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Evaluating five features descriptors in classification of mammography images by artificial neural network

Avaliando cinco descritores de características na classificação de imagens de mamografias por rede neural artificial

Evaluando cinco descriptores de características en la clasificación de imágenes de mamografías por red neural artificial

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Keywords:
Mammography,
Diagnostic Imaging,
Image Processing,
Computer-Assisted

ABSTRACT

Purpose: Comparison of five features descriptors in terms of representation of tissues in mammographies. **Method:** Images had features extracted for producing five features datasets used for training an Artificial Neural Network (ANN), all the feature descriptors were submitted to the very same ANN configuration. The interest is to rank the features descriptor according to ANN's performance in classification of tissues. **Results:** The best descriptor is Pyramid of Histogram of visual Words (PHOW), the second group composed by Pyramid of Histogram of Colors (PHOC), Pyramid of Wavelets (PWAV) and Pyramid of Histograms of Gradients (PHOG), at third place there is Pyramid of Gabor (PGABOR). **Conclusion:** PHOW presents the best performance. Nevertheless, an application of PHOW in Computer Aided Diagnosis would need be funded in a very representative "visual vocabulary", based on a very large mammography database. Although PHOC presents a very simple approach, surprisingly, it takes the second-best performance.

Descritores:
Mamografia, Diagnóstico por Imagem,
Processamento de Imagem Assistida por Computador

RESUMO

Objetivo: Comparação de cinco descritores de características em termos da sua capacidade de representação de tecidos em mamografias. **Metodologia:** Imagens tiveram características extraídas produzindo cinco conjuntos utilizados para treinar uma Rede Neural Artificial (RNA), todos os conjuntos de características foram submetidos à mesma configuração de rede neural. O interesse é ranquear os descritores de características de acordo com o desempenho da RNA na classificação de tecidos. **Resultados:** A Pirâmide do Histograma de Palavras Visuais (PHOW) é o melhor, o segundo grupo composto por Pirâmide de Histograma de Cores (PHOC), Pirâmide de Wavelets (PWAV) e Pirâmide de Histogramas de Gradientes (PHOG), em terceiro lugar há Pirâmide de Gabor (PGABOR). **Conclusão:** PHOW apresenta o melhor desempenho. No entanto, uma aplicação do PHOW em Diagnóstico Assistido por Computador precisaria ser financiada em um "vocabulário visual" muito representativo, baseado em um banco de dados de mamografia muito grande. Embora PHOC apresente uma abordagem muito simples, surpreendentemente, leva o segundo melhor desempenho.

Descriptores:
Mamografia; Diagnóstico por Imagen;
Procesamiento de Imagen Asistido por Computador

RESUMEN

Objetivo: Comparación de cinco descriptores de características en términos de su capacidad de representación de tejidos en mamografías. **Metodología:** Imágenes tuvieron características extraídas produciendo cinco conjuntos utilizados para entrenar una Red Neural Artificial (ARN). El interés es ranquear los descriptores de características de acuerdo con el desempeño del ARN en la clasificación de tejidos. **Resultados:** En el caso de la Pirámide del Histograma de Palabras Visuales (PHOW) es el mejor, el segundo grupo compuesto por Pirámide de Histograma de Colores (PHOC), Pirámide de Wavelets (PWAV) y Pirámide de Histogramas de Gradientes (PHOG), en tercer lugar hay Pirámide de Gabor (PGABOR). **Conclusión:** PHOW presenta el mejor rendimiento. Sin embargo, una aplicación de PHOW en el diagnóstico asistido por computadora tendría que ser financiada en un "vocabulario visual" muy representativo, basado en una gran base de datos de mamografías. Aunque PHOC presenta un enfoque muy simple, sorprendentemente, toma el segundo mejor desempeño.

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INTRODUCTION

Breast cancer earlier detection is the motivation for public health agencies in promoting campaigns for screening the female population based on mammographies, following recommendations from scientific medical societies, such as the brazilian National Cancer Institute (INCA) or American Cancer Society (ACS).

Computer Aided Diagnosis (CAD) is a general designation of software developed for improving the medical performance specially in diagnostic process. Particularly in mammography analysis, this sort of software can help the radiologists in overcoming physical limitations that disturb the diagnosis/prognosis – e.g., low visual acuity or visual fatigue can difficult the detection of microcalcifications on the mammography background[1]. In expectation of contributing to the studies on the development of CAD systems, especially in clinical classification of cases, this paper proposes a comparison of five different feature descriptors. They are applied to mammographies to determine the best descriptor for classifying tissues in labels: BE (benign tissue), NO (normal tissue) or CA (cancerous tissue). For this sake, datasets of patches (image samples) were extracted from DDSM mammography databaseand experiments were done by using a neural network model[2].

All descriptors tested were based on the concept of spatial pyramid by Bosch et al.[3], they are the Pyramid of Histogram of visual Words (PHOW), Pyramid of Histogram of Colors (PHOC), Pyramid of Wavelets (PWAV), Pyramid of Histograms of Gradients (PHOG) and Pyramid of Gabor (PGABOR). The focus here is the efficiency presented by each descriptor in providing an ANN with capacity of classify tissues in mammographies (considering the images dataset). For evaluation of results, the classical metrics ROC (Receiver Operating Characteristic) curve and AUC (Area Under the Curve) were used for comparative analysis. At the best of our effort the comparison of these five descriptors by Artificial Neural Network (ANN) was not found in literature.

The rest of this paper is organized as follows. In section 2 the theoretical framework about the methods and models applied is discussed, the section 3 is focused on the material and methods applied in the experiments. Results and analysis are done in section 4 and conclusions are done in section 5.

THEORETICAL FRAMEWORK

Bosch et al. develop their work using the same basic concept of partitioning the image into increasingly fine sub-regions and computing histograms of local features found inside each one. This process resembles a hierarchical structure composed by levels (*L*), each one presenting 2^L equally sized image's regions, named it as a "spatial pyramid"[3].

In this paper, the overall descriptor is a simple unweighted concatenation of regional descriptors. Figure 1 shows this concept, a descriptor representing local image shape and its spatial layout, the spatial pyramid is found on the right side. The main idea is to capture global and local aspects of the image and represent them as part of an overall descriptor D_{image} composed by concatenation of (non-weighted) regional descriptors obtained by image partitioning, as described in Equation 1, since *U* represents concatenation, D_L corresponds to concatenation of the 2^{2L} regional descriptors *d* at the level *L*. This concept was applied for implementation of the five descriptors discussed, as follows.

$$D_{image} = D_0 \cup D_1 \cup \dots D_L \quad (1)$$

$$\mathrm{D_L} = \bigcup_{k=1}^{2^{2L}} d_L^k \, , L \in Z^+ \cup 0 \quad (2)$$

PHOW - Pyramid Histograms of Visual Words

The so called "visual" words are the centers of clusters determined by K-means applied on result of dense features extraction by SIFT (Scale Invariant Feature Transform) operator. BoW descriptor is a global data represented by one histogram of the "visual words", PHOW as the concatenation of BoW's regional histograms determined in subdivisions of the image[3]. These regions permit a more locally collection of features, so PHOW is

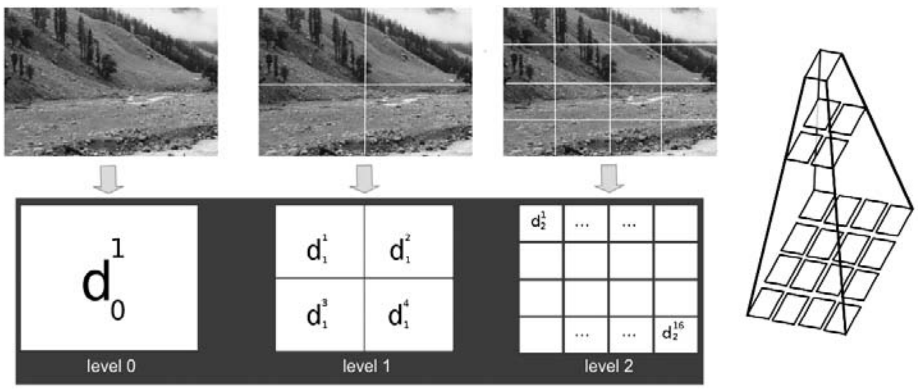

Figure 1 - Descriptor $D_{image} = D_0 \cup D_1 \cup D_2$, since $D_0 = d_0^1$, $D_1 = d_1^1 \cup d_1^2 \cup d_1^3 \cup d_1^4$, $D_2 = d_2^1 \cup d_2^2 \cup d_2^3 \cup d_2^4 \dots \cup d_2^{16}$ a concatenation of the histograms for some feature at each level of partitioning of the original image. In terms of the partition levels, this process resembles a spatial pyramid depicted on the right side of the figure. Adapted from Bosch et al.[3].

more representative of the details of the layout of the image than BoW. In this work the descriptor PHOW is employed in regions determined by spatial pyramid structure in mammographies' patches.

PHOC - Pyramid Histograms of Colors

The same basic concept (pyramid of histograms) is applied for PHOC feature descriptor. In this case, the overall descriptor (D_{image}) is composed by the classical histograms based on pixels' brightness in regions of the image.

PHOG - Pyramid Histograms of Orientated Gradients

The PHOG descriptor also uses a spatial-pyramid, the histogram is calculated on the directions of gradients. The histogram of oriented gradients (HOG) is a classical technique based on the counting of dominant occurrences of gradient directions. For determination of HOG descriptor is necessary to calculate the directions of most strength vector gradients and obtain the histograms of these directions. In this work the descriptor HOG is utilized in regions determined by spatial pyramid structure in mammographies' patches.

PGABOR - Pyramid of Gabor Filtering

In this case the concept of spatial-pyramid is still applied but without histograms in descriptor's composition. The descriptor PGABOR still follows the Eq. 1, but the sub descriptors (d_K^L) aren't histograms, they are one-dimensional representations of features extracted from the image by Gabor filtering. If the response of the filter is two-dimensional, it is reshaped for composing the one-dimensional sub-descriptor at respective level of the spatial-pyramid.

The Gabor filter is a sinusoidal wave modulated by a Gaussian function also named as STFT (Short Term Fourier Transform)[4]. The response of Gabor filter is stronger in locations presenting structures (such as textures or important objects in a mammography) in the same direction that the filter was set. The response returned by Gabor filter were employed in this work for features description of regions determined by spatial pyramid structure in mammographies' patches.

PWAV - Pyramid of Wavelets coefficients

Like PGABOR, the concept of spatial-pyramid is still applied in PWAV, but without histograms. Basically, the proposal here is to apply the wavelet decomposition and to collect wavelets' coefficients for composing the PWAV descriptor.

Splitting a signal into components is very utile in image processing, by doing so it is possible to operate upon certain components for filtering. FFT (Fast Fourier Transform) makes it with sinusoids, which is useful but does not permit an effective frequency localization[5]. STFT (Short Term Fourier Transform) improved FFT but it still presents some drawbacks[5].

In terms of frequency/time resolution the strategy based on wavelet ("small wave") presents advantages which makes it very attractive for signal decomposition. Similarly, to STFT the decomposition by WT (Wavelets Transform) also uses "windowing", but instead of using pure sinusoidal waves with fixed size windows the WT applies flexible shaped windows enveloping a wavelet.

Differently of Fourier transform that uses only sinusoids, there exists various families of wavelets that can be conveniently used for signal analysis depending on the application. A versatile wavelet named Daubuchies-4[6] is suitable for applications in different fields, from military target recognition to low contrast images such as mammographies.

By comparing the signal to the wavelet at various scales and positions, is obtained the CWT response for the processed signal. In practical terms, the wavelet analysis consists in recursive decomposition of the signal in detail coefficients (high frequency noisy) and approximation coefficients (low frequency) by scaling and shifting a small-wave (the mother wavelet properly saying) and applying it on the signal. Here in this work, the coefficients generated in this process were used for composing a descriptor of regions determined by spatial pyramid structure in mammographies' patches. In case of bi-dimensional signals such as images, the decomposition recursively divides the image in four sub images: one approximation (low frequency band) band and three other bands for details (high frequency bands). The CWT response can be reshaped and used as an array of image descriptive features.

Artificial Neural Network ANN

Experiments in this paper were implemented with an ANN, a classical bio-inspired Deep Learning method based on supervised learning that imitates the real neuronal tissues using a network composed by layers of artificial neurons. The choice of the ANN for testing the descriptors was based on its capability to learn non-linear complex models.

The ANN needs to be supervised for learning, in a process looking forward to fitting it to the training set associated with the capacity of generalization (high level of accuracy when it is entered with data that has not been seen during training). Throughout the ANN training, the neurons' weights are adjusted to achieve an optimal learning. Since this process is supervised, after each training iteration, the ANN is tested. The level of error is evaluated and used by a back-propagation algorithm that it goes through each layer in reverse order to measure the error contribution from each connection (reverse pass), and finally makes adjusts in the connection weights to reduce the overall error.

A mammography is very complex image. Such characteristic is extended to the patches extracted from it and to the feature descriptors obtained from the patches. This aspect makes ANN a natural choice, since it is composed by a network of lots of neurons capable to capture an overall complex knowledge.

MATERIAL AND METHODS

DDSM pre-processing

The source of the data used in this work was the database DDSM - Digital Database for Screening Mammography[2], which presents thousands of gray-tone well documented images divided in three classes of cases: Benign, Cancer and Normal.

The experiments were executed in an Oracle Virtualbox environment (10 GB RAM) running SO Ubuntu 16.04 LTS. The host computer was a notebook Vaio, processor Intel, 16 GB RAM. The programming environments were Python 2.7 and Matlab (R2015b).

The Figure 2 shows the main steps applied for preprocessing the database, they are described as follows:

I. DDSM images needed to be converted from the original almost unknown format LJPEG to something workable by the image-libraries for practical use, here the LJPEG images were converted to "png" format by means of the Anmol's library DDSM-Utility[7];

II. For each image (classes Benign, Normal and Cancer), the region of the breast was separated from the image for avoiding artifacts. A thresholding method (e.g. classical Otsu's binarization) was applied resulting in a binary mask. Then, area segmentation was applied for separating the breast region from the rest remainder of the image (noisy background, little spots and artifacts) since the biggest white region corresponded to the breast;

I. Squared patches (256x256 pixels) were extracted from the images obtained from the step II. The idea was to get samples of each kind of the four possible regions in mammography, resulting in 8,000 patches as follows:

a. 2000 benign-patches (label BE),
b. 2000 patches representing background (label BkG),
c. 2000 cancer-patches (label CA) and
d. 2000 normal-patches (label NO).

II. Features extraction using two levels ($L = 2$) spatial pyramid:

a. PHOW dataset was obtained by features extracted from the 8000 labeled patches (BE, BkG, NO, CA) using Matlab library available for download at website of VGG – Visual Geometry Group[8];

b. PHOG dataset was obtained by features extracted from 8000 labeled patches (BE, BkG, NO, CA) using scripts in Matlab and the library available for download at website of VGG[9];

c. PHOC dataset was obtained by features extracted from 8000 labeled patches (BE, BkG, NO, CA) using scripts in Matlab;

d. PGABOR dataset was obtained by features extracted from labeled patches using scripts in Matlab. The Gabor filter was set with directions 0°, 30°, 90° and 135° trying to capture important directional textured features in mammographies.

e. PWAV dataset was obtained by features extracted from 8000 labeled patches (BE, BkG, NO, CA) using scripts in Matlab. The wavelet model was Daubechies-4 which were chosen by Kocur et al.[6] for breast cancer diagnosis.

The Experiment

The preprocessing generated four datasets (PHOW, PHOG, PHOC, PGABOR and PWAV), each one composed by 8000 vector-descriptors equally distributed by label (BE, BkG, NO, CA). The next steps consisted in training the ANN followed by evaluation of the ANN's tests, as explained below:

I. It was applied an ANN implemented by Matlab's ANN toolbox trained and tested by each descriptor dataset. The same ANN's configuration was used for all descriptors:

a. Layers: empirically determined as 2 layers and 100 neurons per layer;

b. Epochs: different numbers were tested; it was chosen 500,000;

c. Neuron activation function: log-sigmoid;

d. Training function: although Carneiro et al.[10] used gradient descent with momentum and adaptive learning rate backpropagation, here was applied scaled conjugate gradient backpropagation as training function;

e. Data percentage for training/teste/validation: 70% for training, 15% for validation and 15% for testing.

II. The ANN's training performance parameter was set up as MSE (Mean Squared Error).

III. Since each features descriptor was trained/tested by the same ANN and running in the same computer, the differences between ANNs' performance in classification depended only on the quality of proposed features descriptors, in terms of their individual capacity of accurately representing the data (tissues in mammographies). So, by measuring an ANN's classification performance one is capable to measure the quality of features descriptor used for training it.

The metrics used for evaluating the performance:

CM (Confusion Matrix), TPR (True Positive Rate, also known as sensitivity) and TNR (True Negative Rate, also known as specificity), as described in Eq.3 and Eq.4 respectively, where: i " {BE, BkG, CA, NO}, TP (True Positive predictions), FP (False Positive predictions) and FN (False Negative predictions).

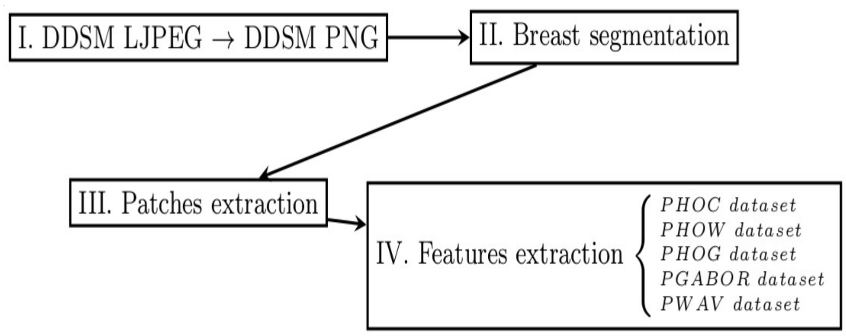

Figure 2 - DDSM preprocessing and generation of features datasets.

$$TPR_i = \frac{TP_i}{TP_i + FN_i} \quad (3)$$

$$TNR_i = \frac{TN_i}{TN_i + FP_i} \quad (4)$$

Construction of CM is based on relation between the set of predictions (neural net assignments) and targets (the known real assignments). CM synthesizes the overall performance of the classiûer, its main diagonal shows the true positive predictions.

TPR and TNR are extracted from the CM, both vary in interval [0.0,1.0]. A Low TPR points out a high number of false negatives, for instance. By its turn, a low FPR indicates a high number of true negatives.

$$FPR_i = \frac{FP_i}{FP_i + TN_i} \quad (5)$$

The concept of ROC (Receiver Operating Characteristic) curve was firstly proposed as a method for evaluating the performance of diagnostic tests(11). A medical diagnosis is based on a pre-determined threshold value applied to clinical variables, determining if the case is a diseased or non-diseased one. ROC curve is a graphic relation between TPR and FPR (False Positive Rate) showing the overall performance of supervised classiûcation procedure at various decision thresholds(12). FPR is also extracted from the CM, it is described in Eq.5, where TN means True Negative.

AUC (Area Under the Curve) is an important metric that quantiûes the area under respective ROC curve permitting quantitative comparisons. AUC varies in the interval [0.0,1.0]:

a) $0.0 \leq$ AUC ≤ 0.5: indicates a practically useless classiûer, which performance is worse than random(12);

b) $0.5 <$ AUC ≤ 1.0: the performance increases inasmuch as AUC gets closer to the unity (interval in which TPR is higher and FPR is lower)(12);

Both metrics, ROC curves and AUCs are used for evaluation of the results obtained from the experiments implemented in this paper.

RESULTS AND ANALYSIS

It is important to emphasize that all the descriptors (PHOC, PHOG, PHOW, PWAV and PGABOR) were submitted to the same ANN's configuration. So that, the ANN performance in classification of the patches depends on the descriptors. The performance evaluation was based on analysis of the graphs AUC, ROC curve and TPR and TNR data. The CMs were not included due to limit of pages.

TPR and TNR

For convenience the values of TPR (sensitivity) and TNR (specificity) were composed respectively in the graphs in Figure 3 and Figure 4. Remembering that the best value for TPR and TNR is the unity (1.0).

By analyzing the Figure 3 it is noticed that all descriptors presented the best performance (with maximum TPR values:1.0) only when operating the identification of true BkG patches. In fact, this is the best performance for TPR and TNR presented by the tested descriptors.

The BkG-patches represent the image background, they were used just to teach the ANN not only what are the objects of interest (tissues), but also what is not important for the application (i.e., the background). This reinforce the ANN's knowledge on differentiates background from tissue patches.

If TPR values were very good for BkG-patches, the same could not be said about TPR values for the other classes-patches involved in the experiment: BE, CA and NO. As seen at the same Figure 3, all descriptors presented TPR values predominantly under 0.6 for BE, CA and NO cases, which is not good enough.

So, although all the descriptors presented a very good performance in classifying BkG, they also presented a poor

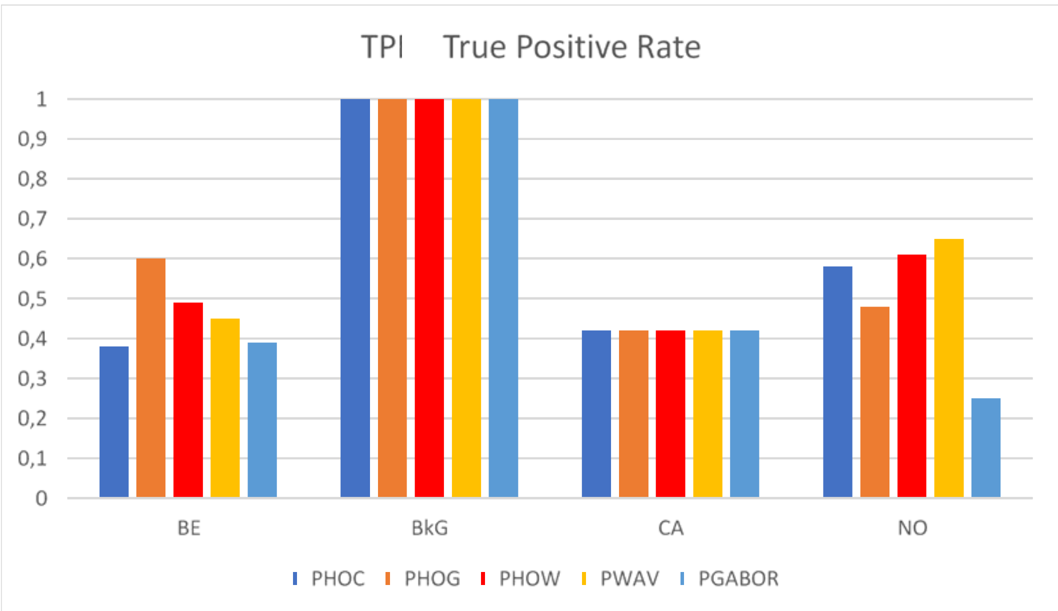

Figure 3 - TPR values for different descriptors and represented classes.

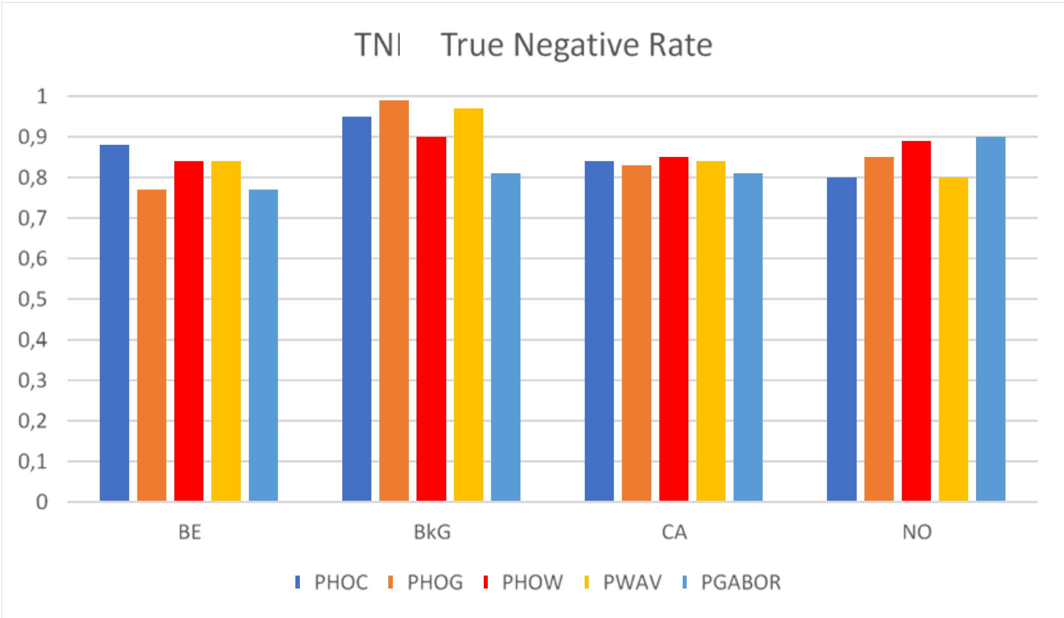

Figure 4 - TNR values for different descriptors and represented classes.

sensitivity performance in identifying the other tissues-patches (BE, CA and NO). In terms of sensitivity, the performance of descriptors presented ups and downs, so, these results are not conclusive.

About the results for specificity (TNR), as seen in Figure 4, all the descriptors present a TNR-value surpassing 0.7 which is significantly better than the TPR performance.

A conclusion about the overall descriptors behavior in terms of both TPR and TNR is that none of them presents a prominent performance. It is necessary to highlight that these results are related to the Confusion Matrix obtained by application of a constant threshold (determined by ANN's implementation) during the test step of the ANN.

The ROC curves give a more global view of the descriptors behavior, since each ROC curve is determined under different threshold-levels. Next section is dedicated to analyzing these curves. So, the analysis of ROC curves gives more perspective and it is more conclusive.

ROC and AUC for each case

ROC curves for PHOW, PHOC, PWAV, PHOG and PGABOR were determined about classification of patches in Benign, Cancer, Normal and Background. For each ROC it was calculated the respective ROC-average curve $(\overline{ROC})$ and its AUC, producing: $(\overline{ROC}, AUC)_{PHOW}$, $(\overline{ROC}, AUC)_{PHOC}$, $(\overline{ROC}, AUC)_{PWAV}$, $(\overline{ROC}, AUC)_{PHOG}$, $(\overline{ROC},$

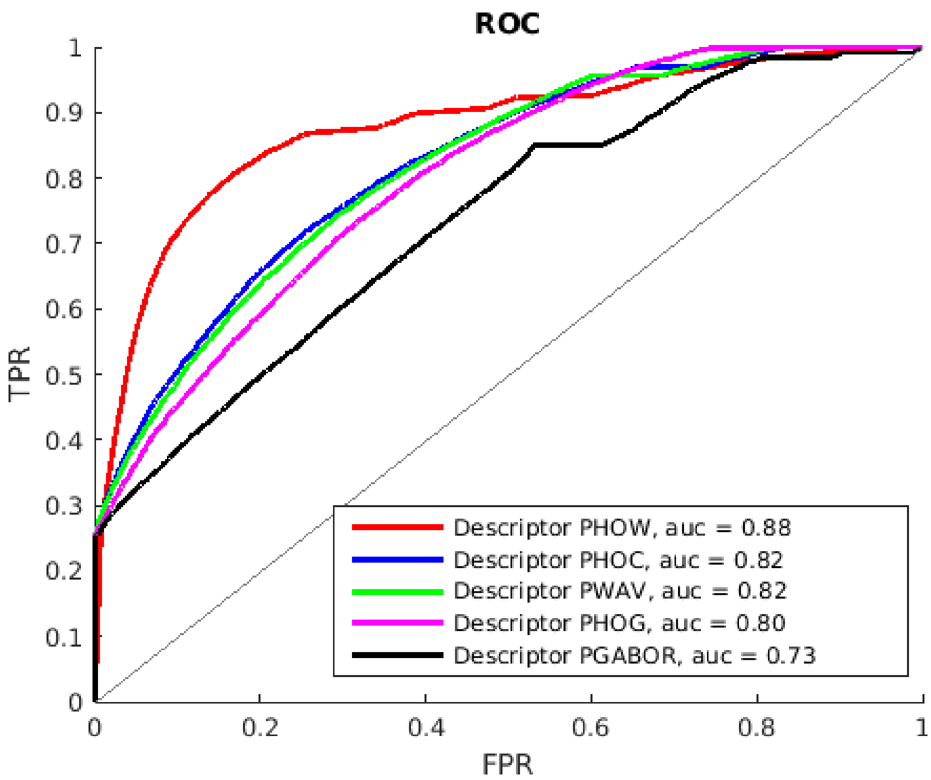

Figure 5 - Descriptor's ROC averaged and respective AUC.

$AUC)_{PGABOR}$

These curves and AUCs are plotted in Figure 5, which is an overall synthesis of descriptors performance. This graph shows the PHOW's superiority depicted by the $\overline{ROC}_{PHOW}$ curve very closed to the upper left corner, presenting a salient profile in comparison to the others. Besides, the $AUC_{PHOW} \simeq 0.9$ reinforcing what was visually perceived.

About the other curves, the second place in performance was practically shared by $AUC_{PWAV} = AUC_{PHOC} = AUC_{PHOG} \sim 0.8$, far from PHOW's performance. The worst performance was $AUC_{PGABOR} = 0.7$.

It was relatively unexpected to see a naive approach such as PHOC presenting a performance comparable to more sophisticated and potentially more descriptive approaches (PWAV, PGABOR and PHOG).

The analysis of ROC curves shows that PHOC, PWAV, PGABOR and PHOG aren't so capable to provide the necessary data representation for adequately training of the ANN. On the other hand, the PHOW feature descriptor was capable to represent the data adequately for training the very same ANN configuration.

Since PHOW results from BoW (Bag of Words), its performance probably is consequence of the high-level data representation that it provides. As discussed before, PHOW results of a sequence of steps that begins with low level features, the determination of the dictionary of visual words (or visual features) until the histogram of "visual words" (PHOW). These steps came from the lower level representation to a level higher than the ones presented by the other descriptors tested. For PHOC, PWAV, PGABOR and PHOG as proposed here, the data representation was based on lower level features, probably too noisy for an efficient training of the ANN.

Independent of the reasons for performances presented by PHOC, PWAV, PGABOR and PHOG, the result is clear and valid. In terms of the proposal and scope of this work the PHOW features descriptor is the best choice in front of the four others.

CONCLUSIONS

Looking for contributing in improvement of CAD systems in breast cancer early detection, this paper described experiments for comparison of five features descriptors namely PHOW, PHOC, PHOG, PGABOR and PWAV, in terms of capacity of representing important mammography's tissues. The interest was to identify what descriptor would provide a better data representation for excelled at training obtaining the best ANN performance in classification of tissues. Evaluation was done based on analysis of metrics TPR, TNR, ROC and AUC. Analysis of TPR and TNR provided results not so conclusive for the proposed scope. About ROC/AUC, these metrics provide a broader evaluation. The results based on ROC/AUC indicated that the best descriptor was PHOW, the second group of descriptors was composed by PHOC (unexpectedly), PWAV and PHOG, and PGABOR in the third place. Analysis indicate that the main advantage of PHOW comes from its capacity of high-level description of data awhile the other descriptors are noisy low-level strategies causing problems in efficiently training of the ANN.

It is important to mention that PHOW method is very dependent on the vocabulary obtained by BoW. In practical terms, an application of PHOW in CAD would need be funded in a very representative vocabulary, based on a very large and general representative mammography database.

Another aspect to be taken in consideration for future work is to use the CBIS-DDSM database, an updated and standardized version of DDSM in DICOM format.

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