Algerian Journal of Engineering Architecture and Urbanism Vol. 5 Nr. 3 2021
ISSN: 2588-1760

UNSUPERVISED SEGMENTATION OF IMAGES BY MARKOV SEGMENTATION INTO REGIONS

Dr. Lalaoui Lahouaoui
Dept electronics, Laboratory LGE department electronics University of M'sila 28000 City Ichbilia M'sila, Algeria,
e-mail: lahouaoui.lalaoui@univ-msila.dz

djaalab abdelhak
Dept electronics, Laboratory LGE department electronics University of M'sila 28000 City Ichbilia M'sila, Algeria,
e-mail: abdelhak.djaalab@univ-msila.dz

Dib Fouad
Dept electronics, Laboratory LGE department electronics University of M'sila 28000 City Ichbilia M'sila, Algeria,
e-mail: fouad.dib@univ-msila.dz

Abstract:
Image segmentation is a preliminary and fundamental step in computer aided magnetic resonance imaging (MRI) images analysis. Markov random field model (MRF) has attracted great attention in the field of image segmentation. Such super pixel-based or region-based MRF models have their own advantages and disadvantages. In order to complement advantages of each other, a unified Markov random field (UMRF) model proposed in this paper. However, the performance of most current image segmentation methods easily depreciated by noise in MRI images. In this paper, we proposed the hidden Markov random field (HMRF) model based on KMeans and Expectation-Maximization (EM) algorithm for image segmentation. We implement a MATLAB toolbox named HMRF-EM-image for 2D image segmentation using the HMRF-EM framework2. This toolbox also implements edge-prior preserving image segmentation, and can be easily reconfigured for other problems, such as 3D image segmentation. We have applied this algorithm segmented different type of image, to evaluate the method a validation of the results provided, demonstrating the strength of the algorithm for image with noise.

Key words: segmentation, level set and watershed, evaluate.

I. Introduction:

In recent years, methods of acquiring medical images have developed rapidly, including methods such as x-ray computed tomography (CT), magnetic resonance imaging (MRI), ultra-sound (US), positron emission tomography (PET) and single photon emission tomography. With the production of more and more images medical, automatic image processing and analysis techniques have become essential [Jiang, 2021]. The field of probability it possible to introduce a segmentation class where the characteristics of regions can be modeled, the random fields of Markov (MRF: Markov Random Field), ([Dubes and Jain, 1990] [Gao J.et al, 2002]), using conditional random fields (CRF: Conditional Random Field) ([Zhang L. et al, 2010][Lee S.H., et al, 2010] or with Gaussian mixture models (GMM: Gaussian Mixture Models) ([Carson C. et al, 2002] [Khan J.F. et al, 2009]).

Although optical image processing technology has been widely used in robotics, most of these methods cannot be used to process medical images. Mage segmentation is a process of partitioning an image into several segments with the aim of simplifying the representation of the image or extracting meaningful objects. Image segmentation is one of the most important tasks of computer vision and it has many applications in many other fields, including pattern recognition, remote sensing, medical diagnostics, computer vision, remote sensing and medical imaging (Gribben, Miller, 2009) etc…, has proposed a fuzzy treatment of masked image segmentation based on an MRF model. Image segmentation is a process of partitioning an image into several segments with the aim of simplifying the representation of the image or extracting meaningful objects (Zhang and Brady, 2001).

Thus, the novelty of this work is threefold, namely, we propose (i) an interface level estimation and prediction approach using MRF, (ii) using an approach simultaneously estimating the parameters of the GMM using using the EM Algorithm to account for MRF spatial constraints, and (iii) validation of the proposed approaches on medical and synthetic images. Markov Random Field Theory (MRF) has been widely used in image segmentation and analysis [Ahmadvand and Daliri, 2015]. The Markov Random Field Model (MRF) is a probabilistic graphical model, which provides a statistical means of model spatial contextual constraints as prior information. For pixel based MRF model, spatial context, but it is time consuming and cannot describe long distance interactions between pixels, i.e. macro texture model. On the contrary, the region-based MRF can capture the macro texture pattern using the region-based information, but it suffers from the irregular spatial context. Image segmentation is a process of partitioning an image into several segments with the aim of simplifying the representation of the image or extracting meaningful objects. We use the expectation maximization (ME) algorithm for parameter estimation, a well-practiced approach to compute model parameters within a maximum likelihood estimation framework (Demrsrsa et al., 1977). MRFs have proven to be a suitable method for solving computer vision tasks such as image segmentation. [Sridhar, B., Reddy, 2013] Showed that with certain user-defined starting values, objects can segmented using strict constraints and histograms for the object and the background. In [16], Gaussian mixture models (GMM), one for the background and one for the foreground; replaced the user seed histograms and a border matting algorithm has been developed to fix the transparency on the edges of segmented objects.

The region-level MRF model has proposed in [Ocegueda, and Fang, 2013]. [Wang C, Ni J, Zhang, 2018] Proposed an approach for fusion of multispectral and panchromatic images exploiting local spatial information using the FCM clustering algorithm based on the MRF. However, their notion of label uncertainty cannot generalized to generic MRF models. In the context of image segmentation, a general notion of uncertainty can be considered as the variance or inequality (Yousif, and Ban, 2014) in the label assignments resulting from the distribution posterior of the label image. In [.. Xia and Sun, 2006] they applied FCM with MRF for the detection of change in synthetic aperture radar (SAR) images. They classified the modified and unchanged regions using FCM with a defined random Markov field energy function. An improved method for color texture image based segmentation on FCM aggregation and for medical image segmentation, we propose an MRI segmentation method combining EM and Markov random field. It is different from [Siyal, 2005], which modified the fuzzy clustering membership of each pixel by the MRF energy function; we keep the standard form of FCM and integrate it into the MAP-MRF framework as a component of extraction and analysis of gray level information in our algorithm.

Major disadvantage of the Markov field model is that approximation algorithms they induce are iterative and very computationally intensive.

Algerian Journal of Engineering Architecture and Urbanism Vol. 5 Nr. 3 2021
ISSN: 2588-1760

In order to reduce the amount of computation and to obtain non-iterative computational algorithms, we can use the hidden Markov chains. The remainder of this article structured as follows: A brief review of the MRF model discussed in section two. The new regional feature of the UMRF model presented in section three. Details of the UMRF model given in section four. The algorithm described in section five. The experiments presented in section six and the conclusion given in section seven.

Problematic:

Problematic, MRF model and image segmentation

Let S denote a set of sites. Y = {ys| s ∈ S} is the observed image defined on S. X = {Xs| s ∈ S} is the label random field defined on S. Each random variable Xs in X represents the class of site s and takes value from the set Λ = {1, 2, , n}, where n is the number of classes. Let x = {xs| s ∈ S} denote a realization of X. In the MRF model, the image segmentation is converted into the estimation of a best realization $\hat{x}$ given the observed image Y, i.e. $\hat{x}$= arg max xP(x | Y).

According to the Bayesian rule, the posterior probability

P(X | Y) is equal to (P(Y | X) P(X))/ P(Y). Since the probability P(Y)is a constant, the estimation of the best realization $\hat{x}$ can be obtained by maximizing P(Y | X)P(X), which needs to determine the forms of P(X)and P(Y | X). First, the joint probability P(X) is used to model the label random field X. Since X is assumed to possess the Markov property in the MRF model, P(X) is of Gibbs distribution according to the theorem of Hammersley –Clifford [21]. That is

P(X = x) = (1/ Z) exp (− U(x)), where Z = ∑xU(x) is the normalisation factor and U(x) = ∑s ∈ SU(xs, xNs) is the energy function. Here U(xs, xNs) = ∑t ∈ Ns V (xs, xt), where Ns is set of sites neigh bouring site s and each V (xs, xt) is the potential function between site s and site t, t ∈ Ns. The multilevel logistic (MLL) model [21] is usually employed to define the potential function V (xs, xt), which is

V (xs, xt) =β if xs≠ xt− β if xs≠ xt, (1)

Where β > 0 is the potential parameter and t ∈ Ns. Based on the MLL model, P(X) would have a large value if the local neighbor labels were same, otherwise small. This characteristic encourages the adjacent pixels to be classified into the same label, which would make the MRF model resist noise and reduce the impact of intraclass variations. Second, the likelihood function P(Y | X = x) is a conditional probability function. It is used to measure the probability that how the observed image Y match a given realization X = x. The sites of the likelihood function are assumed to be independent when the label field is given. That is

P(Y | X = x) = ∏s ∈ S P (y_s| x) = ∏s ∈ S P (ys| xs) .

For the pixel-based MRF model, each site s = (i, j) ∈ S in the above equation denotes a pixel, and its feature ys is the vector that consists of spectral values of each band at site s, i.e. ys= (ys1, ys2, …, ysD). Here, ysi denotes the value of spectral band i, and D is the number of spectral bands for the observed image. The Gaussian distribution is usually employed to model P(ys| xs)in the above equation, i.e.

P(ys| xs) = (2π)−D/2Γ−1/2exp −12(ys− μ)TΓ−1(ys− μ) ,where μ = E(Xs), and Γis the covariance matrix of Xs. At the pixel-based MRF model, the site set S = {s | , 1 ≤ i ≤ M, 1 ≤ j ≤ N} is an M × N discrete rectangular lattice. Due to the regular spatial context, one can conveniently define the neighborhood system N = {Ns| s ∈ S} as the four- or the eight-neighborhood system. However, the pixel-based neighborhood relationship is limited to describe the macro texture pattern of an image. To model complex and macro texture patterns, the multi-resolution MRF (MRMRF) model is introduced into the MRF model [19, 21, 24, 37]. The MRMRF model improves the MRF model by considering the image information at different resolutions. Although the MRMRF model can describe interactions in a lager neighborhood compared with the MRF model, it is still pixel-based method. This would lead to some misclassifications and limit the segmentation accuracy. The region-based MRF models proposed to improve the MRF model by using over-segmented regions as the basic site unit. They are defined on the site set R = {r} of regions, where each r is an over-segmented region and ⋃r ∈ R r = Y, r ∩ t = ∅(∀r ≠ t, and r, t ∈ R). It could make the region-based MRF model to describe more macro spatial interactions. However, the region-based MRF model also suffers disadvantages. First, the initially over segmented regions may be imprecise. As mentioned in [35], the approaches used for initially segmentation, such as watershed, have some imprecise segments that would lead to the unfavourable result. Second, the spatial context relationships between regions are irregular. It will be difficult to define the neigh bourhood system for these regions.

3. THE PROPOSED FRAMEWORK

parameter set, k indicates the Gaussian component in the mixture model, K is the total number of Gaussian distributions constituting the mixture model, and w*k* is the weight of each Gaussian distribution, which satisfies -K k=1wk= 1. Each Gaussian component has the standard normal distribution form as:

Pk(ds| θk)=1σk√2πe−(ds−μk) 22σ2 k (4)

Consequently, the observation parameter set θd includes the distribution parameter rθk, which consists of the mean μk and the variance σk, and the weight for each distribution wk. Let S denote a set of sites. Y ={ys|s∈S} is the observed image defined on S. X ={Xs|s∈S} is the label random field defined on S. Each random variable Xs in X represents the class of site s and takes value from the set Λ={1,2,…,n}, where n is the number of classes. Let x={xs|s∈S} denote a realization of X. In the MRF model, the image segmentation is converted into the estimation of a best realisation x ^ given the observed image Y, i.e. x ^ =arg maxx P(x|Y). According to the Bayesian rule, the posterior probability P(X|Y) is equal to (P(Y|X)P(X))/P(Y) . Since the probability P(Y) is a constant, the estimation of the best realisation x ^ can be obtained by maximising P(Y|X)P(X), which needs to determine the forms of P(X) and P(Y|X). First, the joint probability P(X) is used to model the label random field X. Since X is assumed to possess the Markov property in the MRF model, P(X) is of Gibbs distribution according to the theorem of Hammersley–Clifford [21]. That is

P(X = x)=(1/Z)exp(−U(x)), where Z = ∑xU(x) is the normalisation factor and U(x)= ∑s∈SU(xs,xNs) is the energy function. Here U(xs,xNs)= ∑t∈NsV(xs,xt), where Ns is set of sites neighbouring site s and each V(xs,xt) is the potential function between site s and site t, t ∈ Ns. The multilevel logistic (MLL) model [21] is usually employed to define the potential function V(xs,xt), which is

V(xs,xt)= β if xs ≠ xt −β if xs ≠ xt, (1)

where β >0 is the potential parameter and t ∈ Ns. Based on the MLL model, P(X) would have a large value if the local neighbour labels are same, otherwise small. This characteristic encourages the adjacent pixels to classified into the same label, which would make the MRF model resist noise and reduce the impact of intraclass variations. Second, the likelihood function P(Y|X = x) is a conditional probability function. It is used to measure the probability that how the observed image Y match a given realization X = x. The sites of the likelihood function assumed independent when the label field is given. That is P(Y|X = x)= ∏ s∈S P(ys|x)= ∏ s∈S P(ys|xs). For the pixel-based MRF model, each site s=(i, j)∈S in the above equation denotes a pixel, and its feature ys is the vector that consists of spectral values of each band at site s, i.e. ys =(ys 1,ys 2,…,ysD). Here, ys i denotes the value of spectral band i, and D is the number of spectral bands for the observed image. The Gaussian distribution is usually employed to model P(ys|xs) in the above equation, i.e. P(ys|xs)=(2π)−D/2Γ−1/2exp −1 2(ys−μ)TΓ−1(ys−μ) , where μ= E(Xs), and Γ is the covariance matrix of Xs. At the pixel-based MRF model, the site set S={s|,1≤i≤ M,1≤ j ≤ N} is an M×N discrete rectangular lattice. Due to the regular spatial context, one can conveniently define the neighbourhood system N ={Ns|s∈S} as the four- or the eight-neighborhood system. However, the pixel-based neighborhood relationship is limited to describe the macro texture pattern of an image. To model complex and macro texture patterns, the multi-resolution MRF (MRMRF) model is introduced into the MRF model [19, 21, 24, 37]. The MRMRF model improves the MRF model by considering the image information at different resolutions. Although the MRMRF model can describe interactions in a lager neighborhood compared with the MRF model, it is still a pixel-based method. This would lead to some misclassifications and limit the segmentation accuracy. The region-based MRF models are proposed to improve the MRF model by using over-segmented regions as the basic site unit. They are defined on the site set R={r} of regions, where each r is an over-segmented region and ⋃r∈Rr =Y, r∩t =∅(∀r ≠t, and r,t ∈ R). It could make the region-based MRF model to describe more macro spatial interactions. However, the region-based MRF model also suffers disadvantages. First, the initially over segmented regions may be imprecise. As mentioned in [35], the approaches used for initially segmentation, such as watershed, have some imprecise segments that would lead to the unfavourable result. Second, the spatial context relationships between regions are irregular. It will be difficult to define the neighborhood system for these regions. (3.14)

2.2. The MAP-MRF framework

Markov random field theory provides a convenient and consistent way of modelling context-dependent entities such as image pixels and correlated features [26]. Geman advocates the maximum a posteriori Markov random field (MAP-MRF) framework for statistical image analysis problems [27]. For segmentation, it can be considered to be a labeling problem and the segmented result can be retrieved by seeking the maximum a posteriori estimation of the labeling problem.

Let the rectangular lattice for a 2D image of size MN be defined as follows: S¼fðm;nÞj1mM;1nNg (5) For a lattice S, the set of neighbors of element i is defined as the set of sites within a radius of ▪ ▪ rp from i Ni ¼fpixeli0 2Sj½distðpixeli0;pixeliÞ2 r;i0 6¼ig (6) Clique c in S defined as a subset of sites in S. Single-site clique c ¼f ig, pair-site clique c¼f i;i0g, triple-site clique c ¼f i;i0;i00g,(i;i0;i00 2S and neighbor each other), and so on. The collections of all single-site cliques, pair-site cliques, and triple-site cliques can be denoted as C1; C2 and C3. The collection of all cliques C ¼C1 [C3 [C3: In MAP-MRF framework, the MRI segmentation can be converted to a labeling problem which gives different labels to pixels e.g. WM, GM, CSF etc. The joint probability of each pixel's label in the MR image is modeled by the MRF, denoted by PðfÞ¼Pðf1;:::;fMNÞ (7) where, N and M are the height and the width of the MR image in pixels. S¼fðm;nÞj1mM; 1nNg;fi2S 2f 1;:::;LKg, where i is a pixel in S, and LK;k 21;:::;K, corresponding to labels of the different tissues in the brain. According to markovianity, for each i 2S, PðfijfS figÞ equals to Pðfij fNiÞ, where Ni denotes the neighborhood system of i. By the Hammersley-Clifford theorem, PðfjdÞ¼ 1 Ze 1 TUðfjdÞ (8) where, d ¼d1;:::;dMN is the observation, Z and T are constants. The energy function UðfjdÞ¼X c2C VcðfjdÞ¼X i2S X c2C Vcðfijdi0Þ;i0 2c (9) is the sum of clique potentials VcðfjdÞ over all possible cliques in C. Then, the solution of the original segmentation or labelling problem can be denoted as : f ¼argmax f PðfÞ¼argmin f UðfÞ (10) The computation would take a long time if calculated over all cliques. In practice, execution of the computation over single site cliques and pair site cliques is widely adopted. In other words, the second order neighborhood system is adopted, where the label of i is only decided by the elements in Ni ¼ fi0 2Sj½distðpixeli0; pixel iÞ2 2; I0 6¼ig and i itself. In this situation, the model also called an auto model.

3.2 MAP-MRF Framework

The Bayesian framework helps to obtain statistical inferences, synthesizing the maximum a posteriori (MAP) solution, and incorporating the prior information Greig et al. (1989). The objective of the MAP solution is to maximize the posterior probability, which can be represented as: arg max f ∈F P(f | d) (5) According to the Bayes rule, the posterior probability is P(f | d) ∝ P(d | f)P(f) (6) As a result, the MAP estimation problem becomes: argmax f∈F{P(d | f)P(f)} (7) By applying Hammersly-Cli▪ ord theorem, the posterior probability can be expressed as: P(f | d) ∝ e−U(d|f)e−U(f) (8) Consequently, the posterior probability can be written as: P(f | d) ∝

e−U(f|d) (9) where U(f | d)=U(d | f)+U(f) (10) is defined as the posterior energy and U(d | f) is called the likelihood energy. Therefore, maximizing the posterior probability P(f | d) is equivalent to minimizing the posterior energy function U(f | d), which is given by: argmin f U(f | d)

3.1 Gaussian Mixture Model

Pixel values of an image for segmentation purpose usually have significant di□erences among distinct regions; therefore, the mixture of Gaussian distribution becomes a reasonable choice for modeling the observed image. As a result, the observation model can be formulated in the following form (Bishop, 2006):

P(ds | θd)= K - k=1

wkPk(ds | θk) (3) where ds represents an observed pixel, θd is the observation parameter set, k indicates the Gaussian component in the mixture model, K is the total number of Gaussian distributions constituting the mixture model, and wk is the weight of each Gaussian distribution, which satisfies K k=1 wk = 1. Each Gaussian component has the standard normal distribution form as: Pk(ds | θk)= 1 σk√2πe−(ds−μk)2 2σ2 k (4) Consequently, the observation parameter set θd includes the distribution parameter θk, which consists of the mean μk and the variance σk, and the weight for each distribution wk.

Results and discussion

In this work, we presented the segmentation of images by Markov fields based on the KMeans and EM algorithms and the results obtained. We used the Matlab tool to present the segmentation methods by region that we have proposed. The objective of this introduction to image processing in Matlab to present the notion of image and to perform simple image analysis operations. Image processing is a research topic located between computer science and signal processing. To make an objective comparison of the different methods proposed, we propose to opt as evaluation criteria: mean squared error (MSE), signal to noise ratio (PSNR Peak Signal to Noise Ratio), normalized cross-correlation (NCC), structural content (SC) and normalized absolute error (NAE). We present in tables the values of the validation criteria for all the proposed methods. This will be followed by an interpretation of the results, in order to be able to make a comparison between the segmentation methods used. First, we define the evaluation criteria that we mentioned above.

IV.3 Quality measurement:

The objective of this part is to study and define evaluation criteria to quantify the quality of image segmentation results. There is a multitude of segmentation methods whose effectiveness remains difficult to assess. It seems important to be able to measure the quality of the images. However, there is no ideal solution, especially when there is no reference image for this difficult problem. In this part, we will define some basic metrics. [10]

IV.4 Objective evaluation:

Objective quality measurement (as opposed to subjective assessment of quality by human observers) seeks to determine the quality of images algorithmically. The goal objective assessment quality research is to design algorithms whose quality prediction is consistent with the subjective assessment of human observers. The methods of assessing image quality can be classified into three broad categories:

IV.4 . 1 Methods with full reference,

In which the algorithm has access to a perfect version of the image with which it can compare degraded aversion. The perfect version usually comes from a high quality acquisition device; afterwards it degraded by compression and transmission errors.

IV.4 .2 Methods without reference,

In which the algorithm has access to distorted signal and must estimate the quality of the signal without knowledge of the perfect version.

Since non-reference methods do not require any reference information, they can used in any application where quality measurement is required.

IV.4 .3 Methods with reduced reference,

In which partial information about the perfect version is available.
A channel side exists through which some information about the reference can made available to the quality assessment algorithm.
Reduced reference algorithms use this partial reference information to judge the quality of the distorted signal.
The most widely used quantitative measures are: the mean squared error (MSE), the peak signal to noise ratio (PSNR), the signal to noise ratio (Signal to Noise Ratio: SNR) etc. [50]

IV.5 Methods with reduced reference,

Image quality measurement plays an important role in the development of image processing algorithms and in evaluating the performance of the processed image. Image quality is defined as a characteristic of an image that measures the degradation of the processed image by comparing it to an ideal image. Humans are generally the observers and users of the majority of imaging systems, therefore subjective assessment of image quality considered the reliable method. Temporal applications, the use of the subjective method is limited due to its complexity and difficulty of implementation. Therefore, objective methods have used more widely for the assessment of image quality in recent years. In this work, we consider several measures of image quality and analyze their statistical behavior for eight targeted measures of the SFF method. [48]

IV.5.1 Erreur quadratique moyenne (MSE)

The degraded image Î is always compared to the original I to determine its likeness ratio, this criterion is the most used.

It based on the mean square error (MSE) measurement calculated between the original and gradient pixels:

$$M = \frac{1}{M * N} \sum_{m=1}^{M} \sum_{n=1}^{N} \left(I(m,n) - \hat{I}(m,n) \right)^2$$

Where (M × N) the size of image, et I p et Î p are respectively the amplitudes of the pixels on the original and degraded images.

It is likely that the eye takes much more account of errors at large amplitudes, which favors quadratic measurement.

[50]

IV.5.2 The peak signal to noise ratio **(PSNR)**

The PSNR operator measures the relationship between information and noise in an image, calculated from an initial image img_I, which includes the image and noise, and from an image img_O, which is the segmented version of the initial image img_I.
The images img_I and img_O must have the same dimension and the same type.

The PSNR is to quantify the performance of the algorithms by measuring the quality of reinsertion of the segmented image compared to the original image.

PSNR defined by:

$$PNSR = 10log_{10}\frac{d^2}{EQM} \qquad (\mathbf{IV.2})$$

- d is the dynamics of an image.
In the standard case of an image where the components of a pixel are encoded on 8 bits, d = 255.
- EQM is the mean squared error and defined for two images I image and O image of size M × N.
Maximizing the PSNR amounts to minimizing the squared error.
Typical PSNR values for good quality images vary between 30 and 40 dB. [49]

IV.5.3 Structural content:

This quality metric expressed as follows:

$$SC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}(B_{ij})^2} \qquad (\mathbf{IV.3})$$

A higher value of SC (Structural Content) shows that the image is of poor quality.

IV.5.4 Normalized Cross Correlation:

The NCC (Normalized Cross Correlation) measurement shows the comparison of the processed image and the reference image.
NCC expressed as follows: [48]

$$NCC = \sum_{i=1}^{m}\sum_{j=1}^{n}\frac{(A_{ij} \times B_{ij})}{A^2{}_{ij}} \qquad (\mathbf{IV.4})$$

IV.5.5 Maximum difference:

MD (Maximum Difference) provides the maximum error signal (i.e. difference between the image references). MD defined as follows:

$$MD = Max(|A_{ij} - B_{ij}|) \qquad \textbf{(IV.5)}$$

$$i = 1,2 \ldots \ldots \ldots m \ , \ j = 1,2 \ldots \ldots \ldots n$$

The higher the value of the maximum difference, the higher the quality of the image.

IV.5.6 Normalized absolute error

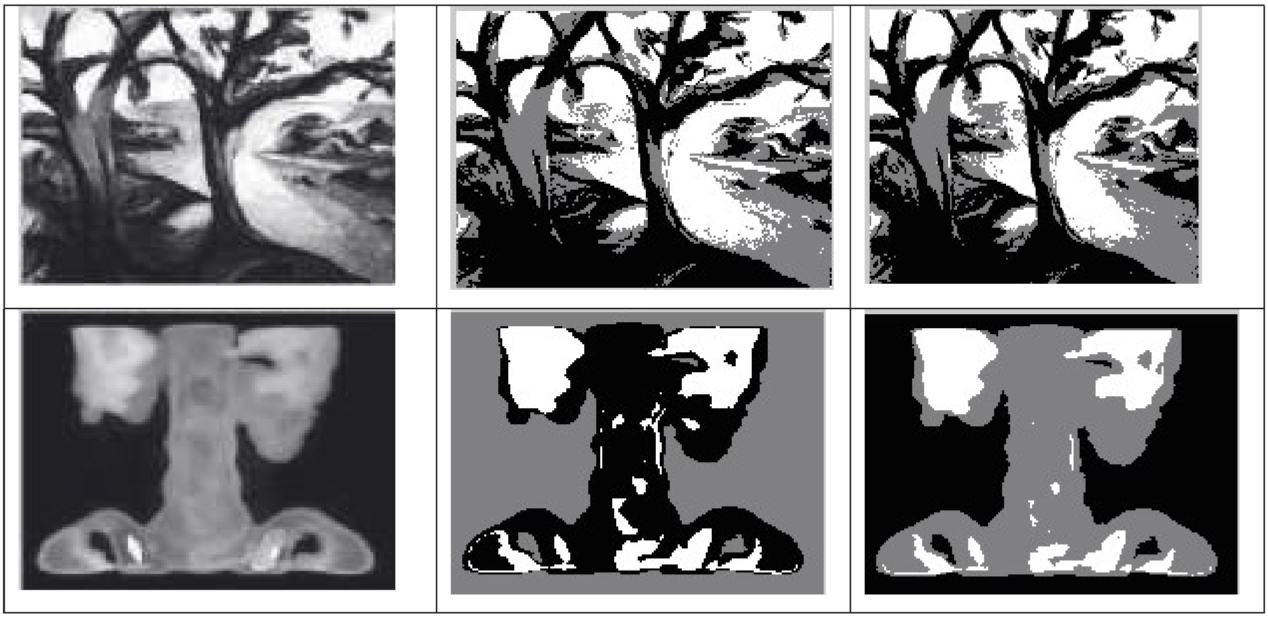
This quality measure can expressed as follows:

$$NAE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(|A_{ij} - B_{ij}|)}{\sum_{i=1}^{m}\sum_{j=1}^{n}A_{ij}} \qquad \textbf{(IV.6)}$$

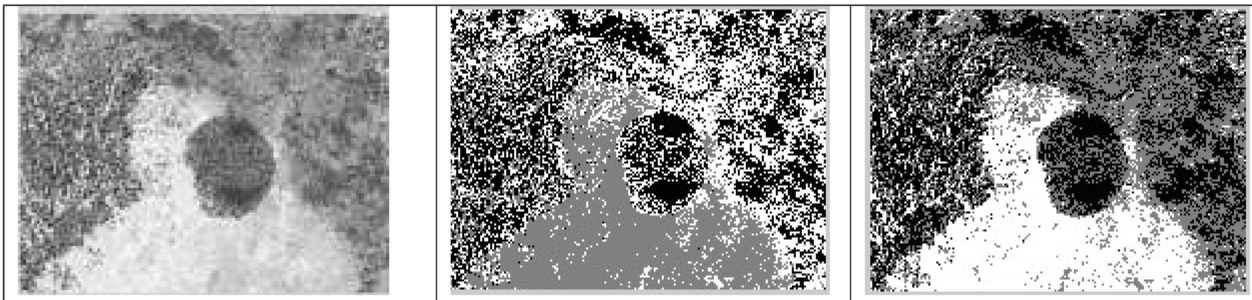
A higher NAE value shows that the image is of poor quality.

IV.6.1 synthetic image Segmentation

In this part, we started to apply the two segmentation methods on the synthetic images and after that; we evaluated these methods by evaluation criteria that we saw previously.
From the values in the table (Table IV.1) (PSNR = 21.5514) and (SC = 170.5034) in can see that the quality of the segmented image is poor by the ICM method based on the EM algorithm versus ICM. An infinite PSNR value corresponds to an undegraded image. In addition, this value decreases according to the degradation of the PSNR therefore links with MSE the maximum energy of the image. Regardless of the value of MSE, the value of PNSR is large.



Algerian Journal of Engineering Architecture and Urbanism Vol. 5 Nr. 3 2021
ISSN: 2588-1760



a) Image original	**b) MRF based K-Means**	**c) MRF based EM**

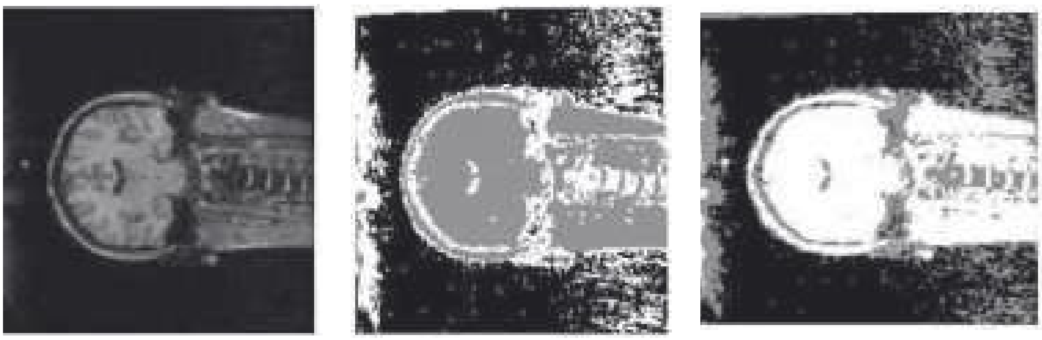
Figure IV.1 a) Image original, b) Segmentation par MRF basée K-Means, c) Segmentation par MRF basée EM based on the KMeans algorithm for synthetic images.

Critères\ Algorithmes	MSE	PSNR	NCC	SC	NAE
KMeans	2.4853e+004	4.1770	0.0132	5.6493e+003	0.9866
EM	2.5019e+004	4.1482	0.0099	5.3427e+003	0.9862
KMeans	454.9593	21.5511	0.0695	170.5034	0.9468
EM	454.9253	21.5514	0.0696	169.8783	0.9466

Tableau IV.1 the Values of the evaluation criteria for image segmentation**.**

IV.7 Real image Segmentation

IV.7.1 Image Segmentation



a) Image originale **b) MRF basée KMeans** **c) MRF basée EM**

Figure IV.2 a) Image original, b) Segmentation parMRF base KMeans, c) MRF base EM

Algerian Journal of Engineering Architecture and Urbanism Vol. 5 Nr. 3 2021
ISSN: 2588-1760

In this part we started to apply the two segmentation methods on real images and synthetic images and then we evaluated these methods by evaluation criteria that we have seen previously the results obtained in the table which shows that the

ICM algorithm based on EM method is better compared to ICM based method for KMeans the actual images.

	K-Means	EM
MSE	2.9142e+003	2.8690e+003
PSNR	13.4856	13.5535
NCC	0.0247	0.0321
SC	809.7124	753.9953
MD	253	252
NAE	0.9558	0.9532

Tableau IV.2 the Values of criteria for image segmentation

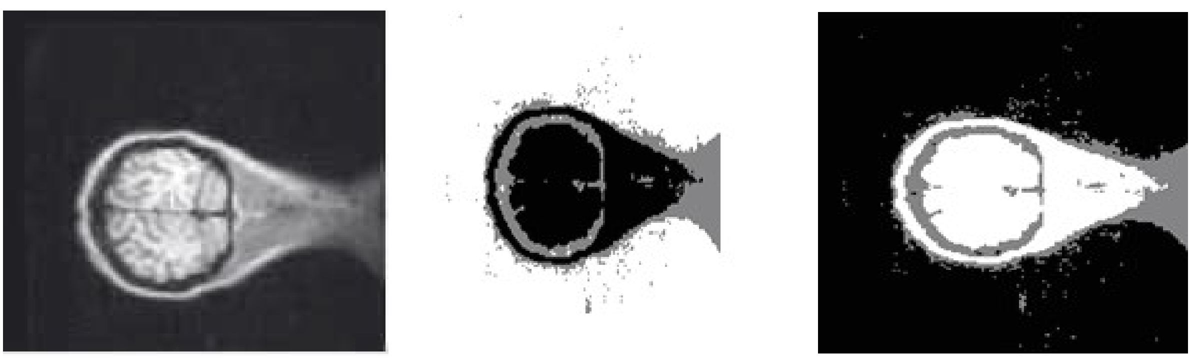
In order to benefit from the advantages of the two methods presented in the previous paper, we decided to use them to segment the images, and we made a table for each result, this table presents the values of some evaluation criteria on the segmentation results the two optimal values (taking into account the direction of variation of the criteria).

We can observe in figure (IV.2) the interest of the segmentation by the method of KMeans it allows to keep precise borders.

The outline image as it appears is a typical image for this kind of segmentation with similar EMs. The values of KMeans are large relative to the value of EM.

So the quality is good and the best EM algorithm.

IV.7.2 image Segmentation



a) Image original b) **MRF based with K-Means** c) **MRF based with EM**

Figure IV.3 a) Image original, Segmentation par b) MRF base K-Means, c) MRF base EM

The results obtained presented in the previous figures where we have presented the segmentation evaluation criteria in the following table: It concluded that the ICM algorithm based on the EM method better compared to ICM based on the method for KMean image real.

Critères	K-means.	EM
MSE	4.8045e+003	4.7178e+003
PSNR	11.3143	11.3934
NCC	0.0112	0.0196
SC	683.0782	1.8686e+003
MD	254	252
NAE	0.9492	0.9678

Tableau IV.3 the Values of criteria for image segmentation

The values of the criteria give the information that the EM algorithm is better than the KMeans algorithm.

IV.8 Conclusion

The work is applied on synthetic and real images, after we carried out a comparative study between the method MRF based on KMeans and MRF based on EM to evaluate these results we used the following criteria: MSE, PNSR, NCC, SC, MD and NAE and two algorithms: KMeanS and EM. The results obtained show that the MRF method sometimes gives bad results (under-segmentation, over-segmentation). The cooperation of these two approaches, which are by nature dual, improves the segmentation result.

In this thesis, we presented different segmentation approaches by region-contour cooperation. Whether sequential or mutual, cooperative segmentation integrates the two types of information (regions and contours) in order to allow better consideration of the characteristics of the objects in the image. The homogeneous zones, as well as the transitions between them, are respected simultaneously. In comparison with segmentation by regions or by contours, the result of cooperative segmentation is more faithful to the reality of the image.

Conclusion and discusion

In this, work we have presented the results of the region segmentation algorithm based on Markov fields, the work applied on synthetic and real images, after we have carried out a comparative study between the MRF method based on KMeans and any image analysis process. It consists of preparing the image in order to make it more usable by an automatic process such as interpretation. There are two main purely local approaches. The contour approach consists in locating the borders of the regions; it based on the notion of dissimilarity. Among these strengths: its simplicity and speed but it sometimes gives open contours. The region approach consists in bringing together the related pixels in a homogeneous region; it

based on the notion of similarity. It is quick and simple, but using only local information MRF based on EM to evaluate these results we used the following criteria: MSE, PNSR, NCC, SC, MD and NAE and two algorithms: KMeans and EM. This work describes the unsupervised classification of images in the framework of hidden Markov models and estimation.
Hidden Markov fields frequently used to impose spatial regularity constraints in parameter estimation and classification steps. This approach produces excellent results in many cases, but our experiences indicate that the estimation of the regularity parameter is a delicate problem. Another disadvantage is the considerable calculation time. The methods based on hidden Markov chains, applied to the Hilbert-Peano traversal of the image, constitute an interesting alternative. The estimation of the regularity parameters, which represent the elements of a transition matrix, seems to be much more robust. Region boundaries are often slightly irregular with this approach, but excellent structures generally better preserved than in the case of hidden Markov fields. In addition to the robust estimation of the regularity parameters, the computational speed is the main advantage of the hidden Markov chain approach. In our experiments, this was about 25 times faster than the program based on hidden Markov fields. Several facts emerge from this experimental study. First, the value of considering spatial information for the classification of the pixels of an image appears clearly in the various examples treated. As expected, the choice of a Gaussian mixture model leads to acceptable segmentations and we observe a clear improvement in the homogeneity of the segmentation with a spatial model. This result is satisfactory because it confirms, in the case of the field, and shows, in the case of strings, that the approximations of a hidden Markov model used preserve Markovian information. In this work, we presented the results of the region segmentation algorithm based on Markov fields. The results obtained show that the MRF method based on EM is better than that based on KMeans.

Reference

Jiang Z, Xie M and Sainju A (2021) Geographical Hidden Markov Tree, IEEE Transactions on Knowledge and Data Engineering, 33:2, (506-520), Online publication date: 1-Feb-2021.

Dubes,R. Jain,A. Nadabar, S. and Chen, C. 1990), MRF model-based algorithms for image segmentation, Pattern Recognition. Proceedings., 10th International Conference on, IEEE, pp. 808–814.

Gribben, H., and Miller,(2009), Map-MRF segmentation of lung tumours in pet/ct images, Biomedical Imaging: From Nano to Macro. ISBI'09. IEEE International Symposium on, IEEE, pp. 290–293.

Ahmadvand, A. ***and*** **Daliri**, **M.R.** (2015) Improving the runtime of MRF based method for MRI brain segmentation, Appl Math Comput 256, 808–818.

Yousefi, S., Azmi, R., ***and*** **Zahedi, M.** (2012), Brain tissue segmentation in MR images based on a hybrid of MRF and social algorithms, *Med Image Anal* **16**, 840–848.

Ryali, S., Chen, T., Supekar, K., and Menon, V. (2013), "A parcellation scheme based on von Mises-Fisher distributions and Markov random fields for segmenting brain regions using resting-state fMRI", Neuroimage, 65 (2), pp. 83-96.

Ashraf, A. B., Gavenonis, S. C., Daye, D., Mies, C., Rosen, M. A., and Kontos, D. (2013), "A multichannel markov random field framework for tumor segmentation with an application to classification of gene expression-based breast cancer recurrence risk", Medical Imaging, IEEE Transactions on, 32 (4), pp.637-648.
Sridhar, B., Reddy, V.S., and Prasad, A. M. (2013), "Automated Medical image segmentation for detection of abnormal masses using Watershed transform and Markov random fields", International Journal on Signal and Image Processing, 4 (3), pp. 56.
Simmons, J., Przybyla, C., Bricker, S., Kim, D. W. (2014), and Comer, M., "Physics of MRF regularization forsegmentation of materials microstructure images". Image Processing (ICIP), IEEE International Conference on, Paris, France: IEEE, pp. 4882- 4886.
Yousif, O., and Ban, Y. (2014), "Improving SAR-Based Urban Change Detection by Combining MAP-MRF Classifier and Nonlocal Means Similarity Weights", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7 (10), pp.4288-4300.
Siyal, M.Y. and Yu, L.; (2005), An intelligent modified fuzzy c-means based algorithm for bias estimation and segmentation of brain MRI, Pattern Recogn Lett 26, 2052–2062
Ocegueda, O., Fang, T., Shah, S. K., and Kakadiaris, I. A. (2013), "3D face discriminant analysis using Gauss-Markov posterior marginals", Pattern Analysis and Machine Intelligence, IEEE Transactions on, 35 (3), pp.728-739.
Wang C, Ni J, Zhang, .X and Huang, .Q (2018), Efficient Compression of Encrypted Binary Images Using the Markov Random Field, IEEE Transactions on Information Forensics and Security, 13:5, (1271-1285), Online publication date: 1-May-2018.
Xia, G.-S., C. He, and Sun, H. (2006), An unsupervised segmentation method using Markov random field on region adjacency graph for sar images, Radar, 2006. CIE'06. International Conference on, IEEE, , pp. 1–4.