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MODEL AND BETTER DECISIONS IN IMAGE PROCESSING

Habiba KHEMILA

Laboratoire d'analyse et de modélisation, Analyse et Conception des Systémes (**MACS**)

Ecole Nationale d'Ingénieurs de Gabes, Tunisie

habiba.khemila@yahoo.fr

CHIBANI Belgacem Rhaimi

Laboratoire d'analyse et de modélisation, Analyse et Conception des Systémes (**MACS**)

Ecole Nationale d'Ingénieurs de Gabes, Tunisie

abouahmed17@gmail.com

***Abstract*——This paper presents an overview of the main methods of data fusion used in image processing. These conventional methods called probabilistic methods Bayesian inference operator, but also non-probabilistic methods employing fuzzy set theory, possibility theory and the theory of functions belief. Thanks to such tools, medical practice (eg) has evolved considerably in recent years, so the clinician can perform the synthesis of different information on diagnosis or a precise and reliable treatment. The doctor's task becomes easy, with fusion tools as it was mentioned.**

***Keywords*—— Fusion Methods ; Image Processing ;Medical Imaging.**

I. Introduction

Data fusion broke into the field of image processing there about five years and has attracted the attention of many teams. Two areas designated satellite and aerial imagery on the one hand, differ [BLOC94]. The interpretation of medical images is also one of the richest areas of research, as it provides facilities for diagnosis and treatment decisions of a number of neurological diseases such as cancer [VIGN88].

When you suspect a brain tumor, the doctor first performs a complete neurological examination to determine the affected area of the brain. This examination is completed with imaging techniques obtained by the scanner, MRI, ... These examples are the most frequent examinations and the most practiced [HAMI01].

In what follows, we will look at the fusion of medical images. This topic has attracted the attention of many researchers such as Bloch and Master [BLOC94] who gave a precise definition of data fusion "information fusion is to combine information from multiple sources to improve decision-making " .

Note that the combination may involve often imperfect information and procedure hétérogènes.This procédure focus on obtaining a better complete global information better and to helps decide and act. This combination approach is addressed by different levels as specified in the related research approach [DASA97]. We distinguish designated levels [DASA97]:

- Low (the data)
- The intermediate level characteristics (*ie*.extracted parameters)
- High level: that of decisions

The choice of fusion level should be based on available data and the architecture of the chosen merger that are related to the application. Recall that the architectural plans to establish a modeling, a combination and a decision that clarified get the indicated levels (low, intermediate, high). Consequently, and according to the level, different methods are used for descriptive modeling and combine knowledge and imperfect information. These methods often draw decision theories, the uncertain and artificial intelligence, can be either numeric or symbolic. We begin by reporting results prepared in image analysis, These are the results that emanate from [BLOC03] [ZADE65] [SHAF76]:

- Bayesian probabilistic theories.

- The theory of fuzzy sets and opportunities introduced by Zadeh.

- The theory of beliefs outcome of the work of recovery by Dempster Schäfer.

Then it will be to present a probabilistic method used in imaging called MRI to locate and evaluate the development of brain cancer in some patients in collaboration with the department of Neurosurgery Hospital Habib Bourguiba Sfax in Tunisia. Finally, we will end this paper with a conclusion.

II. Image fusion and types of architecture

A General problem of image fusion is when one has pictures l of $I_j (j = 1, \dots, l)$ representing heterogeneous data. Let x be the element to which the decision, it can be a pixel in the area covered by the images or other complex images extracted object. The decision is to assign a C_i element of a decision space $D = \{C_1, \dots, C_n\}$. Typically, C_i that represent the

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possible decisions can be of Class covering the images of which you want to assign the pixels, or semantic objects of which we want to award points to recognize .The decision is taken from x to informations $f_j(x)$ given by each of the images I_j (e.g. gray level x in I_j or primitives from more complex treatment) and on which the fusion is based, often through "measures" $M_i^j(x)$, connecting information x extracted from I_j a potential decision C_i for x. These Measures have different interpretations and take various forms depending on the mathematical and theoretical frameworks used for the merger. We distinguish [RANC10]:

- the decentralized systems in which local decisions are taken at each source separately and then are combined into an overall decision.

- Centralized systems are to combine all the observations from the various sensors in a comprehensive manner, and then a decision is made on the result of this combination.

III. The fusion approaches

The main information fusion methods have been studied mainly from two modeling frameworks [DROM98]: probability and fuzzy approaches. Probabilities are derived from Bayesian approaches and theory beliefs. However, fuzzy approaches from the theory of fuzzy sets and possibility theory [DASA97].

III.1. Bayesian Fusion

- ✓ Modeling and estimation

The information is modeled as a conditional probability, for example, the probability that pixel x belongs to a particular class C_i, given the available images I_j be described as: $M_i^j(x) = p(x \in C_i/I_j)$ (1)

The probability $p(x \in C_i/I_j)$ is derived from the Bayes rule and dep $p(I_j/x \in C_i)$, conditional probability of C_i information provided by I_j .

The Bayesian probabilistic model allows many to represent the uncertainty about the information, but this model is incapable of representing the poor information in the case of partial knowledge [CHAU95]. The main disadvantage is the fact that it requires strict constraints when learning and offers a limited palette of operators [CHAU95].

- ✓ Combining his part in a bayesian

The fusion may be carried out in an equivalent way two levels:

- Either at the modeling, and then calculates the shape of probabilities : $p(x \in C_i/I_1, \dots, I_l)$ using Bayes rule. Where different terms are estimated through learning.

- By Bayes rule itself:

$p(x \in C_i I_1, \dots, I_l)$=

$$\frac{\mathrm{p}(I_1/x \in C_i) \dots p(I_l/x \in C_i, I_1, \dots, I_{l-1}).p(x \in C_i}{\mathrm{p}(I_1).p(I_2/I_1) \dots p(I_l/I_1, \dots, I_{l-1})} \quad (2)$$

Combination step also relies on solid mathematical foundations [CHAU95]. Furthermore many operators allow the combination of information from sources with regards to the classification but also the estimation of parameters. However, it is contraignée as for modeling, by the axioms of probability.

- ✓ Decision:

The most common rule for Bayesian probabilities decision is the maximum a posteriori.

$$x \in C_i \; si \; p(x \in C_i/I_1, \dots, I_l) = max_{k=\{1,\dots,n\}} \, p(x \in C_k/I_1, \dots, I_l) \quad (3)$$

But many other criteria were developed by probabilistic and statisticians; eg including maximum likelihood, maximum entropy, the maximum marginal, the maximum expectancy and the minimal risk, etc [BLOC04].

III.2. Fusion and Fuzzy possibilistic

- ✓ Fuzzy modeling and estimation:

As part of the fuzzy set theory [DUBO85] [GERA00], inaccurate information is expressed in the form of Measurement of membership functions $M_i^j(x)$ that takes the form of : $M_i^j(x) = \mu_j^i(x)$ (4)

Where $\mu_j^i(x)$ for example, means the degree of membership of an element x to the class $C_i$according to I_j image or translation of a symbolic information expressed by a variable language [DELL92].

Under the theory of possibility [ZADE78] [DUBO88], the ambiguity and uncertainty are both represented by π possibility distributions on a set S (which are membership functions of fuzzy sets) and two features that characterize the events: the possibility Π and necessity N defined from the possibility of distribution for $A \subset S$. event.

The $M_i^j(x)$ measure is the degree of possibility that the class takes the x value depending C_i on the image I_j:

$$M_i^j(x) = \pi_j(c_i)(x) \quad (5)$$

- ✓ Fuzzy and possibilistic Combinations:

In the theory of fuzzy sets and possibilities, multiple combination rules are possible [DUBO85] [YAGE91]. The choice of such an operator can be based on multiple criteria for image fusion [BLOC94], the first criterion is the operator's behavior which are suspected of [BLOC96]

- Constant Behaviour '(. Connective operator, eg T-norms)

- Variable behavior (disjunctive operator, *eg*. T-conorms)

- Behavior depends on context (Compromise operator, *eg*. Averages.

One of the major interests of the fusion of information by the blur is the great choice of merging operators enabling the combination of membership functions and possibility distributions.

- ✓ Decision

Once the information from different sources are combined, the decision is deducted from the maximum degrees of membership:

$$x \in C_i \; si \; \mu_i(x) = max_{k=\{1,\ldots,n\}} \, \mu_k(x) \qquad (6)$$

Where μ_k designates the membership function to the class k of the resulting combination; the quality of the decision is essentially measured by two criteria [BLOC94]:

- Sharpness: degree of comparison of belonging to a threshold selected according to the application (possibly according to the combination of operator selected).
- the "discriminatory" character evaluated by comparing the two values μ_k (x) the strongest, this can take a negative decision if the two criteria are not checked.

III.3. The belief functions theory in fusion

The theory of evidence was historically introduced by Schäfer [SHAF76], it is particularly suited to medical issues addressed in [TALE02]. We show in this part what are the characteristics of this theory to justify that one is important , both from the point of view of knowledge representation and their imperfections (imprecision, uncertainty, doubt, ignorance, conflict) instead of combination.

- ✓ Modeling and estimation:

The frame of discernment contains all the necessary hypothisis θ_i of the description of a situation presented in a closed world:

$$\Theta = \{\theta_1, \theta_2, \ldots, \theta_n\} \qquad (7)$$

The set of observations X of θ_i :

$$X = \{x_1 \,, x_2 \,, \ldots, x_N \,\} \qquad (8)$$

.The Assembly Θ is comprehensive and exclusive [MERC 14]:

- exhaustif : $\forall x \in X, \exists \theta \in \Theta$ $Information(x) = \theta$
- exclusif : $\forall x \in X, \exists! \, \theta \in \Theta$ $Information(x) = \theta$

In this theory, the rationale is focused or the set 2^Θ, that is the whole set $2^N$of all subsets of S de Θ :

$$2^\Theta = \{S/S \subseteq \Theta\} = \{\emptyset, \{\theta_1\}, \{\theta_2\}, \ldots, \{\theta_N\}, \{\theta_1, \theta_2\}, \ldots, \Theta\} \qquad (9)$$

To express the degree of confidence of a source for each element S S de 2^Θ ,, we associate it with an obvious elementary mass $m(S)$ indicating all the confidence we can have in this proposal without focus on assumptions. The function m is 2^Θ defined on [0, 1] by [SHAF76]]:

$$\textstyle\sum_{S \subseteq \Theta} m(S) = 1 \qquad (10)$$

This theory explicitly provides a measure of ignorance that one has a S event and its complement, as the length of the confidence interval [Bel (S), Pls (S)]. If one of the masses affects only with simple assumptions [SHAF76] ($m(S)$ = 0 for Card (S)> 1), then the three functions: m, Bel and Pls are equal and are Probability .

The theory of fonctiond belief allows, in analogical way the theory of opportunities,to represent both imprecision and uncertainty, the ability to assign weights to the assumptions made, and thus to work on rather 2^Θ as Θ it is an advantage of this theory. [BLOC03]. Indeed, it allows a very flexible and very rich modeling, particularly of ambiguity.

- ✓ Combination :

As well as the equation of Bayes probabilities requires molten rule, the combination rule is imposed in the belief theory (orthogonal combination rule Dempster [SHAF76] can be written (the mass being m_j function set for image j), for any subset S non-empty Θ [SHAF76]:

$$\forall S \in \Theta, \; (m_1 \oplus \ldots \oplus m_l)(S) = \qquad (11)$$

$$\frac{\sum_{B_1 \cap B_2 \cap \ldots \cap B_l} m_1(B_1) \ldots m_l(B_l)}{1 - \sum_{B_1 \cap B_2 \cap \ldots \cap B_l = \phi} m_1(B_1) m_2(B_2) \ldots m_l(B_l)}$$

$$(m_1 \oplus \ldots \oplus m_l)(\phi) = 0$$

If the denominator of the above equation (11) is non-zero, that is to say if:

$$k = \sum\nolimits_{B_1 \cap B_2 \cap \ldots \cap B_l = \phi} m_1(B_1) m_2(B_2) \ldots m_l(B_l) < 1$$

In an open world hypothesis, a positive mass of the empty set is also provided for not representing a solution in Θ. Under the assumption of closed world, or anything that is possible is represented in Θ, this interpretation is not acceptable, leading to normalize the result of the combination (normalization factor k) [BLOC04].

The rule of Dempster connective behavior as it provides focal elements that are the intersections of the focal elements of the initial mass functions. It this strengthens the focus and decreases confidence interval length denoted $[Bel, Pls]$ [SHAF76].

Other ways of combination, such as disjunctive ways or compromises are possible, replacing the intersection Dempster in the formula (equation (9)) with another set operation such as Union.

- ✓ Decision :

The theory of evidence has almost as many decision rules as authors in the field. In general, the decision is made on simple assumptions to facilitate interpretation of results.

Among the most common decisions, there are the following rules [YAGE93]

- Credibility Maximum: On the same frame of discernment, This criterion is "optimistic" because it does not account for potential conflicts. If the choice is made only on singletons assumptions, then it means choosing the hypothesis that was the maximum mass of evidence, namely:

$$x \in S \; si \; Pls(S)(x) = max\{Pls(S)(x), 1 \leq j \leq 2^n\} \quad (12)$$

- Plausibility Maximum: This choice can be described as "cautious" because it takes into account the uncetain opinions but not conflicting.

$$x \in S \; si \; Bel(S)(x) = max\{Bel(S)(x), 1 \leq j \leq 2^n\} \quad (13)$$

- Pignistic probability: Some authors, like Smets, [SMET98] [SMET94], prefer to use a probability function and then applying conventional methods making in the probabilistic framework. The construction of this probability, known pignistic, is given by [SMET98]

$$S \subseteq \Theta \; si \quad PigP(S) = \sum_{B \subseteq \Theta} m(B) \frac{|B \cap S|}{|B|} \quad (14)$$

$$x \in S \; si \; PigP(S)(x) = max\{Pig(S)(x), 1 \leq j \leq n\} \quad (15)$$

If this theory seems to be very attractive, it nevertheless has certain limits: the main drawback of this approach is its complexity exponentially with the size of the frame of discernment [SMET04]. However recent work [SMET04] [RIST04] propose an extension of the theory to the case of continuous discernment frames, paving the way for the resolution of estimation problems. The frame of discernment is then written as a set of intervals, which increases the complexity.

IV. Probabilistic Fusion in medical image

In order to locate and evaluate the evolution of the brain injury in a cancer patient, the fusion method was applied to two scan images of a patient of 16 years.

IV.1. Pretreatment images

Typically, followed tumors requires [JANN05]:

- Good data visualization interest, we restrict ourselves to the restoration of the images (noise suppression / filtering).

- The registration by geometric operations. It aims at overlay the precisely as possible the pixels corresponding to the same object observed in the two images [DROM98].

IV.2. Principle of the method:

In the course of our work, we used a method of low level. We considered only gray m1 and m2 primitive levels of a couple of pixels of the same address (x, y) respectively from the two images to be merged.

To demonstrate the fusion stages, we will first identify the two classes of scanner images by the method of segmentation Kmeans classification, thereafter, the melting process by probabilistic approach is carried out in three steps [DUBO88] [GERA00]:

- ✓ Data Modeling

i. We fixed the classes *Ci* of the image result: The number of classes of the image is achieved from the combination of the classes already defined in the two images to be merged.

ii. We establish the histograms of two images

iii. Assigning the pixels of two images to be merged to one of the classes of the result image.

Apply Bayes' rule for all Gaussian assumptions and for all gray levels of pairs $(\mathrm{m}_1, \mathrm{m}_2)$. Decision-making: The class that will affect the to values couple $(\mathrm{m}_1, \mathrm{m}_2)$. is the class of which the likelihood function $\mathrm{P}(\mathrm{m}_1, \mathrm{m}_2/\mathrm{C}_\mathrm{i})$ is highest.

IV.3. Application

- ✓ Presentations data

The development of the subject involved a 16 year old boy was sent to the emergency room on December 15, 1994, that morning, he lost consciousness twice, a few minutes after getting up. The first loss of consciousness was accompanied by a loss of urine. The second resulted in facial trauma with contusion of the root of the nose and lower lip wound.

During a physical examination, the doctor decided to do two brain scans with contrast injection (gadolinium) injection without the other as shown in Figure 1:

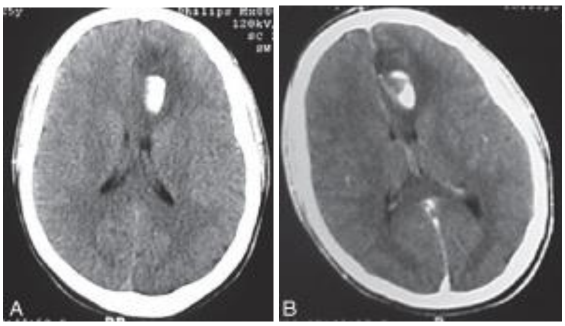


Fig.1.Séquences Scanner cérébral
A. *avec injection* B. *sans injection*

The picture (1-A) is a scanner section with injection of contrast medium format 145x177 pixels (1-B) is a scanner section without injection of gadolinium format145x177 pixels.

- ✓ images Pretreatment:

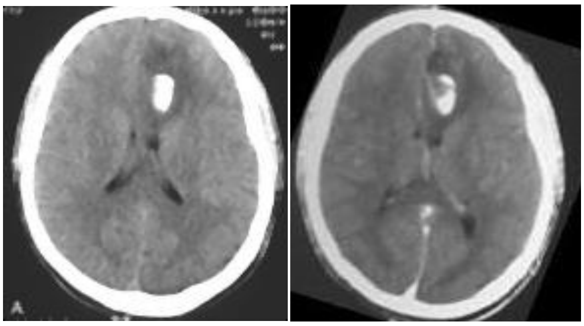


Fig.2. Preprocessing result (filtering and recalibration) Segmentation K Means

Our goal is to segment the brain, which causes us to fix at three the number of classes to be identified (C = 3) corresponding to the three brain tissues present in the brain [Hawk-92] ie the white matter (MB), gray matter (GM) and cerebrospinal fluid (CSF).

For the scanner B and following the histogram of pixel intensities, we defined three peaks of high intensity C_n^1 or:

- 1: B scanner,

- N: class number

whether

- C_1^1: class 'white material' MB

- C_2^1: class 'gray matter' G.

- C_3^1: class 'the cerebrospinal fluid' LCR

For the image scanner A are also defined three classes such as:

- 2: A scanner

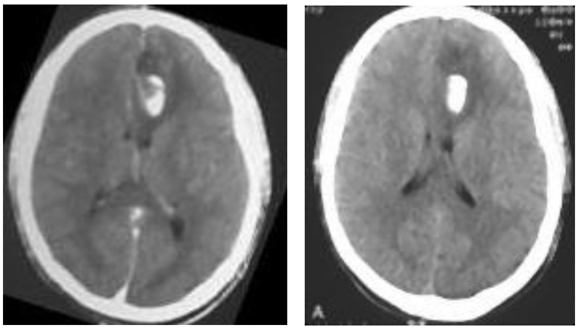
- N: class number

either:

- C_1^1 : class 'white material' MB

- C_2^1: class 'gray matter' G.

- C_3^1: class' the cerebrospinal fluid 'LCR'



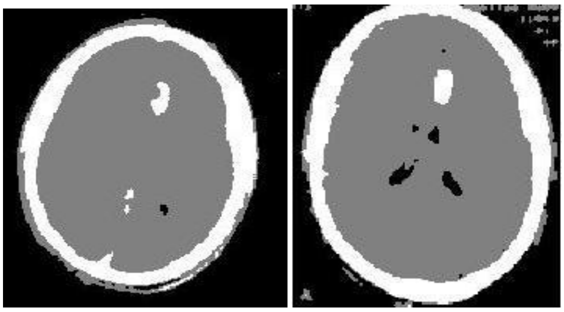


Fig.3. Definition segmentation results of image and modeling classes result histograms

By combining the classes defined above, we determined three classes $C_i=\{C_1, C_2, C_3\}$ to the result image correspond to:

C1: Class MB 'white matter'

C2: Class MG 'gray matter'

C3: Class LCR 'The cerebrospinal fluid

Both histograms of the two images to be merged are modeled by Gaussian whose number is given by the number of classes defined for both images. Thus, the likelihood function $P(m_j\ /C_i^j)$ that estimate the probability of having a level of gray m_j (where j represents the image in question), given the C_i^jclass , are determined using the Gaussian assumption. These functions are written [DUBO88]

$$P(m_j\ /C_i^j)\ = \frac{1}{\sigma_i\sqrt{2\pi}}\ e^{-\frac{(m_j-\overline{C_i^j})^2}{2\sigma_i^2}} \qquad (16)$$

C_i^j is the average class et $\overline{\sigma_1}$ standard deviation.
The histograms of these transformed images are modeled by Gaussian (Figure 4-5):

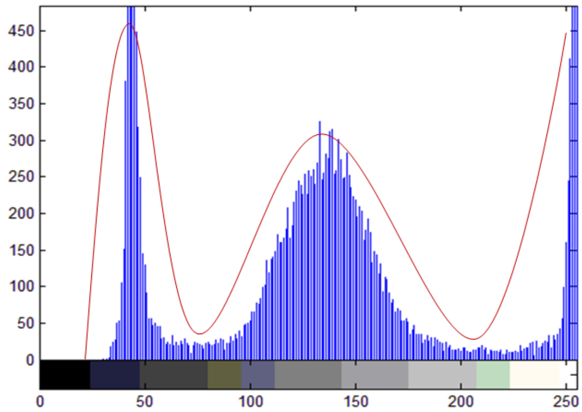


Fig.4. Modeling of the histogram of image scanner B

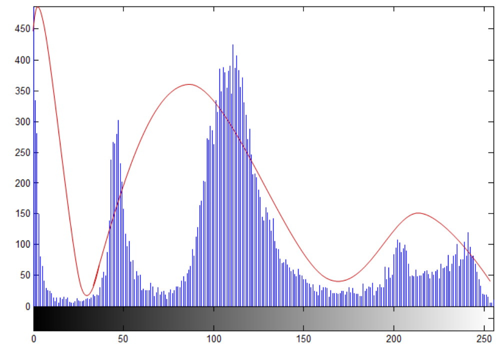


Fig.4. Modeling of the histogram of image scanner A

From modeling histograms of the two images to be merged, we apply Bayes' rule for all Gaussian assumptions and for all gray levels of pairs (m_1, m_2) . We obtain three posterior probabilities, which depend solely on the likelihood functions. These probabilities are written [TUPI04]

$$P(C_i/m_1,m_2\ ) = \frac{P(C_i).P(m_1/C_i^1).P(m_2/C_i^2)}{\sum_{t=1}^{3} P(C_t).P(m_1/C_t^1).P(m_2/C_t^2)} \qquad (17)$$

The class that will be affected the torque values (m_1, m_2) corresponds, according to the MAP principle

(The Maximum A Posteriori criterion) to the class whose probability a posteriori is the highest. Thus, a melting matrix is constructed:

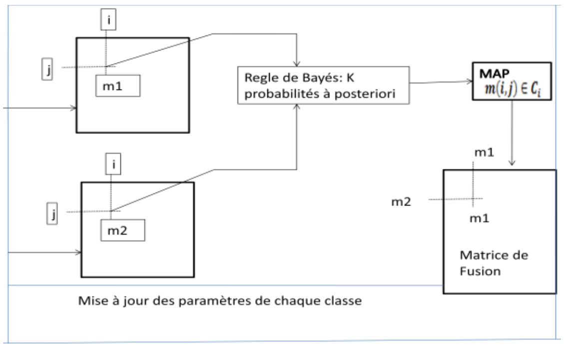


Fig.6. Construction of the melting matrix.

The resulting image of the fusion is then obtained using the following correspondence matrix. The operation is repeated until convergence of the method, that is to say until the melting matrix remains constant from one iteration to another.

- ✓ Decision making

In the absence of any information on the distribution of classes in the image result, we put ourselves in the assumption of equal probability of different classes. The likelihood of the C_i class for a result image containing 3 classes is given by:

$$P(C_i) = \frac{1}{3} \quad avec\ i = 1,..,3$$

From which this modeling, likelihood functions were calculated. These functions are calculated by taking into account the definition of the different class C_n^j; they are calculated using the following relations [AMEU07]:

$$\begin{aligned} P(m_1,m_2/C_1) &= P(m_1/C_1^1).P(m_2/C_1^2) \\ P(m_1,m_2/C_2) &= P(m_1/C_2^1).P(m_2/C_2^2) \qquad (18) \\ P(m_1,m_2/C_3) &= P(m_1/C_3^1).P(m_2/C_3^2) \end{aligned}$$

The class that will be affected the torque values ($m1$, $m2$) is the class of which the likelihood function P ($m1$, $m2$ / Ci) is the highest.

The final image obtained after melting and classification is given by the figure (Fig.7.).

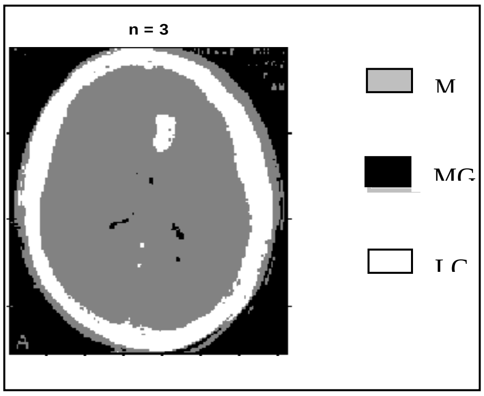


Fig.7. Image resulting from the merger of two segmented scanners

5. Conclusion:

This work was aimed at the brain lesion evolution by image fusion technique based on a probabilistic method. The image produced by fusion based on an unsupervised segmentation (kmeans) is an image containing information extracted simultaneously from two scanned cuts.

The choice of melting to the pixel level has developed the Gaussian modeling method histograms. This is a very fast method combining a very simplistic information (only grayscale). It shows, however, that the results are promising and already good for our purposes of segmentation regions by fusion.

This method causes a disadvantage of not modeling ignorance which results in the assumption of priori équiprobability This requires the design of ever more rapid methods, more reliable as the approach based on the fuzzy theory or approach based on the belief theory.

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