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Image Classifying Registration for Gaussian & Bayesian Techniques: A Review

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ABSTRACT
A Bayesian Technique for Image Classifying Registration to perform simultaneously image registration and pixel classification. 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, etc. A Bayesian Technique for Image Classifying Registration is well-suited to deal with image pairs that contain two classes of pixels with different inter-image intensity relationships. We will show 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, then it can be applied to lesion detection by image comparison. Experiments have been conducted on both real and simulated data. It show that in the presence of an extra-class, the classifying registration improves both the registration and the detection, especially when the deformations are small. The proposed model is defined using only two classes but it is straightforward to extend it to an arbitrary number of classes.
Keywords - Bayesian; medical product development; survey; Image registration.

I. INTRODUCTION

A Bayesian Technique for Image Classifying Registration to perform simultaneously image registration and pixel classification. 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, etc. Image registration consists in mapping domains of several images onto a common space and results in some corrections of geometric differences between the images.

A Bayesian Technique for Image Classifying Registration is well-suited to deal with image pairs that contain two classes of pixels with different inter-image intensity relationships. We will show 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. Experiments have been conducted on both real and simulated data. It show that in the presence of an extra-class (e.g. a lesion class in mammograms), the classifying registration improves both the registration and the detection, especially when the deformations are small. 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. The application of the classifying model was illustrated on medical imaging data. But, the proposed model is very generic and can be adapted to many other situations. In particular, we believe that the model could also be helpful for motion estimation. The introduction of a second intensity relationship class in the model would enable to deal with occlusions, which are a major issue of motion estimation.

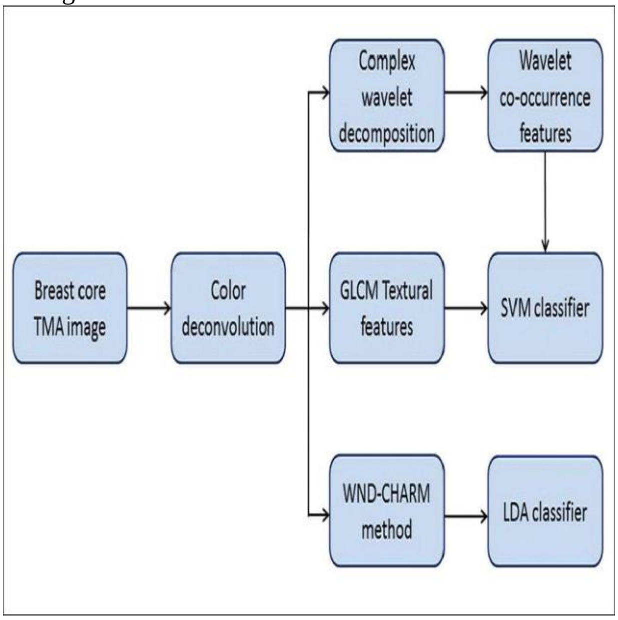
II. RELATED WORK

Image registration is a central issue of image processing, which is particularly encountered in medical applications. Image registration consists in mapping domains of several images onto a common space and results in some corrections of geometric differences between the images. Most of classical registration techniques rely upon the assumption that there exists a relationship between intensities of images to be registered and that this relationship remains the same all over the image domains. This assumption is typically made when applying registration techniques based on intensity criteria such as the sum of squared differences, the correlation ratio, the correlation coefficient or the mutual information. But such an assumption is not always satisfied. As an example, let us mention the medical imaging case when a contrast agent is used to enhance some pathological tissues . After enhancement, intensities of normal tissues and lesions are likely to differ, even though they can be the same before enhancement. So, a same intensity before enhancement may correspond to several intensities after enhancement. Hence, with contrast-enhanced imaging modalities, the relationship between image intensities is neither unique, nor spatially invariant. It mainly depends on the type of observed tissues. In such cases, ignoring the spatial context may lead to locally establishing an inaccurate or even inconsistent correspondence between homologous geometric structures. This issue was documented in, where it is shown that such non-rigid registration would wrongly change the size of non-deformed contrast-enhanced structures. In the literature, there have been several works dealing with image registration in the presence of multiple pixel classes. These works can mainly be divided into two categories: those based on robust estimation and mixture models, and those combining registration and classification (or segmentation). Robust estimation is a statistical approach which has been widely applied to image processing . This approach involves the definition of outliers, which are characterized as elements deviating from a normal model, detected and possibly rejected. Applied to optical flow estimation and image registration, robust estimation helps to reduce the influence of large insignificant image differences on the optical flow or the deformation estimation. However, these approaches offer poor characterizations of outliers, which are usually described as pixels generating large image differences. They cannot deal with complex situations arising from medical imaging applications. More general robust estimation approaches are based on mixture models.

III. PROBLEM FORMULATION : WORK PLAN & METHODOLOGY & OBJECTIVE

This list was incorporated into a questionnaire which asked respondents to rate each topic as low, medium or high clinical priority as well as low or high economic priority. It was made clear that respondents would be rating the priority for each topic to be included in a clinical guideline to be published in two years' time. The questionnaire also asked respondents to suggest any additional topics they would like to see included with an equivalent assessment of their priority. Questionnaires were subsequently sent to the Breast Cancer Advisory Groups of all 37 cancer networks in England and Wales with a request for a 4-week turnaround. (A list of all cancer networks can be found on the Cancer Action Team website at the DH). Questionnaires were also sent via the Patient and Public Involvement Programme (PPIP) at NICE to all relevant patient/carer stakeholder organizations . The scores from each completed questionnaire were aggregated by NCC-C staff and ranked. These results together with information on identifiable practice variation (see needs assessment) were presented to the GDG at its first meeting. The list of prioritised topics produced via the questionnaire survey was in no way definitive and the GDG used these results to agree their final priorities for the clinical questions.

For clinical questions about interventions, the PICO framework was used. This structured approach divides each question into four components: the patients (the population under study – P), the interventions (what is being done - I), the comparisons (other main treatment options – C) and the outcomes (the measures of how effective the interventions have been – O). Where appropriate, the clinical questions were refined once the evidence had been searched and, where necessary, sub-questions were generated.



3.1 BAYESIAN APPROACH

A typical Bayesian analysis can be outlined in the following steps.

1. Formulate a probability model for the data.
2. Decide on a prior distribution, which quantifies the uncertainty in the values of the unknown model parameters before the data are observed.
3. Observe the data, and construct the likelihood function based on the data and the probability model. The likelihood is then combined with the prior distribution to determine the posterior distribution, which quantifies the uncertainty in

the values of the unknown model parameters after the data are observed.

4. Summarize important features of the posterior distribution, or calculate quantities of interest based on the posterior distribution. These quantities constitute statistical outputs, such as point estimates and intervals.

The main goal of a typical Bayesian statistical analysis is to obtain the posterior distribution of model parameters. The posterior distribution can best be understood as a weighted average between knowledge about the parameters before data is observed (which is represented by the prior distribution) and the information about the parameters contained in the observed data (which is represented by the likelihood function). From a Bayesian perspective, just about any inferential question can be answered through an appropriate analysis of the posterior distribution. Once the posterior distribution has been obtained, one can compute point and interval estimates of parameters, prediction inference for future data, and probabilistic evaluation of hypotheses.

3.2 REGISTRATION MODEL

We address a complex image registration issue arising while 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. The model also includes a class map which locates pixels of the two classes and weighs the two mixture components. The registration problem is formulated both as an energy minimization problem and as a maximum a posteriori 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 simultaneously, leading to an original combination of registration and classification that we call image classifying registration. Whenever sufficient information about class location is available in applications, the registration can also be performed on its own by fixing a given class map. Finally, we illustrate the interest of our model on two real applications from medical imaging: template-based segmentation of contrast-enhanced images and lesion detection in mammograms. We also conduct an evaluation of our model on simulated medical data and show its ability to take into account spatial variations of intensity dependencies while keeping a good registration accuracy.

3.3 GAUSSIAN DISTRIBUTION

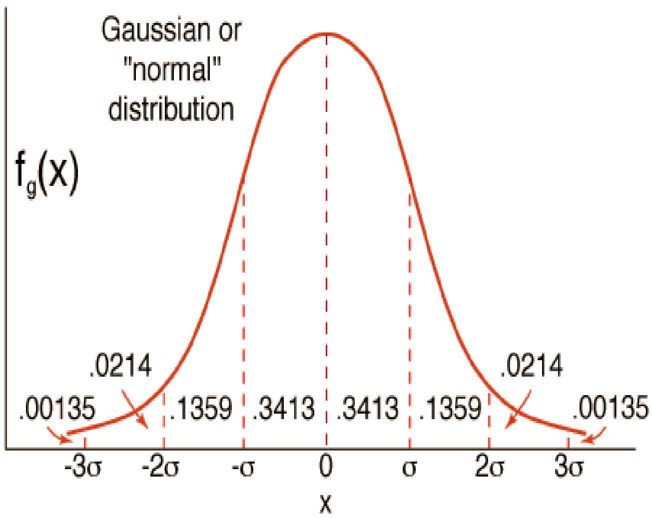
Gaussian Distribution Function

Distribution	Functional Form	Mean	Standard Deviation
Gaussian	$f_g(x) = \frac{1}{\sqrt{2\pi\sigma^2}}\ e^{\frac{-(x\cdot}{2(}}$	a	σ

If the number of events is very large, then the Gaussian distribution function may be used to describe physical events. The Gaussian distribution is a continuous function which approximates the exact binomial distribution of events.

The Gaussian distribution shown is normalized so that the sum over all values of x gives a probability of 1. The nature of the Gaussian gives a probability of 0.683 of being within one standard deviation of the mean. The mean value is a=np where n is the number of events and p the probability of any integer value of x (this expression carries over from the binomial distribution). The standard deviation expression used is also that of the binomial distribution.

The Gaussian distribution is also commonly called the "normal distribution" and is often described as a "bell-shaped curve".



The full width of the gaussian curve at half the maximum is

$$\Gamma = 2\sqrt{2\ln 2}\sigma \quad = 2.355\sigma$$

IV. CONCLUSION

In this paper, we propose a novel architecture for wireless sensor network based on the cloud computing platform. To solve the problems of middle attacks and Cloud will work as a backup for storing large amount of data and will also help in sharing of resources.

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