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Classification of Contrast Ultrasound Images: Improvement of the GMM Using Gaussian Filter

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***Abstract*—Contrast agent microbubbles play an important role in ultrasound images. These agents are small and safe, and are administered intravenously in the systemic circulation to enhance the vascular zone of interest. The backscattered signals issued from the agent area are not considerable enough to be differentiated from the backscattered signals derived from the surrounding tissues. Therefore, applying further image processing techniques is mandatory to improve the visualization of the contrast ultrasound images, to achieve a satisfactory classification, and even to quantify the agent concentration in the perfused zone. The nonlinear physical property of the agent results in a relatively high backscattered signal with respect to the tissue characterized by a quasi-linear response. In this paper, a Gaussian mixture model (GMM) is used to discriminate between the biological tissues and the contrast agent. The efficiency of the GMM classifier is obviously consolidated if the data distribution fits to Gaussian. Therefore, we propose to apply a Gaussian filter as a pre-processing phase that allows the non-Gaussian distribution to match slightly the Gaussian. Consequently, Gaussian filter lends positive impact on the quality of the image and improves the performance of the GMM classification of the contrast-ultrasound images.**

Keywords—Contrast agent, ultrasound images, classification, segmentation, Gaussian mixture model, Gaussian filter;

I. INTRODUCTION

Ultrasound techniques have highly evolved owing to their several advantages. Indeed, the echography scanner is simple, safe, cost effective, and does not need heavy equipment. Innovative technologies employed in ultrasound field such as probes, new implemented image-processing approaches, and the use of ultrasound contrast agents further increase the usefulness of the ultrasound medical equipment in detecting a large number of diseases and better visualizing organs and blood vessels. Unfortunately, ultrasonic images are characterized by their speckle noise due to the ultrasound waves' interference. This major drawback is partially alleviated using an ultrasound contrast agent formed of gas microbubbles. The echogenicity of the microbubbles is immense in comparison to the echogenicity of the surrounding soft tissues. Thus gas microbubbles enhance the ultrasound reflected waves leading to high difference aspect in the echographic images. Despite the image quality improvement due to the contrast agent, the post-image processing phase is still required to upgrade the visualization of organs and blood vessels and to perform the segmentation of the contrast images. Moreover, the ability to quantify the agent concentration in the circulation could provide important information about blood perfusion and organ blood-flow rate.

Ultrasound contrast agents are small bubbles injected intravenously in the systemic circulation. Their small diameter of 1-10 μm permits the passage through the pulmonary capillaries. The microbubbles are encapsulated by a coated or surfactant shell to prevent the agent destruction against the high pressure in the cardiac cavities and aorta [1]. The acoustic and physical properties such as compressibility and rigidity influence on the behavior of the contrast agent response [2-3]. Indeed, the agent microbubbles oscillate nonlinearly by generating harmonics, sub-harmonics and ultra-harmonics of the incident frequency [4]. In opposition, the tissue responds more linearly by generating dominant fundamental frequency and negligible harmonic components of low amplitude [5-6]. For these reasons, in the contrast ultrasound images, the value of the pixel issued from the tissue linear scatterer is low while that issued from the agent nonlinear scatterer is relatively tremendous. The localization of the agent with significant quality by means of classification and segmentation techniques boosts the physicians' ability to make the diagnosis and detect the disease.

In this study, the contrast ultrasound image is segmented using the Gaussian mixture model (GMM) into two classes: contrast and tissue. The low pixel values associated with tissue scatterers are modeled by one Gaussian, whereas the high pixel values associated with contrast scatterers are modeled by a second Gaussian. Thus, the more modeled distributions correspond to Gaussian, the better the classification is. Unfortunately, the statistical distributions of the agent and tissue of the harmonic image do not fit Gaussian [7], but they correspond to Rayleigh distributions [8-10] or k-distribution functions [11-12]. To provide an efficient classification by the GMM technique, a Gaussian filter should be applied on the image to ensure that the statistical distributions of the two partitions are close to Gaussian. As a result, the filtered images classified by the GMM indicate a remarkable improvement in quality when a Gaussian filter is applied in the preliminary phase.

II. GAUSSIAN MIXTURE MODEL (GMM)

The Gaussian probability density function [13] denoted by $\mathcal{N}(x, \mu_x, \sigma_x^2)$ is characterized by its mean μx and its variance σ_x^2 as shown in equation (1)

$$f_x(x) = \frac{1}{\sqrt{2\pi}\,\sigma_x} \exp\left[-\frac{(x - \mu_x)^2}{2\,\sigma_x^2}\right] \quad (1)$$

The Gaussian mixture model (GMM) combines many density functions possessing different parameters and linearly scaled by wi weights (2)

$$F_x = \sum_{i}^{G} w_i\, \mathcal{N}_i(x, \mu_x, \sigma_x^2) \quad (2)$$

A problem resides in the choice of the optimal size G of the mixture to obtain a better classification. The statistical studies of the contrast ultrasound images indicate the presence of two distribution categories: low values for tissue and relative high values for agent. Based on this property, we propose to implement a GMM model formed of two Gaussians $\mathcal{N}(T, \mu_T, \sigma_T^2)$ and $\mathcal{N}(A, \mu_A, \sigma_A^2)$ in order to model the pixels distributions of the tissue and the agent, respectively. The subscript indices T and A represent the tissue and the agent, respectively. Indeed, the tissue pixels distribution yields a low mean μT and a small variance σ_T^2 since the tissue scatterers' response is linear and relatively homogeneous. While for the agent distribution, the mean μA is large since the agent's scatterers are nonlinear and characterized by high reflectivity [14]. Moreover, the dissolution of the agent in the blood is non-homogeneous so that the scatterers' position is randomly localized, which leads to a high variance value σ_A^2.

A. Gaussian Filter

The Gaussian filter is a non-uniform low pass filter where the central coefficients have a higher weighting than those on the periphery. The farther away the neighbor pixels are, the smaller the weight is. The Gaussian filter realizes an effective smoothing of the image. Based on the central limit theorem, the outcome image of a Gaussian filter has quite a Gaussian distribution [13]. The GMM classifies contrast and tissue distributions by identifying the corresponding Gaussian to each distribution. A perfect classification is accomplished if the two distributions fit well Gaussians and the overlapped area between them is disregarded. However, many studies have shown that the distributions of the contrast harmonic images conform to Rayleigh [8-10] or k-distribution functions [11-12]. Thus, it is substantial to apply the Gaussian filter on the image to promote the efficiency of the GMM classifier. Quantitatively, the Goodness-Of-Fit (GOFT) parameter [14] is used to confirm that the fitting-to-Gaussian of each distribution is improved when applying Gaussian filter.

Algorithm Procedure

The algorithm is composed of two subroutines: the Gaussian filter and the GMM technique. The first step applies the Gaussian filter on the contrast ultrasound harmonic mode image to guarantee that the distributions of agent and tissues are close to Gaussian. So at this stage, they can be easily modeled and efficiently represented by two different Gaussians. In the second subroutine, the GMM is implemented starting by an initial phase where the values of the parameters of the two Gaussians (μT, μA, σ_T^2, and σ_A^2) are determined based on the statistics of the image pixels using a threshold algorithm. In fact, the filtered-image pixels are configured into two categories: higher or lower than the threshold value. Then, for each category the computed mean and variance are set as initial parameters of the mixture model. Progressively, the image pixels are iteratively classified by GMM using maximum likelihood criteria. Indeed, at a given iteration, the statistical parameters (mean and variance) for each class of pixels are assigned as the new parameters of the GMM model in the next iteration. Thereby, the pixels are addressed to the updated contrast and tissue Gaussians. The program is stopped when the GMM recognizes the image complexity and feature. The number of pixels alternating their classes could be used as the stopping criteria.

III. EXPERIMENTAL SETUP

The experimental set-up consists of a water reservoir, a mechanical flow regulator and a non-recirculating Doppler flow phantom (ATS laboratories) containing a tube vessel of 4 mm diameter.

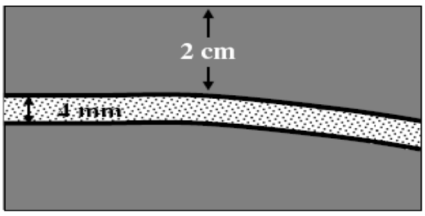


Fig. 1. Experimental mechanism.

The tube is localized at 2 cm depth as the experimental disposition shows in Fig. 1. The Sonovue (Bracco research, Geneva) contrast agent is dissolved in a liquid with a dilution factor of 1/1000. The ultrasound waves are emitted by the VF13-5 probe connected to Siemens scanner that operates in User Research Interface mode. The data acquisition is realized at a transmitted frequency of 4 MHz in harmonic mode. The experimental objective is to differentiate the tissue from the contrast agent and to delimit the tube boundary representing and modeling the blood vessel.

IV. RESULTS

A. Preliminary study

Based on the physical and acoustic characteristics of the contrast agent and the nonlinear behavior of its backscattered signal, the corresponding mean μA and variance σ_A^2 values should be higher than those of the tissue. To consolidate the consequences of the theoretical outcomes, we propose to perform statistical studies for the images using histogram diagrams. In addition, our assumption is validated by computing the statistical parameters as mean and variance of both tissue and agent regions. The histograms in Fig. 2 depicted, at the same scale show obviously that the classification is feasible in spite of the minor overlapping area between these two distributions.

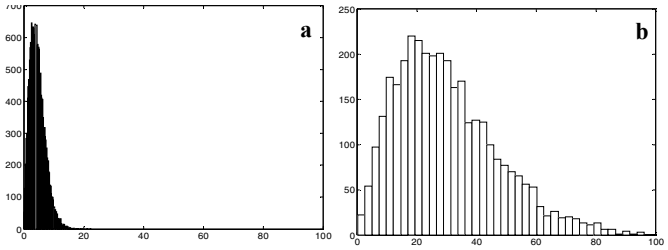
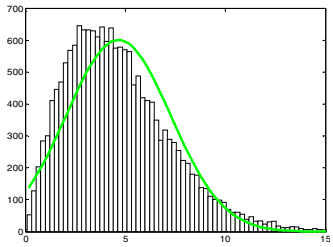


Fig. 2. Tissue (a) and agent (b) statistical distributions of the harmonic image displayed at the same scale. The agent mean and variance are greater than their corresponding tissue mean and variance.

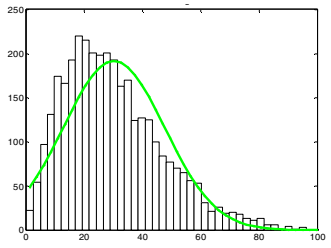
Quantitatively, the tissue and agent mean values, μT and μA, are 4.7 and 30, respectively. These values validate the fact that the agent's backscattered signal is higher than the tissue's backscattered signal due to the agent large reflectivity. As for the variances, σ_A^2 is very high and attains 301 expressing the nonlinear feature of the agent, whereas σ_T^2 has a value of 7 indicating the homogeneity of the tissue and its linear response. Therefore, the two distributions have low overlapping area, which confirms our assumption to classify the ultrasound images using Gaussian mixture model.

B. *Gaussian Filter Effect*

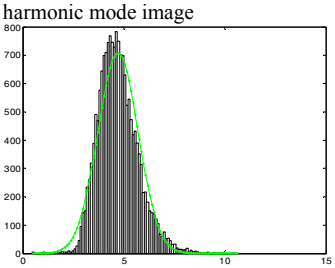
Gaussian filter achieves an effective smoothness of the image where the resultant filtered image owns characteristic distributions close to Gaussian. To study the impact of the Gaussian filter on the harmonic mode image, we investigate the modifications that happen on the distributions of the filtered image. The upper images in Fig. 3 illustrate the histogram diagrams of the tissue (Fig. 3a) and the agent (Fig. 3b) of the harmonic mode image, while bottom images show the histogram diagrams of the tissue (Fig. 3c) and the agent (Fig. 3d) of the filtered harmonic mode image.



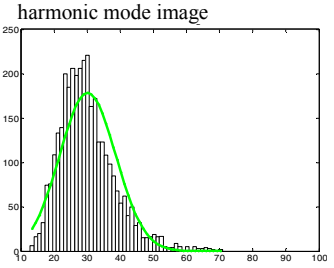
(a) Histogram of the tissue distribution associated with harmonic mode image



(b) Histogram of the agent distribution associated with harmonic mode image



(c) Histogram of the tissue distribution associated with the filtered harmonic mode image.



(d) Histogram of the agent distribution associated with the filtered harmonic mode image.

Fig. 3. Statistical distributions for the harmonic mode image (up) and the images after filtering (bottom). The distributions variances decreases and the overlapping is reduced leading to more classification capability.

It is to be noted that Fig .3a is similar to the image in Fig. 2a but the scale of the tissue region is zoomed in order to visualize well the Gaussian curve on the histogram bins. Many important conclusions can be derived from these histograms. First, the variances of the distributions decrease progressively which lead to an overlap reduction and thereby increases the capability of classification. In fact, the agent (resp. tissue) variance decreases from 301 to 72 (resp. 7 to 1) while the means are slightly modified. Hence, an enhancement of the differentiation between contrast and tissue is achieved and the feasibility of an effective classification is easily managed. Furthermore, the histograms of the tissue and agent of the filtered image (Fig. 3c & 3d) are characterized by a higher degree of fitness to Gaussian with respect to non-filtered image (Fig. 3a & 3b).

C. *Quantitative Results*

The full detection of the agent in the ultrasound image is achieved by smoothing the image by Gaussian filter followed by GMM classification. To compare the performance of the proposed technique, quantitative parameters are implemented and evaluated, as Fisher criterion, ATR parameter and GOFT measurement. GOFT measurement [15] is used to evaluate quantitatively the fitting-to-Gaussian assumption.

Table I. GOFT values associated to tissue and contrast distributions obtained from the harmonic image and the filtered image.

GOFT	Harmonic mode	Filtered harmonic mode
Tissue	1.26	1.25
Agent	1.47	1.23

GOFT measurement is calculated as the normalized least mean square error between the best Gaussian function that fits the histogram bins and the interpolation function constituted by bins center. As shown in Table I, the GOFT value decreases for both the agent and tissue distributions, but it is more significant for the agent. GOFT values demonstrate the influence of the Gaussian filter on the image and confirm the correspondence of the filtered distributions to Gaussians.

On the other hand, Fisher (3) and ATR (4) parameters evaluate the effectiveness of the applied techniques by comparing the performance between different images. They are calculated generally by means of two identical windows localized in tissue and agent regions respectively, and disposed at the same depth in order to endure the same depth damping effects. Since this configuration is a bit difficult for the tissue in the tested image, we propose to introduce two windows disposed over and under contrast region and the computed average result is utilized.

Fisher criterion [16] is a statistical parameter based on the mean and standard deviation values. It demonstrates the classification feasibility and gives an idea about the overlapping between the contrast and tissue zones. The classification is better when the Fisher criterion is around 1 or greater.

$$\text{FISHER} = \frac{|\mu_A^w - \mu_T^w|}{\sigma_A^w + \sigma_T^w} \quad (3)$$

The superscript index w indicates that the parameters μ and σ are calculated according to the windows values.

On the other hand, the Agent to Tissue Ratio (ATR), which is similar to signal to noise ratio in signal processing domain, is frequently used in the ultrasound imaging to compare the methods' efficiency [17]. The greater the ATR value the better the performance of the image.

$$\mathrm{ATR} = 20 \log_{10}\left(\frac{\mu_A^w}{\mu_T^w}\right) \quad (4)$$

Fisher and ATR parameters are computed for both harmonic mode images before and after filtering. The numerical values are depicted in Table II.

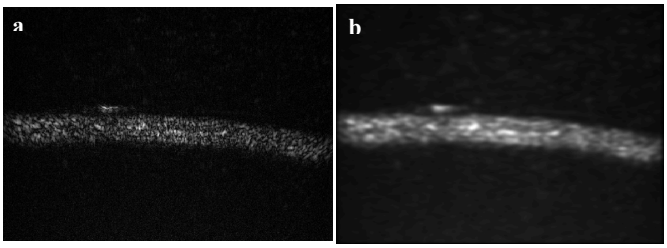
Table II. Values of ATR factor and Fisher criterion for the harmonic mode and the filtered image.

	ATR parameter	Fisher criterion
Harmonic mode	15.52 dB	1.32
Filtered harmonic mode	15.42 dB	2.94

ATR parameter conserves almost the same value where a slight decrease of 0.1 dB (0.67%), considered as negligible, is observed. In contrast, our approach yields a better Fisher parameter value that increases to reach 2.94. Fisher value proves that the classification becomes better and the differentiation between contrast agent and tissue is improved. The variations of ATR and Fisher parameters are justified since these parameters are directly related to the means and variances. In fact, the tissue and agent variances decrease simultaneously but the decrease of the agent variance is more apparent.

D. Graphical results

Applying the Gaussian filter to the harmonic mode image results in a change of the statistical features and a modification of the performance values as seen in the previous section. Fig. 4 obviously shows that an improvement in the image visualization is fulfilled after filtering.



Harmonic mode image (a) and the one filtered (b) by a Gaussian filter. It is clear that Gaussian filter smoothes the image and permits to delimit gradually the two zones.

In the harmonic mode image (Fig. 4a), the contrast agent zone is not clear enough because the agent concentration in the circulation is not isotropic, while in the filtered image (Fig. 4b), the contrast agent zone is smoothed and it becomes more delimited and visibly localized.

The filtered image classified using Gaussian mixture model is shown in Fig. 5 for the first two iterations.

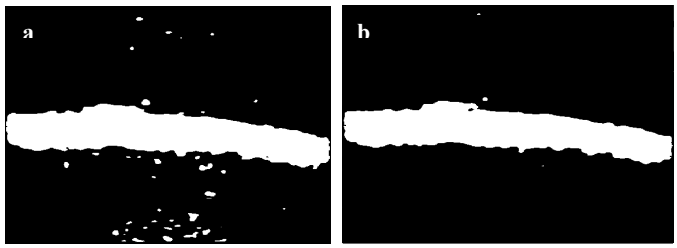


Fig. 4. Classification of the filtered harmonic mode image using GMM during the first (a) and the second (b) iterations. It is clear how the contrast region is delimited gradually.

The iterative procedure of the GMM permits to arrange gradually the distributions and to assign the pixels to their appropriate fitting Gaussians. In addition, it allows a progressive localization of the contrast zone and a clear determination of the separation contour. The strong observation extracted from the GMM classifier is that only two executed iterations are sufficient and adequate. The performance of the classification is exceedingly perfect where an evident differentiation between agent and tissue is attained. However, to obviously outline the effectiveness of the Gaussian filter in the first phase of the algorithm, the Gaussian mixture model is applied directly on the harmonic mode image. The first two iterations of the classified images shown in Fig. 6 reveal a poor performance and a very noisy disturbed classification. Thus, the discrimination between agent and tissue is quite difficult.

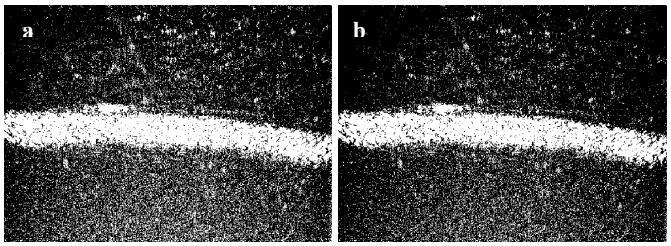


Fig. 5. Classification of the harmonic mode image using GMM during the first (a) and the second (b) iterations. The classification is very noisy and its performance is not satisfying.

These results validate our proposition to use Gaussian filter in a preliminary step in order to improve GMM classification and to obtain a significant segmentation between the agent and tissues.

V. Conclusion and Discussion

In this paper, we have proposed a new classification technique based on Gaussian mixture model in order to distinguish the agent from the tissue in the ultrasound contrast images. The main idea behind this approach consists of modeling the tissue and agent distributions by Gaussian functions. To enhance the performance classification by GMM, the image is smoothed by Gaussian filter that promotes the correspondence of the distributions to Gaussians. The validation of our approach and the attainable improvement is perceived using three parameters: GOFT measurement, ATR value, and Fisher criterion. Moreover, a good discrimination between tissue and perfused zones is obtained even during a low number of iterations. We think that the use of GMM based

on many Gaussian functions may lead to contrast agent image quantification and this constitutes our future perspectives.

This completed study is managed on *in-vitro* images. Similar results are obtained for different tube vessel diameters and for various contrast agent concentrations. Our future aim is to manipulate our proposed technique in *in-vivo* images in order to study, analyze and examine the method efficiency.

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