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A BAYESIAN TECHNIQUE FOR IMAGE CLASSIFYING REGISTRATION

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ABSTRACT
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 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 .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. Segmentation of the various elements among the particles is very important to medical decision. In order to eliminate the background noises of images, we need pre-processing of images. After the pre-processing method, Bayesian classifier is used for classifying of particles in the image. Bayesian classifier is a powerful probabilistic graphical model that has been applied in computer vision. In this paper, we adapted some of the existing segmentation algorithms using Bayesian classifier and focused the effect of Bayesian classifier in segmentation algorithms.

KEYWORDS: (Image registration, image processing and analysis, image segmentation, image classification).

INTRODUCTION
As an example, let us mention the medical imaging case when a contrast agent is used to enhance some pathological tissues (lesions). 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.

Bayes Classification to Enhance Image Registration Image classification attempts to provide useful suggestions for some applications that range from automatic diagnosis in medical systems to aim at recognition in remote sensing images. Important visual properties for instance shape, texture, and colour are often made use to describe images in recognition applications. The term digital image refers to processing belonging to two dimensional pictures using a digital computer. Within a broader context, it implies digital processing of almost any two dimensional data. A digital image can be considered an array of real or complex numbers represented by a finite number of bits. An image given in the sort of a transparency, slide, photograph or perhaps an X-ray is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then is processed and/or exhibit a high-resolution television monitor. For display, the reputation is kept in a rapid-access buffer memory, which refreshes the monitor on a rate of 25 frames per second to produce a visually continuous display. An image processor does the functions of image acquisition, storage, pre-processing, segmentation, representation, recognition and interpretation and ultimately displays or records the finished result is an image. The following block diagram gives the fundamental sequence involved with an image processing system.

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.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.

BEYSIAN CLASSIFICATION

PROPOSED SYSTEM

Local Naive Bayes nearest Neighbour for Image Classification.

The selectivity introduced in the previous section shows that we do not need to update each class's posterior for each descriptor. This section shows that by focusing on a much smaller, local neighbourhood (rather than on a particular log odds threshold), we can use an alternate search strategy to speed up the algorithm, and also achieve better classification performance by ignoring the distances to classes far from the query descriptor. Instead of performing a search for a query descriptor's nearest neighbour in each of the classes' reference sets, we search for only the nearest few neighbours in a single, merged dataset comprising all the features from all Labelle training data from all classes. Doing one approximate k-nearest-neighbour search in this large index is much faster than querying each of the classes' Approximate -nearest-neighbour search structures. Bayesian statistician should just report the a posteriori probability distribution, and refrain from producing any decisions which should be left to the final user. In fact, choosing a loss function is a highly problem-dependent issue which turns out, more often than not, to be dominated by computational tractability consideration (even if this is rarely acknowledged). Once the a posteriori probability minimizes some loss function is just one possibility.

BEYSIAN DECISION THEORY

The main arguments in favour of the Bayesian perspective can be found in a paper by Berger whose title, "Bayesian Salesmanship," clearly reveals the nature of its contents. Also highly recommended by its conceptual depth and the breadth of its coverage is Jaynes' (still unfinished but partially available) book. Recent advances are reported in workshops and conferences (special emphasis should be given to) and in several scientific journals (for example, the Journal of the American Statistical Association and the Journal of the Royal Statistical Society). Bayesian frameworks have been used to deal with a wide variety of problems in many scientific and engineering areas. Whenever a quantity is to be inferred, or some conclusion is to be drawn, from observed data, Bayesian principles and tools can be used. Examples, and this is by no means an exhaustive list of mutually exclusive areas, include: statistics, signal processing, speech analysis, image processing, computer vision, astronomy, telecommunications, neural networks, pattern recognition, machine learning, artificial intelligence, psychology, sociology, medical decision making, econometrics, and biostatistics. Focusing more closely on the topic of interest to this book, we mention that, in addition to playing a major role in the design of machine (computer) vision techniques, the Bayesian framework has also been found very useful in understanding natural (e.g., human) perception this fact is a strong testimony in favour of the Bayesian paradigm. Finally, it is worth pointing out that the Bayesian perspective is not only important at a practical application level, but also at deeper conceptual levels, touching foundational and philosophical aspects of scientific inference, as the title of Rozenkrantz's book so clearly shows: "Inference, Method ,and Decision: Towards a Bayesian Philosophy of Science". On this issue, the book by Jaynes is a fundamental more recent reference.

Statistical Decision Theory

Basic Elements

The fundamental conceptual elements supporting the (formal) theory of statistical decision making are the following:

i. Formalization of the underlying unknown reality. This is done by considering that all that is unknown but relevant for the decision maker, the so-called state of nature, can be represented by an entity s taking values on a state space S. Often, this will be a single unknown numerical quantity (a parameter), or an ordered set of numerical parameters (a vector). In other problems, the elements of S may not be of numerical nature. Throughout most of this chapter, we will implicitly assume that s is a single quantity.

ii. Formal model of the observations. The observations, based on which decisions are to be made, are possibly random and depend on the state of nature s. In formal probabilistic terms, this dependence is expressed by assuming that the observations are a sample x of a random variable (or process, or vector, or field) X, taking values on a sample space X, whose probability (density or mass) function, for $x \in X$, is conditioned on the true state of nature s, i.e., we write fX(x|s).

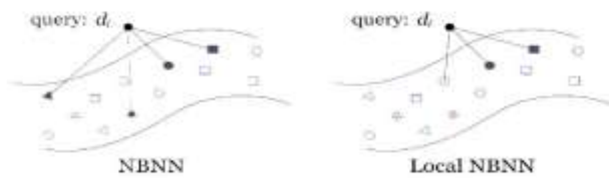
iii. Formal decision rules. These are the goal of decision theory in the following sense: based on the observations, a decision rule has to choose an action amongst a set A of allowed decisions or actions. Formally, a decision rule is a function1 $\delta(x)$ from X into A, specifying how actions/decisions are chosen, given observation(s) x. A set or class D of allowed decision rules may be specified.

iv. Quantification of the consequences of the decisions. This is formally expressed via a loss function L(s, a): S × A −→ IR, specifying the “cost” that is incurred when the true state of nature is s and the chosen decision is a. It is usually required that L(s, a) ≥ Lmin > −∞, often (but not necessarily) with Lmin = 0. Although L(s, a) is required to be a real valued function, its range does not necessarily have to be IR; it can be some subset of IR, with typical examples being IR+ 0 and {0, 1}. Below, we will look more in detail at how this is done, both under the (so-called) classical (or frequentist) and Bayesian frameworks.

Beysian Estimation

Medical image analysis typically involves heterogeneous data that has been sampled from different underlying anatomic and pathologic physical processes. In the case of glioblastoma multiform brain tumour (GBM), for example, the heterogeneous processes in study are the tumour itself, comprising a necrotic (dead) part and an active part, the edema or swelling in the nearby brain, and the brain tissue itself. To complicate matters, not all GBM tumours have a clear boundary between necrotic and active parts, and some may not have any necrotic parts. In Figure 1, we show a 2D slice of an MR image in the T1 weighted and T2 weighted channels presenting an enhancing GBM brain tumour. On the right, we outline the different heterogeneous regions of the brain tumour and label them as edema, active, or necrotic. nonrigid image alignment is a crucial requirement in a variety of applications in medical imaging, including automatic segmentation, motion tracking and morphometric analysis. A large number of different successful approaches have been proposed to the problem of nonrigid image registration. However, since most of the research focuses on registration of images with differences that can always be matched, there is a significant need for improved robustness on images with structures that appear just in one of the images, such as pathologies, and on images with acquisition artefacts like intensity inhomogeneity. In medical imaging, several methods have been proposed for registration of images with mismatches, focusing on robustness, tumour models or bayesian models. However, all these methods need a prior knowledge of what a “mismatch” is in order to detect and/or ignore them. Additionally, a number of methods based on mutual information have been proposed to reduce the effect of intensity in homogeneities in the registration .The concept of normalised image gradients was introduced to the field of medical image registration by Pluim *et al*. In this work, normalised mutual information (NMI) is weighted voxelwise by the normalised image gradients in order to incorporate spatial information. After this initial work, the first similarity based solely on normalised gradients was proposed by Haber *et al.* [10]. Since its introduction, this measure has been successfully utilised. However, as we show in this paper, this cost functional is less robust to image inhomogeneities and is affected when gross outliers, such as lesions or tumours, are present in the images. To the best of our knowledge, there is no previously proposed similarity measure in nonrigid image registration that is robust to both imaging artefacts such as intensity inhomogeneities caused by bias fields and outliers in the images, e.g. in form of pathology. To this end, we utilize a simple, but effective similarity measure based on the angle between gradient orientations, which are obtained from the normalized image gradients. A similar approach has been recently successfully applied for the robust affine alignment of facial images and shown to be robust towards occlusions and changes in illumination. Specifically, we employ this similarity measure within a widely and successfully used no rigid registration framework based on free-form deformations (FFD). We provide theoretical evidence of its robustness and evaluate on manually segmented data. We obtain favorable overlap measures for images with intensity in homogeneities. We also confirm robustness of the proposed similarity measure on simulated pathological data from a tumour database.

The next thing is the pre-processing step where the image is enhanced being fed as an input into the other processes. In order to best represent images, one common strategy consists in identifying possibly the most accurate feature vector (description).However, in many instances there are plenty of features you can find possessing reasonable performance. By means of these situations, one may employ feature combination approaches in order to strengthen their individual recognition rates, since different features may provide different, but complementary details about images. Several works cope with the issue by getting to know the most reliable features and weighting them as per some “reliability”-based measure. Other works address this difficulty through the use of linear discriminate Analysis and Principal Component Analysis in the following figure.



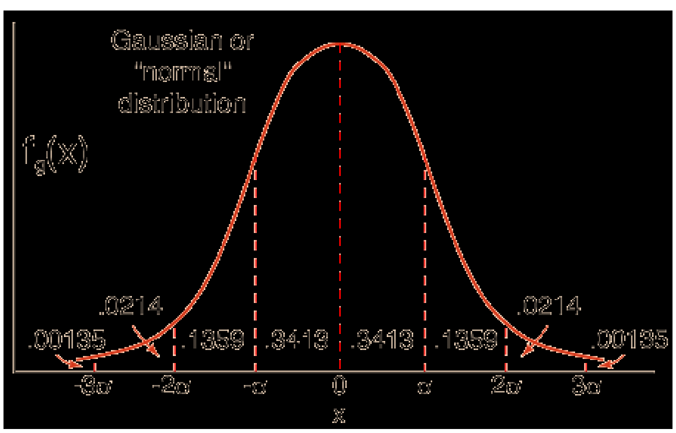
NBNN finds the nearest neighbour from each of the classes (the shapes, in this figure). Local NBNN retrieves only the local neighbourhood, finding nearest neighbours from only some of the classes. The shaded descriptors are those that would be used for updating the distance totals. We only use the closest member from any class, and don’t find an example from each class.

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 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.

GAUSSIAN DISTRIBUTION

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".

CONCLUSION AND FUTURE SCOPE

To better understand brain diseases, many neuroscience studies focus on the anatomical differences between control and diseased subjects. In order to find these differences, scientists often analyze medical images for brain structures which seem to be influenced by the disease. The analysis is frequently based on segmentations of the structures of interest that are mostly performed by human experts. However, this manual process is not only very expensive, but in addition, it increases risks related to inter- and intra-observer reliability. Neuroscientists are keenly interested in automatic methods, which often rely on prior information, to perform this task). With notable exceptions, these methods first register the prior information, i.e., an atlas, to the medical image and then segment the medical image into anatomical structures based on that aligned information. The goal of this work is to unify this process into a single Bayesian framework in order to overcome biases caused by commitment to the initial registration. When automatic segmentation methods are guided by prior information, they frequently are used to segment anatomical structures defined by weakly visible boundaries in medical images. For example, the intensity properties of the thalamus in T1-weighted magnetic resonance (MR) images are very similar to those of the neighbouring white matter.

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