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Assessing the performance of the normalised radial length and convex polygons in distinguishing breast tumours on ultrasound images

Avaliação do desempenho da distância radial normalizada e dos polígonos convexos na distinção de tumores de mama em imagens por ultra-som

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Abstract
This work aims at investigating the potentiality of morphometric parameters in distinguishing breast tumour on ultrasonic images. At first, a segmentation procedure, based on Mathematical Morphology, was applied to depict the tumour contours. Then, seven parameters of the normalised radial length and of convex polygons were extracted from 152 segmented tumour images. The Linear Discriminant Analysis was applied and the parameters performances in discriminating irregular from regular breast tumour contours, and also malignant from benign ones were assessed. In distinguishing tumour contours, the best performances for individual parameters were normalised residual mean square value (*nrv*) and circularity (*C*). Taking these two parameters together with roughness (*R*) led to the best separation performance, i.e., specificity of 96.7% and sensitivity of 95.7%. Furthermore, in distinguishing malignant tumours from benign ones, the best performance (sensitivity = 88.0%, specificity = 90.4%) was achieved by using also the combining parameters *nrv*, *C* and *R*. These findings confirm the relation between the contour irregularity and the possibility to establish a diagnostic hypothesis. Therefore, these three parameters together may aid the diagnostic of breast tumour on ultrasound images.
Keywords: Normalised radial length, Convex polygon, Breast tumours, Ultrasound.

Resumo
Este trabalho tem como objetivo investigar a pontencialidade de parâmetros morfométricos em distinguir tumores de mama em imagens por ultra-som. Para tal, aplicou-se um método de segmentação baseado em Morfologia Matemática para determinar o contorno dos tumores. Assim, sete parâmetros morfológicos foram calculados a partir das técnicas de distância radial normalizada e polígonos convexos, para as 152 imagens segmentadas. A análise discriminante linear foi aplicada, e o desempenho dos parâmetros na distinção dos tumores de mama em irregular ou regular, bem como entre maligno ou benigno, foi avaliado. O melhor desempenho na distinção dos tumores quanto ao contorno (irregular ou regular) foi obtido com os parâmetros valor médio quadrático residual normalizado (nrv) e circularidade (C). Tomando estes dois parâmetros em conjunto com a rugosidade (R), resultou no melhor desempenho (especificidade e sensibilidade de 96,7% e 95,7%, respectivamente). Na distinção dos tumores entre maligno ou benigno, o melhor desempenho foi obtido para este mesmo conjunto (nrv, C e R), com valores de 88,0% de sensibilidade e 90,4% de especificidade. Tais achados confirmam a relação entre a irregularidade do contorno e o estabelecimento de hipótese diagnóstica, indicando que nrv, C e R juntos podem auxiliar no diagnóstico de tumores de mama em imagens por ultra-som.
Palavras-chave*: Distância radial normalizada, Polígonos convexos, Tumor de mama, Imagem ultra-sônica.*

Introduction

Mammography has been considered as the only diagnostic technique that contributes, through a periodic accompaniment program, to early detection and mortality reduction by breast cancer (Skaane, 1999). However, mammography accuracy depends on the composition of mammary parenchyma and tumour tissue characteristics, since a dense parenchyma can mask a tumour (Azevedo, 1994). Besides, a considerable number of suspicious solid masses are usually recommended to surgical biopsy (Dennis *et al*., 2001) although only 10% to 30% of them are malignant (Horsch *et al*., 2002). Thus, breast examination through ultrasound (US) images has been used as the most important complementary exam for patients with palpable mass and inconclusive mammograms (Skaane, 1999).

Morphologically, benign tumours generally present regular and well-defined contours on US images (Hagen-Ansert, 2003), while malignant ones usually infiltrate adjacent tissues thus producing irregular and angled edges (Chou *et al*., 2001). Hence, contour analysis from breast solid tumours, using US images, has potential to aid in reducing biopsies carried through benign tumours (Rahbar *et al*., 1999).

In this work, potentiality of morphometric parameters in distinguishing breast tumour on ultrasonic images is investigated. Firstly, tumour contours are depicted using a segmentation procedure (Alvarenga *et al*., 2003), based on Mathematical Morphology. Then parameters extracted from the Normalised Radial Length (NRL) (Chou *et al*., 2001) and from Convex Polygons (Alvarenga *et al*., 2004) are estimated. Finally, the performance of these parameters in distinguishing irregular from regular tumours contours, and also malignant from benign ones is assessed.

Material and Methods

Database

One hundred and fifty-two breast US images (with the respective diagnostics) were acquired in TIF format, using a 7.5 MHz US transducer (*Sonoline – Sienna® Siemens*) at the Brazilian National Cancer Institute (INCa). The tumour contours were determined by a segmentation method (the Semi-Automatic Contour procedure – SAC) based on morphological operators (Alvarenga *et al*., 2003), as illustrated for an irregular contour of a malignant breast tumour (Figure 1a) and for a benign one (Figure 1b). Furthermore, an experienced radiologist classified all tumour contours as irregular (92) or regular (60). The histopathological diagnoses were also established, resulting in 100 malignant and 52 benign tumours.

Morphometric Parameters

For each SAC-defined contour with a perimeter *P*, Normalized Radial Length (NRL) is calculated as (Chou *et al*., 2001):

$$d_n(i) = \frac{d(i)}{\max[d(i)]} \tag{1}$$

where $d(i) = \sqrt{(x(i) - X_0)^2 + (y(i) - Y_0)^2}$, $1 \le i \le N$ (X_0, Y_0) and $(x(i), y(i))$ are the coordinates of the centroid and of the i^{th} pixel on *P*, respectively. *N* is the number of pixels on *P* and $\max[d(i)]$ is the maximum value of the radial length (normalised factor).

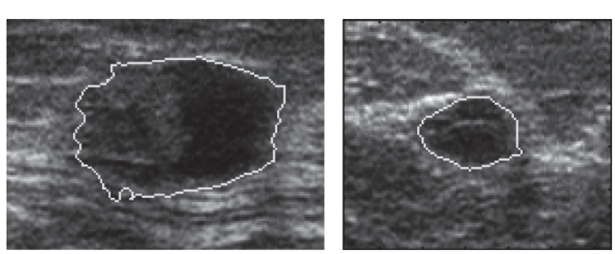
From equation (1), three parameters are obtained: standard deviation (D_{NRL}), area ratio (*RA*) and contour roughness (*R*). The first, as a measure of contour variations is expressed as (Chou *et al*., 2001):

$$D_{NRL} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(d_n(i) - \bar{d}_n)^2} \tag{2}$$

where $\bar{d}_n$ is the mean value of $d_n(i)$ and can be interpreted as the radius of a circular region. By taking into account the number of times $d_n(i)$ is greater than $\bar{d}_n$, *RA* measures the percentage of the tumour which is outside this circular region, that is (Chou *et al*., 2001):

$$RA = \frac{1}{\bar{d}_n \cdot N}\sum_{i=1}^{N}(d_n(i) - \bar{d}_n) \tag{3}$$

where $d_n(i) - \bar{d}_n = 0 \quad \forall\, d_n(i) \le \bar{d}_n$. Therefore, *RA* in-



(a) **(b)**

Figure 1. Contour established by SAC for (a) malignant tumour and (b) benign one.

creases with the number of pixels outside the circular region and so with contour irregularity.

Contour roughness can be defined as the average distance between neighbouring pixels over tumour contour (Chou *et al*., 2001):

$$R = \frac{1}{N}\sum_{i=1}^{N}\left|d_n(i) - d_n(i+1)\right| \quad (4)$$

With such a definition, R increases with contour irregularity.

The convex polygon (S_o), which contains the contour, is established for each region (S) indicated by SAC-defined contour. As illustrated in Figure 2, the more irregular is the contour, the greater is the difference from its convex polygon. This feature can be quantified using two parameters: overlap ratio (RS) and normalised residual mean square value (nrv). The parameter RS is given by (Horsch *et al*., 2001):

$$RS = \frac{Area(S_o \cap S)}{Area(S_o \cup S)} \;\therefore\; RS = \frac{Area(S)}{Area(S_o)} \quad (5)$$

where the symbols $\cap$ and $\cup$ indicate the intersection and union, respectively. The S, S_o and $Area(.)$ are in number of pixels. If S and S_o have the same shape and size and also are in the same position, $RS = 1$.

The residual region (S_r) can be calculated as (Infantosi *et al*., 1998):

$$S_r = \left|Area(S_o) - Area(S)\right| \quad (6)$$

and if S and S_o are identical (shape and size) and also in the same position then $S_r = 0$. Based on equation (6), nrv is expressed as:

$$nrv = \frac{\psi_r^2}{\psi_o^2} \quad (7)$$

where ψ_r^2 and ψ_o^2 are the mean squared values of S_r area and the convex polygon perimeter (P_o), respectively. Instead of using P_o, the S_o area could be used in the definition of equation (7), as pointed out by Infantosi *et al*. (1998). Nevertheless, considering nrv as a ratio between the residual area and convex polygon perimeter, the sensitivity of nrv is improved (Alvarenga *et al*., 2004).

Two other parameters are also calculated, i.e., the circularity (C) and the morphological-closing ratio (*Mshape*). The first has been pointed out as an important parameter in correct classifying breast tumours (Chou *et al*., 2001). It is defined as:

$$C = \frac{P^2}{Area(S)} \quad (8)$$

As the overlap ratio, *Mshape* is also defined as an area ratio but it considers the morphological-closing area (S_c) instead of the convex polygon (S_o) which contains the contour, that is:

$$Mshape = \frac{Area(S)}{Area(S_c)} \quad (9)$$

This morphological operator allows filling small holes and gaps (possible missing data) on SAC-defined contour (Soille, 1999). By applying this operator, the morphological-closing area (white in Figure 3) tends to be greater than S area (grey in Figure 3). Hence, the more irregular is contour, the smaller is *Mshape*.

Performance Assessment

Linear Discriminant Analysis (LDA) is applied to all possible combinations of the seven parameters calculated (normalised between 1 and -1). This technique, commonly used for data classification and dimensionality reduction, maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separation. More details can be found elsewhere (Discriminant Function Analysis - Electronic Statistics Textbook, 2006). The parameters combinations performance in distinguishing between irregular and regular breast tumour contours is assessed in terms of accuracy (Ac), sensitivity (Se), specificity (Sp) (details in Appendix) and the area A_z under the Receiver Operator Character-

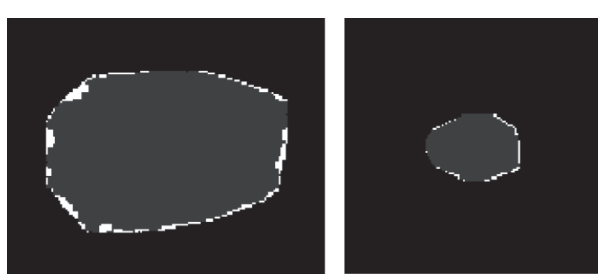


Figure 2. Convex polygon (in white) of segmented breast tumours using SAC: (a) irregular (malignant) and (b) regular (benign).

(a) **(b)**

Figure 3. *Morphological-closing* area (in white) of the defined segmented breast tumours using SAC: (a) irregular and (b) regular.

istic (ROC) curve. The ROC curve consists of a variety of sensitivity-specificity pairs, which are generated by changing the threshold over LDA results. Further details regarding ROC curve computation are available elsewhere (The magnificent ROC, 2006).

Results

The performance of each one of the seven parameters in distinguishing irregular from regular tumours for all 152 US images is presented in Table 1. Based on A_z, the best performance is achieved by *nrv* (0.97) and the worst by *Mshape* (0.55). Also, the highest values of accuracy (93.4%) and specificity (91.7%) are obtained to *nrv*. On the other hand, although *Mshape* has presented the highest sensitivity (95.7%), it leads to a low accuracy (60.5%) and the lowest specificity (6.7%). Among the parameters calculated from Normalized Radial Length parameters, the highest *Ac* are reached by D_{NRL} and *RA*, with similar values of *Se* and *Sp*, while *R* results in the second lowest accuracy among the seven parameters studied. Based on A_z, parameter *C* is the second best in performance with very close *Ac*, *Se* and *Sp* values, around 88.0%. Furthermore, it is worth to point out that *RS* is ranked as the third best, based on A_z but with the lowest sensitivity. The ROC curves of *nrv*, *C* and *RS*, which presented best A_z values, are depicted in Figure 4.

Using pairs of parameters, the highest performance is achieved with *nrv* and *C* (Table 2). Furthermore, this pair of parameters allows a performance improvement (*Ac* = 94.7%, *Se* = 95.7% and *Sp* = 93.3%) in comparison to the results obtained to individual parameters. The scatter diagram of *nrv* × *C* (Figure 5) indicates that *nrv* tends to concentrate irregular tumours (estimated mean value $\mu_{nrv} = 0.71$ with a standard deviation $\sigma_{nrv} = 0.17$) and spread out regular ones ($\sigma_{nrv} = 0.44$, $\mu_{nrv} = 0.08$). On the other hand, *C* has an opposite behaviour (irregular: $\sigma_C = 0.37$, $\mu_C = -0.45$; regular: $\sigma_C = 0.08$, $\mu_C = -0.87$).

The best performance is reached taking together *nrv*, *C* and *R* (Table 2). Compared to results achieved with the pair (*nrv*, *C*), both *Ac* (96.1%) and *Sp* (96.7%)

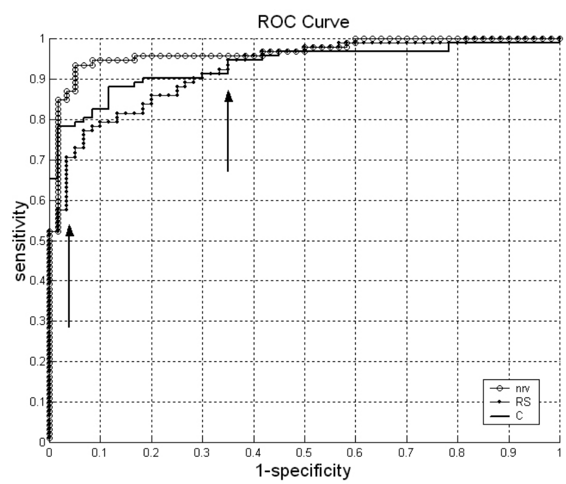


Figure 4. ROC curves for parameters *nrv*, *RS* and *C* used in distinguishing tumours contours as irregular or regular. The arrows indicate the specificity range for which the *nrv* sensitivity is higher compared to those of *C* and *RS*.

Table 1. Individual performance of each of the seven parameters in distinguishing tumour contours irregularity, sorted by A_z.

Parameters	A_z	***Ac* (%)**	***Se* (%)**	***Sp* (%)**
nrv	0.97	93.4	94.6	91.7
C	0.93	88.2	88.0	88.3
RS	0.91	83.6	81.5	86.7
RA	0.71	71.7	87.0	48.3
D_{NRL}	0.70	71.7	85.9	50.0
R	0.61	65.8	87.0	33.3
Mshape	0.55	60.5	95.7	6.7

Table 2. Performance of the best parameters combinations in distinguishing tumour contours irregularity, sorted by A_z.

Parameters	A_z	***Ac* (%)**	***Se* (%)**	***Sp* (%)**
nrv & *C*	0.97	94.7	95.7	93.3
D_{NRL}, *C* & *R*	0.91	87.5	81.5	96.7
nrv*,*C* & *R	0.97	96.1	95.7	96.7

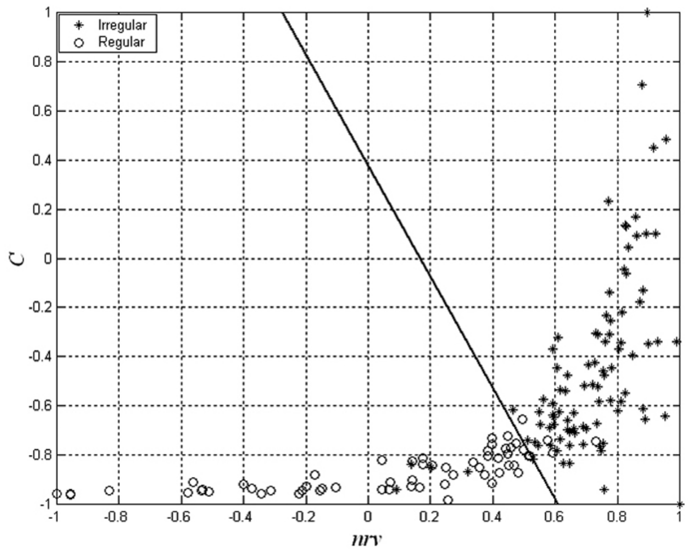


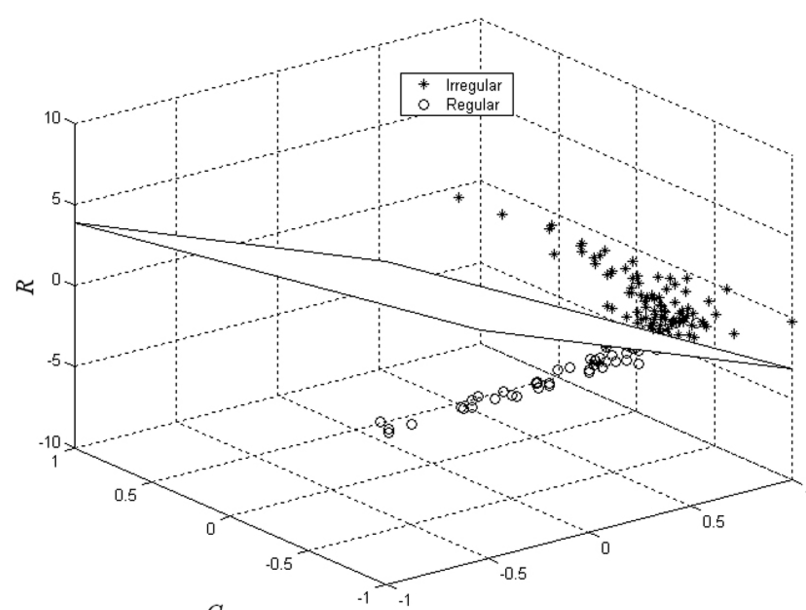
Figure 5. Scatter diagram for the parameters pair *nrv* and *C*. The best linear separator for the tumour contour irregularity is also shown (y = -2.26x + 0.38, where x refers to the normalised residual mean square value *nrv*, and y to the circularity *C*). The symbol (*) indicates an irregular tumour contour and (o) a regular one.

are increased whilst sensitivity remains the same (95.7%). Despite of *R* weak individual performance, scatter diagram of *nrv* × *C* × *R* (Figure 6) shows that *R* improves the performance of *nrv* and *C* in distinguishing tumour contours. Moreover, increasing the number of parameters to four or more does not lead to a performance improvement. ROC curves of pair *nrv* & *C* and combination *nrv*, *C* & *R* are presented in Figure 7.

The performance of each one of the seven parameters in distinguishing malignant from benign tumours (Table 3) reveals *nrv* as the best parameter based on A_z (0.91). The highest accuracy (88.2%) and specificity (92.3%) are also obtained to *nrv*. Although *RA* has presented the highest sensitivity (93.0%), its specificity is the worst (34.6%). Among parameters calculated from NRL, D_{NRL} and *RA* obtained the highest *Ac*, while *R* presented the second worse accuracy among all parameters. Parameter *C*, the second best considering A_z, presented similar values of *Ac* (80.3%), *Se* (79.0%) and *Sp* (82.7%).

Among all parameters combinations, the set *nrv*, *C* and *R* leads to maximum performance in distinguishing malignant from benign breast tumours, resulting in an accuracy of 88.8%, specificity of 90.4% and sensitivity of 88.0% (Table 4). In the scatter diagram of Figure 8, it is shown the best plane whereby tumours are separated. It is important to emphasise

Figure 6. Scatter diagram for the parameters *nrv* × *C* × *R*. The best plane that separates irregular (*) from regular (o) tumour contours is z = -6.53x - 3.03y + 0.38 (x refers to the normalised residual mean square value *nrv*, y to the circularity *C*, and z to the contour's roughness *R*).



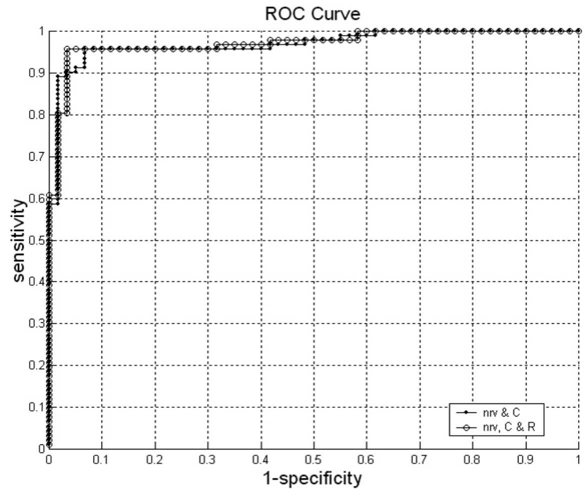


Figure 7. ROC curves for the parameters pair *nrv* and *C* and for the combination *nrv*, *C* and *R*, both used in distinguishing tumours contours as irregular or regular.

that the same accuracy (88.0%) is achieved changing *C* by D_{NRL} (Table 4) but with a decrease of *Se* (86.0%) and an increase of *Sp* (94.2%). Although D_{NRL} and *R* led to a poor individual performance, they contribute in distinguishing between breast tumours when combined with *nrv*.

ROC curves obtained from *nrv*, *R* & *C* and *nrv*, *R* & D_{NRL} are presented in Figure 9. Arrows indicate which ROC curve and respective region provide best values of sensitivity (*nrv*, *R* & D_{NRL} – thin arrow) and specificity (*nrv*, *R* & *C* – thick arrow).

Discussion

Among all individual parameters, and based on A_z, normalised residual mean square value (*nrv*) leads to the best performance (0.97) in distinguishing irregular from regular tumours. Overlap ratio (*RS*), also calculated from the convex polygon, has the third best individual performance (0.91). *Nrv* and *RS* have already been used in a previous work (Alvarenga *et al.*, 2004) but with a better performance for the latter (0.93). Tumour circularity (*C*), ranked as the second best parameter (0.93), has been considered by Chou

Table 3. Individual performance of each of the seven parameters in distinguishing tumours as malignant or benign, sorted by A_z.

Parameters	A_z	***Ac*** **(%)**	***Se*** **(%)**	***Sp*** **(%)**
nrv	0.91	88.2	86.0	92.3
C	0.84	80.3	79.0	82.7
RS	0.81	74.3	68.0	86.5
R	0.64	69.1	82.0	44.2
D_{NRL}	0.62	71.7	90.0	36.5
RA	0.61	73.0	93.0	34.6
Mshape	0.57	56.6	42.0	84.6

Table 4. Performance of the best parameters combination in distinguishing tumours as malignant or benign, sorted by A_z. The best result obtained by Chou *et al.* (2001) is presented in last line.

Parameters	A_z	***Ac*** **(%)**	***Se*** **(%)**	***Sp*** **(%)**
nrv	0.91	88.2	86.0	92.3
nrv, D_{NRL} & *R*	0.92	88.8	86.0	94.2
nrv*, *C* & *R	0.92	88.8	88.0	90.4
R, D_{NRL} & *C*	0.83	80.9	81.0	80.8
R, D_{NRL} & *C* (Chou *et al.*, 2001)	0.97	91.0	97.2	80.0

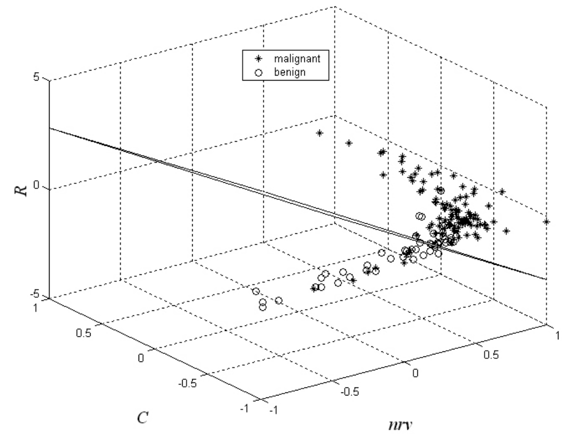


Figure 8. Scatter diagram for the parameters *nrv* × *C* × *R*. The best plane for separating malignant (*) from benign (o) tumours is depicted as a line due to the scatter diagram rotation to allow turning visible both kinds of tumours. Thus the plane is defined as $z = -1.43x - 0.99y - 0.05$ where *x* refers to the normalised residual mean square value *nrv*, *y* to the circularity *C* and *z* to the contour's roughness *R*.

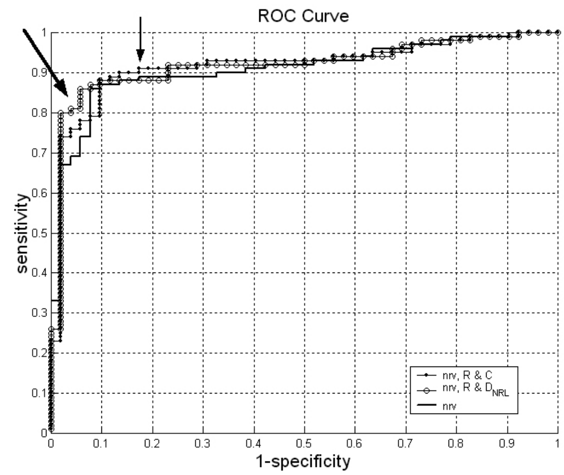


Figure 9. ROC curves for *nrv* and for two sets of three parameters, i.e., (*nrv*, *R* & D_{NRL}) and (*nrv*, *R* & *C*). All of them aim at distinguishing tumours as malignant or benign. The arrows indicate which ROC curve and respective range provides the best values of sensitivity (*nrv*, *R* & D_{NRL} – thin arrow) and specificity (*nrv*, *R* & *C* – thick arrow).

et al. (2001) as an important parameter for classifying breast tumours in malignant or benign.

Analysing ROC curves from *nrv*, *C* and *RS*, for *nrv* specificity ranging from 65.5% to 98.0%, sensitivity of this parameter is higher than that of *C* (superior in ≈5.7%) and also that of *RS* (≈14.8%) (Figure 4). Considering the pair *nrv* and *C*, a decrease in numbers of false positive (regular contour considered as irregular) and false negative (irregular contour considered as regular) has occurred. Hence an increasing in sensitivity and in specificity is noted in its ROC curve (Figure 7). Besides, joining parameter *R* to this pair, leads to a further improvement in specificity but maintaining sensitivity value (Figure 7).

For all 152 images, taking together parameters *nrv*, *C* and *R*, the area under the ROC curve indicates the best global performance (A_z = 0.97) whilst D_{NRL}, *C* and *R* gives an A_z = 0.91. This finding is due to the lower sensitivity of the latter (*Se* = 81.5%), despite a very close specificity (96.7%).

As for discrimination between irregular or regular tumour contours, the same set of three parameters (*nrv*, *C* and *RS*) resulted as the most accurate one in distinguishing malignant from benign tumours. This finding confirms the close connection between contour irregularity and possibility to establish a diagnostic hypothesis, as indicated by several authors (Chou *et al*., 2001; Huber *et al*., 2000; Skaane, 1999; Rahbar *et al*., 1999). It is worth to emphasise the superior performance of *nrv*, also observed in a previous study (Alvarenga *et al*., 2004).

Chou *et al*. (2001) have reported that the best performance in classifying breast tumours as malignant or benign was obtained with *R*, D_{NRL} and *C* (Table 4). Although a higher sensitivity (97.2%), these authors also reported a much lower specificity (80%). On the other hand, using the same set of parameters, but extracted from a different database, we have found higher specificity and lower sensitivity (Table 4).

In the present work, the roughness (*R*) and standard deviation (D_{NRL}) led to an improvement of *nrv* performance (Table 4). ROC curves show that set *nrv*, *R* and D_{NRL} presents higher sensitivity (87%) than *nrv*, *R* and *C* (79%), assuming specificity ranging from 92.3% to 98.1% (thick arrow in Figure 9). If a lower specificity is considered (range from 78.9% to 88.5%, thin arrow in Figure 9), set *nrv*, *R* and *C* furnishes higher sensitivity (91%).

Conclusion

Morphometric parameters calculated from normalised radial length and convex polygons were used to distinguish irregular from regular tumour contours in breast US images, and malignant from benign tumours as well. With this aim, normalised residual mean square value (based on convex polygon) and circularity can be considered the most relevant parameters. It is worth to emphasise that both parameters are calculated as a ratio between area and perimeter. The best performance, sensitivity of 95.7% and specificity of 96.7%, in distinguishing irregular contours from regular was achieved by combining these two parameters with contour roughness. Moreover, in distinguishing malignant tumours from benign ones, the best performance, sensitivity of 88.0% and specificity of 90.4%, was achieved by the same trio of parameters (*nrv*, *C* and *R*). These findings confirm the relation between contour irregularity and possibility to establish a diagnostic hypothesis. Therefore, these three parameters together may aid the diagnostic of breast tumour on ultrasound images. Nevertheless, additional parameters to quantify other tumour characteristics like echotexture, which may possibly help to improve malignant or benign breast tumour classification, are being presently studied.

Appendix

The sensitivity of a test can be described as the proportion of true positives (*TP* – patient with a malignant tumour and a positive test) it detects of all the positives. All positives are the sum of true positives and false negatives (*FN* – patient with a malignant tumour and a negative test). Sensitivity (*Se*) is therefore (General Practice Notebook – a UK medical encyclopaedia on the World Wide Web, 2005):

$$Se = \frac{TP}{TP + FN} \cdot 100\% \qquad \text{(A1)}$$

The specificity of a test can be described as the proportion of true negatives (*TN* – patient with a benign tumour and a negative test) it detects of all the negatives. It is thus a measure of how accurately it identifies negatives. All negatives are the sum of true negatives and false positives (*FP* – patient with a benign tumour with a positive test). Specificity (*Sp*) is therefore (General Practice Notebook – a UK medical encyclopaedia on the World Wide Web, 2005):

$$Sp = \frac{TN}{TN + FP} \cdot 100\% \qquad \text{(A2)}$$

Accuracy (*Ac*) is a term which describes the proportion of all tests which have given the correct result (true positives and true negatives as a proportion of all results) (General Practice Notebook – a UK medical encyclopaedia on the World Wide Web, 2005):

$$Ac = \frac{TN + TP}{(TP + FP + TN + FP)} \cdot 100\% \qquad \text{(A3)}$$

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