# Chapter two
## Literature review

There are a number of different definitions of texture, when applied to image data. All definitions have in common the fact that they describe texture as an attribute of an image window. These attributes can represent spatially deterministic aspects of the grey level, including its stochastic colour distribution properties (Wagner1999). Gool et al. (1984) defined texture as structure composed of a large number of more or less ordered similar patterns without any one of these drawing special attention. A pattern like a checkerboard is said to have a deterministic texture, having a regular or non random texture. Conversely the structure might resemble noise as on a television monitor screen, and such a texture is said to be stochastic or statistically based random fluctuations. The two major characteristics of textures are its coarseness and directionality, thus the two major texture analysis approaches are statistical and structural. Texture is one of the important characteristics used in characterising objects or regions of interest. Haralick et al. (1973) and Haralick (1979) developed a set of statistical features for classifying pictorial images. The statistical features are based on a matrix derived from the spatial distribution of grey level values in the pixels of the image.

**Structural** approaches (Levine 1985) represent texture by well defined primitives (*microtexture*) and a hierarchy of spatial arrangements (*macrotexture*) of those primitives. To describe the texture, one must define the primitives and the placement rules. The choice of a primitive (from a set of primitives) and the probability of the chosen primitive to be placed at a particular location can be a function of location or the primitives near the location. The advantage of the structural approach is that it provides a good symbolic description of the image; however, this feature is more useful for synthesis than analysis tasks. The abstract descriptions can be ill defined for natural textures because of the variability of both micro- and macrostructure and no clear distinction between them. A powerful tool for structural texture analysis is provided by mathematical morphology (Serra 1982, Chen 1994). It may prove to be useful for bone image analysis, e.g. for the detection of changes in bone microstructure.

In contrast to structural methods, **statistical** approaches do not attempt to understand explicitly the hierarchical structure of the texture. Instead, they represent the texture indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image. Methods based on second-order statistics (i.e. statistics given by pairs of pixels) have been shown to achieve higher discrimination rates than the power spectrum (transform-based) and structural methods (Weszka 1976). Human texture discrimination in terms of texture statistical properties is investigated in (Julesz 1975).

Accordingly, the textures in grey-level images are discriminated spontaneously only if they differ in second order moments. Equal second order moments, but different third-order moments require deliberate cognitive effort. This may be an indication that also for automatic processing, statistics up to the second order may be most important (Niemann 1981).

The most popular second-order statistical features for texture analysis are derived from the so-called co-occurrence matrix (Haralick 1979). They were demonstrated to feature a potential for effective texture discrimination in biomedical-images (Lerski 1993, Strzelecki 1995). The approach based on multidimensional co-occurrence matrices was recently shown to outperform wavelet packets (a transform-based technique) when applied to texture classification (Valkealathi 1998).

**Model based** texture analysis (Cross 1983, Pentland 1984, Chellappa 1985, Derin 1987, Manjunath 1991, Strzelecki 1997), using fractal and stochastic models, attempt to interpret an image texture by use of, respectively, generative image model and stochastic model. The parameters of the model are estimated and then used for image analysis. In practice, the computational complexity arising in the estimation of stochastic model parameters is the primary problem. In (Yin 1994), MRF and Kohonen ANN were used for unsupervised texture segmentation, while genetic algorithms were applied in (Andrey 1998). Using the MRF for colour texture segmentation was introduced in (Panjwani 1995). A Maximum pseudo likelihood scheme was elaborated for estimation model parameters from texture regions.

The final stage of the segmentation algorithm is a merging process that maximizes the conditional likelihood of an image.

The problem of selecting neighbours during the design of colour RMF is still to be investigated. Its importance is justified by the fact that large number of parameters that can be used to define interactions within and between colour bands may increase the complexity of the approach. Colour texture MRF models are considered in (Bennett 1998).

The problem of texture discrimination using Markov random fields and small samples isinvestigated in (Speis 1996). The analysis revealed that 20×20 samples contain enough information to distinguish between textures and that the poor performance of MRF reported before should be attributed to the fact that Markov fields do not provide accurate models for textured images of many real surfacesThere is an observation that the fractal dimension (FD) is relatively insensitive to an image scaling (Pentland 1984) and shows strong correlation with human judgement of surface roughness. It has been shown that some natural textures have a linear log power spectrum, and that the processing in the human visual system (i.e. the Gabor type representation) is well suited to characterise such textures. In this sense, the fractal dimension is an approximate spectral estimator, comparable to other alternative methods (Chaudhuri 1995). The fractal dimension of six images derived from the original texture and the concept of multifractal model that implies a continuous spectrum of exponents were utilised in (Chaudhuri 1995) for natural texture segmentation.

The ability of fractal features to segment mosaics of natural texture images was investigated in (Duibuisson 1994). In was concluded that fractal dimensions will not segment all types of texture. There were attempts to segment the grey and white matters and lateral ventricles in magnetic resonance (MR) images based on fractal models – as reported by (Lundhall 1986) and (Lachman 1992).

One of methods for liver segmentation from MRIs is presented in (Hermoye et al. 2005) to determine liver volume in living liver transplant donors. The actual graft volume is inferred by its weight value, manual delineations and corrections of the liver segments are required after the segmentation method In (Lu et al. 2007), and liver nodule detection is performed using MRI. Fuzzy c-means (c=3) classification is used for nodule, vessel and parenchyma segmentatation.

The method should be investigated for different resolutions and applied to more than two patients. Another fuzzy c-means (c=2) based liver MRI segmentation method has been proposed in (Positano et al. 2007) for assessment of iron overloaded in liver. This method achieves classification of an image dataset by calculating a fuzzy membership measure at each pixel for two classes, which are parenchyma and vessels in this study. K-means and fuzzy c-means based methods are not directly adapted to noisy abdominal images. And edges, which connect these vertices. The energy function is minimized by summing the weights of cut edges. The energy function consists of a region term (which assigns penalties by using neighborhood context and also labels each voxel as background or object region) and a boundary term (which assigns penalties by using the dissimilarity values of neighborhood voxels).

The other approach to segment the liver organ from MRIs is explained in (Platero et al. 2008). This anisotropic diffusion processing based method is performed without using a control parameter. Not only edge detection, analysis of histograms and binary morphological image processing techniques but also active contour evolution has been implemented. The luminance variance between liver and its closest neighborhood has been used to evaluate the active contours. The required computation time for a volume of 350x250x55 pixels is given as 28s for diffusive filtering and morphological post-processing operations, and 6s is given for evolution of the active contour.

In (Cheng et al. 2008), a variational level set technique that incorporates prior knowledge of the liver shape into the improved Chan-Vese's method has been proposed. Usually, the boundary parts of the liver are not clear in MRIs because of liver movement and blood flow. Also, inhomogen intensities exist, where the Chan-Vese model does not work well. . The proposed algorithm needs an initial segmentation image, which has been obtained by implementing the Chan-Vese method. However, there are some flaws such as over segmenting and leakage due to the low quality of the liver in abdominal MRIs. The experimental results from MRI data sets reveal that the level set based shape prior technique can segment the liver precisely.

Fenchel et al. used active shape model for liver segmentation to reconstruct liver shape and position from MRI slices (Fenchel et al. 2008). The active shape model is created from a training set of liver segmentations from a group of volunteers. The training set is set up with semi-manual segmentations of T1-weighted volumetric MRIs. Searching for the optimal shape model that best fits to the image data is done by maximizing a similarity measure that is based on local appearance at the surface. However, for high-quality clinical liver segmentations, more generalizability of the model search to unknown datasets have to be integrated for this method.

Chen et al. proposed a multiple-initialization, multiple-step LSM to overcome the over-segmentation and leakage problems (Chen et al. 2009). In this method, a rough contour of the liver is obtained by combining multiple initialized curves, which are first evolve separately, and a convex hull algorithm. Contour evolution is performed by using LSMs and the fast marching methods. Precise boundaries of the liver are obtained by evolving the contour with global level set smoothing. An important difficulty for multiple-initialization of LSMs is to determine the number of initializations automatically. Therefore, under-segmentation problem occurs at lower sharp corners because of the low-gradient of the lower half of the liver. Starting from a seed point or a ranking order of liver area, a segmentation result of liver in MRI has been obtained by a quadtree decomposition, regional morphology operation and ordering of ROI in (Dongxiang and Tiankun 2009). The main problem with quadtree decomposed liver images is that the zigzag outline of the initial segmented image does not conform to smooth human tissues.

A neural network based approach has been used for liver detection in MRIs in (Rafiee et al. 2009). In this method, the abdominal MRIs are partitioned to some regions and feed forward neural network is used to extract liver features in training stage. These features are used in liver recognition. An intensity-based liver segmentation method in (Ruskó and Bekes 2010), which uses probabilistic approach to increase the precision of the segmentation. The probabilistic model is built by using sixty manually contoured CT images. Different intensity statistics at different parts of the liver is used after the partitioning of the model according to the functional anatomy of the liver. The used approach provides a modality independent model by registration, which exploits some characteristics of LAVA images, some characteristics of LAVA images, which shall be eliminated for adaptation of the segmentation algorithm for a wide range of MRIs, are exploited by with position probabilities in a probabilistic framework is formulated by the authors in (Gloger et al. 2010). The automatic three dimensionals liver segmentation approach is based on a modified region growing algorithm and a further thresholding method has been proposed. In this liver approach, multiclass linear discriminate analysis is applied as a dimensionality reduction method and probability maps are generated and used for segmentation.

In (Tang and Wang 2010), liver is extracted from CT images by hand. Active contour is used to extract liver region from MRIs. As the next step, B-spline based free form deformation is used to register the extracted liver regions from CT and MRIs. A clustering algorithm for liver lesion segmentation of diffusion weighted MRIs incorporates spatial information and geometric constraint in (Jha et al. 2010). Finite Gaussian Mixture Model is applied for liver segmentation but this model does not take spatial information into account. There might be pixels whose intensities are different from other pixels in the same region. The proposed method in (Chen et al. 2010) applies K-means based liver segmentation approach by using Open-MRIs. The authors apply K-means method before implementation of Graph-Cut algorithm to identify liver pixels.

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Although there are only a few studies for liver MRI segmentation, it has been observed that different algorithms with different MRI modalities have been applied for liver segmentation each of them has their own advantages and disadvantages in terms of accuracy, robustness or computational cost. However, SPIR images have not been used until now the model fitting In contrast to previous methods for segmentation of the liver from MR data sets, available MR With position probabilities in a probabilistic framework is formulated by the authors in (Gloger et al. 2010). The automatic three dimensionals liver segmentation approach is based on a modified region growing algorithm and a further thresholding method has been proposed. In this liver approach, multiclass linear discriminant analysis is applied as a dimensionality reduction method and probability maps are generated and used for segmentation. It is identified by the authors that the proposed segmentation method gives successful results in the automatic liver segmentation of three dimensionals MR data sets and provides important potential for the assistance of volumetric analysis of the liver.