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Classification of Small Contrast Enhancing Breast Lesions in Dynamic Magnetic Resonance Imaging Using a Combination of Morphological Criteria and Dynamic Analysis Based on Unsupervised Vector-Quantization

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Abstract

Purpose—To evaluate the diagnostic value of breast magnetic resonance imaging (MRI) in small focal lesions using dynamic analysis based on unsupervised vector quantization in combination with a score for morphologic criteria.

Materials and Methods—We examined 85 mammographically indeterminate lesions (BIRADS 3–4; 47 malignant, mean lesion size 1.2 cm; 38 benign, mean lesion size 1.1 cm). MRI was performed with a dynamic T1-weighted gradient echo sequence (1 precontrast and 5 postcontrast series). Lesions with an initial contrast enhancement $\geq 50\%$ were selected with semiautomatic segmentation. For conventional dynamic analysis, we calculated the mean initial signal increase and postinitial course of all voxels included in a lesion. Secondly, all voxels within the lesions were assigned to 4 clusters using minimal-free-energy vector quantization. Dynamic and morphologic criteria were summarized in a diagnostic score and evaluated by receiver operating characteristic analysis.

Results—In the present collection of small lesions, morphologic criteria [area under the curve (AUC) = 0.610] were inferior to dynamic criteria in the detection of breast cancer. Dynamic analysis with vector quantization (AUC = 0.760) presented slightly better results compared with standard dynamic analysis (AUC = 0.693). There was no benefit for combined morphologic and dynamic analysis.

Conclusion—In small MR-mammographic lesions, dynamic analysis with vector quantization alone tends to result in a higher diagnostic accuracy compared with combined morphologic and dynamic analysis.

Keywords

breast cancer; breast MRI; vector quantization

Contrast-enhanced MR imaging of the breast was reported to be a highly sensitive method for the detection of invasive breast cancer.^{1,2} Different investigators described that certain dynamic signal intensity (SI) characteristics (rapid and intense contrast enhancement followed by a wash out phase) obtained in dynamic studies are a strong indicator for malignancy.³

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Morphologic criteria have also been identified as valuable diagnostic tools.^{4–6} Recently, combinations of kinetic and morphologic characteristics have been reported.^{7–10} Combinations of different dynamic and morphologic scores can reach diagnostic sensitivities up to 97% and specificities up to 76.5%.¹¹ Many of these studies were performed in the preoperative staging of patients with suspicious lesions (BI-RADS 4 and 5) including predominantly tumors with an extension greater than 2cm. In such cases, magnetic resonance imaging (MRI) reaches a very high sensitivity in the detection of invasive breast cancer due to both, the typical appearance (ill-defined shape, stellate borders, and rim enhancement) of malignant tumors and characteristic SI time-courses of contrast enhancement. However, the value of dynamic MRI is not well established in small lesions when clinical findings, mammography, and ultrasound are unclear. In the present study, a multifactorial protocol, including morphologic and dynamic criteria was evaluated in predominantly small lesions (mean size 1.1 cm). Most of malignant lesions were in situ or T1 tumors.

In addition to standard evaluation methods, neural networks have been used previously to analyze complex patterns of SI time series in dynamic MR imaging.^{12–17} The present study investigates the application of unsupervised vector quantization (VQ) in dynamic breast MRI. Unsupervised learning is a method of machine learning where a model is fit to observations. It is distinguished from supervised learning by the fact that there is no a priori output. In unsupervised learning, a data set of input objects is processed, where the goal of the learning procedure is not to identify a classification of the input objects with regard to a given output in the sense of “learning with a teacher,” but to analyze and visualize the input data in an exploratory manner.

In the context of dynamic MR analysis, we obtain, for each pixel, a signal time-series that may be interpreted in the light of the experimental conditions. Here, the difference between “supervised” and “unsupervised” refers to 2 different approaches to the analysis of such dynamic biomedical image time-series data: The first is a model-driven approach that tries to interpret the time-series data as a result of dynamically changing experimental input parameters, given a specific model that defines the pattern of interaction between underlying physiological processes and the observed signal dynamics. This “supervised” cause and effect concept is the mainstream approach to the interpretation of biomedical image time-series data. However, this model-based, supervised data analysis based on the underlying knowledge of experimental conditions and model assumptions, may be difficult or even impossible, see.¹³ Therefore, unsupervised techniques, such as VQ applied in this study, have been increasingly accepted in the literature as an alternative to the conventional supervised model-based approaches. Hierarchical VQ is a method to create subgroups of voxels with similar SI-time courses. According to the literature, it is hoped that such clusters obtained by VQ represent clinically relevant dynamic effects of interest.¹⁸ With this approach, several clusters of prototypical time-series can be calculated.

The purpose of the present study was to evaluate if a VQ-based subdifferentiation of time series within focal lesions in combination with standardized morphologic evaluation by 2 experienced radiologists, could improve diagnostic accuracy in small, previously indeterminate breast lesions. Morphologic and dynamic criteria were evaluated in the total group of selected lesions and within different size groups of lesions.

MATERIALS AND METHODS

Patients

From 1997 to 2003, we performed dynamic breast MRI in 399 patients with indeterminate mammographic breast lesions. All patients were consecutively selected after clinical examination, mammography in standard projections (cranio-caudal and oblique medio-lateral

projections) and ultrasound. Only lesions classified BIRADS 3 and 4 in mammography were selected. In addition, at least 1 of the following criteria had to be present: nonpalpable lesion, previous surgery with extensive scarring, location difficult for biopsy (eg, close to chest wall). Patients with contraindications for MRI (eg, pacemakers, metallic implants) were excluded from the study. All patients gave their informed consent for dynamic breast MRI. Two hundred seventy-three patients had no or minor contrast enhancement in dynamic MRI, meaning an increase of SI below 50% after application of contrast material within the respective lesion. In 2 of these patients a DCIS was confirmed. All other lesions confirmed as benign in follow-up examinations or biopsies. Of the remaining 126 data sets, 44 were excluded because of either a diffuse contrast enhancement of breast parenchyma, major movement artifacts, or missing follow-up data. Remaining 85 focal lesions (from 82 patients), were analyzed.

Histologic findings were malignant in 47 and benign in 25 lesions. Another 13 lesions were classified as benign by follow-up examinations for more than 24 months. Lesion size was derived from mammography images. Mean size of malignant lesions was 1.2 cm (median = 1.0 cm, range = 0.4–3.5 cm), mean size of benign lesions was 1.1 cm (median = 0.9 cm, range = 0.3–3.0 cm).

MR Imaging

MRI was performed on a 1.5 Tesla system (Magnetom Vision, Siemens, Germany) equipped with a dedicated surface coil to enable simultaneous imaging of both breasts. Patients were placed in a prone position. First, transversal images were acquired with a STIR (short TI inversion recovery) sequence (TR = 5600 milliseconds, TE = 60 milliseconds, FA = 180 degrees, TI = 150 milliseconds, matrix size 256×256 pixels, slice thickness 4 mm). Then a dynamic T1-weighted gradient echo sequence (3D fast low angle shot sequence (FLASH); TR = 12 milliseconds, TE = 5 milliseconds, FA 25 degrees, matrix size 256×256 pixels, FOV 350 mm, effective slice thickness 4 mm) was performed in transversal slice orientation. The direction of phase encoding was selected right to left to avoid pulsation artifacts. The dynamic study consisted of 6 measurements, each with a measurement time of 83 seconds, and an interval of 110 seconds. The first frame was acquired before injection of paramagnetic contrast media (gadopentate dimeglumine, 0.1 mmol/kg body weight, Magnevist, Schering, Germany) immediately followed by the 5 other measurements.

Morphologic Data Analysis

The initial localization of suspicious breast lesions was performed by computing subtraction-images, ie, subtracting the image data of the first from the fourth acquisition. A correlation and localization of lesions was performed under consideration of corresponding mammographic images by 2 experienced radiologists. For evaluation of morphologic characteristics, we used a score system proposed by Baum et al¹⁰ which takes the margin and the shape of hypervascularized lesions into account. Moreover, the pattern of contrast enhancement within the lesion was evaluated. Evaluation of morphologic criteria and respective score assignment was performed by 2 experienced radiologists with long lasting experience in the interpretation of breast MRI. Score values were collected after readers had reached a consensus. Formulas used for the calculation of the appropriate scores are presented in Table 1.

Dynamic Data Analysis—Standard Method

As a first step, the respective lesion had to be segmented from the total image information. Data processing was performed with a software application based on IDL (IDL Research Systems, Inc. Boulder, Colorado). In an automated approach, all pixels with an initial signal increase of at least 50% were marked. Subsequently, the respective lesion was extracted with a region growing algorithm. With this method, a voxel within each lesion was selected by mouse-click, and all adjacent voxels, also those from neighbor slices, were included in the

segmentation. So, the 3-dimensional extension of the lesion was taken into account.¹⁹ Lesion segmentation as a preparative step for dynamic analysis was performed by only 1 observer. To test the stability of the method, the interobserver-variability was analyzed in a sample of 20 lesions. For conventional data analysis, we calculated the mean initial signal increase and the mean postinitial signal course of all voxels in the segmented lesion. The initial contrast enhancement was calculated according to the following equation:

$$(SI_{2nd \text{ frame postcontrast}} - SI_{precontrast})/SI_{precontrast} \times 100 [\%]$$

The postinitial signal course was calculated as:

$$(SI_{5th \text{ frame postcontrast}} - SI_{\text{maximum 1st to 2nd frame postcontrast}})/SI_{\text{maximum 1st to 2nd frame postcontrast}} \times 100 [\%]$$

Three types of postinitial SI curves were defined: continuous increase (increase >10%); plateau (deviation of the signal curve between +10 and -10%); and wash out (decrease >10%). Depending on the correlation between the described evaluation criteria and the probability of malignancy 0 to 2 points were given for each of the criteria (Table 2).

Dynamic Data Analysis—VQ

VQ represents a fast clustering technique grouping image pixels together, based on the similarity of their SI profile in time. In the clustering process, a time course with n points is represented by 1 point in an n -dimensional Euclidean space, which is subsequently partitioned into clusters based on the proximity of the input data. These groups or clusters are represented by prototypical time-series called codebook vectors (CV) located at the center of the corresponding clusters. The details of the method were described previously.^{10,12,17,20} VQ approaches determine the cluster centers w_i by an iterative adaptive update based on the following equation:

$$\vec{w}_i(t+1) = \vec{w}_i(t) + \varepsilon(t) a_i [\vec{x}(t), C(t), k] [\vec{x}(t) - \vec{w}_i(t)]$$

where $\varepsilon(t)$ represents the learning parameter, a_i a codebook $C(t)$ dependent cooperativity function, κ a cooperativity parameter, and χ a randomly chosen feature vector.

In the fuzzy clustering technique based on deterministic annealing, the update equation for the CVs can be derived from Eq. (1) as a so-called softmax activation function, where the outputs lie in the interval [0,1] and sum up to 1. Given this setting, the learning rule¹ describes a stochastic gradient descent on an error function which is free energy in a mean-field approximation. The algorithm starts with 1 cluster representing the center of the whole data set. Gradually, the large clusters split up into smaller ones representing smaller regions in the feature space. This represents a major advantage over fuzzy c-means clustering since this algorithm does not employ prespecified cluster centers.

We did not apply additional normalization to the SI-time curves, to include information about the signal amplitude. The computer application assigns the SI-time courses of all voxels to a number of prototypical time series (CV) using the method of minimal distance. In the present study, we defined the number of CV for each lesion to be $n = 4$. Voxels assigned to 1 codebook vector were superimposed with the morphologic images (cluster assignment maps (CAM)). For each codebook vector, the initial signal increase and the postinitial signal course were

calculated. Subsequently, the CV were classified according to the score system for dynamic evaluation described above (Table 2).

Statistics

For statistical evaluation, the codebook vector with the highest score was compared with the score derived from conventional dynamic analysis. In addition, the average score of the 4 CV was calculated. Finally, we compared the mean score values of malignant and benign breast lesions concerning morphologic evaluation, conventional dynamic evaluation and VQ, taking the lesion size into account. Receiver operating characteristic (ROC) analysis was performed for the score values of morphologic data, standard dynamic data, and dynamic data derived from VQ. In addition, ROC analysis for combined morphologic and dynamic analysis was computed. ROC analysis was performed using SPSS (standard version 14.0; SPSS; Chicago, IL). Paired comparisons of ROC curves from different evaluation methods (morphologic, dynamic, and combinations) were performed and *P* values were calculated.

RESULTS

Histologic Findings

Histologic findings were malignant in 47 lesions (8 DCIS, 24 invasive ductal carcinoma, 9 lobular carcinoma, 2 undifferentiated carcinoma, 1 medullary carcinoma, 1 adeno carcinoma, 1 papillary carcinoma, 1 hemangiopericytoma). According to the TNM classification, the malignant lesions were subdivided in 8 Tis, 3 T1a, 15 T1b, 18 T1c, 3 T2 tumors. 38 lesions were proven as benign (10 intraductal epithelial proliferations, 6 fibroadenoma, 4 scars, 2 papilloma, 2 granuloma, 1 benign lymph node, 13 benign in follow-up).

Score Differences in Different Size Group

All lesions were subdivided into 3 groups according to their lesion size in mammography. Group 1 comprised lesions ≤ 1 cm (24 malignant and 24 benign lesions). Group 2 included lesions >1 cm and ≤ 2 cm (20 malignant and 11 benign lesions). Lesions >2 cm (3 malignant and 3 benign lesions) were assigned to group 3. In the MR images, the mean number of voxels within the lesions was 69 in group 1, 280 in group 2, and 802 in group 3. Data analysis of the morphologic scores from benign and malignant lesions showed the smallest differences in score values of lesions ≤ 1 cm. The difference was greatest in lesions >2 cm (Table 3). Scores derived from benign and malignant lesions in standard dynamic analysis showed the greatest difference in lesions between 1 and 2 cm (Table 4). In lesions ≤ 1 cm dynamic data analysis performed best after VQ, when using the highest dynamic score of the 4 CV for lesion characterization (Table 5). There was no benefit when using the mean cluster score of all CV for the estimation of malignancy (Table 6).

ROC Analysis

At first, ROC analysis for solely morphologic criteria, using the score of morphologic evaluation (range 0–4 points), was computed. In a second step, ROC curves for dynamic analysis derived from the standard evaluation method were compared with the ROC curves computed from VQ. The cluster with the highest score value (range 1–4 points) was selected for characterization of each lesion. For combined analysis of morphologic and dynamic criteria, the total of each morphologic and corresponding dynamic score value (with and without VQ) was calculated (range 1–8 points). For morphologic criteria, an area under the curve (AUC) of 0.610 [standard deviation (SD) = 0.061] was found (Fig. 1). The discrimination from the null-hypothesis (AUC = 0.5) was not statistically significant ($P < 0.082$). For the standard dynamic score the AUC was 0.693 (SD = 0.058), compared with 0.760 (SD = 0.054) for the dynamic score based on VQ (Fig. 2). Discrimination from null-hypothesis reached a higher level of

significance using VQ compared with using the standard method ($P < 0.0001$ compared with $P < 0.02$). ROC analysis for the total score of combined morphologic and dynamic criteria resulted in an AUC of 0.682 (SD = 0.058) for standard evaluation and an AUC of 0.722 (SD = 0.056) for VQ (Fig. 3). Results of ROC analysis, including SD, confidence intervals and P -values (discrimination from null-hypothesis) are summarized in Table 7. AUC values for standard dynamic analysis and for dynamic analysis based on VQ did not differ significantly ($P < 0.4$). The difference of AUC values for combined morphologic and dynamic analysis was either not significant ($P < 0.7$).

Interobserver Variability for Lesion Segmentation

The evaluation of the total study was performed with only 1 observer. To test the stability of lesion segmentation, we analyzed the interobserver-variability in a sample of 20 lesions. Lesion sizes (number of voxels included in each lesion) were determined by 2 unbiased observers. A high correlation ($R^2 = 0.98$) was found.

Example

Figure 4A–D shows an example of a 66-year-old woman with previous breast-conserving therapy. The small focal lesion in the left breast was classified BIRADS III in mammography. Preceding images were not available. Breast MRI shows an unclear lesion in the left breast. Description of the figures is provided in detail within figure legends.

DISCUSSION

Morphologic Evaluation

The purpose of the present study was to evaluate whether a VQ-based subdifferentiation of SI time series within focal MR-mammographic lesions and a combination with morphologic evaluation could improve diagnostic accuracy in small, indeterminate breast lesions.

In this study, morphologic criteria tended to perform worse compared with dynamic criteria in the detection of breast cancer. Previous studies in the field of MR mammography described morphologic features like spiculated margin and rim-enhancement as valuable criteria for malignancy.^{3–5} Many studies included predominantly preoperative patient groups containing lesions of an average size of 2 cm or higher. We selected mammographically indeterminate lesions (BIRADS 3 and 4) for further MR evaluation, to arrange a group of diagnostically challenging lesions. This resulted in a small mean lesion size very close to 1 cm in subsequent MRI evaluation. In our study, the presence of typical morphologic patterns for the evaluation of malignancy was most frequent in lesions >1 cm. In small focal lesions, for the most part, these criteria were absent. As a consequence, the prevalence of specific morphologic criteria as diagnostic markers for malignancy was quite small. Better results may be achieved when optimizing acquisition protocols for higher spatial resolution and fat-suppressed contrast-enhanced images. Breast MRI on scanners with higher field strengths (3T) might be able to improve signal-to-noise ratio and decrease slice thickness. A recent study at 3T indicates significant improvements concerning spatial resolution despite short acquisition time for a high temporal resolution.²¹ These factors may contribute to an improved morphologic characterization, especially in small lesions.

Dynamic Evaluation

Dynamic analysis based on VQ improved diagnostic accuracy in small lesions compared with morphologic criteria and compared with standard dynamic analysis, however, findings were not statistically significant. Predominantly in small lesions, a subdifferentiation of different time series within focal lesions tended to provide an additional benefit (Tables 4, 5). Different

studies from other workgroups have described the diagnostic value of neural networks in the evaluation of suspicious lesions in breast MRI. Lucht et al have found a diagnostic accuracy of 80% in 243 suspicious lesions, which is comparable to our findings.²² However, an ROC analysis had not been performed in that work.

Compared Evaluation of Dynamic and Morphologic Score

Dynamic analysis based on VQ presented slightly better results compared with standard dynamic analysis. There was no benefit for combined morphologic and dynamic analysis compared with isolated dynamic analysis, the differences were not statistically significant. When looking at the results of stand-alone morphologic evaluation this is not surprising. The relatively poor performance of the morphologic scores is somewhat comparable with findings in magnetic resonance elastography studies. Both methods fail once the lesions are getting too small.²³

Cluster Validity

Because of the predominantly small lesion size in the present population, the number of clusters for each lesion was defined $n = 4$. The appropriate choice of the number n of clusters is a difficult issue and refers to the so called “cluster validity problem” which can be considered as an unsolved problem of unsupervised learning in general.²⁴ Although a wide range of so-called “cluster validity indices” have been proposed in the literature to cope with this problem, they are mostly of limited value in practical pattern recognition applications, as already shown by eg.,²⁵ We have performed extensive analyses referring to the cluster validity problem in the field of MR time-series clustering for other applications.²⁶ However, the current choice of $n = 4$ was based on grounds of practicability rather than on a calculation of a cluster validity index. If the number (n) of clusters is chosen too small, an appropriate lesion subdifferentiation regarding different signal patterns within a lesion cannot be performed. Vice versa, if n is chosen too large, the number of voxel time-series assigned to each cluster would be too small to represent prototypical signal patterns within the lesion. Our choice of $n = 4$ was taken as a compromise between these 2 divergent requirements.

Impact on CAD Systems and MR Guided Biopsy

The classification between benign and malignant lesions in breast MRI based on dynamic analysis tends to result in an improvement of lesion characterization using VQ, as quantitatively demonstrated by ROC analysis. Recently, color-coded visualization tools have been established to simplify the diagnostic workflow in breast MRI.²⁷ Color-coding of different clusters within a lesion might further improve practicability of the method. We conjecture that the approach used in this work can be usefully integrated in CAD systems to improve the practicability of such systems.^{19,28} Other groups have confirmed that clustering methods can be useful for CAD in dynamic MR mammography.²⁹ In larger areas with diffuse enhancement, VQ and color-coding of enhancement characteristics might simplify the localization of areas that are most relevant for tissue biopsy. MRI-guided biopsy has been introduced into clinical routine and is relevant in lesions that are occult on other imaging modalities.³⁰ Recently, automated devices for MR-guided breast biopsies and preoperative localization have been developed and might simplify the interventional workflow in the near future.^{31,32}

Limitations of the Study

The relatively high number of exclusions can be seen as a limitation of the present study. This was predominantly caused by data sets with movement artifacts. In the presence of movement artifacts, the analysis of pixel-specific contrast agent uptake-curves, such as by cluster analysis used in this article, cannot be performed properly. Therefore, the integration of appropriate movement correction methods is an important topic in further research work. Lesion

segmentation was performed automatically by a region growing algorithm after positioning a seed within the lesion. Only voxels with an initial enhancement of $\geq 50\%$ were marked and included into further analysis. Improved region growing algorithms might be able to define margins in a more flexible approach. As a stop criterion of lesion segmentation, the maximization of the interclass variance between tumor and background voxels has been described.³³

The differentiation of fibrocystic changes from malignant tumors is challenging. Morphologic characteristics like a non-mass-like regional enhancement have been described.³⁴ Additionally, SI time curves predominantly show a continuous signal increase in such tissue areas. Extraction of focal lesions from laminar enhancing areas might be feasible with VQ and should be evaluated in the future. In the present study, areas with diffuse enhancement were excluded.

In conclusion, dynamic analysis with VQ alone tended to result in a higher diagnostic accuracy compared with combined morphologic and dynamic analysis in the present study population. Morphologic information did not improve the diagnostic accuracy. VQ might be a valuable diagnostic tool which could be integrated in CAD applications to support a subdifferentiation of MR-mammographic lesions.

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ROC Analysis

FIGURE 1.

ROC analysis of morphologic criteria; AUC = 0.610, SD = 0.061, $P < 0.061$. At first, only morphologic criteria were applied to the relatively small lesions in this study. The study included only BIRADS 3 and 4 lesions. There was only little diagnostic value for solitary morphologic evaluation in these predominantly small lesions. [AUC = area under the curve, SD = standard deviation, CI = confidence interval (95%), P = statistical significance, discrimination from null hypothesis (AUC = 0.5)].

FIGURE 2.

Comparison of dynamic scores derived from standard evaluation (AUC = 0.693, SD = 0.058) and analysis based on vector quantization (AUC = 0.760, SD = 0.054). The study included only BIRADS 3 and 4 lesions. The score for dynamic analysis performed slightly better if applied to values derived from vector quantization. The level of significance was $P < 0.02$ for standard dynamic evaluation and $P < 0.0001$ for evaluation based on vector quantization. [AUC = area under the curve, SD = standard deviation, CI = confidence interval (95%), P = statistical significance, discrimination from null hypothesis (AUC = 0.5)].

FIGURE 3.

Combination of morphologic criteria and standard dynamic criteria (AUC = 0.682, SD = 0.058) and combination of morphologic criteria and dynamic criteria after vector quantization (AUC = 0.722, SD = 0.056). The study included only BIRADS 3 and 4 lesions. *P*-values (null-hypothesis) were $P < 0.004$ for standard dynamic analysis and $P < 0.0001$ for values determined from vector quantization. In the present collection of small focal lesions, morphologic criteria could not improve the diagnostic value of the method compared with dynamic evaluation alone. [AUC] area under the curve, SD = standard deviation, CI = confidence interval (95%), *P* = statistical significance, discrimination from null hypothesis (AUC = 0.5)].

FIGURE 4.

A–D, Study of a 66-year-old woman with breast-conserving therapy 10 years ago (right breast). Mammographic examination displayed a newly developed nodular lesion without microcalcifications (size 1 cm) in the left breast. A, displays a small contrast-enhancing lesion in left lateral position. Morphologic lesion characterization of MR-images scored 0 points (oval shape = 0 points, well-defined border = 0 points, homogenous contrast enhancement = 0 points). Standard dynamic analysis shows an initial signal increase of 89% followed by a plateau in the postinitial contrast phase, resulting in a score of 2 points (B). Subsequently, vector quantization of the respective lesion was performed. The signal intensity time-courses of each cluster ($n = 4$) are displayed in C. Cluster assignment maps show the distribution of voxels within the 4 clusters (D). Cluster 0 shows a strong initial signal increase (184%) followed by a wash-out phase (–22%), resulting in a score of 4 points. Clusters 1, 2, and 3 show minor or moderate initial enhancement followed by a plateau phase. Histologic examination of the enhancing lesion presented a ductal in situ carcinoma (DCIS).

TABLE 1

Score System for Morphological Evaluation, Baum et al, 2002.¹⁰ All Focal Lesions Were Evaluated According to This Table. Values Were Collected in a Statistical Analysis File

Points	0	1	2
Shape	Round	Dendritic	—
	Oval	Irregular	—
Border	Well-defined	Ill-defined	—
Contrast enhancement	Homogeneous	Inhomogeneous	Rim-enhancement

TABLE 2Evaluation of Signal-Intensity Curves Were Evaluated According to the Score Proposed by Baum et al, 2002¹⁰

Points	0	1	2
Initial signal increase (%)	<50	50–100	>100
Postinitial signal course	Continuous increase [*]	Plateau [†]	Wash out [‡]

^{*} >+10%.

[†] Ranging from +10 to –10%.

[‡] <–10%.

TABLE 3

Morphologic Scores in Different Size Groups. Solitary Morphologic Evaluation for Determination of Malignancy Performed Best in Lesions >2 cm. In Lesions ≤ 1 cm the Morphologic Score Does Not Provide Valuable Diagnostic Information

	Lesion Size		
	≤ 1 cm	[>1 cm; ≤ 2 cm]	>2 cm
Score malignant lesions	1.13	2.05	3.00
Score benign lesions	0.83	1.64	1.67
Difference malignant – benign	0.29	0.41	1.33

TABLE 4

Dynamic Scores After Standard Calculation of SI Time Curves. The Discrimination Between Benign and Malignant Lesion Was Best in Lesions Between 1 and 2 cm in Size. In Lesions ≤ 1 cm Standard Dynamic Evaluation Produces a Poor Result

	Lesion Size		
	≤ 1 cm	[>1 cm; ≤ 2 cm]	>2 cm
Score malignant lesions	2.13	2.80	2.67
Score benign lesions	1.92	1.55	1.67
Difference malignant – benign	0.21	1.25	1.00

TABLE 5

Dynamic Scores of SI Time Curves After VQ. The Cluster With the Highest Score Was Used as a Base for Descriptive Analysis. Compared With the Standard Method, VQ Improves the Performance of the Score Predominantly in Lesions ≤ 1 cm

	Lesion Size		
	≤ 1 cm	[>1 cm; ≤ 2 cm]	>2 cm
Score malignant lesions	3.25	3.45	3.67
Score benign lesions	2.58	2.27	2.67
Difference malignant – benign	0.67	1.18	1.00

TABLE 6

Dynamic Scores of SI Time Curves After VQ. The Mean Cluster Score Was Used as a Base for Descriptive Analysis. No Improvement Was Observed Compared With the Calculation in Table 5

	Lesion Size		
	≤ 1 cm	>1 cm; ≤ 2 cm]	>2 cm
Score malignant lesions	2.26	2.53	2.67
Score benign lesions	1.80	1.52	1.75
Difference malignant – benign	0.46	1.00	0.92

TABLE 7

ROC Analysis of Different Combinations of Evaluation Criteria in Small Focal Lesion Produces Best Results for VQ-Based Evaluation of SI Time Curves, When the Cluster With the Highest Score Was Used for Lesion Characterization. In the Present Study Population, Which Predominantly Included Lesions <1 cm, Morphologic Criteria Did Not Add a Diagnostic Value To The Performance of Contrast-Enhanced Breast MRI

	AUC	SD	CI	P
Morphologic criteria	0.610	0.061	0.490–0.730	0.082
Dynamic criteria (standard evaluation)	0.693	0.058	0.580–0.806	0.02
Dynamic criteria (vector quantization)	0.760	0.054	0.654–0.866	0.0001
Morphologic and dynamic criteria (standard evaluation)	0.682	0.058	0.568–0.795	0.004
Morphologic and dynamic criteria (vector quantization)	0.722	0.056	0.612–0.831	0.0001

AUC indicates area under the curve; SD, standard deviation; CI, confidence interval (95%); P, statistical significance, discrimination from null hypothesis (AUC = 0.5).