Texture Based Segmentation

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Abstract. The ability of human observers to discriminate between textures is related to the contrast between key structural elements and their repeating patterns. Here we have developed an automatic texture classification approach based on this principle. Local contrast information is modelled and a hybrid metric, based on probability density distributions and transportation estimation, are used to classify unseen samples. Quantitative and qualitative evaluation, based on mammographic images and Wolfe classification, is presented and shows segmentation results in line with the various classes.

1 Introduction

Texture is one of the least understood areas in computer vision. Although no generic texture model has emerged so far a number of problem specific approaches have been developed successfully [1,2,3,4]. More recently, approaches have been investigated which aim to automatically determine a feature vector to be used for segmentation purposes [5,6] or provide a more fundamental approach to texture segmentation [7,8,9].

The work described here can be seen as such a more generic approach towards texture modelling. The principles behind this modelling are based on the notion that human observers are able to distinguish between textures if there is significant contrast difference between the main structural elements and the way those specific (sub-)structures form a repeating pattern. To achieve this we have investigated the modelling of the distribution of texture structural elements within specific grey-level bands. Subsequently, unseen texture regions can be compared with the developed models. The comparison can be based on various distance metrics.

In this paper we consider the segmentation of texture information within mammographic images. Here the main aim is to distinguish between a number of textures that appear in mammographic images (e.g. the various textures associated with Wolfe [10] or Tabar [11] based risk assessment) and use the extracted information to obtain segmentation of texture images. We have investigated the use of a *Hybrid Metric* which can be regarded as the non-integer approximation of the transportation cost approach. We provide both quantitative and qualitative assessment of the developed approach.

The layout of the paper is as follows. In Sec. 2 the local contrast based texture segmentation approach is presented, which covers the extraction of the local contrast information and the use of a novel *Hybrid Metric* to measure the similarity between

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distributions. In Sec. 3 quantitative and qualitative results based on real textures are presented. The paper concludes with discussion and conclusions sections.

2 Methods

The aspects discussed in the section cover: a) the model describing the local contrast structures, b) the way that these are used to provide texture models, and c) the approach to evaluate the difference between local contrast structure models and new local areas within unseen images.

2.1 Local Contrast Structures

One of the motivations behind this research is that texture recognition is driven by the contrast between key structural elements. Images are decomposed into distinct grey-level bands. The binary images, $B(x, y)$, representing only distinct grey-level bands are determined by

$$B(x,y) = \begin{cases} 1 \text{ if } \delta_{low} <= I(x,y) < \delta_{high} \\ 0 \text{ otherwise} \end{cases} \tag{1}$$

where $I(x, y)$ is a grey-level image, and δ_{low} and δ_{high} are low and high threshold values.

It should be clear that the distinct structures that represent the textures are only present in very specific grey-level bands and that a specific position within the image can only become equal to 1 once if the high and low threshold values in Eq. 1 form a non-overlapping series (as will be the case throughout the presented work).

2.2 Modelling

Modelling the repeating key (sub-)structures that are essential to describe textures can be achieved by estimating local aspects using a set of binary images determined by Eq. 1, where the set is based on a sequence of n $(\delta_{low}, \delta_{high})$ values covering the full range of grey-level values within the images and $(\delta_{high} - \delta_{low})$ is constant (e.g. a possible $(\delta_{low}, \delta_{high})$ set would be $\{(0, 64), (64, 128), (128, 192), (192, 256)\}$, and some binary images based on such sets can be found in Fig. 1). Once such a set of images has been obtained a model of local structures needs to be obtained. To achieve this for a specific binary image in the set a region of interest (with size equal to $(2w+1)\times(2w+1)$) is extracted at each position in $B(x, y)$ with value equal to one. For each region of interest the segment containing the central position is extracted using simple four-connectivity. Using each position in the obtained segments provides a summation over $B(x, y)$ restricted by $\pm w$. After normalisation with respect to total occurrence, this results in a probability density distribution representing local structures within a specific grey-level range (as specified by Eq. 1). Such a probability density is denoted as $P_m(i, j)$, where the subscript indicates the level in the set of binary images for which the probability density is derived, $m \in [1, n]$, n represents the number of grey-level bands, and (i, j) covers the region of interest, i.e. $i, j \in [-w, w]$.

Subsequent to the modelling it becomes possible to determine if a new region of interest extracted from an image that was not part of the modelling data belongs to the