World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:7, No:2, 2013

Influence of Ambiguity Cluster on Quality Improvement in Image Compression

Safaa Al-Ali, Ahmad Shahin, and Fadi Chakik

International Science Index, Computer and Information Engineering Vol:7, No:2, 2013 waset.org/Publication/9794

***Abstract*—**Image coding based on clustering provides immediate access to targeted features of interest in a high quality decoded image. This approach is useful for intelligent devices, as well as for multimedia content-based description standards. The result of image clustering cannot be precise in some positions especially on pixels with edge information which produce ambiguity among the clusters. Even with a good enhancement operator based on PDE, the quality of the decoded image will highly depend on the clustering process. In this paper, we introduce an ambiguity cluster in image coding to represent pixels with vagueness properties. The presence of such cluster allows preserving some details inherent to edges as well for uncertain pixels. It will also be very useful during the decoding phase in which an anisotropic diffusion operator, such as Perona-Malik, enhances the quality of the restored image. This work also offers a comparative study to demonstrate the effectiveness of a fuzzy clustering technique in detecting the ambiguity cluster without losing lot of the essential image information. Several experiments have been carried out to demonstrate the usefulness of ambiguity concept in image compression. The coding results and the performance of the proposed algorithms are discussed in terms of the peak signal-to-noise ratio and the quantity of ambiguous pixels.

***Keywords*—**Ambiguity Cluster, Anisotropic Diffusion, Fuzzy Clustering, Image Compression.

I. Introduction

AFTER the last technological progress spreading worldwide, the information in all its forms becomes the most important product of contemporary society. Therefore, researchers are challenging to offer efficient algorithms which reduce the amount of data required to represent a given source of information. In fact, the need to save storage space and shorten transmission time has been the driving factors behind image compression methods.

Image compression deals with minimizing the amount of data needed to represent a digital image by removing redundant data. It involves encoding a 2-D array of pixels into a statistically uncorrelated data set. This transformation is applied before image storage or transmission. Afterward, the coded image is decompressed in order to reconstruct either the exact original image or an approximated version of the original one. For this reason, data compression system requires the definition of two functions: compression and decompression.

Most of the contemporary image coding techniques exploit the quantization principle, such as the JPEG standard based on the Discrete Cosine Transform (DCT) [1] or in the Log-exp transformation model [2]. The major limitation in JPEG is the blocky appearance of the decoded image. The Log-exp model suffers from its computation time which will be penalizing in real-time applications. The quantization stage is the core of every lossy image encoding algorithm: in the encoder part, quantization means partitioning of the input data into a smaller set of values [3].

Increasingly, many studies had proved the involvement of PDEs in the image processing field. They are largely the essential element of image compression and restoration [4]. The basic idea of applying PDEs is to encode some image points (landmarks) selected according to many criteria such as edges or corners whereas in the decompression phase, the decoded image with incomplete information will be fulfilled by applying PDE's anisotropic diffusion [5].

In this study, we suggest the exploitation of fuzzy clustering with ambiguity and PDEs in order to achieve good image quality after compression with a possibility to define image features by the mean of clustering or segmentation. This work is an extension of the proposed approach illustrated in [6].

Image segmentation is an essential and important phase in image analysis in order to produce meaningful features of interest. The purpose behind this step is to formulate the image into regions or clusters. In our work, we chose the fuzzy logic and more precisely fuzzy sets-based algorithms to offer a clustering tool [7, 8, 9]. The fuzzy sets are a generalization of the classical set theory but they offer greater flexibility to detect accurately the various aspects of vagueness or imperfectness in image information.

The remainder of this paper is structured as follows: Section 2 presents our system architecture and the description of the related theories such as fuzzy clustering, entropy encoding and anisotropic diffusion process. The description of these theories is useful to better understand the core of our work. In section 3, the assessment of our proposed approach is illustrated with the help of experimental results and comparisons. The paper concludes with section 4 by providing an overview of the contributions and some potential perspectives.

II. System Workflow and Related Theory

In main purpose of this section is to explain the relevant theories which will be helpful for further understanding and discussion. Fig. 1 illustrates the system architecture and the principal steps performed in our proposed approach.

S. Al-Ali, A. Shahin, and F. Chakik are with the Laboratory of Mathematics and Applications, Doctoral School of Sciences and Technology, the Lebanese University, Mitein Street, face to Malaab High School, Tripoli, Lebanon (e-mails: Safaa_alali@hotmail.com, ashahin@ul.edu.lb, fchakik@ul.edu.lb).

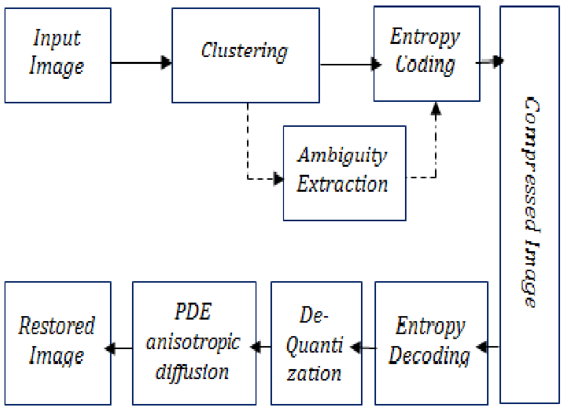


Fig. 1 The proposed image compression and decompression paths applying fuzzy clustering and nonlinear anisotropic diffusion

In our model, the compression algorithm is performed in the following way:

1) Firstly, Unsupervised Fuzzy clustering algorithm is applied on the input image. The FcM proposed by Bezdeck [8] is often a good tool to segment an image. In our work, we also compare the FcM result to the AFcM [9] which is based on the FcM but converges faster. At the end of this step, well-defined members are assigned to the cluster C with the highest and certain membership. Pixels with uncertain memberships will be assigned to a special class that contains all rejected points.

2) Define the vector of ambiguous points indexed by the ambiguity cluster.

3) A second stage of entropy encoding is executed. It's applied on both image clusters and the vector of ambiguous points separately. This will help reducing the large amount of redundancy. Multiple studies was performed and improved to find effective techniques in order to encode information without dropping their principal entities. Among several algorithms recently applied, we suggest the use of Huffman or Arithmetic coding algorithms.

Accordingly, the order of processing appears reversed in the corresponding decompression phase:

1) Apply entropy decoding.

2) De-quantization which assigns the well-defined members with the corresponding cluster center is carried out. For the ambiguity cluster, indexing based on the vector of ambiguous points is used.

3) Apply nonlinear anisotropic diffusion. We suggest the use of Perona–Malik filter [10]. It is an iterative process that continues until a sufficient degree of smoothing is obtained. The used equation encourages diffusion (hence smoothing) within regions and prohibits it across strong edges. The process convergences once the image quality is degraded from the previous iteration.

The quality of the decoded image is controlled by many parameters such as the choice of the number of clusters, the ambiguity threshold for uncertainty decision, the maximum number of iterations in the diffusion phase, etc.

In the remaining part of this section, we will describe the methods used in the proposed compression/decompression algorithms.

A. Fuzzy Clustering with Ambiguity Class

Clustering is the process of organizing objects in groups having similar properties. Clustering methods can be used to create groups of pixels that are similar in regard to a measure, often their color or gray level; therefore simplifying the image by reducing the number of discrete possible pixel values. Image clustering can be used to get a simple segmentation of the image.

The Alternative Fuzzy c-Means algorithm (often abbreviated to AFcM) [9] is an iterative algorithm inspired from FcM proposed by Bezdeck [8]. These algorithms find clusters in data and use the concept of fuzzy membership: instead of assigning a pixel to a single cluster, each pixel will have different membership values on each cluster.

The AFcM attempts to find clusters in the data by minimizing an objective function shown in the equation below:

$$J = \sum_{i=1}^{C} \sum_{j=1}^{N} \mu_{ij}^{m} d^2(x_j, c_i) \tag{1}$$

Where:

- $\boldsymbol{J}$ is the objective function, a kind of quality criterion to minimize
- $\boldsymbol{N}$ is the number of pixels in the image
- $\boldsymbol{C}$ is the number of clusters used in the algorithm, and which must be decided before execution
- $\boldsymbol{\mu}$ is the membership matrix of NxC entries which contains the membership values of each pixel to each cluster
- $\boldsymbol{m}$ is a fuzziness factor (a value larger than 1)
- $\boldsymbol{x_j}$ is the *jth* pixel in the image
- $\boldsymbol{c_i}$ is the *ith* cluster
- d($\boldsymbol{x_j}$, $\boldsymbol{c_i}$) is the distance between $\boldsymbol{x_j}$ and $\boldsymbol{c_i}$. In the FcM, the Euclidean distance is used while in the AFcM it's defined as:

$$d^2(x, y) = 1 - e^{-\beta \|x-y\|^2} \tag{2}$$

Where $\beta > 1$ and could be estimated from the image variance $\bar{x}$ as:

$$\beta = \left(\sum_{j=1}^{n} \|x_j - \bar{x}\|^2 / n\right)^{-1} \tag{3}$$

This metric is a robustness estimator because it is insensitive to small variations and robust against noise [9]. The steps of the algorithm are:

1. Initialize μ with random values between zero and one; but with the sum of all fuzzy membership elements for a particular pixel being equal to 1. In other words, the sum of the memberships of a pixel for all clusters must be one.
2. Estimate β using (3)
3. Calculate an initial value for J using (1).

4. Calculate the centroids of the clusters $\boldsymbol{c_i}$ using
5.

$$c_i = \frac{\sum_{j=1}^{n} \mu_{ij}^{m} \, [1-d^2(x_j,c_i)] \, x_j}{\sum_{j=1}^{n} \mu_{ij}^{m} [1-d^2(x_j,c_i)]} \tag{4}$$

6. Calculate the fuzzy membership μ_{ij} using

$$\mu_{ij} = \left(\sum_{k=1}^{C} \frac{[d^2(x_j,c_i)]^{1/(m-1)}}{[d^2(x_j,c_k)]^{1/(m-1)}} \right)^{-1} \tag{5}$$

7. Recalculate *J*.
8. Go to step 4 until a stopping condition was reached.

Some possible stopping conditions are:

- A number of iterations were executed, and we can consider that the algorithm achieved a "good enough" clustering of the data.
- The difference between the values of *J* in consecutive iterations is small (smaller than a user-specified parameter ε), therefore the algorithm has converged.

Traditionally the algorithm *defuzzify* its results by choosing a "winning" cluster, i.e. the one which is closer to the pixel in the feature space, is the one for which the membership value is highest/certain and using that cluster center as the new values for the pixel. These membership values can be obtained for any kind of images (grayscale, RGB, etc…). The algorithm is adaptive and can be used with image of multiple channels.

The ambiguity cluster is built by grouping all pixels with uncertain memberships, i. e. they cannot belong to a precise class due to vagueness in properties. The criterion used to unclassify pixels is threshold based and is object to experimental evaluation.

B. Non-Linear Diffusion

The PDEs used in image restoration (smoothing, denoising, enhancing of image...) [11] are almost the same PDEs used in image compression by the diffusion (linear isotropic or nonlinear anisotropic).

Typical PDE techniques for image smoothing regard the original image as initial state of a parabolic (diffusion-like) process, and extract filtered versions from its temporal evolution.

Many evolution equations for restoring images can be derived as gradient descent methods for minimizing a suitable energy functional, and the restored image is given by the steady-state of this process.

This theory was proposed by Malik and Perona [10]. Their main idea is to introduce a part of the edge detection step in filtering itself, allowing distinguishing noise from edge. The principle is to spread strongly in areas with low gradients (homogenous areas), and low in areas with strong gradients (edges). These filters are difficult to analyze mathematically, as they may act locally like a backward diffusion process.

Perona and Malik proposed a nonlinear diffusion method for avoiding the blurring and localization problems of linear diffusion filtering. They applied an inhomogeneous process that reduces the diffusivity at those locations which have a larger likelihood to be edges. This likelihood is measured by $\|\nabla u\|^2$. The Perona-Malik filter is based on the equation:

$$\partial_t u = div(g(|\nabla \mathrm{u}|^2)\nabla u) \tag{6}$$

and uses the diffusivity:

$$g(s^2) = \frac{1}{1+s^2/\lambda^2} \quad (\lambda > 0) \tag{7}$$

The experiments of Perona and Malik were visually very impressive: edges remained stable over a very long time. It was demonstrated that edge detection based on this process clearly outperforms the linear Canny edge detector. For more details, see [10].

III. Results and Discussions

In order to evaluate the effectiveness of the proposed methods, we have tested our algorithm with the help of three benchmarks of grayscale images: Lena, Barbara and Baboon of size 512*512. In order to control the parameters on which the approach depends, we divided our study into many parts.

A. Compression without Ambiguity

We will start our experiments using fuzzy clustering without ambiguity class. It means that pixels are assigned to the cluster of the highest membership. The results are summarized in Table I. AFcM and FcM produce similar image quality in most of the cases. AFcM converges faster. In some situation, FcM produces better quality but with PDE operator, AFcM also achieves good image quality. The quality of the image is enhanced when we choose higher number of clusters and the PDE operator enhances slightly the image quality.

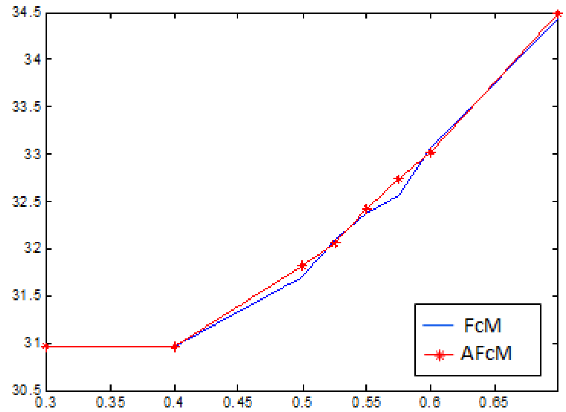
TABLE I
PSNR Results Applying Fuzzy Clustering in the Proposed Approach

Benchmark	Number of classes	FcM without PDE	FcM with PDE	AFcM without PDE	AFcM with PDE
Lena	4	22.9033	22.9037	22.9085	22.9069
	8	30.9650	30.9650	30.9664	30.9661
	16	37.0802	37.0683	37.0505	37.0874
Barbara	4	23.2006	23.2006	23.2021	23.2029
	8	30.6522	30.6532	30.6531	30.6530
	16	36.9588	36.9214	36.9612	36.9543
Baboon	4	23.9814	23.3814	23.3824	23.3822
	8	29.9185	29.9222	29.9173	29.9225
	16	32.2582	36.2508	36.0599	36.2513

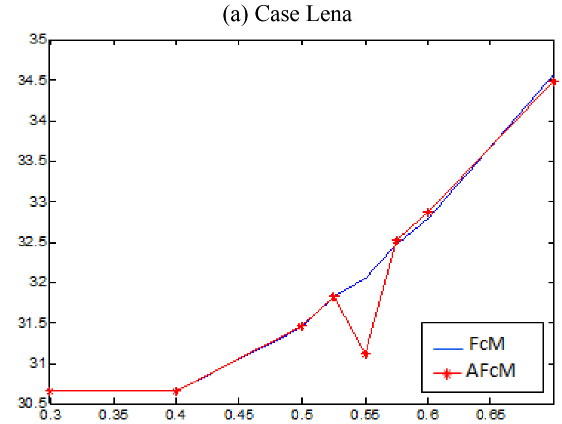
AFcM produces similar results compared to FcM

B. Compression with Ambiguity

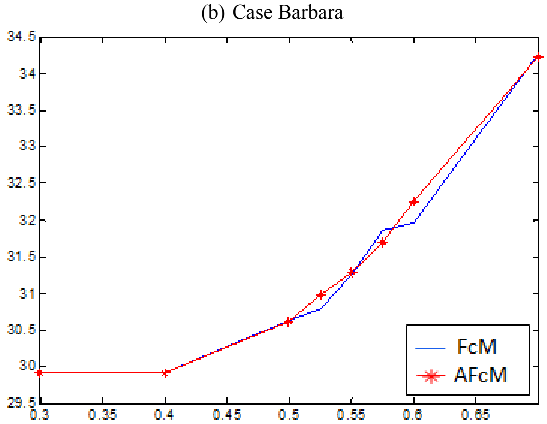
In Fig. 2, we compared the quality of the tested images by using FcM and AFcM in the clustering phase. The threshold value controls the quantity of ambiguous points. We have concluded that AFcM converges faster and gives similar quality compared to FcM.



(a) Case Lena



(b) Case Barbara



(c) Case Baboon

Fig. 2 The horizontal axis represents the ambiguity threshold. The vertical axis indicates the PSNR for the clustering algorithm for C=8 classes

In Table II, we have the results of applying FcM and AFcM on the three test images. These experiments were controlled by the ambiguity threshold which is highly related to the size of the ambiguity cluster. Again AFcM can give good image quality with smaller ambiguity cluster.

TABLE II
QUALITY FINDINGS WITH DIFFERENT FUZZY CLUSTERING ALGORITHMS

Number of classes	Benchmark	Ambiguity Threshold via FcM	PSNR via FcM	Number of Ambiguous Points	Ambiguity Threshold via AFcM	PSNR via AFcM	Number of Ambiguous Points
	Lena	0.575	24.161	9.661	0.55	23.841	7.315
4	Barbara	0.6	24.306	9.384	0.6	24.305	7.384
	Baboon	0.6	24.542	9.032	0.6	24.621	9.690
	Lena	0.5	38.122	8.136	0.5	38.086	7.665
16	Barbara	0.5	38.148	9.088	0.525	38.241	9.593
	Baboon	0.525	37.885	9.288	0.525	37.560	7.744

Results of ambiguity tests varying the number of segmented regions

In Fig. 3, we show how the size of the ambiguity cluster is related to the ambiguity threshold value. They increase linearly.

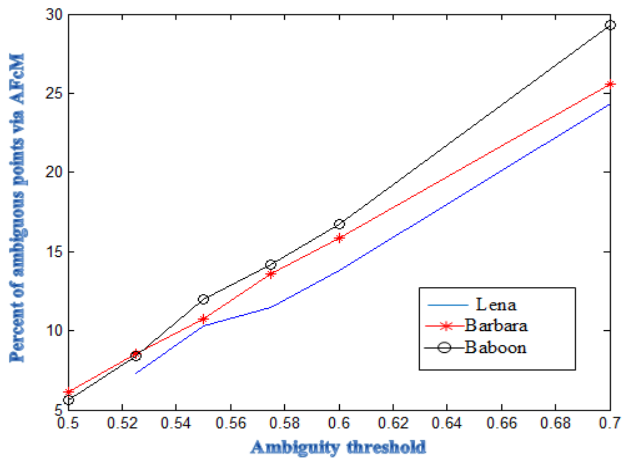


Fig. 3 The quantity of ambiguity pixels depends on the threshold value using AFcM fuzzy clustering with C=8 classes

From table III, we can clearly affirm that the Perona-Malik diffusion does not have a remarkable influence on enhancing the quality of the decoded sparse images.

TABLE III
AFCM WITH AMBIGUITY AND PDE

Number of classes	Benchmark	Ambiguity threshold	PSNR with PDE	% of ambiguous points	PSNR without PDE
	Lena	0.55	23.945	8.028	23.841
4	Barbara	0.6	24.305	9.384	24.305
	Baboon	0.6	24.621	9.690	24.621
	Lena	0.5	38.196	8.520	38.086
16	Barbara	0.5	38.120	8.307	38.241
	Baboon	0.5	37.758	9.183	37.560

Results of PDE influence with AFcM and ambiguity cluster

IV. CONCLUSION

We investigated an efficient image compression technique based on fuzzy clustering and ambiguity concept.

We studied the quality of compressed images without extracting ambiguous points. The AFcM gave better results compared to FcM using anisotropic diffusion.

We also applied fuzzy concept provided with its ambiguity part. A comparative study had shown the effectiveness of the AFcM algorithm in the clustering stage in our compression path. The AFcM algorithm has the advantage of reducing the convergence time and the ability to produce a good quality for the coded image with the minimal size of ambiguity consideration.

We have also conducted different experiments to evaluate the performance of the Perona-Malik diffusion on the test images by varying the threshold value and the number of clusters in AFcM. The PDE operator increases very slightly the image quality and may not be beneficial in some conditions. More attention needs to be carried out with the use of that filter. We should conduct tests on better anisotropic filters such as tensors [5], CED or EED [4] to enhance the diffusion quality.

We believe that introducing ambiguity factor in the clustering phase was beneficial for the decoding phase. We'd like to work on segmentation algorithms that integrate this ambiguity notation such as the Fuzzy c+2 Means introduced by [11].

This work could be extended in many ways. We'd like to test the efficiency of our approach on the compression of big pictures in order to work on these pictures with normal PCs, notebooks, iPad etc. We shall also try to evaluate our algorithms on color images and videos.

REFERENCES

[1] G. K. Wallace. "The JPEG Still-Picture Compression Standard". Communications of ACM, pp.30-44, Apr. 1991.

[2] N. Somasundaram and Y. V. RamanaRao." Modified LOG-EXP Based Image Compression Algorithm", IJCSNS International Journal of Computer Science and Network Security, VOL.8 No.9, 179-184, Sept. 2008.

[3] A. Gersho and R. M. Gray.,"Vector Quantization and Signal Compression", Kluwer Academic, 1991.

[4] J. Weickert, "Anisotropic Diffusion in Image Processing", B.G. Teubner Stuttgart 1998.

[5] Martin Welk, David Theis, Thomas Brox, and Joachim Weickert, "PDE-Based Deconvolution with Forward-Backward Diffusivities and Diffusion Tensors", in Scale Space 2005, Springer LNCS 3459, pp. 585-597, Hofgeismar, Germany, Apr. 2005

[6] A.Shahin, F.Chakik, and S.Al-Ali, "Complexity Reduction and Quality Enhancement in Image Coding", ICIMT 2012, Kuala Lumpur, Malaysia, December 2012, submitted for publication.

[7] Lizarazo, Ivan and Barros," Fuzzy image segmentation for urban land-cover classification", Photogrammetric Engineering and Remote Sensing, Joana, pp. 151-162, 2010.

[8] J. C. Bezdek. "Pattern Recognition with Fuzzy Objective Function Algoritms", Plenum Press, New York, 1981.

[9] Miin-Shen Yang, Yu-Jen HU, Karen Chia-Ren-Lin, Charles Chia-Ren-Lin, "Segmentation techniques for tissue differentiation in MRI of Ophthalmology using fuzzy clustering algorithms", Magnetic Resonance Imaging (20),pp.173–179, ELSEVIER, 2002

[10] P. Perona and J. Malik, "Scale-space and edge detection using anisotropic diffusion," *IEEE Trans. Pattern Anal. Machine Intell.*, vol.12, pp. 629–639, 1990.

[11] M. MÉNARD. "The fuzzy c+2 means: solving the extended ambiguity reject in clustering". Traitement du Signal. Volume 16 - n°2. 1999.

Safaa Al-Ali has obtained a BS degree in Mathematics in October 2010 and a Master degree in Mathematics "Image Option" in July 2012 from the Lebanese University. Safaa is a junior researcher focusing on image processing and will start soon her PhD studies in France.

Ahmad Shahin has a BSc degree in Mathematics and Computer Science from the Lebanese University, a Masters Degree in Automatic and Computer Engineering from La Rochelle University – France (LRUF), a and PhD in Computer Science from LRUF. Ahmad has worked on Doppler Color aliasing correction with the Research Center of Poitiers Hospital in France from 1994 to 1996. He was also lecturer at LRUF from 1994 till 1999. Since 1999, he is lecturing at the Lebanese University. Actually, he is part of the Laboratory of Mathematics and their Applications (LaMA-Lebanon) at the Lebanese University. For several years, he was the Head of the CIS Department at the Lebanese University – Faculty of Business Administration. Dr. Shahin's research is focusing now on Image and Data Processing and more precisely on Compression in Image and Video, Face and Hand Identification for Biometrics, Classification in Hyper-Spectral Imaging, and Data Mining for Medical Predictions. He is actually the Chairman of the IT Association in Lebanon and IEEE member.

Fadi Chakik has received his undergraduate degree from the Lebanese University and Master degree from Toulon and Var University in France. From 1995 till 1998, he pursued his PhD studies in Cognitive Science at the INPG in France inside the LEIBNIZ Laboratory. He joined the Lebanese-French University as full-time professor and led the computer science department from 1998 till 2007. He is actually an Associate Professor at the Lebanese University since 2008. Fadi's research areas focus on the conception and development of new algorithms for intelligent and robust object tracking in video sequences derived from the artificial intelligence domain mainly using Support Vector Machines and Neural Networks. Dr. CHAKIK published more than 20 scientific papers in the areas of support vector machines and neural networks, image recognition, object tracking, virtual advertisement and its applications. He is currently with the Group of Bioinformatics and Modeling in the research center of biotechnology and its applications in the Lebanese University.