TEXTURE ANALYSIS AS A TOOL FOR MEDICAL DECISION SUPPORT. PART 2: CLASSIFICATION OF LIVER DISORDERS BASED ON COMPUTED TOMOGRAPHY IMAGES

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Abstract: Texture analysis has already demonstrated its great potential in many digital image-based diagnostic systems. It allows to extract from an image many important diagnostic information, impossible to capture with only the visual appreciation. The first attempts to use a texture analysis (TA) as a tool for characterization of an image content took place in the 70's of the last century. Since then a variety of methods have been proposed and found their application in many domains, also – in the medical field. However, it is still difficult to indicate a method that would ensure satisfactory results for any diagnostic problem.
The present work gives an overview of the texture analysis methods, that have been applied for hepatic tissue characterization from Computed Tomography (CT) images. It includes details of about forty studies, presented over the past two decades, devoted to (semi)automatic detection or/and classification of different liver pathologies. Quoted systems are divided into three categories: (i) based on a single-image texture of non-enhanced CT images of the liver, (ii) based on a single-image texture of contrast-enhanced images, and (iii) based on a multi-image texture. The latter ones concern a simultaneous analysis of sets of textures, each of which corresponds to the same liver slice, but is related to a different contrast agent concentration in hepatic vessels.

Keywords: medical imaging, image analysis, texture characterization, feature selection, Computer Aided Diagnosis, CAD, medical decision support, liver, computed tomography, CT

A list of abbreviations is given at the end of this article.

1. Introduction

In clinical practice, when dynamic CT of the liver is performed, three image series are usually acquired: the first one – before the contrast agent injection, the next two

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ones – after its injection, at arterial and at portal phase of its propagation [1]. The two post-injection acquisition moments correspond, respectively, to the maximal concentration of contrast agent that reaches the liver first via the hepatic artery, next – via the portal vein. The arterial phase starts after about $25 \div 35$ seconds after the intravenous injection of contrast agent, the portal one – after about $60 \div 70$ seconds. In some cases a fourth – delayed hepatic phase is considered [2]. It takes place after about $5 \div 10$ minutes succeeding the injection. Each of the three (or even four) images enhances a different tissue property, that could reveal a development of a pathology. In the case of the liver CT – it can be excessive or insufficient growth of the arterial or of the portal vascular tree. After injection of the contrast agent, the high vascularization regions are more enhanced than those with normal vasculature, and less vascularized regions appear darker. The presence of contrast agent in hepatic vessels results also in changes of texture properties, imperceptible to the naked eye.

In the first part of the study [3], several approaches to characterization of image textures were presented. They based on:

- Gray Level Histogram (GLH), giving the First Order Statistics (FOS),
- Co-Occurrence Matrices (COM) [4–6],
- Run Length Matrices (RLM) [7–9],
- Gray Level Difference Matrices (GLDM) [10],
- Gradient Matrices (GM) [11],
- Texture Feature Coding Method (TFCM) [12],
- Autocorrelation Coefficients (AC) [13],
- Fractal Model (FM) [14–24],
- Discrete Wavelet Transform (DWT) [25],
- Laws' Texture Energy (LTE) [26].

The aim of this part is to examine which of these methods have found their application in Computer-Aided Diagnosis (CAD) systems, based on CT images of the liver.

The first attempts to liver texture characterization from CT images (about 20 years ago) considered only the non-enhanced images. Over the time, with a development of imaging technique and with more and more wider access to studies it has become possible to perform frequent imaging after administration of contrast agent. Despite the availability of several series of images depicting the same part of liver, texture analysis was performed yet for a long time on only one image (contrast-enhanced, or still non-enhanced) . It is about 10 years ago, that the systems adapted for multi-image texture analysis were introduced. Such systems tried to find tissue characteristics based on analysis of several CT liver images, acquired at the same slice location, but under different conditions (different moments of contrast agent propagation). Given the above, the review will present at first the systems based on the analysis of a single image, acquired without contrast. Next, the systems dealing with single-image textures, acquired after administration of contrast agent, will be described. Finally, the multi-image texture-based systems will be quoted. The work will be finished by general conclusions, drawn on the basis of the three parts of the review.

2. Application of texture analysis in classification of liver disorders based on CT images

2.1 Texture analysis of single liver CT image acquired without contrast agent

One of the earliest studies on the possibility of applying a texture analysis for the characterization and recognition of liver tissue, from CT images, was presented in 1995 [27]. This work had two main objectives. The first was to investigate whether the texture could be used to discriminate between various tissue types, providing the information not accessible to human perception. The second was to find the most useful features, in terms of tissue classification. In the study textural features obtained by the COM (12 features), RLM (15 features) and the GLDM (20 features) methods were used. Three types of hepatic tissue were characterized: normal liver, abnormal liver with the clearly visible malignancy, and abnormal one with the invisible malignancy. The performance of features was compared on the basis of statistical significance. It was found that the three features: *entropy*, *local homogeneity* (COM method) and *gray level distribution* (RLM method) were the most appropriate to detect an invisible (early) liver malignancy with a confidence level of above 99%

From this moment, quite a lot of semi-automatic systems for liver tissue recognition from CT images have been proposed. In many of them, especially in the earlier ones, the tissue was characterized on the basis of only one image, acquired without injection of contrast agent [16, 28–38]. Quoted systems utilized several methods for extraction of textural features. They included: gray-level histogram, co-occurrence matrices, run length matrices, gray level difference matrices, fractal model, Laws' texture energy measures, autocorrelation coefficients, or different frequency methods. A list of systems and tested methods is given in Table 1. Due to the fact that each of the systems used different classifiers and that the methods for their quality assessment were also different, the table do not contain the best classification results.

For example, the system evaluated by Chen et al. [16] was able to automatically find the liver, to extract its boundaries and to recognize two types of liver tumors: hepatoma and hemangioma. In this system, the image texture was characterized by

Table 1. Comparison of systems based on single liver CT images acquired without contrast agent

Work	Year	TA Methods	Tissue Classes and number of cases
Mir et al. [27]	1995	– COM – RLM – GLDM	– normal (200) – abnormal, clearly visible (200) – abnormal invisible (200)
Chen et al. [16]	1998	– COM – FM	– hepatoma (20) – hemangioma (10)
Husain et al. [28]	2000	– FOS – COM	– normal – abnormal
Sariyanni et al. [29]	2001	– FM	– healthy (99) – HCC (50)
Gletsos et al. [30]	2003	– COM – FOS	– healthy (76) – liver cysts (19) – hemangioma (28) – HCC (24)
Valavanis et al. [31]	2004	– FOS – COM – GLDM – LTE – FM	– healthy (76) – liver cysts (19) – hemangioma (28) – HCC (24)
Mala et al. [32]	2005	– OWT & FOS – OWT & COM	– steatosis (70) – cirrhosis (70)
Huang et al. [33]	2006	– AC	– malignant (80) – benign (84)
Stoitsis et al. [34]	2006	– FOS – COM – GLDM – LTE – FM	– healthy (76) – liver cysts (19) – hemangioma (28) – HCC (24)
Mougiakakou et al. [35]	2007	– FOS – COM – GLDM – LTE – FM	– healthy (76) – liver cysts (19) – hemangioma (28) – HCC (24)
Ganeshan et al. [36]	2009	– filters & FOS – filters & COM	– absence of malignancy (15) – malignancy not related to the liver (9) – liver metastases (8)
Kumar et al. [38]	2013	– FOS – COM – CCT & FOS – CCT & COM – WCT & FOS – WCT & COM	– HCC (150) – hemangioma (150)

features obtained from the co-occurrence matrices (here, the *correlation* and *sum entropy* turned out to be the best ones) and its fractal dimension, evaluated from a fractional Brownian motion model (the method developed by authors and described in their work). A probabilistic Neural Network (NN) [39] was used as a classifier. The proposed system was tested on 30 liver cases and shown to be quite efficient.

Another system, described in [28], was also able to recognize a liver region (normal and abnormal) on CT images. The system used the gray-level histogram features (*mean gray level*, *standard deviation*, and *skewness*) in combination with the COM-based features (*entropy*, *homogeneity*), and a back-propagation Neural Network [40] as a classifier. The system was able to recognize correctly more than 95% of analyzed cases.

Sariyanni et al. [29] tried to recognize a healthy liver tissue and a tissue affected by hepatocellular carcinoma (HCC). As texture descriptors, they used a fractal dimensions calculated from four different methods: the power spectrum method (belonging to the fractional Brownian motion methods) [21], the box-counting method, the morphological fractal estimator (belonging to the area measurement methods) [22], and the kth-Nearest Neighbor estimator (k-NN), proposed by authors. The Fuzzy C-Means algorithm [41] was then applied for clustering the input data into two clusters. It revealed that the k-NN estimator, introduced by authors, outperforms the other methods.

The work of Gletsos et al. [30] described a CAD system adapted to the recognition of four types of liver tissue: healthy, liver cysts, hemangioma, and hepatocellular carcinoma. It used 48 texture descriptors derived from the co-occurrence matrices, and the average gray level of the Regions of Interest (ROIs). The classification module consisted of three sequentially placed feed-forward Neural Networks, each adapted to perform a pairwise classification. The first one distinguished normal from pathological liver regions, the second one recognized pathological regions and distinguished cysts from "other pathologies", and the third one distinguished between "other pathologies" – hemangioma and HCC. Three feature selection techniques were used separately for each binary classifier: the Sequential Forward Selection (SFS) [42], the Sequential Floating Forward Selection (SFFS) [43], and Genetic Algorithm for feature selection (GAs) [44] with the implementation based on the work [45]. The feature selection used a criterion based on the squared Mahalanobis distance between the populations of the two classes for each binary NN classifier. Finally, several subsets of features were considered for classification experiments. The CAD performance was tested with validation and testing sets, each containing a portion (1/5) of the initial data. Results obtained for different sub-sets of features differed from one another. The best overall classification accuracy was of 97%.

A more developed system was presented by Valavanis et al. [31]. It was evaluated in the process of recognition of four types of focal liver lesions, the same that were considered in [30]. The number of ROIs for each tissue class was also the same. Here, the relevance of the five texture characterization methods was assessed. Among the tested methods were: the method based on the gray-level histogram, the co-occurrence matrices, the run length matrices, the Laws' texture energy measures, and the fractal model. The most useful features were found using a feature selection, based on Genetic Algorithms. Classification was carried out by Neural Networks (three-layer feed-forward NN and Radial Basis Function (RBF) NN) and statistical methods (k-NN [46] with different k). Here, the best classification accuracy was equal to 90.63%. Similar works have been described, some years later, in [34], and further – in [35]. The continuation of this research has finally resulted in the creation of a telematics-enabled system for image archiving, management, and diagnosis support [37]. This integrated CAD system performed an image preprocessing, a semi-automatic image segmentation, an extraction of texture features, and a classification.

Another CAD system was proposed by Mala et al. [32], in order to classify two diffused liver diseases, steatosis and cirrhosis. First, it performed an automatic extraction of liver, using adaptive threshold and morphological processing. Second, images were transformed into frequency domain using the Orthogonal Wavelet Transform (OWT). Then, the statistical features were calculated based on the horizontal, the vertical, and the diagonal details extracted from the images. They included: *mean*, *standard deviation*, *contrast*, *entropy*, *homogeneity*, and *angular second moment*. Finally, the two-layer probabilistic Neural Network was used as a classifier. The system was trained on 40 cases and tested on 100 ones. Both classes were equally numerous in the train end the test set. The classification accuracy of 95% was achieved.

The next CAD example was described by Huang et al. [33]. Their system was adapted for differentiation between two groups of liver tumors: malignant (primary tumor – HCC or secondary tumors – metastases) and benign. As texture parameters, only the normalized autocorrelation coefficients were used. The classification was performed with the Support Vector Machines (SVM) [47]. The k-fold cross-validation [48] was used to evaluate the performance of the proposed diagnostic system. The classification accuracy was of nearly 82%.

The objective of yet another research, presented by Ganeshan et al. [36], was to determine whether the textures corresponding to the apparently healthy liver regions were altered by the presence of malignancy in patients with colorectal cancer. Three types of liver tissue were considered. The first one corresponded to an absence of malignancy, the second one – to the presence of a malignancy but not related to the liver, and the third one – to the presence of liver metastases. Here the frequency methods in combination with statistical approaches were used to characterize hepatic tissue. The following statistical descriptors of texture were derived from both unfiltered and filtered images (highlighting fine, medium, and coarse texture): *mean gray level*, *entropy*, and *uniformity*. The experiments showed that textural features obtained from the filtered images were statistically different for each of the three considered tissue classes.

The most recently, Kumar et al. [38] developed a texture-based CAD system, specialized in discrimination between malignant (hepatocellular) and benign (hemangioma) liver tumors. Their work tested several sets of features: gray-level texture features (first order statistics and second order, COM-based texture descriptors), Wavelet Coefficient Texture (WCT) features (first- and second- order statistics), and Contourlet Coefficient Texture (CCT) features [49, 50] (also of the first- and of the second order). As numbers of considered features were quite large (in total about 300 features were tested) the Principal Component Analysis (PCA) [51] was applied for a dimensionality reduction. The ability of each feature set in differentiating malignant from benign tissues was assessed with a probabilistic Neural Network classifier. The areas under the Receiver Operating Characteristic (ROC) curves (AUC) [52] were used for measuring the system performance. The highest classification accuracy (96.7%), as well as the highest sensitivity and specificity (97.3% and 96%, respectively) were obtained with the contourlet coefficient co-occurrence features.

2.2 Texture analysis of single liver CT image acquired after administration of contrast agent

Preliminary studies on processing of contrast-enhanced CT images for semi-automatic recognition of liver disorders were reported by Krętowski [53]. The work aimed at comparing the classification accuracy obtained for the three acquisition moments, typical for the CT of abdominal organs (without injection, arterial phase, portal phase). Five types of liver tissue were differentiated: the healthy liver and four types of its metastases: insulinoma, adenocarcinoma (kidney), adenocarcinoma (intestine) and leiomyosarcoma. The image database was divided into three parts, each of which being composed of images corresponding to one (of the three considered) acquisition moment. The tissue was characterized by features calculated with the FOS, GM, COM and RLM methods. The texture classification was performed by oblique (multivariate) Dipolar Decision Trees [54], separately for each of the three parts of the database. The classification accuracy for acquisitions with contrast material outperformed the results obtained for those without contrast. The highest classification accuracy was observed for the arterial phase.

The systems for liver tissue characterization and recognition from enhanced CT images began to appear after this moment [55–65]. The texture analysis in these systems was performed with the following methods: FOS, COM, RLM, GLDM, LTE, or frequency methods (see the comparison in Table 2). However, all of those systems were still limited to the analysis of only one image at a time and they did not consider the changes in texture properties during the propagation of contrast material.

For example, Bilello et al. [55] presented a system working on portal-phase images. It combined the methods for detection, characterization and classification of liver hypodense hepatic tissue (cysts, hemangiomas, and metastases). Its texture was characterized with the frequency methods. Then the Support Vector Machines were used to perform a pairwise lesion classification. In order to evaluate the system performance, the Free-Response Receiver Operator Characteristic Curves (FROC) [66] were utilized. The system assured perfect discrimination (100% of correctly recognized cases) between hemangiomas and cysts, good discrimination between cysts and metastases (at 95% sensitivity for detection of metastases, only about 5% of cysts were incorrectly classified as metastases), and was least accurate in discriminating between hemangiomas and metastases (at 90% sensitivity for detection of hemangiomas, about 28% of metastases were incorrectly classified as hemangiomas).

The system described by Lambrou et al. [56], differentiated between healthy and tumorous tissue. To extract texture features, it used a wavelet transform method, in combination with three statistical methods (based on the gray level histogram, the co-occurrence matrices, and the run length matrices). Three statistical classifiers were employed in the study: minimum distance classifier, quadratic minimum distance classifier, and Bayes classifier [46]. The performance of the classifiers was assessed with the leave-one-out method [48]. The first- and the second order statistics turned out to be better (yielding the classification accuracies exceeding 90%) than those derived from the wavelet-based techniques.

Another system, developed by Smutek et al. [57], focused on the analysis of focal liver lesions (HCC and cysts). It used the first- and the second order texture features (COM-based). The analyzed images corresponded to the late portal phase. In the system, an ensemble of Bayesian classifiers was applied. The classification accuracy was assessed by leave-one-out method. The system was able to classify correctly even 100% of recognized cases.

Mala et al. [58] presented a system adapted to the recognition of four types of liver diseases: HCC, cholangiocarcinoma, hemangeoma and hepatoadenoma. This system was able to automatically detect the areas affected by a disease, to characterize a tissue (using Biorthogonal Wavelet Transform (BWT) and co-occurrence matrices derived from the transformed images), to select the best texture features, and, finally,

Table 2. Comparison of systems based on single liver CT images acquired after administration of contrast agent

Work	Year	TA Methods	Tissue Classes and number of cases
Krętowski [53]	2002	– FOS – GM – COM – RLM	– healthy (192) – insulinoma (126) – adenocarcinoma / kidney (104) – adenocarcinoma / intestine (107) – leiomyosarcoma (68)
Bilello et al. [55]	2004	– filters	– hemangiomas (11) – cysts (25) – metastases (52)
Lambrou et al. [56]	2006	– WT & FOS – WT & COM – WT & RLM	– healthy (425) – tumor (425)
Smutek et al. [57]	2006	– FOS – COM	– HCC (425) – cysts (110)
Mala et al. [58]	2007	– DTW & COM	– HCC (60) – cholangiocarcinoma (60) – hemangeoma (60) – hepato adenoma (30)
Lee et al. [59]	2009	– FOS – GTF	– cyst (70) – hepatoma (70) – cavernous hemangioma (33) – normal liver (60)
Wang et al. [61]	2009	– FOS – COM – GLDM – RLM	– HCC (30) – hemangioma (30) – normal (30)
Mala et al. [62]	2010	– BWT & FOS – BWT & COM)	– fatty (100) – cirrhotic (100)
Kayaalti et al. [63]	2014	– COM – RLM – GTDM – LTE – DWT – DFT – GF – FOS	– fibrosis, stage 0 (21) – fibrosis, stage 1 (16) – fibrosis, stage 2 (12) – fibrosis, stage 3 (16) – fibrosis, stage 4 (13) – fibrosis, stage 5 (13) – fibrosis, stage 6 (25)
Rao et al. [64]	2014	– filters & FOS – filters & COM	– without metastases (15) – synchronous metastases (10) – metachronous metastases (4)
Simpson et al. [65]	2014	– COM	– postoperative liver failure (12) – no liver failure (24)

to classify tissues, using a probabilistic Neural Network. The BWT enabled to obtain horizontal, vertical, and diagonal details of images. Then, 10 features were extracted for each of three resulting images. Feature selection was performed here with a Sequential Backward Elimination (SBE) [42]. Regarding the classification experiments – all the available data were randomly divided into two equally numerous sets (for training and testing). Each experiment was repeated 5 times. The best classification result was of 90.2%.

The aim of another work [59] was to automatically discriminate liver diseases using a sigmoid Radial Basis Function Neural Network with growing and pruning algorithm (described by the authors). This time cyst, hepatoma, cavernous hemangioma, and normal liver tissue were recognized. The ROIs were characterized using gray level and Gabor Texture Features (GTF) [67, 68]. The ROC curves were used to evaluate the diagnosis performance, and the area under ROC curve measured the classification accuracies. The best classification result exceeded 99%.

The study presented in [60] aimed at the assessment of the utility of texture analysis of liver CT images, and at the comparison of the abilities of texture analysis and hepatic perfusion CT to help predict survival for patients with colorectal cancer. The texture analysis comprised two stages. The first one was the image filtration (here, a Laplacian of Gaussian band-pass filter was chosen). The second one was the quantification of texture (here, the *mean gray-level intensity* and *uniformity* were used). The study provided preliminary evidence that analysis of liver texture on portal phase CT images was potentially a superior predictor of survival for patients with colorectal cancer than the CT perfusion imaging.

Wang et al. [61] tested yet another diagnostic system, which worked with the three types of liver tissue: HCC, hemangioma, and normal one. This system used four texture analysis methods (based on the gray level histogram, the co-occurrence matrices, the gray level difference matrices, and the run length matrices). As a classifier the Support Vector Machines were used, and two strategies were considered in order to ensure a multi-class classification: One-Against-All (OAA) [69] and One-Against-One (OAO) [70]. The performance of the CAD system was estimated by the 5-fold cross-validation. The experiments on 90 ROIs, described by set of 22 textural features, gave the overall classification accuracy of about 94% and 98%, for the OAA and the OAO strategy, respectively.

In yet another work [62], a CAD system used the wavelet-based statistical textural features as tissue descriptors. The system was able to extract the liver, and to recognize between fatty and cirrhotic liver tissue. In this work, the original images were first decomposed using a biorthogonal wavelet transform. Then, as in the previous work of the same team [32], the second order statistical features were extracted in horizontal, vertical and diagonal directions. After performing a feature selection, the most robust texture descriptors were fed to the three types on Neural Networks. The 10-fold cross-validation procedure was used to evaluate the system abilities. The experiments on 200 patients resulted in quite high percentages of correctly recognized characters (reaching 96%).

The most recent studies, published this year, are also based on texture analysis of contrast-enhanced CT images, acquired at portal venous phase [63–65]. For example, Kayaalti et al. [63] recognized seven possible stages of liver fibrosis. For this purpose, eight methods for texture feature extraction were tested. They were based on: co-occurrence matrix, run length matrix, Gray Tone Difference Matrix (GTDM) [71], Laws' filters, Discrete Wavelet Transform [72], Discrete Fourier Transform (DFT), Gabor Filters (GF) [73], and first order statistics. For each combination of classes, a sequential floating forward selection and exhaustive search methods were used in order to find the best texture descriptors. The pairwise classification experiments with Support Vector Machines and *k*-NN classifier showed that DWT, Gabor, COM, and Laws' features were more successful than the others. The performances of the classifiers were assessed by 2- or 3-fold cross-validation. When only 5 features were used, the mean classification accuracy in pairwise group comparisons was approximately 95% for both the *k*-NN and the SVM method.

Rao et al. [64] evaluated the potential of analysis of the whole liver with apparently disease-free parenchyma, for discriminating between three types of colorectal cancer patients: without liver metastases, with synchronous liver metastases, and with metachronous metastases. In their work, a texture characterization comprised two stages. First, images were filtered with a Laplacian of Gaussian band-pass filter with different bandwidths. Afterwards, three features were calculated from the filtered and the unfiltered images: *entropy*, *uniformity*, and *mean gray-level intensity*. The ROC analyses were conducted to determine the diagnostic performance of the considered features. As a result, mean *entropy and uniformity* in patients with synchronous metastases were significantly different compared with the non-metastatic patients, while texture parameters for the metachronous metastases group were not significantly different neither from the non-metastatic group nor from synchronous metastases group.

Finally Simpson et al. [65] used some COM-based features of preoperative CT images of the liver, in order to predict a postoperative liver failure after hepatic resection. The study was undertaken on 36 patients. It was discovered that the following features: *contrast*, *correlation*, *cluster prominence*, and normalized *inverse difference moment* were significantly different between patients with and without postoperative liver failure.

2.3 Multi-image texture analysis, involving non-enhanced and contrast-enhanced liver CT images

In [74] a simultaneous analysis of triplets of liver textures, corresponding to the three aforementioned typical acquisition moments, was proposed. At first, the three corresponding simple textures were characterized separately by features obtained from gray-level histogram, Laws' filtering, COM and RLM methods. As a result, three feature sets, each characterizing one of the three textures, were obtained. Then, all the features from those three sets were placed together in one feature vector, characterizing a multi-image ("triphase") texture. As a classifier, an oblique Decision Dipolar Tree was used. The 5-times repeated 10-fold cross-validation procedure was applied to estimate the classification accuracy. Three types of liver tissue were recognized: healthy liver and its two main primary malignant tumors (HCC and cholangiocarcinoma). The classification accuracies obtained for triphase textures were significantly higher than those corresponding to each acquisition moment separately. For example, the best classification accuracies obtained with the set of the 8 RLM-based features were: 95.5%, 93.9%, and 95.5% for the no-contrast, the arterial, and the portal phase, respectively, while considering simultaneously the three phases resulted in the 99.7% of correctly diagnosed cases. Further work of the same team [75] has confirmed that a simultaneous analysis of images, corresponding to the three acquisition moments could lead to better results that the simple texture analysis – performed when only one acquisition moment is considered.

An approach similar to the two preceding ones was used by Quatrehomme et al. [76]. In their work, the analysis of multi-image textures was performed on four-phase CT scans of the liver: the first one – taken in pre-injection phase, the next three ones – after injection of contrast material, in arterial, portal and late phase. Five types of hepatic lesions were differentiated: cysts, adenomas, haemangiomas, HCC and metastases. Four techniques for feature extraction were used. They based on: gray-level histogram, Gaussian Markov Random Fields (GMRF) measures [77], LTE measures, and Unser Histograms Statistics (UHS) [78]. Features, calculated separately for four considered acquisition moments were placed side by side in a multiphase vector, describing four-phase textures. As a classifier, the SVM were used. Its performance was evaluated by the leave-one-out technique. The results obtained with multi-image approach were significantly better than for the case of a single-image texture analysis.

A multi-phase liver images, derived from the four image series (non-enhanced, arterial, portal, and delayed) were also considered by Chi et al. [79]. Their system was designed in order to help radiologists in characterization of various focal liver lesions. Six types of lesions were considered: HCC, hemangioma, cysts, liver abscess, Focal Nodular Hyperplasia (FNH), and metastases. The latter class included: pancreatic carcinoma, sigmoid carcinoma, rectal carcinoma, colorectal carcinoma, and gallbladder carcinoma. The system first localized a lesion on multi-phase CT using a hybrid generative-discriminative method [80]. Then, a lesion was selected in one phase, and nonrigid B-spline registration [81] was employed in order to align the images of all the four phases. The tissue was characterized by a simultaneous analysis of textures corresponding to the four considered phases. Feature vectors were composed of multi-phase density characteristics and combinations of the co-occurrence matrix-based parameters, calculated for each of four phases. The system compared a tested lesion with the model lesions from a reference database (characterized by vectors of features), and measured their similarities using the L1-norm-based similarity scores. The reference cases which were the most similar to the examined one were finally provided to the users for their later studies. The system was tested on a database of 69 cases and evaluated using the precision-recall curves and the "Bull's Eye Percentage" (BEP) score [82]. A multi-image texture analysis resulted in a BEP value of 78%, while the best results for a single-phase cases were about 63% – 65%.

The aim of two other studies [83, 84] was to determine preliminarily how some of the hepatic texture features (*entropy*, *uniformity*) change during the propagation of contrast agent and to assess whether the differences in these changes between tumorous and non-tumorous liver tissue were statistically significant. The potential utility of Dynamic Contrast-Enhanced (DCE) texture analysis of the liver was compared to the potential of the measurements of hepatic attenuation and perfusion, obtained from the kinetic modeling. The study concerned patients following a resection of colorectal cancer and having apparently normal hepatic morphology. It showed that the temporal changes of the two considered textural features were different from those for hepatic attenuation and they were statistically significant between tumorous and non-tumorous patients. It also demonstrated that the textural features were less sensitive to changes in CT acquisition conditions (current and voltage variations).

In yet another work [85], four images of the same slice location, corresponding to subsequent moments of contrast agent propagation (pre-contrast, arterial, portal venous and delayed phase) were analyzed simultaneously. Here, four hepatic tissue classes were differentiated: normal, cyst, haemangioma and HCC. In contrast to the above cited works, this work considered only the combinations of the mean pixel values of ROI in different phases as temporal features. These were: *relative signal intensity*, *intensity change tendency*, and *signal enhancement ratio*. In addition, a few sets of textural features (gray-level histogram-based, COM-based, and selected features) were used in the four single-phase classification tasks. As a classifier, three hierarchically organized binary SVMs were used. The classification accuracy was assessed by k-fold cross validation. Here, the application of temporal characteristics did not result in better tissue recognition, in comparison with the best results obtained with textural features for each separate moment of contrast agent propagation. It is with a set of combined features (FOS, COM, and temporal) that the best classification accuracy was achieved: 95.5%, 97.2% and 96.4% for normal vs abnormal, cyst vs other disease and carcinoma vs haemangioma sub-problems, respectively.

Finally, in [86], 61 textural features were evaluated in the task of distinguishing between four classes of liver tissue: HCC, cholangiocarcinoma, cirrhosis, and healthy. The study involved: 4 first order statistics, 4 gradient-based features, 11 COM features, 8 RLM features, 5 GLDM features, 19 features obtained with Laws' filtering, 2 fractal dimension estimates, 7 TFCM-based statistics, and 1 normalized autocorrelation coefficient. Such features were calculated separately for each for the three considered moments of contrast agent propagation: no-contrast, arterial phase, and portal phase. In total $3 \times 61 = 183$ tissue descriptors were considered. The choice of the most useful features proceeded in two stages. At the beginning, unstable features (sensitive to small changes in ROI size and/or in ROI position) were rejected. Then, a simplified Monte Carlo feature selection (initially proposed by Draminski et al. [87]) was performed in order to find the most robust features. Classification experiments were performed using an Adaptive Boosting (AdaBoost) algorithm [88] with a C4.5 tree [89]. They revealed that a small set of 12 features was able to ensure classification accuracy exceeding 90%, while all of the 183 features provided an accuracy rate of 88.94%.

Table 3 summarizes the most important information about selected CAD systems, adapted for characterization of multi-image liver CT textures.

3. Conclusion

A vast variety of CAD systems adapted for recognition of liver disorders from CT images were developed over the past 20 years. The most frequently diagnosed pathologies were: primary malignant liver tumors (like HCC or cholangiocarcinoma), secondary tumors (different types of metastases), benign liver tumors (hemangiomas) or other benign liver changes, like steatosis (fatty change), cirrhosis, or fibrosis. Despite numerous proposals for texture analysis methods, that can be found in the literature, the presented systems use only a few approaches for texture characterization. The most popular are those that use: co-occurrence matrices, run length matrices, first order statistics, fractal models, Laws' texture energy measures, and different frequency methods. Each of described systems was tested on different data (different were: image resolutions – spatial and in gray levels, preprocessing techniques, numbers of

Table 3. Comparison of selected CAD systems based on multi-image texture analysis, involving non-enhanced and contrast-enhanced liver CT images

Work	Year	TA Methods	Tissue Classes	Phases
Duda et al. [74]	2006	– FOS – COM – RLM – LTE	– healthy (150) – HCC (150) – cholangiocrcinoma (150)	– no contr. – arterial – portal
Ye et al. [85]	2009	– FOS – COM	– normal (64) – cysts (14) – haemangioma (27) – HCC (26)	– no contr. – arterial – portal – delayed
Quatrehomme et al. [76]	2013	– FOS – MRF – LTE – UHS	– cysts (25) – adenomas (10) – HCC (13) – metastases (38)	– no contr. – arterial – portal – delayed
Chi et al. [79]	2013	– FOS – COM	– HCC (16) – hemangioma (16) – cysts (15) – liver abscess (7) – FNH (5) – metastases (10)	– no contr. – arterial – portal – delayed
Duda et al. [86]	2013	– FOS – COM – RLM – GLDM – GM – TFCM – AC – LTE	– normal (573) – cirrhosis (433) – HCC (319) – cholangiocarcinoma (222)	– no contr. – arterial – portal

ROIs, ROI sizes, classification algorithms, ...). Different methods were used for the evaluation of the system classification performance (leave-one-out, cross-validation, using a training set). Therefore, it is difficult to conclude which TA method could be the best possible one. Nevertheless, it can be noticed, that some methods have proven to be reliable for each classification task. For example, the COM-based method was successfully used for both the classification of non-enhanced images (acquired without contrast agent) and of enhanced images (acquired after administration of contrast agent). Other methods were frequently considered only for one type of images. In the case of the cited works, the fractal model-based texture features were of frequent consideration for non-enhanced images, whereas the first order statistics and run length matrices were most often utilized for the enhanced ones. Some experiments have also shown that image pre-filtering (like with WT, DWT, BWT, DFT), performed before extraction of the first- and the second order texture features, could lead to better tissue characterization (in terms of classification process) than the use of statistical methods alone. The comparison of results for non-enhanced an enhanced single-image textures shows that considering the texture changes introduced with the presence of the contrast agent could be a better solution. Finally, it is with the multi-image texture analysis, that the best results could be achieved.

Abbreviations

AdaBoost: Adaptive Boosting algorithm
AUC: Area Under the ROC Curve
BEP: "Bull's Eye Percentage"
BWT: Biorthogonal Wavelet Transform
CAD: Computer-Aided Diagnosis
CCT: Contourlet Coefficient Texture features
COM: Co-Occurrence Matrix
CT: Computed Tomography
DCE: Dynamic Contrast-Enhanced
DFT: Discrete Fourier Transform
DWT: Discrete Wavelet Transform
FM: Fractal Model
FNH: Focal Nodular Hyperplasia
FOS: First Order Statistics
FROC: Free-Response ROC Curves
GAs: Genetic Algorithm for feature selection

GF: Gabor Filters
GLDM: Gray Level Difference Matrix
GLH: Gray Level Histogram
GM: Gradient Matrix
GMRF: Gaussian Markov Random Fields
GTDM: Gray Tone Difference Matrix
GTF: Gabor Texture Features
HCC: Hepatocellular Carcinoma
k-NN: *k*-Nearest Neighbors (classifier)
LTE: Laws' Texture Energy
NA: Autocorrelation Coefficients
NN: Neural Network (classifier)
OAA: One-Against-All
OAO: One-Against-One
OWT: Orthogonal Wavelet Transform
PCA: Principal Component Analysis
RBF: Radial Basis Function
RLM: Run Length Matrix
ROC: Receiver Operating Characteristic
ROI: Region of Interest
SBE: Sequential Backward Elimination
SFFS: Sequential Floating Forward Selection
SFS: Sequential Forward Selection
SVM: Support Vector Machines (classifier)
TA: Texture Analysis
TFCM: Texture Feature Coding Method
UHS: Unser Histograms Statistics
WCT: Wavelet Coefficient Texture features

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ANALIZA TEKSTUR JAKO NARZĘDZIE WSPOMAGANIA DECYZJI MEDYCZNYCH. CZĘŚĆ 2: KLASYFIKACJA PATOLOGII WĄTROBY NA OBRAZACH TOMOGRAFII KOMPUTEROWEJ

Streszczenie: Analiza tekstur jest szeroko stosowana w wielu cyfrowych systemach wspomagania decyzji medycznych, na podstawie danych obrazowych. Pozwala ona wydobyć z obrazu istotne szczegóły, których nie można dostrzec podczas analizy wizualnej. Pierwsze próby analizy tekstur miały miejsce w latach siedemdziesiątych ubiegłego wieku. Od tamtej pory zaproponowano wiele metod analizy tekstur. Trudno jest jednak wskazać metodę uniwersalną, która zapewniłaby zadowalające wyniki dla każdego problemu diagnostycznego. Niniejsza praca stanowi przegląd metod analizy tekstur, stosowanych do opisu tkanki wątrobowej na obrazach tomografii komputerowej. Przedstawia informacje o około czterdziestu systemach diagnostycznych, zaproponowanych w ciągu ostatnich dwóch dekad, poświęconych (pół)automatycznemu wykrywaniu lub / i klasyfikacji schorzeń wątroby. Opisywane systemy zostały podzielone na trzy kategorie: (i) opierające się na teksturze pojedynczego obrazu, pozyskanego bez podawania pacjentowi środka kontrastującego, (ii) opierające się na teksturze pojedynczego obrazu, pozyskanego po podaniu pacjentowi środka kontrastującego, oraz (iii) opierające się na jednoczesnej analizie wielu tekstur. Te ostatnie odnoszą się do analizy zestawów tekstur przedstawiających ten sam wycinek wątroby, lecz odpowiadających różnym stężeniom środka kontrastowego w jej naczyniach krwionośnych.

Słowa kluczowe: obrazowanie medyczne, analiza obrazów, tekstura, selekcja cech, wspomaganie decyzji medycznych, diagnoza wspomagana komputerowo, wątroba, tomografia komputerowa

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