Chapter 23
A Survey of Bayesian Techniques in Computer Vision

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ABSTRACT

The Bayesian approach to classification is intended to solve questions concerning how to assign a class to an observed pattern using probability estimations. Red, green and blue (RGB) or hue, saturation and lightness (HSL) values of pixels in digital colour images can be considered as feature vectors to be classified, thus leading to Bayesian colour image segmentation. Bayesian classifiers are also used to sort objects but, in this case, reduction of the dimensionality of the feature vector is often required prior to the analysis. This chapter shows some applications of Bayesian learning techniques in computer vision in the agriculture and agri-food sectors. Inspection and classification of fruit and vegetables, robotics, insect identification and process automation are some of the examples shown. Problems related with the natural variability of colour, sizes and shapes of biological products, and natural illuminants are also discussed. Moreover, implementations that lead to real-time implementation are explained.

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INTRODUCTION

Learning techniques can be employed to learn meaningful and complex relationships automatically in a set of training data, and to produce a generalisation of these relationships in order to infer interpretations for new, unseen test data (Mitchell et al., 1996). Statistical learning uses the statistical properties observed in a training set. As an example of this, Bayesian theory provides a probabilistic approach to inference, which proves successful both for segmentation of images and classification of objects in computer vision.

The Bayesian approach to classification is intended to solve questions concerning how to assign a class to an observed feature pattern using probability estimations. This means that this approach is aimed at estimating the probabilities of an observed pattern's belonging to each of some pre-defined classes in a classification problem, and then assigning the pattern to the class to which it is most likely to be a member. This set of probabilities, which henceforth are called *a posteriori* probabilities, is determined using the Bayes theorem, expressed in equation (1). The Bayes theorem calculates the *a posteriori* probability, $P(\Omega_i|x)$, that an observed pattern x, constituted by a series of j features ($x_1 .. x_j$), belongs to class Ω_i from the *a priori* probability of this class, $P(\Omega_i)$, and the conditional probabilities $P(x|\Omega_i)$, which are the probabilities of finding this pattern in class Ω_i. We will refer to this term as *conditional probabilities* for short.

$$P(\Omega_i \middle| x) = \frac{P(x \middle| \Omega_i)P(\Omega_i)}{P(x)} \tag{1}$$

$P(x)$ is the probability that a pattern x is present throughout the population data, and this probability can be determined from the total probability theorem as:

$$P(x) = \sum_{i=1}^{N} P(x \middle| \Omega_i)P(\Omega_i) \tag{2}$$

The Bayes theory assumes that a pattern x, whose class is unknown, belongs to the class Ω_i, as follows:

$$x \in \Omega_i \Leftrightarrow \max_{r=i}\{P(\Omega_r \middle| x)\} \tag{3}$$

From equation (2), we can consider that $P(x)$ is only a factor of scale for the *a posteriori* probabilities to be standardized between 0 and 1. This factor is essential for normalization of $P(\Omega_i|x)$ and for verification of probability axiomatic principles. However, a look at the numerator of the Bayes theorem (equation 1) is enough to deduce whether a pattern belongs to one class or another. Thus, it can be deduced that the condition shown in (3) is completely analogous to the condition described in (4), which simplifies the calculations required to take a decision.

$$x \in \Omega_i \Leftrightarrow \max_{r=i}\{P(x \middle| \Omega_r)P(\Omega_r)\} \tag{4}$$

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