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ICA applied to microcalcification clusters CAD in mammograms

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1. Introduction

The incidence of breast cancer in western women varies from 40 to 75 per 100,000, being the most frequent tumour among the feminine population. Latest statistics published by Cancer Research UK (Cancer Research, 2006) for year 2006 show 44,091 new cases of breast cancer diagnosed in the UK, being 99% of them detected in women. The importance of the problem in the European countries can be observed in Figure 1 where the the highest incidence rate appears in Belgium with more than 135 cases per 100,000 and a mortality rate of more than 30 per 100,000.

These pessimistic statistics illustrate the problem magnitude. Although some risk factors have been identified, **effective prevention measures or specific and effective treatments are unknown**.

The graph in Figure 2 (Cancer Research, 2006), allows to see that breast cancer treatment in an early stage of development can increment considerably the patient's survival chance. In fact, early breast cancer detection increases possibilities to allow for a conservative surgery instead to mastectomy, the only solution in advanced breast cancers (Haty et al., 1991).

The absence of a clear risk factor, different from the age, with high significance in disease's appearance makes difficult to establish any effective measure in breast cancer prevention. Nowadays, early detection of breast cancer constitutes the most effective step in this battle.

To improve early detection of breast cancer, all the health systems of developed countries perform what are known as "screening programs". In these screening programs, a review of all women at risk age is performed with a given periodicity. The most common test for the studies is mammography.

Like any other radiological test, mammography should be reviewed by expert radiologists, looking for abnormalities (asymmetry, masses, spicular lesions and clusters of microcalcifications or MCCs, mainly), being the mammography one of the more complex plates to analyze due to its high resolution and the type of abnormalities to look for.

Among the abnormalities discussed above, MCCs (groups of 3 or more calcifications per cm^2) can be one of the first signs of a developing cancer.

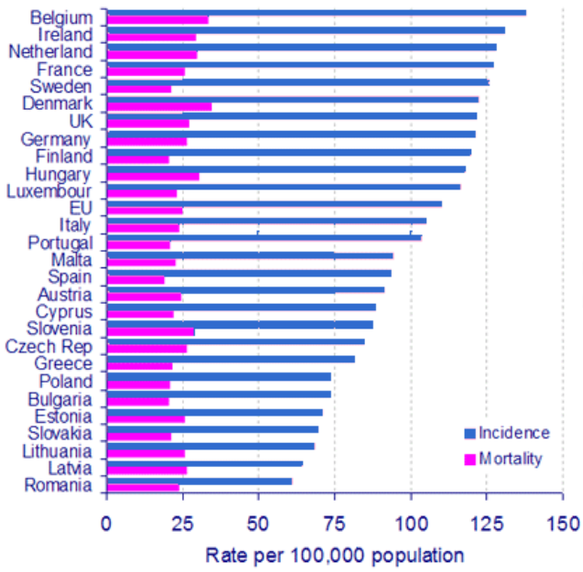

Fig. 1. Age standardized (European) incidence and mortality rates, female breast cancer in EU countries.

A microcalcification is a very small structure (typically lower than 1 millimetre), and, when they appear grouped in some characteristic shapes (microcalcification cluster, MCC) usually indicates the presence of a growing abnormality.

The detection of such structures sometimes presents an important degree of difficulty . Microcalcifications are relatively small and sometimes appear in low contrast areas, so that they must be detected by a human expert, who can be fatigued or can have variations in his attention level. This later reason makes very interesting the possibility to use a Computer Aided Diagnostic system (CAD) as a way to reduce the possibilities of misdetection of a developing breast cancer.

In order to provide a trusted helping tool for the radiologists, a CAD system must have a high sensitivity, but also a low rate of false positives per image (FPi). A too alarmist CAD system (ie, with a rather high FPi rate), is of no value in screening because it either causes the radiologist to distrust, or generates a great number of biopsies, making unfeasible the screening program. Approximately 6 in every 1,000 screening tests (0.6%) indicate the presence of cancer. Currently there are several CAD systems for mammography, some of them commercial and approved by the FDA. However, there are independent studies which indicate that their use does not provide clear benefits. In many cases, the performance of these systems is not known clearly enough, in part because results are given over their own databases, making very complicated an objective validation and comparison.

The studies by (Taylor et al., 2005) and (Gilbert et al., 2006) are performed in the context of the British Health Service. Those by (Taylor et al., 2005) do not use a great quantity of mammograms, but however, the study by (Gilbert et al., 2006) is developed with 10.267 mammograms, with a proportion of cancer similar to what can be found in screening. These studies try to evaluate the difference in performance between a "double reading" strategy and a "simple reading plus CAD".

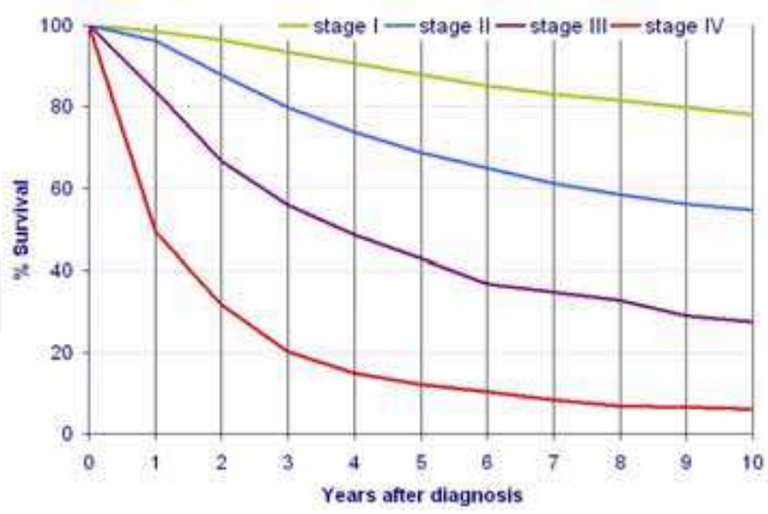

Fig. 2. 0-10 year relative survival for cases of breast cancer by stage diagnosed in the West Midlands 1985-1989 followed up to the end of 1999, as at January 2002

The studies by (Taylor et al., 2005) indicate that there is no significant improvement neither in sensitivity nor in specificity (they even talk about an increase in the cost), indicating that it should be due to the low specificity of the system. They conclude that the subject must be studied in deep before adopting.

On the other hand, the study by (Gilbert et al., 2006) conclude that there is obtained an improvement on the sensitivity, but also an increase in the recall rate, when CAD is used. The final conclusion is that the system must be evaluated better, an that a successfully implantation of the CADe system depends on its specificity (i.e., on reducing the number of FP).

Another interesting study is by (Fenton et al., 2007). This study is different from the other two, it is a statistical analysis of the screening data from 43 centers, between 1998 and 2002. They compare the results of the centers using CAD with those centers that do not. The final conclusion is that the CAD usage reduces the precision when interpreting mammograms while the number of biopsies increases (and, therefore, the "positive prediction value" (PPV)).

PPV has three different variants depending on different diagnostic stages. When referred exclusively to screening it is named as PPV1. This value provides the percentage of all positive screening examinations that result in a tissue diagnosis of cancer within one year. The two other kinds of parameters provide information about cases recommended for biopsy or patients with clinical signs of the disease. PPV1 values recommended by Agency for Health Policy and Research rely on the range 5 to 10% (ACR, 2003). Few studies provide values for this parameter, being more common to provide sensitivity and specificity or false positive rate as outcome measures.

Although screening can be useful to detect different signs of malignancy (good defined or circumscribed lesions, stellate lesions, structural distortion, breast asymmetry, etc), the clearest sign to detect early breast cancer is the presence of microcalcification clusters (MCCs) (Lanyi, 1985). Indeed, from 30 to 50% mammographic detected cancers present

MCCs (Chan et al., 1988; Dhawan and Royer, 1988); and 60–80% of breast carcinomas reveal MCCs upon histological examinations (Sickles, 1986).
Even nowadays, the automatic interpretation of microcalcifications remains very difficult. It is mainly due to their fuzzy nature, low contrast and low distinguishability from their surroundings. One microcalcification is very small, its size varies between 0.1 and 1.0 mm, being the average size 0.3 mm. Those smaller than 0.1 mm are very difficult to distinguish from the high frequency noise present in the mammogram. Besides, they present different size, form and distribution, and therefore it is not possible to fit a template.
In this field, the different approaches range from the most simple consisting in improving the visibility of what are known *regions of suspicion* in the mammogram, in order to make easier the work of the radiologist, to proposals of complete computer aided diagnosis systems. The radiologists define a region of suspicion as that region which is more brilliant than the surrounding tissue, has a uniform density, circular shape and diffuse edges. To treat these regions, several techniques are normally used, as for instance: contrast stretching, enhancement by histogram equalization (Karssemeijer, 1993), convolution mask enhancement (Chan et al., 1987) and adaptive neighbourhood enhancement (Woods et al., 1991; Dhawan et al., 1986).
Other groups of techniques include works based on region-based enhancement (Morrow et al., 1992; Shen et al., 1994); and feature-based enhancement. In the last subgroup we can distinguish two different lines. The first one consist on increasing the contrast in suspicious areas and the other one is to remove background structures and noise according to microcalcifications features. There have been used many different techniques for contrast enhancement, as higher order statistical (HOS) (Gurcan et al., 1997); fuzzy logic (Chen et al., 1998) and multi-scale analysis (Laine et al., 1994). Among those proposals based on background removal we can find techniques as fractal modelling of the background tissue (Li et al., 1997), morphological processing (Dengler et al., 1993) or wavelet reconstruction (Wang & Karayiannis, 1998).
A higher step than enhancing is developed by different proposals to detect microcalcifications or masses based on different feature extraction methods. In the literature we can find different approaches among which we can point out:

- Individual microcalcification features. Features extracted directly from mammogram such as perimeter, area, compactness, elongation, eccentricity, etc. (Nam & Choi, 1998; Bottema & Slavotinek, 2000).
- Statistical texture features. Including different methods like Surrounding Region Dependence method (SRDM) (Kim & Park, 1999), Spatial Gray level dependence method (Ferrari et al., 1999), Gray level difference method (GLDM) (Lee et al., 1998) or Spatial Gray Scale Co-Occurrence Matrix (SGLCM) (Yang et al., 2005) for the detection of MCCs.
- Multi-scale texture features. Methods based on wavelet transform (Yu et al., 1999), Gabor filter bank (Bhangale, 2000) or Laplacian of Gaussian filter (Netsch & Peitgen, 1999).
- Fractal dimension features (Caldell et al., 1990).

The last step corresponds to the approaches which study the malignancy of the abnormalities detected in the mammograms. Normally, they use feature vectors very similar

to those used in the approaches of individual calcifications detection, along with a classifier which can be neural network-type (Jiang et al., 1997), K-nearest neighbour (Zadeh et al., 2001), Bayesian networks (Bankman et al., 1994) or binary decision trees (Zheng & Chan, 2001).
Finally, we can also cite several commercial equipments as can be ImageChecker® by R2 Technology, MammoReader™ by Intelligent Systems Software or SecondLook™ by CADx. These three equipments have obtained the approval of the Federal Food and Drug Administration (FDA) for their use in medical dependencies. Nevertheless, as we commented above, there exist diverse opinions regarding their reliability, according to different studies (Taylor et al., 2005; Gilbert et al., 2006; Fenton et al., 2007; Serio & Novello, 2003).
The rest of chapter follows with the methodology that we have used in our work. Next, we describe the details of system implementation. After that, we show our results and finally we deal with the conclusions.

2. Methodology

Our work proposal is based in the use of a technique known as Independent Component Analysis (ICA), as an efficient image feature extractor which will be used in a neural classifier. Independent Component Analysis is a technique which, unlike some classic methods as variance or standard deviation, uses high order statistics. Moreover, using samples from the signal space to model, is able to infer a base which let us represent any image (signal) belonging to the space with a low number of components.

This is the same task we carry out when we decompose a signal in its Fourier components or build wavelet decomposition, in the multiresolution field. But there are important differences between the mentioned methods and ICA. First, both Fourier and wavelet decompositions use fixed bases. On the other hand, ICA bases are generated to fit as better as possible the data space to model. In addition, an ICA development builds base matrices which maximize the non gaussianity of the input data space; this means that ICA bases model the most interesting characteristics of the modelled space. And this is precisely the key fact which leads us to use ICA as a feature extractor block instead of other more extended techniques as the previously mentioned wavelet transform or principal component analysis.

The second important element in our architecture is the neural classifier. This kind of systems has characteristics which are especially interesting to broach the problem. Perhaps the most well-known can be the capability to adjust its operation by means of “samples”. Colloquially, we can say they have learning capability. Moreover, these systems have another important characteristic which is known as generalization capability. Generalization in neural classifiers is the capacity to provide a right response for a completely unknown input. As can be inferred, this characteristic makes a neural classifier a great choice for a classification task like our, where input data variability is very high (contrast variations, mammography errors, artifacts, etc.).

2.1 Data source

Although nowadays digital mammography systems have become popular, up to date the main data source in research investigation tasks has been digitized mammograms. Mammographic scanners provide a high resolution level: pixel sizes ranging in tenths of micron, and grey level resolution from 11 to 16 bits (2,048 to 65,536 grey values). This gives us an idea of the precision level which can be used working with mammograms.

The current data source for our work is the mammographic database known as Digital Database for Screening Mammography (DDSM). Developed by the Island Vision Group at the University of South Florida may be the most extensive and better quality free to use database for research purposes. It comprises about 2,500 complete cases, providing the four typical views in a mammographic study (left and right cranio-caudal and medio-lateral-oblique). Furthermore, it provides useful information for the case as age, film type, scanner, etc. But the most interesting feature for our work is that it provides what is called *ground truth marks* when a breast presents a biopsy proven abnormality, specifying its type and distribution in the ACR internationally accepted nomenclature named BIRADS.

There are other databases in this field, as can be MIAS or Nijmegen; but they are unavailable or its distribution is restricted. MIAS group provides a reduced version free of charge (miniMIAS), but its low spatial and spectral resolution makes it useless for microcalcification detection problems.

2.2 Dataset prototypes generation

This was probably one of the slowest phases of this development because we propose, as a first approximation, to carry out pixel level diagnostic. So, with the help of an experienced radiologist we made a pixel labelling work using predefined classes over mammogram regions, once converted to optical density. These set of regions correspond to all ROIs defined in the DDSM database but also include some manually selected regions which contain significant mammogram structures like vascular calcifications or artifacts.
The set of classes to study includes not only microcalcifications belonging to a cluster (hence malignancy indicatives) but also benign microcalcifications, large rod-like calcifications, round calcifications, lucent–centered calcifications, healthy tissue and several kinds of artifacts.
Totally we have inserted a training set of more than 4,600 microcalcification prototypes, over 6,700 benign and more than 100,000 healthy or benign prototypes.
Due to the high number of available prototypes and foreseen the following training step, we decided to build different training sets by varying different prototypes percentages while including all malignant microcalcification prototypes. These new training sets will be used in the following training steps carried out in the project.

2.3 Independent Component Analysis (ICA)

Independent Component Analysis appears as a possible solution to the problem of blind source separation (BSS) (Jutten & Herault, 1991; Comon, 1994). Basically, the goal in BSS is to recover the signals generated by unknown sources using sensor observations which provide a number of signals supposed to be a linear mixture of independent and unknown

source signals. ICA can be used to solve this problem supposing statistical independence of these sources. The problem can be stated in equation (1).

$$\mathbf{x} = \mathbf{A} \cdot \mathbf{s} \tag{1}$$

Being **x** the observed signals, **A** the mixture coefficients and **s** the unknown sources (Hyvärinen et al., 2001). To apply this technique in feature extraction on mammography, we must suppose that a region of a given size in the mammography (called 'patch') is as linear combination of a series of independent unknown sources, a priori. These unknown sources can be seen as statistical independent 'patches', and can be estimated by ICA using samples. The process provides us a base of functions (small squared images in our case) that lets us expand a given 'patch' from the mammography in terms of it. The mentioned procedure can be expressed graphically as shown in Figure 3.
Where a_i coefficients represent the features to extract and which let us characterize a region from its sources.
The use of coefficients from a linear combination as parameters to characterize patterns has been widely used, for example in wavelets transforms or Gabor filters. Nevertheless, we think that ICA value added is that the base functions are specifically created for the image space under study on the opposed to wavelet transforms.
There exist many studies that have used ICA as a feature extraction technique and in particular for image analysis (Bell & Sejnowski, 1997; Hyvärinen et al., 1998; Jenssen & Eltoft, 2003).

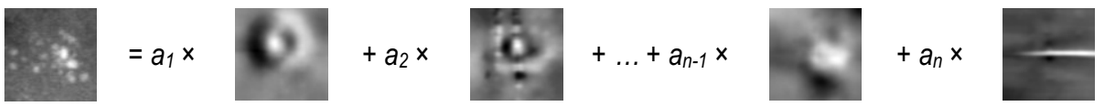

Fig. 3. ICA expansion.

The studies carried out by (Christoyianni et al., 2002) conclude that results obtained with ICA improve results obtained by different statistical parameters (GLHM and SGLDM). However, the study is carried out using only 58 regions of suspicion from the free version of the MIAS database. Ignoring the big difference in the number of cases which provide each database, the key difference between them is resolution (200μm/pixel for MIAS and 43.5μm/pixel for DDSM). This characteristic along with grey level depth can be a key factor for a successful handling of microcalcifications.
Other authors also apply ICA to extract features in mammograms. For instance, in (Campos et al., 2005) a similar scheme to (Christoyianni et al., 2002) is followed, but including the feature selection carried out by means of the forward-selection method. The work is also carried out with the mini-MIAS database.
In relation to these works and also to our previous exposition about the databases, we would like to remark that almost all the papers broach the usage of ICA to describe complete regions of interest (ROIs), scaled or centered. We think that this strategy, although may be valid with mini-MIAS and mass detection, is totally unsuitable for the DDSM database and microcalcification based approaches. A greater spatial resolution will lead to bigger ICA input for each ROI, increasing computational requirements in ICA matrices procurement phase and the number of features to obtain an effective ROI classification. We

are using ICA at vicinity-of-pixel level, instead of considering complete ROIs, what means that we needed to label groups of pixels individually within each ROI.

2.4 Neural classifiers

Our work in microcalcification clusters CAD is not only centered on isolated prototypes evaluation. We have developed a complete software system to detect ROIs in mammograms and analyze its malignancy. The pattern recognition block is implemented by using a neural network with only one hidden layer. The number of neurons that includes the hidden layer is adaptable from 50 to 200. The selected training algorithm is RPROP (Riedmiller & Braun, 1992), a well known, fast converging and robust algorithm. The training system is implemented using the kernel abstraction characteristics provided by Stuttgart Neural Network Simulator (SNNS). This feature permits us to build standalone trainers which can be run in our Beowulf cluster, allowing us to study an important number of configurations and to evaluate performance dependence on ICA window size and the number of features to be used.

2.5 ROI generation

The previously described classifier provides a map of suspicious pixels for each input mammogram. This map is filtered to eliminate spurious single-pixel positives. The filtered image is further fed into a ROI builder subsystem which groups neighboring microcalcifications into zones of interest.

The first step of the ROI builder consists in an object detector that isolates microcalcifications and computes its sizes. In a second step, we carry out an object grouping phase by means of a density map. For each pixel of the mammogram we compute the number of neighbour microcalcificacions in an area of $1cm^2$. After that, we filter the density map retaining only those zones which have a density value equal to or greater than 3, following the classic definition provided in (Sickles, 1986). This procedure provides us an easy way to obtain ROIs avoiding costly region growing and merging operations because they are completely inherent to the process and don't need further calculations.

Each possible generated ROI in a mammogram, is tagged as true positive (TP) if it overlaps with the ROI provided in the DDSM database (if present). Analogously the ROI is tagged as false positive (FP) if there exist no overlapping with an actual zone of interest of the mammogram or the mammogram is healthy. On the contrary, if DDSM contains malignant ROIs for a mammogram and our system fails to find them we compute all those ROIs as false negatives (FN).

And finally, a healthy mammogram successfully diagnosed is considered as a true negative (TN). In a computerized diagnosing system, the previous four parameters are usually expressed in terms of mean values per image, being false positives per image (FPi) a common performance index. Figure 4 shows a processed mammogram which yields one TP ROI (the upper one) and four FPs. The true positive ROI includes a detailed view which shows the microcalcifications that define it.

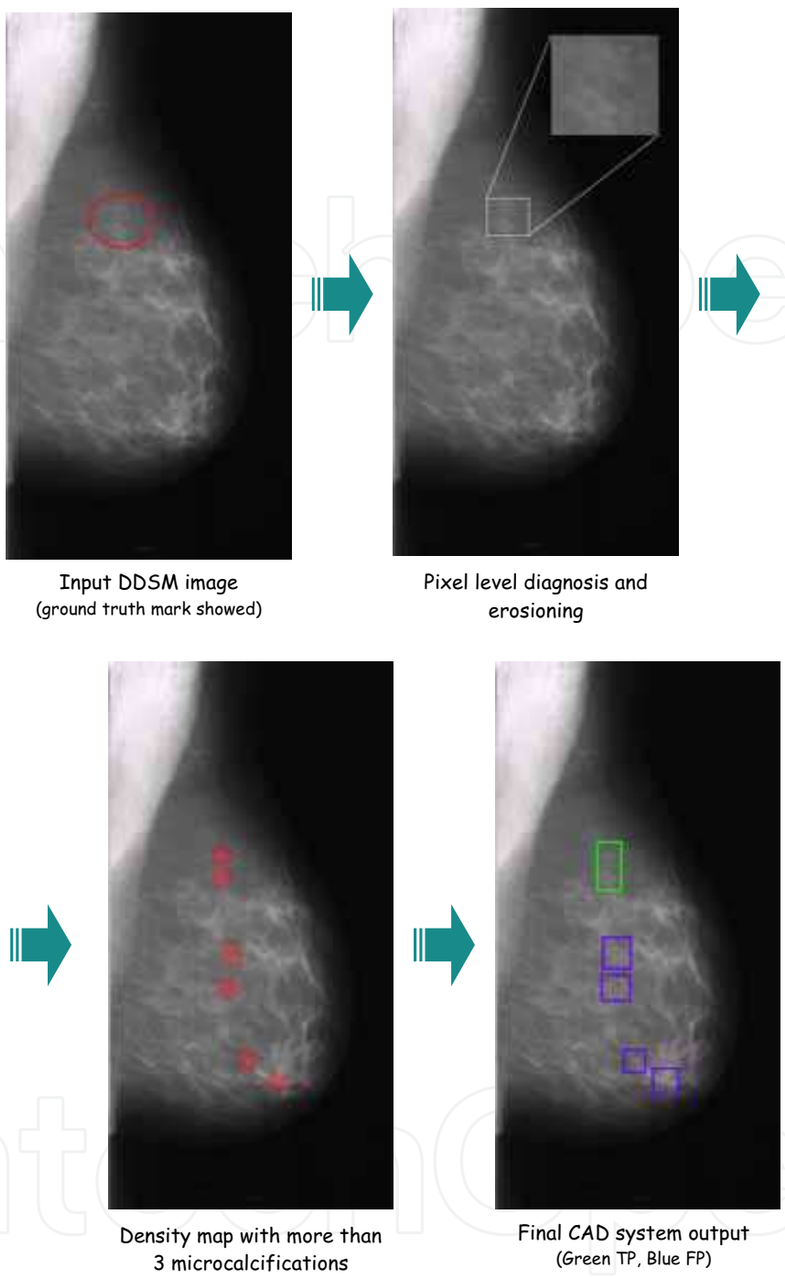

Fig. 4. Example of mammogram process (case D-4183, with 1 TP and 4 FP).

2.6 False positive correction

An automated ROI generator may lead to an excessively big region if the output of the neural network classifier provides an scattered microcalcifications distribution over the whole mammogram. Considering the previously stated evaluation criterion, large ROIs can lead to a misleading low FP rate.

In order to deal with the possibility of an excessive ROI growth, instead of using false positives per image (FPi) as a performance index, we have defined a new parameter called weighted false positive per image (WFPi). A false positive ROI increases this parameter as many times as it exceeds the maximum estimated ROI size (MRS) plus one. The MRS is the area of the largest MCC–ROI defined in DDSM database calcification subset (39.69 cm^2). Moreover, WFPi is also increased if a true positive ROI exceeds the MRS, see (2) for reference. Thus this parameter penalizes not only false positives but also unjustified true and false ROI growths.
Hence, WFPi improves common FPi confidence degree and makes it a preferable figure of merit for a completely automated system. Nevertheless, it is important to note that providing results in terms of this parameter leads to a worsening of overall results.

$$WFPi = \sum_{FP\#} \left(1 + \frac{area(FP_i)}{MRS}\right) + \sum_{TP\#} \left(\frac{area(TP_i)}{MRS}\right) \quad (2)$$

2.7 Evaluation of different sets

To test our system robustness we have defined four different database subsets with the aim of stating that the system performance depends on this choice. The four views provided for each case are used in this study. Table 1 summarizes the main characteristics of the chosen subsets and includes the total number of mammograms processed.
Firstly, we have created a big set of cases (GLOBAL) which includes an important number of clearly normal cases (all cases from normal volumes) and as much malignant MCCs cases as possible (all cancer cases from cancer volumes whose lesion type is diagnosed as a kind of microcalcification cluster). This subset should allow us to test our overall system performance on a more realistic situation than that proposed in (Heath et al., 2000), which only comprises malignant MCC cases.
Secondly, we decided to use the validation subset proposed in (Heath et al., 2000) (CALC 1) which contains all cases of the BCRP CALC 1 subset as specified by DDSM creators. It must be noted that none of this cases have been considered to train the neural classifier used in this system. Results obtained over this subset can be compared with those obtained in research works that follow the guidelines provided by DDSM authors in (Heath et al., 2000).
Furthermore, we studied a third subset (SET 1) which includes the same cases studied in (Roffilli, 2006). It is comprised of all the cases from normal volumes 8 and 10 plus all MCC cases from cancer volumes 2,7 and 12.
Finally, SET 2 is a favorable selection of cases from GLOBAL subset.

Set	Description	Mammograms
GLOBAL	Vols. normal and cancer	4,372
CALC_1	BRCP_CALC_1	200
SET_1	Vols. 8 and 10 of normal and vols. 2, 7 and 12 of cancer	408
SET_2	Selection of favourable cases	1,622

Table 1. Data included in the considered sets.

3. System Implementation

As can be deduced from the previous sections, the proposed system is very complete and somewhat complex. In this section we describe in deep the elements which constitute the system and its characteristics.

3.1 Computational infrastructure

The DDSM database provided by Island Vision Group is accessible by FTP, so we dumped it to a dedicated server with a storing capacity of 290 gigabytes where 240 gigabytes are used exclusively to store the images and configuration files which constitutes the database.
As previously mentioned, DDSM provides case information in file form. As this format is not adequate to work with this data in an intensive way, we have decided to insert this information in a SQL database server which runs in one of our Linux servers.
At the same time this database engine allows us to store some information for different project phases, letting us to centralize all needed data, both input as output, and facilitating statistics procurement task.

Some project phases require high computational resources and volatile memory requirements. Fortunately our research group owns various multiprocessor servers with important memory resources which have allowed us to carry out the project; obviously typical hardware infrastructure is insufficient to deal with a project like the proposed here.
We can point out an Opteron bi-processor server with 16 gigabytes of RAM, a second 64-bit server Athlon64 four-cores-processor with 8 gigabytes of RAM and various 32-bit bi-processor servers which hold the database engine, the distributed file system and backup.
A special mention is due to the most important computation resource of the group, a Beowulf type cluster with 45 Phenom 9850 nodes each one equipped with 4 gigabytes of RAM. This is the resource where all massive calculations are carried out and lets us reduce dramatically simulation times, thanks to its 180 CPU cores.

3.2 Management interface

A reliable image work requires developing a tool that makes easy to visualize these images and to make different operations with them like marking or correcting. The tool developed by our group is called Mamoprot and lets us to solve many different issues arisen in various development stages of the project.
Mamoprot is a modular application written in C++ and developed against the widget library QT, which runs under Linux environment. It is completely integrated with the relational database server that manages the project. This tool lets to carry out many different operations. Besides basic visualization operations (contrast adjustment, brightness, basic filtering and enhancement) working with overlays allows us to perform many interfacing operations. Specifically Mamoprot is the tool that we used to visualize and mark prototypes in overlays, and also let us to diagnose the visualized overlay with a given configuration, visualize ICA decomposition of the overlay and rebuild the image using only some components. The first module of Mamoprot was used by experts to insert training prototypes in the database.
Mamoprot is also designed to deal with mammograms, letting us to visualize them with overlapped expert marks and stored regions of interest. The application also permits us to

carry out a diagnostic of the whole mammogram, viewing pixel based classification and the possibly generated ROIs with that system configuration. Finally, this module allows us to create new overlays and to add new prototypes for interesting regions.
And finally, Mamoprot permits to insert visually new diagnostic configurations, selecting system characteristics to be studied. In Figure 5, we can see a Mamoprot snapshot for the mammogram module; particularly we show the diagnostic results for a complete mammogram. Discontinued blue rectangles mark benign auxiliary ROIs previously added to the database, red discontinuous rectangle marks the original DDSM malignant overlay, green solid line rectangle accounts for true positive finding and the blue solid border rectangle is a false positive generated by the system.

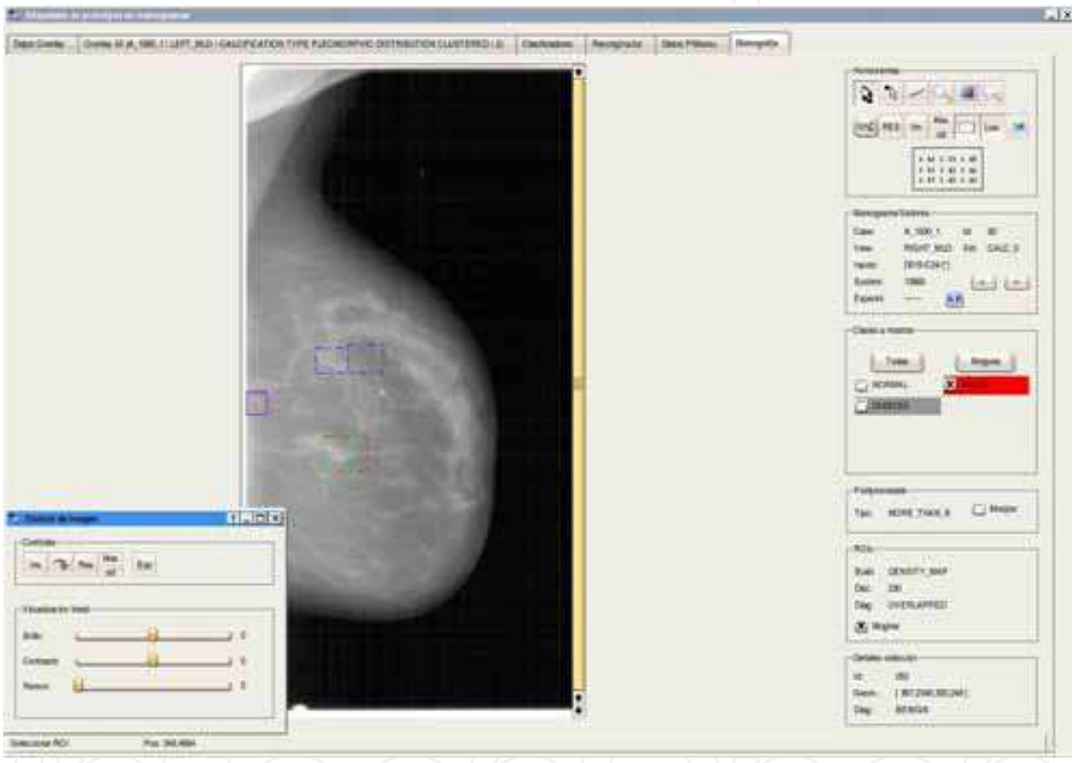

Fig. 5. Mamoprot interface.

4. Results

In our work we have trained more than 4,000 classifiers, we have evaluated more than 140,000 complete mammograms (with different classifiers and decision systems), and more than 450,000 ROIs have been generated.With these numbers, it is clear the importance of the SQL database in order to get the results in an easy way.
To evaluate complete mammogram performance we have decided to use FROC curve analysis (Free-response Receiver Operating Characteristic), as a widely accepted technique. Furthermore, we have decided to use “Weighed False Positive per Image” (WFPi) instead of “False Positive per Image” (FPi).

4.1 Global results

First, we present the results over the BCRP_CALC_0 and BCRP_CALC_1 subsets of DDSM database.

The use of WFPi instead of FPi deteriorate our results, but it is evident that it provides a more reliable vision of the overall system performance. Table 2 shows the values of these parameters for one of the best configurations obtained for global results, and Figure 6 shows FROC curves globally and for the subsets BCRP_CALC_0 and BCRP_CALC_1 (showing in every case WFPi instead of FPi). These results are obtained for a 13x13 patch size with 40 ICA components.

FPi	WFPi	Sens. (%)
0,40	0,40	24,5
2,18	2,20	54,1
2,79	2,83	63,8
3,33	4,17	84,1
2,78	4,20	88,5
2,65	4,35	90,4
3,57	6,74	97,6

Table 2. Global results.

4.2 Results over different sets

We thought that it could be interesting to compare the results obtained when we use different sets of mammograms to test the performance. As we said before, we have defined four different subsets of DDSM (Table I).

Figure 7 shows the modified FROC curves obtained for each of the subsets defined in Table 1. In the x-axis we have replaced regular FPi values with the previously defined WFPi performance index.

We can observe that modified FROC curves for GLOBAL and BCRP_CALC_1 groupings follow a similar trend. Due to we are restricting our study to MCC detection and diagnosis, and given the previous definition of BCRP_CALC_1, this behaviour seems to suggest that this set of mammograms is an adequate sample to provide results over the whole DDSM database.

On the other hand, results for subset SET 1 show a clear improvement over GLOBAL and BCRP_CALC_1 subsets; we can observe better sensitivity values for the same or even lower WFPi. However, it is evident that this subset does not reflect valid results for the whole database.

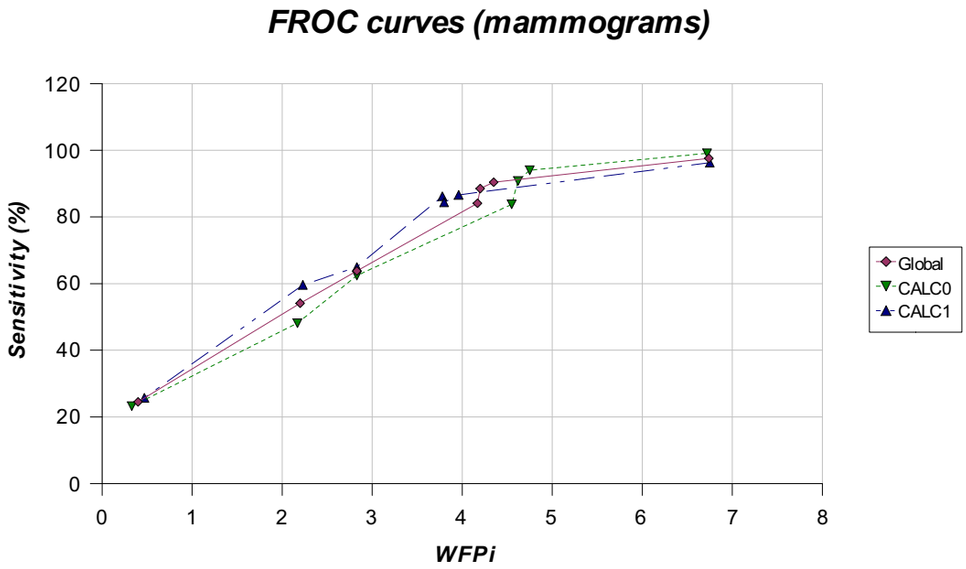

Fig. 6. FROC curves corresponding to complete mammograms.

Finally, we can observe an important improvement in the modified FROC curve for SET 2. We obtain high sensitivity values at low WFPi rates even when this subset has approximately 1,600 mammograms, a number of mammograms higher than those included in both BCRP_CALC_1 and SET 1.
Table 3 shows a WFPi and FPi comparison at a common sensitivity value of 80% for each analyzed subset. As can be seen, WFPi values are higher than the corresponding FPi. This effect is stronger in the GLOBAL subset (the most comprehensive one) where the WFPi value is a 13% higher than the associated FPi.

Set	FPi	WFPi	Sensitivity
GLOBAL	3,75	3,97	78,04 %
CALC_1	3,26	3,67	80,65 %
SET_1	2,24	2,29	81,82 %
SET_2	1,03	1,25	80,09 %

Table 3. Performance parameters for the proposed subsets.

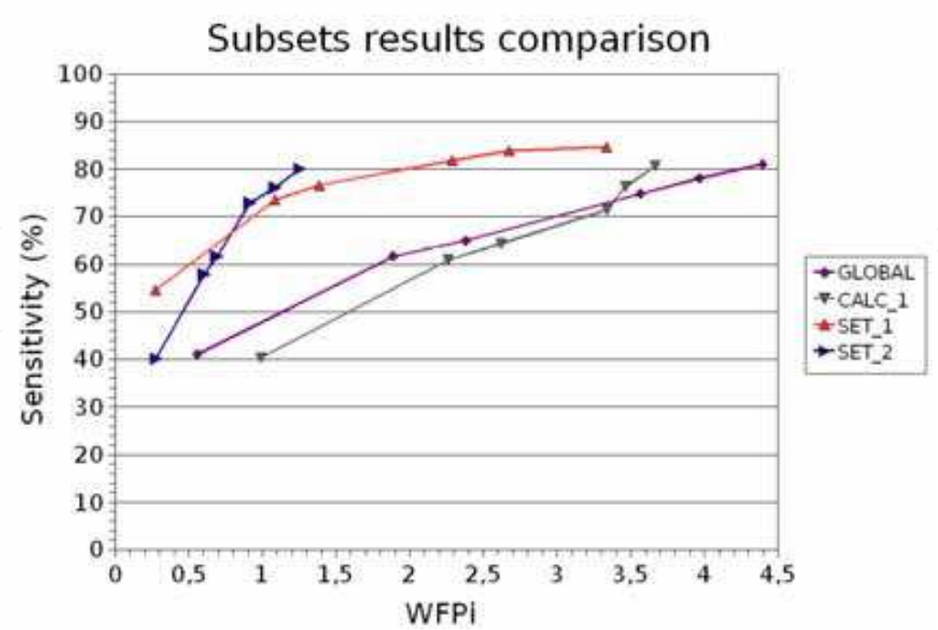

Fig. 7. FROC curves for proposed subsets.

5. Conclusions

The previously described results show that ICA lead to systems with an acceptable performance for mammograms taken from the BCRP_CALC_1 of the DDSM database.
The results showed in Figure 6 and the previous analysis let us to state that the election of the specific subset used in this research work has an important influence on the results provided by our CAD system, at least from the MCC detection and diagnosis point of view.
Hence, we think that, in this particular research field, not only raw results, but also a clear specification of the set used to provide them, should be provided.
Finally, we must conclude that Independent Component Analysis is a valid technique to deal with the microcalcification detection problem. However, as a future research plan, we are studying the possibility of improving the system performance by adding new prototypes in particular zones where diagnostic results deteriorate the overall performance.

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