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Classification of Microcalcifications into BI-RADS™ Morphologic Categories – Preliminary Results

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In the paper, preliminary results for the classification of microcalcifications (MCs) into the three BIRADS™ morphologic categories (punctate, pleomorphic and linear) are presented. To classify the microcalcifications into morphologic types the set of 27 shape descriptors was constructed. The morphology of the cluster was determined as the mean values of shape descriptors for single microcalcifications. SVM classifier was used to differentiate MCs clusters into BI-RADS morphologic types. Classification of the clustered MCs into linear or pleomorphic morphologic types obtained accuracy ranging from 84 to 88% depending on the MCs features and the SVM parameters. The most discriminate features for the classification of clustered linear and pleomorphic MCs are: inner compactness, major axis and first invariant shape moment calculated from binary image of segmented MCs.

K e y w o r d s: clustered microcalcifications, microcalcifications morphology, BI-RADS, classification, SVM (Support Vector Machine)

1. Introduction

Breast cancer remains the most frequently diagnosed female malignancy in the industrialized countries. Currently, the most effective and most commonly used tool for early detection of breast cancer is screening mammography. Clustered microcalcifications (CMCs) are one of the mammographic hallmarks of the early breast cancer, and their description for diagnostic classification still remains a complex and challenging task. An ability of breast cancer diagnosis according to standard expert procedures is

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limited due to many technological and human factors [1]. Thus the procedures with second-look support of computer aided diagnosis (CAD) systems were optimized and became useful last years [2, 3]. However, automatic interpretation of the image content including CMCs offers still unsatisfied efficiency for significant number of applications due to almost unlimited pathology pattern variability and lack of case-invariant lesion descriptors.

1.1. The Problem Statement

The classification of MCs in CAD system is composed of two stages, the first – detection, and the second – diagnosis of MCs. In the first stage the lesion is localized by some automated techniques, and in the second stage classified for determining its character as malignant or benign. The goal of the detection stage is to improve sensitivity, in the second stage the specificity is improved. The methods used for detection and diagnostic classification of MCs were studied to a large extent in the literature with pointed out limitations [4]. The estimation of lesion diagnostic characteristics is based on different specific features of MCs, including the morphology as one of the important factors. Lesion descriptors are used to classify a case and to formulate its automatic interpretation as malignant or benign [5]. However, expert decision making for diagnosis and therapy suggestions in practice is much more complex and fuzzy. The BI-RADS™ system [5] was designed to provide a standardized terminology for lesion description and reporting, to improve accuracy and consistency of the mammographic interpretation and in consequence to decrease the variability in radiologist's opinions. Several studies evaluated the system usefulness [1, 6, 7]. They report on improvement in consistency of observers' opinions when the BI-RADS™ controlled vocabulary is used for lesion description [6,7], but relatively large inter-observer variability, especially in interpretation of microcalcification clusters still remains [1].

The classification of clustered microcalcifications into the BI-RADS™ morphological categories, the aim of the paper, has a number of potential applications. Describing the lesion features into the BI-RADS™ morphologic categories that reflects human experts' reasoning using numerical descriptors is expected to make automatic diagnosis process more evidence-based, objective with case-invariant high performance. In details, potential applications firstly address the problem of the observer variability in the interpretation of mammographic features. Associating the important semantic categories with numeric descriptors and similarity measures has the potential to decrease the variability in lesion description and thus partially in interpretation. Another potential field of applications of lesion numeric descriptors is the CBIR system [8]. In the medical imaging context, the main aim of the CBIR (Content Based Image Retrieval) system is to provide radiologists with a diagnostic aid in the form of a display of cases relevant to the query, with proven pathology and clinical information. According to [8] one of the main obstacles to the use of

CBIR in medicine includes lack of effective representation of the medical content by low-level mathematical features. The key to the successful CBIR system lies in the use of quantitative features reflecting the salient characteristics of the pathologies and appropriate similarity metrics. The relevant salient characteristics of the lesion include not only its diagnosis but also a number of other important features, the morphology in the case of CMCs.

We studied the classification of MCs into the BI-RADS™ morphologic categories. It is assumed that a lesion is already detected and segmented and initially uses only shapes features. The research clue is association of the objective numeric descriptors of MCs with terms used in the BI-RADS™ system for automatic describing morphology of MCs There are some papers [9–11] on classifying of shapes of mammographic masses, which showed promising results, but to the best of the authors knowledge very little work has been done to classify CMCs into the BI-RADS™ morphologic categories.

1.2. The Assumptions and the Stages

The BI-RADS™ system includes terms for describing the calcifications' morphology. The main morphologic types of MCs are punctate (round), pleomorphic and linear. Examples of typical and regular punctate, pleomorphic and linear MCs' clusters are presented in Fig. 1, with schemas in black and white showing typical shapes of the punctate, pleomorphic and linear MCs. The radiologist determines cluster morphology based on the presence and the prevalence of MCs with geometric properties typical for given morphology. If MCs are characterized with a set of descriptors that are able to capture the salient features of their geometry, it should be possible to determine the whole cluster morphology as the mean values of shape descriptors for single microcalcifications. This rather simplified approach assumes that the number of MCS with typical shapes in a cluster is sufficiently large, what is not always true.

As it was reported in [12], shape features (compactness, difference of shape moments ShM1-ShM2 and Fourier shape measure applied to a set of 143 single MCs) can classify MCs as benign or malignant with high accuracy. That's why any classification of MCs based on the shape features should be carefully designed. For the pilot study it was decided to perform classification only on malignant, more irregular MCs. The main reason for this decision was elimination of any interpretation problems due to possible double features' significance and keeping the statistical issues as simple as possible and providing a reasonable number of cases.

To evaluate the appropriateness of shape descriptors (described in more details in section 2), it was decided to conduct a feasibility study by classifying in the first attempt the sets composed of single MCs (SMCs) representing the typical features of the investigated morphologic categories. Not all MCs in a cluster have to be representative for the cluster morphology. For example round MCs can be found in clusters of all morphological types, single pleomorphic MCs more or less regular can also be found in round or linear clusters (see Fig. 1). The three sets were composed of single MCs showing geometrical features of the morphologic categories under investigations, with little irregularity, all MCs have been extracted from malignant clusters. The sets of SMCs were used in three binary classifications: linear – pleomorphic SMCs, linear – round SMCs and pleomorphic – round SMCs. All classification tasks showed very promising results, proving the usefulness of the descriptor set, and the initial set of the shape descriptors was applied to the classification of real lesions as linear CMCs or pleomorphic CMCs. The morphology of typical linear and pleomorphic MCs differ more than in the case of linear and round MCs but less then in the case of round and pleomorphic MCs, representing an intermediate level of difficulty between the three classifications tasks.

The paper is organized as follows: first section introduces the aim of the work, second section describes samples for the two classifications stages, set of shape descriptors, features selection methods and classifier; third part presents classifica-

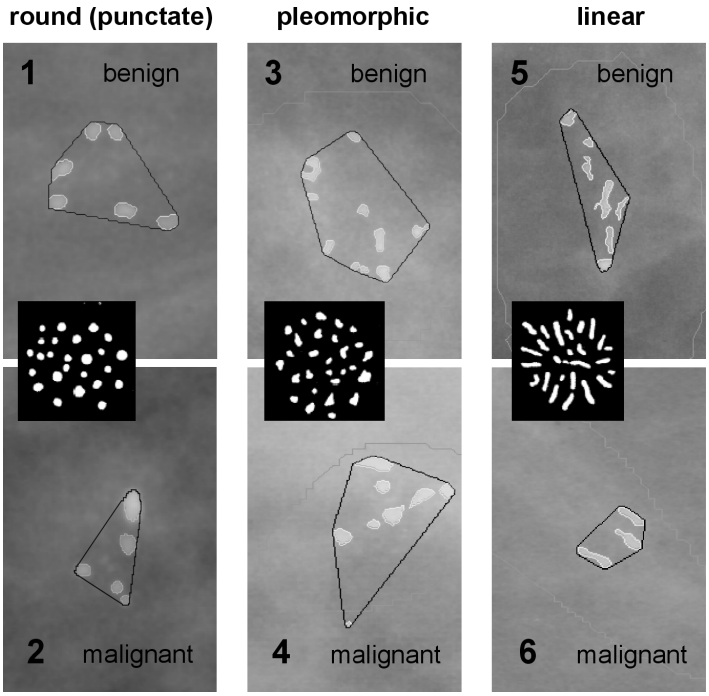

Fig. 1. Examples of typical clustered punctate, pleomorphic and linear MCs presented in panels numbered from 1 to 6. In black quadrant showed in white typical shapes of punctate, pleomorphic and linear MCs. Black envelopes around MCs' (panels 1, 2, 4, 5) – clusters outlines marked by MammoViewer. Ovals in light grey – lesions localization marked in DDSM (panels 3, 5, 6). Morphology of the cluster is important but not always the decisive feature for predicting cluster diagnosis, there are benign and malignant clusters in every morphologic category, but with different probability

tion results: achieved accuracy and the most discriminate features; fourth section concludes the paper.

2. Material and Methods

2.1 Material for the Classifications

The images containing clusters of MCs for this study were obtained from the Digital Database for Screening Mammography, the largest publicly available data-set of digitized mammograms [13]. Material for the classifications of SMCs' sets has been collected from 15 clusters of punctate MCs, 28 clusters of pleomorphic MCs, 10 clusters of linear MCs. Three from linear clusters have been segmented from the area of segmental (segmental MCs occupy large area of the breast). Each set of SMCs, round, pleomorphic and linear contained 120 objects.

Material for the classification of the cluster morphology has been collected from 45 pleomorphic clusters, 37 linear clusters and 7 areas of segmental linear microcalcifications. Data sets for cluster classification into BI-RADS™ morphologic categories consisted of 45 pleomorphic clusters and 44 linear clusters, in total 89 clusters. All the clusters and segmental MCs were segmented from DDSM catalogues containing malignant lesions.

2.2. Features Set, Selection Methods and Classification

MammoViewer [10], a computer aided diagnosis (CAD) application for X-ray mammograms, was used to segment single MCs, MCs clusters and for feature extraction. Shape features were extracted from boundaries of MCs and from binary images of the segmented MCs. The geometric features of MCs were characterized with 27 shape descriptors described in the general literature for shape analysis [15–17] and in the analysis of MCs features [12, 18, 19]. According to their intended role in the morphologic analysis, all these features can be divided into three main groups:

1) general shape features – area, perimeter, shape moments and binary invariants moments and moment ratios (called effective radiuses),

2) shape features reflecting the visual properties of MCs morphology – compactness, elongation, major axis, box ratio, ellipticity and triangularity,

3) features measuring irregularity of the shape – first irregularity descriptor computed as difference of shape moments (ShM3-ShM1) , second irregularity descriptor computed as the squares of distances of contour points from the region centroid and normalized Fourier Shape Measure [20].

Before selection and classification, the features were normalized to have a mean of zero and standard deviation of one. The data in each of four data sets (three sets of single MCs and one of clustered MCs) were randomly sorted and divided into training and testing sets. The training and testing sets for the classification of single

MCs contained 60 objects each, for the classification of CMCs the training and test sets count 45 and 44 clusters respectively.

To reduce the initial set of MCs features Feature Selection and Classification Tool [21] software (FSCT) was applied. The features selection methods implemented in the FSCT which yielded the best classification results are Corrcoef [22, 23], GFlip [24], Simba [19] and Relief [23]. Feature selection resulted in a relatively small feature vector – four descriptors in the case of the sets of SMCs, and three descriptors for CMCs (see section Results). The selected features were employed to differentiate between MCs morphology types using the SVM classifier. The SVM technique [24] was chosen, because of its good performance when applied to data outside the training set [25]. SVM was already applied with good results to the problem of MCs' classification [26–28]. In the case of SMCs' sets the effects of the feature selection on classification accuracy were checked using the SVM classifier embedded in the FSCT, with the RBF kernel recommended for its general good performance, and with the penalty parameter $C = 1$. Classification accuracy for the linear and pleomorphic CMCs was estimated with more precision using the SVM classifier implemented in Data Mining module of Statistica ver. 8.0. Four kernels, linear, polynomial, RBF and sigmoid were checked, and the SVM parameters including the kernel parameters were optimized using embedded cross-validation methodology.

3. Results

Accuracy achieved in classification among the three sets of the single MCs is very high, ranging from 94% to 100%, depending on the classification task (see Table 1). This good result is certainly due to the regularity of MCs' shapes in the three sets.

According to the intuition, the set of the most discriminative features selected by Corrcoef method is the same for both linear – pleomorphic SMCs and linear – round SMCs classification tasks.

Classification accuracy in differentiation of the real lesions, linear and pleomorphic CMCs is lower than accuracy for pleomorphic and linear SMCs' sets because real clusters contain irregular and atypical MCs. For the test sample, the classification accuracy ranges from 84% to 88%, depending on the features and the SVM parameters, the type of kernel functions which yields the best results, sigmoidal and RBF, indicates that the sets of clusters are not linearly separable. Detailed results are presented in the Table 2.

The difference between morphology of typical linear and typical pleomorphic MCs is less than in the case of linear and round MCs, and the set of best discriminative features selected with the CorrCoef method is the same for both classification tasks. Taking it into consideration, it is highly probable that the classification of linear and round CMCs is possible and will yield similar results as the classification of linear and pleomorphic CMCs.

Table 1. Accuracy in three binary classifications among sets of SMCs, SVM classifier with RBF kernel, that indicates that sets of SMCs are not linearly separable and penalty parameter $C = 1$. For all classification tasks training and test sets contained 60 SMCs

Classification Task	Features Selection Method	The Most Discriminate Features	Feature Weight	Classification Accuracy %
Linear–Pleomorphic	CorrCoef	Shape Moment 1	1.00	98
		Shape Moment 3	0.98	
		Inner Compactness	0.92	
		Major Axis	0.91	
Round – Pleomorphic	Simba	Ellipticity	1.00	94
		Bin. Invariant Moment 3	0.87	
		Bin. Invariant Moment 1	0.47	
		Area	0.39	
Round – Pleomorphic	LogRatio	Ellipticity	1.00	94
		Efective Radius 3	0.83	
		Bin. Invariant Moment 1	0.82	
		Bin. Invariant Moment 3	0.81	
Linear - Round	CorrCoef	Shape Moment 1	1.00	100
		Shape Moment 3	0.92	
		Major Axis	0.91	
		Inner Compactness	0.90	
Linear - Round	Simba	Shape Moment 3	1.00	100
		Shape Moment 1	0.92	
		Efective Radius 3	0.75	
		Major Axis	0.51	

Table 2. Classification accuracy for pleomorphic and linear CMCs, γ – parametr of the kernel function, ν – parameter of the error function. Training and test samples contain 45 and 44 clusters respectively. Two of the most discriminate features – compactness and major axis – are the same as for differentiation of pleomorphic SMCs from linear SMCs

Kernel function ; Model parameters; Selection method	The most discriminate features	Classification accuracy (%) for samples		
		training	test	all
Sigmoid; $\gamma=0.3$, $\nu=0.5$; CorrCoef	Binary Invariant Moment 1	86.7	88.6	87.6
	Major Axis			
	Compactness Inner			
RBF; $\gamma=0.3$, $\nu=0.5$ CorrCoef	Binary Invariant Moment 1	84.4	86.4	85.4
	Major Axis			
	Compactness Inner			
Sigmoid; $\gamma=0.5$, $\nu=0.5$; GFlip	Binary Invariant Moment 1	82.2	86.4	84.3
	Roughness = ShM3-ShM1			
RBF; $\gamma=0.5$, $\nu=0.5$; GFlip	Binary Invariant Moment 1	82.2	84.1	83.1
	Roughness = ShM3-ShM1			

In Figure 2 the scatter-plots of the most discriminative features for the classification of linear and pleomorphic MCs are presented. In the case of classification of single MCs' sets with regular shapes, shape moments play the role of the most

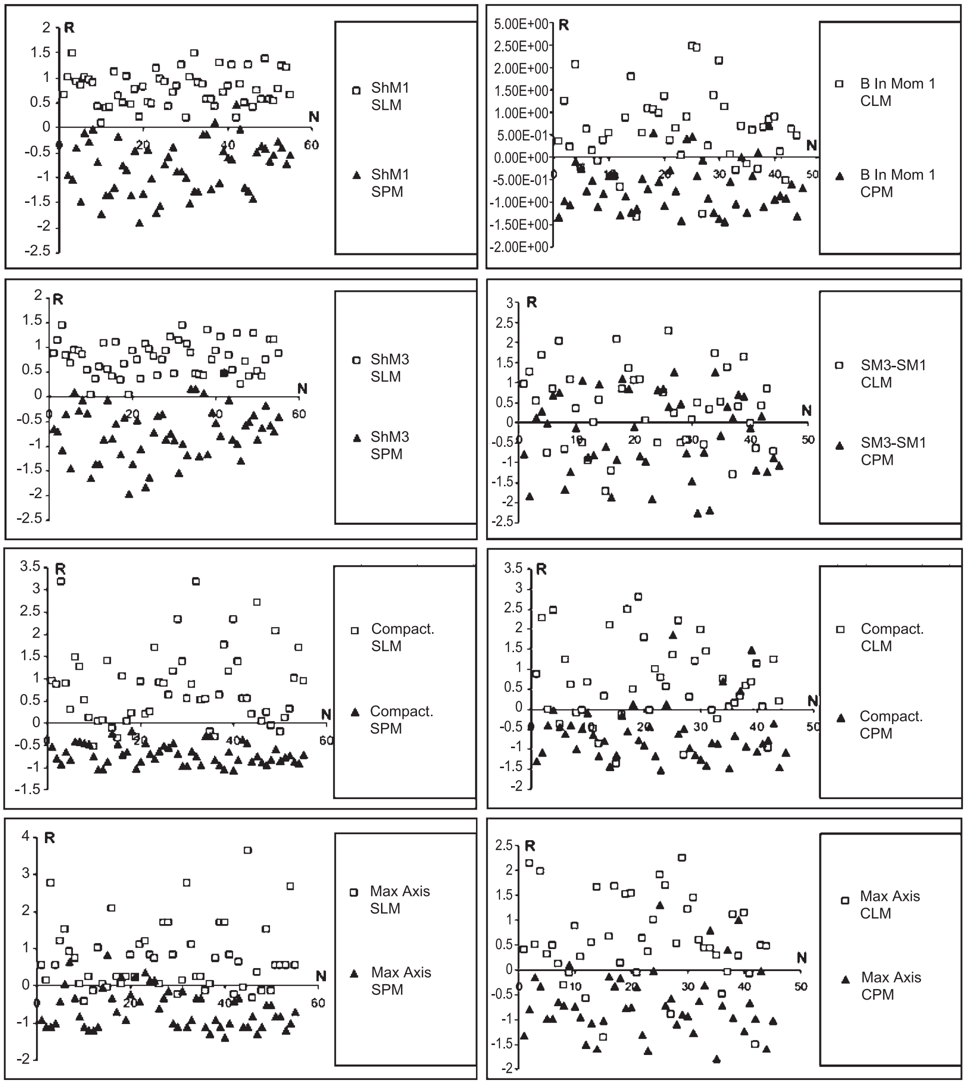

Fig. 2. The scatter-plots of the most discriminative features for the classification of MCs as linear and pleomorphic – on the left for SMCs, on the right for CMCs. On X-axis – object number, on Y-axis – normalized, unit-less feature values. Short-cuts used in the legend: SLM – single linear microcalcifications, SPM – single pleomorphic microcalcifications, compact. – compactness, ShM1 – Shape Moment 1, ShM3 – Shape Moment 3, B In Mom1 – binary invariant moment 1

important features complemented with inner compactness and major axis. In the classification of clustered linear and pleomorphic MCs, the most discriminative features are compactness and major axis, and the shape moments are replaced with the first invariant shape moment, more robust, invariant to scale, rotation and translation shape descriptor.

With the transition from single microcalcifications to clustered shape moments are replaced with more robust, invariant to translation rotation and scale descriptor, binary invariant moment 1, and the descriptor measuring average shape irregularity in ShM3-ShM1 cluster is added (see four bottom panels). Compactness and major axis, two descriptors reflecting the salient differences in microcalcifications' morphology remains among most important discriminative features (see four upper panels) for both SMCs and CMCs.

4. Conclusions

In the paper, the preliminary results for the classification of MCs into the three BIRADS™ morphologic categories (punctate, pleomorphic and linear) have been presented. The research can be divided into two stages. The first consisted of three binary classifications of single MCs' sets using most discriminative features selected from the initial feature set. Achieved high classification accuracy – 100% for classifying of SMCs as linear or round, 98% for classifying of SMCs as linear or pleomorphic and 94% for classifying of SMCs as pleomorphic or round – has been the proof that the proposed feature set is able to carry sufficient information to discriminate among different types of the MCs morphology.

During the second stage the differentiation of the clustered MCs into linear or pleomorphic morphologic types was performed. Obtained accuracy ranges from 84 to 88 %. The cluster morphology is described as mean values of single MCs shape descriptors. This simplified approach limits the area of application to the clusters with sufficient number of MCs with typical shapes. The data sets in both experiments are not linearly separable.

The results of the classification of clustered linear and pleomorphic CMCs show that it is possible to differentiate them into the BI-RADS™ categories with three simple and computationally efficient descriptors, inner compactness, major axis and first invariant moment calculated from binary image with the accuracy ranging from 86 to 88 %.

The presented results should be also confirmed on MCs from benign clusters and future research should extent the lesion feature set to others (i.e. textures, edges) in order to complete diagnostic rules of classification. Moreover, these results should be complemented with similarity metrics to be useful in the CBIR application.

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