be accurately determined. Hence, the contrast enhancement technique improves the performance of our algorithm in detecting both benign and malignant classes.

In order to ensure the convergence of the algorithms, we repeated the experiments for all images over 100 iterations: no degradation of segmentations is observed. First, for parameters' estimation, we used the ICE algorithm which has the advantage that it is not expensive from computing time point of view. The number of iterations of ICE is set to 100 and we calculated only a posterior realization by iteration. Then, to achieve the segmentation task, we opted for an unsupervised classification method that minimizes the number of misclassified pixels based on the MPM estimator. Note that the performed classification is direct without any need of iterative calculation. Thus, the Gaussian distribution is well adapted to mammographic images.

Another subjective evaluation is used by comparing the selected sub-images after thresholding without and with contrast improvement (local and global). The number of detected microcalcifications is also checked with respect to the expert's opinion in benign and malignant cases of an infected breast. From Figs.10 (c1) - (c3), it is clearly seen that detection based on the proposed method does not capture the same details on the analyzed image, namely the number and the size of microcalcifications, with and without the use of one of the two contrast enhancement techniques. In order to facilitate the visual comparison, an area delimited by a circle is selected in the different sub-images. It can be seen that detection with local improvement of the contrast clearly outperforms detection without any contrast enhancement or with global improvement. Tab.1 summarized the details of these results by referring to the objective evaluation criteria given by Eqs. (3) - (4) and considering the three types of breast density.

	Nature of the lesion			
Type of breast density	Malignant (M)		Benign (B)	
	TPR	FPR	TPR	FFP
Dense-glandular (D)	0.725	0.275	0.825	0.175
Fatty-glandular (G)	0.814	0.186	0.85	0.15
Fatty (F)	0.7	0.3	0.9	0.1

Tab.1 objective evaluation criteria for the three types of breast density in the case of malignant and benign lesions

The experimental results reported in Tab.1 show that our approach is more efficient for the detection of microcalcifications of benign lesions regardless of the types of breast density. The best obtained rate of true positive is 90.00% realized with images of the Fatty breast density of benign lesions whereas this rate is of the order of 70% when we apply our method to the images of the same density but of malignant lesions. This decrease is explained by the fact that in dense tissues where the skin is thick, the suspect zones are not very distinct, amorphous, too small or fuzzy and almost invisible so they cannot be detected as microcalcifications. Thus, we conclude that our detection method based on hidden

Markov chains is well adapted to the analysis of mammographic images.

Several facts come out from this experimental study. First, the relevance of considering spatial information for pixels' classification is evident in the various investigated examples. Secondly, the choice of a Gaussian mixing model leads, as expected, to acceptable segmentation results and there is a notable improvement in the homogeneity of the segmentation using a spatial model. This shows that the used approximations of hidden Markov chains preserve the Markovian information. Finally, the performed comparisons on the three breast densities prove that the proposed approach gives better analysis results and then better performance.

The speed and flexibility of our method based on the use of hidden Markov chains, Hilbert-Peano-type scans, data attachment parameters' estimation and a priori conditional probabilities for unsupervised segmentation may open up original perspectives to resolve the problem of unsupervised spatiotemporal statistical image segmentation. More generally, these techniques are also applicable to other related fields such as unsupervised segmentation of 3D images or even sequences of 3D images.

IV. Conclusion

In this paper, we present an automated algorithm for the detection of microcalcifications using a specific processing of mammographic images. This helps the experts in their work because the number of images to be valued is very large. The proposed method consists first of highlighting the spatial information present in the mammographic images by improving the contrast of pixel groups representing microcalcifications. The second main contribution concerns the confirmation that the use of hidden Markov **c**hains constitutes a more effective and powerful tool for microcalcifications' detection because HMCs rely mainly on the spatial regularity constraint for image processing. The experimental results prove that the proposed combination between contrast enhancement as a pre-processing phase and HMC-based segmentation block provides accurate microcalcifications' detection.

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