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# A Bayesian Technique in Medical Image Segmentation for Classifying Registration

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**Abstract-**
In the image, we address a complex image registration issue arising when the dependencies between intensities of images to be registered are not spatially homogeneous. Such a situation is frequently encountered in medical imaging when a pathology present in one of the images modifies locally intensity dependencies observed on normal tissues. Usual image registration models, which are based on a single global intensity similarity criterion, fail to register such images, as they are blind to local deviations of intensity dependencies. Such a limitation is also encountered in contrast enhanced images where there exist multiple pixel classes having different properties of contrast agent absorption. In this paper, we propose a new model in which the similarity criterion is adapted locally to images by classification of image intensity dependencies. Defined in a Bayesian framework, the similarity criterion is a mixture of probability distributions describing dependencies on two classes. A common assumption in nonlinear mixed-effects models is the normality of both random effects and within-subject errors. However, such assumptions make inferences vulnerable to the presence of outliers. More flexible distributions are therefore necessary for modeling both sources of variability in this class of models.

The registration problem is formulated both as an energy minimization problem and as a Maximum A Posteriori (MAP) estimation problem. It is solved using a gradient descent algorithm. In the problem formulation and resolution, the image deformation and the class map are estimated at the same time, leading to an original combination of registration and classification that we call image classifying registration.

***Keywords:*** *MAP,Baysian technique,classifying*

## I INTRODUCTION

Image registration is a central issue of image processing, which is particularly encountered in medical applications , Medical image registration is critical for the fusion of complementary information about patient anatomy and physiology,
for the longitudinal study of a human organ over time and the monitoring of disease development or
treatment effect, for the statistical analysis of a population variation in comparison to a so-called digital atlas, for image-guided therapy [1], This
paper introduced the idea of inverse probability, which, through the works of Laplace and others,
became known as Bayes' Theorem. displays the data and the fitted curves obtained through a Bayesian approach using the Gaussian assumption on random effects and within-subject error. This plot suggests that one observation of patients 5 and 9 deviates from the others and that they are poorly fitted.[2], Bayesian methods provide a framework for leveraging prior information and data from diverse sources to determine probabilities relevant to inferences about issues arising at all stages of medical product development, including realistic quantification of the benefits and risks essential to health economic evaluation.[3] The decision-makersmostly use experience for their decisions - that is, they selectactions that previously have worked well in similar situations.What they do is to extract the most significant characteristicsfrom the situation.[4]

## BACKGROUND BAYESIAN SURVEY

To identify the gaps in knowledge and use of Bayesian methods,implementation difficulties with Bayesian methods, and specific educational needs about Bayesian methods for statisticians involved in medical product development. The survey included questions related to respondent demographics as well as implementation of Bayesian methods. The first

draft was completed in early 2012 and went through several rounds of review by the Education sub-team and the DIA BSWG full team before it was finalized. On April 30, 2012, the survey was sent out using a Web Link collection system via SurveyMonkey to 17 organizations (identified by members of the DIA BSWG) including pharmaceutical companies, regulatory bodies, and other contract/medical research institutions. To preserve anonymity, the names or email addresses were not tracked. The survey was closed on June 8, 2012

## II RELATED WORK

### The Bayesian framework

**Definition 1**. Prior probability is the probability determined by the historic materials or the judgment of somebody. Since this kind of probability is not validated by experiment, it is called prior probability.

**Definition 2**. Posterior probability is the probability which revised according to Bayesian equation and new information obtained by investigation.

**Definition 3**. **Total Probability Theorem**. If A can be only influenced by factors B1, B2…and Bi Bj =(i j), P(Bi) > 0, i = 1, 2,…then we have:

P(A) = P(Bi)P(A/Bi)

**Definition 4**. Bayesian Equation is also called posterior probability equation,, and it is widely used. If the prior probability is P(Bi), and the additional information obtained by investigation is P(A|Bi), where i = 1,2,…, n, then the posterior probability is:

$$P(B_i|A) = \frac{P(B_i)P(A|B_i)}{\sum_{k=1}^{n} P(B_k)P(A|B_k)} \quad [5]$$

In biomedical applications, a number of papers suggested the use of Bayesian methods in healthcare evaluation, the pharmaceutical industry , and clinical trials . Ashby provided a 25-year review of Bayesian thinking including applications and uses in clinical trials, epidemiology, meta-analyses and evidence synthesis, spatial modeling, longitudinal modeling,survival modeling, molecular genetics, and decision making.[4]

Examples for integrating the best of Bayesian and frequentist ideas can be found in. For example, Little advocated 'calibrated Bayes', a concept that builds uponwork by Box, Rubin, and Gelman. In this approach, focus is placed on model development rather than methods, along with utilization of model diagnostics and an understanding of frequentist properties. Berry *et al.* discuss many examples of Bayesian clinical trials and their frequentist operating characteristics.More generally, the assessment of frequentist properties of Bayesian procedures has a long history.[1]

Bayesian belief network (BN) technology is widely used in a variety of domains for situation assessment and decision aiding, including battlefield situation assessment, because it possesses a variety of theoretical and practical advantages relative to other approaches in dealing
with the issues of uncertain inferencing, computational tractability, and causal and diagnostic reasoning

## III THETWO-CLASS REGISTRATION MODEL

We now outline our new model. It is an extension of the model described in the previous section. The main feature is the introduction and the estimation of a pixel classification to take into account the spatial variations of the statistical relationships between the intensities of J and Iφ.

*1) Intensity relationships:* In Equation (2), the probability distribution _(J(x)|Ib(x); _) describing the intensity relationship is spatially homogeneous. We now assume that the pixels of image J can be divided into two classes (labeled 0 and 1) where the intensity relationships are different and denoted
respectively by _j(J(x)|Ib(x); _j) , j ∈ {0, 1}. Let also L(x) be the probability for a pixel x to belongto the class 1. Then, the intensity relationship at pixel x is described by the mixture distribution.

$$\pi(J(x)\,I^{\mathbf{b}}(x), L(x); \theta) = \pi_0(J(x)|I^{\mathbf{b}}(x); \theta_0)\,(1 - L(x)) + \pi_1(J(x)|I^{\mathbf{b}}(x); \theta_1)\,L(x),$$

*2) Classes and deformations:* In some situations, one must locally adapt the deformation field to
structures that must be kept rigid, using a tissue-dependent filtering technique. Otherwise, rigid tissue, such as bone, could be deformed elastically, growth of tumors may be concealed, and contrast-enhanced structures may be reduced in volume [5]. Such a specificity could be taken into account in our Bayesian framework by defining a distribution on deformations that would depend on classes: setting distributions _0(b) and _1(b) respectively for the two classes, we could define a distribution _(b;L) as a mixture of the distributions _0(b) and _1(b).

*3) MAP estimations:* In our Bayesian framework, the registration problem consists in maximizing the
posterior distribution _(b,L|I, J; _) with respect to the deformation b and to the class map L.In this new formulation, registration and classification are both integrated in a single maximization problem, and have to be performed simultaneously.Using Bayes' Theorem, it comes that

$$\pi(\mathbf{b},\mathbf{L}|I,J;\theta) = \frac{\pi(J|I,\mathbf{L},\mathbf{b};\theta)\,\pi(\mathbf{b},\mathbf{L}|I)}{\pi(J|I;\theta)} = \frac{\pi(J|I,\mathbf{L},\mathbf{b};\theta)\,\pi(\mathbf{b})\,\pi(\mathbf{L})}{\pi(J|I;\theta)}$$

*4) Parameters:* The distributions defined above involve several parameters. In our application, we used the prior deformation distribution defined and set manually the Lame constants _ and μ from experiments. We also set manually the mean μ0 and the variance _0 of the Gaussian distribution_0 of the class 0, and the weights _1 and _2 of the Gaussian or Bernoulli model in.The other parameters, which are the mean μ1 and the variance _1 of the Gaussian distribution _1 on class 1, are estimated from the data. We assume that μ1 belongs to an interval [μmin, μmax] and _1 to another interval [_min, _max] and put, as a prior, uniform independent distributions of μ1 and _1 on these intervals.

This parameter _1 is then estimated, together with the deformation and the classification by solving the following MAP estimation problem,

$$(\tilde{\mathbf{b}},\tilde{\mathbf{L}},\tilde{\theta}_1) = \arg\max_{\mathbf{b},\mathbf{L},\theta_1} \pi(J|I,\mathbf{L},\mathbf{b};\theta_0,\theta_1)\,\pi(\mathbf{b})\,\pi(\mathbf{L})\,\pi(\theta_1).$$

## IV BLOCK DIAGRAM

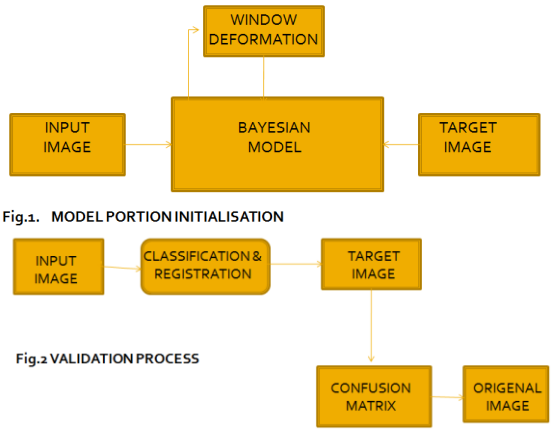



Fig.1. MODEL PORTION INITIALISATION




Fig.2 VALIDATION PROCESS

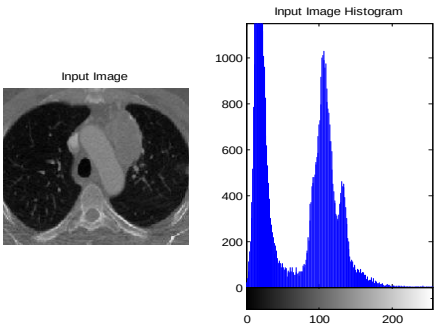
Validation and comparison of medical image registration algorithms are two important issues [1].The requirements to perform a validation are: the definition of a validation methodology, which should include the design of validation datasets, the definition of a corresponding ”ground truth”,a validation protocol and some validation metrics. Now, there is rarely if ever a “ground truth” correspondence map that would enable judging the performance of a non-rigid registration algorithm. In our approach, we will use simulated deformations and images to get a “ground truth” to get an evaluation of registration and classification algorithms.

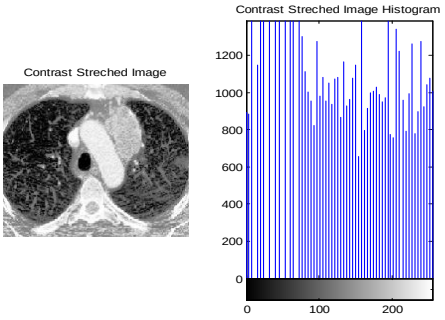
We perform the registration of each pair of the database with both the full classifying model and the SSD model. For the classifying registration, we use a Gaussian mixture where _0 is a Gaussian distribution N(0, 9) while the parameters (μ1, _1)of _1 are all estimated. For the regularization of the lesion map,we use a Bernoulli model (binary lesion map) with empirical choices _1 = 7 and_2 = −0.7.

Confusion matrix: In the field of machine learning, a **confusion matrix**, also known as a contingency table or an error matrix , is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a **matching matrix**). Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. The name stems from the fact that it makes it easy to see if the system is confusing two classes.

## V RESULT

Lets now determine the intensity of defrent images,from this histogram we will get the intensity relationship of the diffrent location,we have find the histogram of input image and the histogram of the streached image.



**A simulated pair of images :**

**Fig.(a)**
The source image extracted from a real mammogram

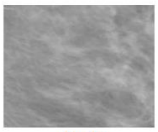


**Fig.(b)**
The deformed source image

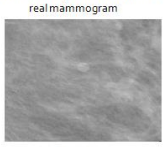


Fig.(c)
The target image obtained by adding a Gaussian noise with distribution N(μ1, 9) on a disk-shaped region of the image (b)

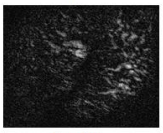


Fig.(d)
Differences between the source and the target images.

We use two criteria for the evaluation of the registration. The first one involves the ground truth and compares the real displacement ($u_{real}$) and the estimated ($u_{estim}$) one. The registration error is defined as the mean distance between them, counted in pixels:

$$ErrL2 = \sqrt{\frac{1}{N}\sum_{i=1}^{N} ||u_{\text{real}}(x_i) - u_{\text{estim}}(x_i)||^2}$$

The second criterion is computed as the percentage of reduced differences between the source and target images:

$$DiffImg = 100 \cdot \left(1 - \frac{\sqrt{\sum_{i=1}^{N}(J(x_i) - I^b(x_i))^2}}{\sqrt{\sum_{i=1}^{N}(J(x_i) - I(x_i))^2}}\right)$$

When the values of the criterion DiffImg are negative, the L2 distance between the registered images is higher than the one between unregistered images. When it is computed only over lesion pixels, the second criterion can also be used for the evaluation of the detection. Negative values occuring on lesion regions show that the model preserves and enhances the image differences on points of the lesion class and thus improves lesion detection.

## VI APPLICATIONS OF BAYESIAN CLASSIFIER IN MEDICAL IMAGING

### 1. Glioblastoma Multiforme Brain (GMB) tumor Segmentation:

The GBM tumor is the most common primary tumor of the central nervous system, accounting for approximately 40% of brain tumors across patients of all ages, and the median postoperative survival time is extremely short (eight months) with a five-year recurrencefree survival rate of nearly zero. Quantifying the volume of a brain tumor is the key indicator of tumor progression However, like most segmentation problems, automatic detection and quantification of a brain tumor is very difficult. In general, it is impossible to segment a GBM tumor by simple thresholding techniques. Brain tumors are highly varying in size, have a variety of shape and appearance properties, and often deform other nearby structures in the brain. In the current clinic, the tumor volume is approximated by the area of the maximal cross section, which is often further approximated to an ellipse. Such a rough approximation is used because the time cost to compute a more accurate manual volume estimate is too high. However, no completely automatic segmentation algorithm has yet been adopted in the clinic.

### 2. Brain activation from functional brain images:

Functional magnetic resonanceimaging (fMRI) and positron emission tomography (PET) are popular modalities to image the working human brain. Functional brain studies acquire a series of head scans while the subject is alternatively performing a major sensory or cognitive task and a baseline task, where the input stimulus to the brain takes the form of an ON–OFF box-car pattern. The first step in the analysis of functional brain images is to detect brain regions that are activated by input stimuli. This may be seen as a classification or segmentation of brain voxels into activated voxels and inactive voxels during a functional experiment.

### *3.* Topology correction of cortical surfaces:

Segmenting under topological constraints is difficult. Segmentation algorithms, which operate on the intensity or variations of the texture of the image, are sensitive to the artifacts produced by the image acquisition process. Most often, segmentation techniques that do not integrate any topological constraints generate segmentations that contain small deviations from the true anatomy of the structures of interest. In the case of cortical segmentations, these deviations can form handles [or holes, which are topologically equivalent] that erroneously connect parts of the volume. Integrating topological constraints into the segmentation process significantly complicates the task. Topology is both a global and a local property; small and local modifications of a geometric shape can change its global connectivity. At the same time, topology is intrinsically a continuous concept, and topological notions are difficult to adapt into a discrete framework. For these reasons, the number of techniques available and applicable to the segmentation of images is quite limited.

## VII CONCLUSION

In this paper, we have proposed a Bayesian approach to perform simultaneously image registration and pixel classification.The proposed technique is well-suited to deal with image pairs that contain two classes of pixels withdifferent inter-image intensity relationships. We have shown

through different experiments that the model can be applied in many different ways. For instance if the

class map is known, then it can be used for template-based segmentation. If the full model is used (estimation of the class map, the registration and the parameters of the distribution of the outliers), then it can be applied to lesion detection by image comparison. The proposed model is defined using only two classes but it is straightforward to extend it to an arbitrary number of classes. However, the estimation of the number of classes would then appear as a critical issue. This will be part of some future research and it will certainly require the use of model selection techniques.

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