CHAPTER 2

LITERATURE SURVEY

2.1 RELATED WORK

2.1.1 False Positive Reduction Based on Analysis of Unilateral and Bilateral Mammograms

Computer aided detection (CADe) systems help radiologists avoid overlooking of abnormalities by locating suspicious regions with high sensitivity on the screening image; however, the associated drawback of CADe systems is that they yield a large number of false positives. Thus, a false positive reduction step has become an inevitable step following the detection phase to increase radiologists’ confidence in CADe systems (Llado et al 2009).

As mammograms have low contrast and the breast abnormalities are often subtle on mammograms, enhancement techniques are used to improve the image quality and hence the detection and diagnostic performance (Rangayyan et al 2007). Two kinds of enhancement techniques include the direct and indirect contrast enhancement. While direct contrast enhancement involves direct manipulation of the contrast using a contrast measure, in indirect contrast enhancement the image contrast is not manipulated directly. Though many approaches (Cheng & Xu 2002, Morrow et al 1992, Rangayyan et al 1997) exist for enhancing mammograms using direct contrast enhancement, wavelet-based direct contrast enhancement (Tang et al 2007) is more advantageous as it can be applied to the wavelet coefficients in the decompression stage thereby reducing time. Many indirect contrast
enhancement techniques like unsharp masking, histogram equalization and wavelet enhancement are also popular (Tang et al. 2009). Again, much attention has been drawn towards wavelet-based enhancement technique due to its advantages (Sakellaropoulos et al. 2003). The multiscale analysis of wavelets has enabled features of the mammogram at different scales to be enhanced.

During the process of image enhancement, noise in the image may also be accentuated and this necessitates its suppression before enhancement of the image (Tang et al. 2009). Filtering methods like median filtering (Lai et al. 1989) and wavelet domain methods like wavelet shrinkage (Scharcanski & Jung 2006) have been employed for removing noise in mammograms. Filtering techniques are simple and fast and their effectiveness depends on the choice of filter size and shape. Wavelet shrinkage technique employs thresholding of the wavelet coefficients so that noise is removed, while image features are retained; however the choice of the threshold is usually done in an adhoc manner.

Prior to the detection of masses on mammograms, segmentation of the pectoral muscle is usually performed to avoid its interference with the segmentation of regions of interest (ROIs). Hough transform has been employed to detect the pectoral edge. However, the drawback of this approach is that the pectoral edge is assumed to be straight, which may not be the case. To overcome this drawback, refinement of the linear approximation to a curve was suggested. Seeded region growing is another popular approach for pectoral muscle removal. However, proper placement of seed points is critical in this method (Saltanat et al. 2010).

Many CADe algorithms have been proposed for false positive reduction in the detection of mammographic masses, based on unilateral
analysis and bilateral analysis. These analyses are based on two common practices that radiologists follow for locating suspicious regions on mammograms. Normally, increased density regions in mammograms draw the attention of radiologists, in the process of detecting abnormalities. Further analysis of the characteristics of these regions is used to rule out false positives. This process which involves a single mammogram is called unilateral analysis. It is also very common for radiologists to compare bilateral mammograms, i.e., right and left mammograms, and judge the nature of ROIs. This analysis called bilateral analysis, involving the candidate mammogram (mammogram under consideration) and the contralateral mammogram (bilateral counterpart of the candidate mammogram), is suggestive of abnormality when there exists an asymmetry; on the other hand, symmetry increases the probability that the suspicious region is a false positive (Wang et al 2010).

Algorithms for detection of suspicious regions in unilateral analysis of mammograms can be broadly categorized into two types, i.e., pixel-based methods and region-based methods. The idea behind pixel-based methods is extraction of features from each pixel, based on which the pixel is labelled as suspicious or normal. Edge orientations at pixels have been determined for detection of spiculated masses that have a high likelihood of malignancy (Karssemeijer & Te Brake 1996). For detection of masses of other kinds, the use of adaptive thresholding has also been explored (Kom et al 2007). The large number of computations in pixel-based methods can be reduced using multiresolution analysis. The detection of an abnormal finding in the coarser resolution reduces the number of pixels to be classified (Liu et al 2001). Nevertheless, the lack of spatial details of masses and requirement of different features for different types of masses render pixel-based methods less attractive. Unlike the pixel-based methods, features are extracted from a region
formed by a group of pixels, in region-based methods. These ROIs are obtained as a result of segmentation. In region-based methods employing matched filtering, a model is created for a mass, which acts as a filter on the image (Kobatake et al 1999). As this method is limited by the large variation in the size of masses, multiresolution region-based methods (Qian et al 1999) have been preferred. Consideration of spatial information and lesser computational complexity are the advantages of region-based methods when compared to pixel-based methods. Following detection, unilateral features are extracted from the ROIs for subsequent false positive reduction.

In bilateral analysis, registration of the candidate mammogram with the contralateral mammogram is the most important and non-trivial step. Registration is necessitated by factors including differences in positioning of the breasts and the amount of pressure applied to them during image acquisition, resulting in non-alignment of corresponding points in bilateral mammograms. Thus, registration of bilateral mammograms becomes essential to compensate for these effects, before comparing or matching right and left breasts (Wirth et al 1999). Medical image registration techniques may be divided into three categories based on the transformation model used. These techniques include rigid registration, affine registration and non-rigid registration. In rigid registration, the transformation model involves rotation and translation. Affine registration involves scaling and shearing in addition to rotation and translation and hence is better than rigid registration in the sense that it can correct for scaling and skewing differences. The third category called non-rigid registration involves a non-linear transformation model that adjusts the image for warping. Affine registration is a crude approximation to non-rigid registration and is always orders of magnitude faster than the latter due to lesser number of unknowns involved (Chumchob & Chen 2009). Another categorization is based on whether features such as curves and points
are used for matching the images, or the image gray level values are used. The former is called feature-based registration and the latter is called intensity-based registration (Richard & Cohen 2003). Bovis & Singh (2000) have used rigid registration with the nipple as the reference point for determining the rotation parameter for registering bilateral mammograms. Wirth et al (1999) have employed non-rigid registration, with the control points being chosen from the breast contour.

Following registration, bilateral features are computed for false positive elimination. In one approach (Bovis & Singh 2000, Kupinski & Giger 1997), features are extracted from ROIs in the difference image (difference between bilateral images); in the other, features are extracted from each of the bilateral ROIs (candidate ROI and contralateral ROI), from which the bilateral features are derived. Following the latter approach, Wang et al (2010) computed the difference between corresponding features from the bilateral ROIs, whereas Wu et al (2007) determined the ratios of maximum feature value to minimum feature value.

Morphological features of ROIs, which characterize their shape and margin, represent the properties analysed by radiologists. On the other hand, though textural features cannot be perceived by human eyes, i.e., radiologists, they are effective in capturing important diagnostic characteristics (Bovik 2005). In both unilateral and bilateral analysis, textural features have been widely adopted for elimination of false positives. Gray level co-occurrence matrix (GLCM)-based features (Haralick features) is popular for classification of ROIs as normal regions or lesions (Bellotti et al 2006, Sahiner et al 2001). Other textural features that have also been employed for the task include ranklet features (Masotti et al 2009), Laws features (Kegelmeyer et al 1994) and local binary patterns (LBP) (Llado et al 2009). Few researchers (Mudigonda 2001 et al, Wei et al 2005a) have also explored the use of
morphological features either separately or in combination with textural features, for this purpose.

To determine a reduced optimal set of features, two different approaches have been followed. One of these is feature extraction which transforms the coordinate system of the data to improve the classification performance while also reducing the dimensionality. The other technique is feature selection, which simply reduces the dimensionality without transforming the coordinate system. Principal component analysis (PCA) is a popular feature extraction technique, which projects the data onto the directions specified by eigen vectors of the covariance matrix. PCA has been widely employed for optimizing the feature vector in the classification of ROIs (Christoyianni et al 2002). Stepwise feature selection has also been used to determine the most significant features (Wu et al 2007).

Different kinds of classifiers have been employed for discriminating normal regions and lesions. Linear discriminant analysis (LDA) has been employed for discriminating masses and false positives in mammographic CADe systems (Wei et al 2005a). LDA determines linear combinations of features that maximize the separation between different classes. Though simple, the linear nature of LDA makes it unsuitable for handling nonlinearly separable data. The use of decision trees has also been explored for classifying ROIs as masses or normal tissues (Karssemeijer & Te Brake 1996). A decision tree is a simple tree structure in which each node splits the data according to some criterion, unless it is a terminal node. Though very simple, its performance depends on the appropriateness of the classification rules. Artificial neural network (ANN) has also been widely employed for classification of ROIs (Bellotti et al 2006). ANN is a popular classifier that mimics human brain in learning adaptively from examples. Although ANNs are robust and widely applicable, they are affected by problems such as
overfitting and long training time. In some studies (Campanini et al 2004, Moayedi et al 2007), support vector machine (SVM) has been employed for the task. SVM, a supervised learning technique, optimizes the hyperplane that separates different classes of the data in the higher dimensional space. An SVM can be trained faster than ANNs and usually yields a good performance.

As opposed to the above mentioned techniques that involve training, template matching is a technique that is based on image retrieval and has been employed by few researchers (Cheng et al 2006). In this method, a similarity metric is used to determine the class of a test case. As no training is required, new data can be easily added to the system. However, requirement of a large dataset and a uniform source of images are the associated drawbacks.

Wu et al (2007) developed a CADe system in an attempt to exploit the advantages of both unilateral analysis and bilateral analysis for false positive reduction. In this method, the symmetric ROI (the corresponding ROI in the contralateral mammogram) is determined following image registration. Haralick textural features as well as morphological features including normalized radial length, perimeter, area, circularity, rectangularity, contrast and Fourier descriptor measure are then extracted from both the candidate ROI and the symmetric ROI (the contralateral counterpart of the candidate ROI). While unilateral features are extracted from the candidate ROI, bilateral features, derived from both the candidate and symmetric ROI features, are determined as the ratio of the maximum of the two feature values to the minimum. Unilateral and bilateral features are used to train two LDA classifiers and this yields the unilateral and bilateral scores, respectively. Linear discriminant fusion is then employed to fuse the scores from these two classifiers. Herein, the unilateral and bilateral scores are concatenated and given as input to a third LDA. The final score from this LDA is used for classifying the suspicious regions as masses or false positives. It has been
reported that linear discriminant fusion has reduced the false positive rate when compared to the unilateral scheme. Though fusion of unilateral and bilateral information has shown to improve the false positive reduction performance when compared to the unilateral scheme, comparison has not been made with respect to the bilateral scheme. Due to the absence of this validation, it has not been possible to verify whether the fusion-based scheme meets the expectation of yielding a performance that is superior to both the single-source schemes.

2.1.2 Mass Classification Based on Analysis of Ipsilateral Mammograms

Computer aided diagnosis (CADx) systems intend to help radiologists in classifying lesions as benign or malignant, so as to reduce the number of unnecessary biopsies. Many studies have focussed on CADx algorithms for mammographic mass classification. Pre-processing techniques that are performed prior to image segmentation can improve the quality of the mammogram image, aiding in better detection of subtle masses. The quality of mass segmentation plays an important role in determining the accuracy of a CADx system in classifying the masses as benign or malignant (Jalalian et al 2013). A survey of various pre-processing techniques and segmentation algorithms for detection of mammographic masses has been presented in Section 2.1.1. Following segmentation of the mass from the background, features that differentiate malignant and benign masses are extracted. With the aid of these features, masses are classified as benign or malignant

Radiologists analyze masses using their morphological properties which include shape and margin (Oliver et al 2010). Generally, a mass with irregular shape and ill-defined boundary has more probability of being malignant. On the contrary, a mass with regular shape and well-defined boundary has more chances of being benign (Tang et al 2009). Many CADx systems for mass classification utilize morphological features (Guliato et al
2003, Rangayyan et al 2000). Textural features are more effective than morphological features in discriminating benign and malignant masses and are widely used in CADx systems (Mencattini et al 2010). Haralick textural features have been widely employed by researchers for mass classification (Sahiner et al 1998). A combination of morphological and textural features has also been attempted (Mudigonda et al 2000). The descriptors of mammographic abnormalities defined in the breast imaging-reporting and data system (BI-RADS) have been used in some studies (Gupta et al 2006a). PCA, stepwise feature selection and recursive feature elimination have been employed for dimensionality reduction in mass classification applications (Zwiggelaar et al 1999, Gupta et al 2006b, Majumder et al 2005).

In the final step of a CADx system, the ROIs are classified into one of the two classes, i.e., benign or malignant. The k-nearest neighbour, LDA, ANN and SVM classifiers are popular tools for pattern recognition and have been used widely for mass classification (Jalalian et al 2013, Gupta et al 2006b, Abbass 2002, Akay 2009).

A routine mammographic examination involves recording ipsilateral views, which are two standard views of the breast. These are the mediolateral (MLO) view, which is the side-to-side view, and the craniocaudal (CC) view, which is the head-to-toe view. Radiologists usually read both views simultaneously to arrive at a decision. Many studies have shown that two-view mammographic analysis has improved the cancer detection rate and has also reduced the number of call-back examinations (Blanks et al 1999, Hackshaw et al 2000).

Gupta et al (2006a) combined ipsilateral information for classification of mammographic masses using BI-RADS descriptors and patient age as features. Decision fusion rules including maximum rule,
minimum rule and sum rule, and feature fusion based on concatenation were used to produce the two-view score. The sum rule has been reported to outperform all the other methods in terms of area under the curve (AUC). Further, all fusion schemes that have been considered have resulted in performance improvement when compared to both single view schemes (MLO and CC), which justifies the use of information fusion.

Gupta et al (2006b) explored several approaches for combining information from ipsilateral mammograms for classification of breast masses, using Haralick features. Single-view classifiers were first built for either view using LDA classifiers. Following this, two-view classifiers were designed using different feature fusion and decision fusion schemes. Feature fusion techniques including concatenation and averaging were investigated. Also, different decision fusion schemes including minimum rule, maximum rule, sum rule, product rule and linear discriminant fusion were explored. It was reported that only the sum rule outperformed both the single-view schemes in terms of AUC, while all the other schemes are superior to the MLO scheme and not the CC scheme. This observation is contrary to the results of the previous work (Gupta et al 2006a) in which all fusion schemes had outperformed both single view schemes. This observation is true, especially for the fair comparison between fusion schemes (maximum rule, minimum rule, sum rule and concatenation) that are employed in common in the two studies. This performance difference could be attributed to the use of different validation datasets in these two studies, resulting from the use of different random cases chosen from a given database and the use of features of differing nature. This observation indicates that the datasets involved have a strong impact on the performance of a particular fusion scheme for a given diagnostic task.
Ipsilateral information fusion has also been explored in other breast cancer diagnostic tasks such as content-based image retrieval (CBIR) for BI-RADS description of masses (Narvaez et al 2011), elimination of false positives in the detection of masses (Samulski & Karssemeijer 2011) and classification of microcalcification clusters (MCCs) as benign or malignant (Wei et al 2005b).

2.1.3 Mass Classification Based on Analysis of Multiple Modalities Including Sonography and Mammography

With the increased use of sonography (ultrasound imaging) for achieving better discrimination of benign and malignant masses, many sonographic CADx algorithms have been studied for mass classification.

Similar to mammograms, sonograms (ultrasound images) should also be subjected to a series of processing steps prior to segmentation and classification. Speckle noise and low contrast are the major limitations of sonograms (Cheng et al 2010). Filtering methods and wavelet domain methods are commonly used for speckle reduction in sonograms (Jalalian et al 2013). Speckle reduction is followed by enhancement of sonograms, in order to improve their contrast before they could be subjected to segmentation. Techniques like histogram equalization and the stick technique are commonly employed for contrast enhancement in sonograms (Cheng & Shi 2004, Awad et al 2003). The drawback with the latter technique is that it enhances only edges, while the non-line features are unaffected.

Following the pre-processing steps, segmentation is performed to detect the ROIs from the sonograms. Several segmentation algorithms have been proposed for detection of ROIs in sonograms. Histogram thresholding has been employed for segmentation of breast sonograms (Joo et al 2004). Though
this method is simple and fast, it yields poor performance for images with unimodal histograms. Markov random field (MRF) has also been explored for segmenting sonograms (Boukerroui et al 2003). The algorithm performs image segmentation by iteratively assigning labels to pixels such that the posterior estimation is maximized. The advantage of MRF model is that it makes good utilization of pixel correlations for labeling the pixels. Though accurate, the MRF model is complex and time consuming. Classification-based segmentation using neural networks has also been employed for segmentation of sonograms (Chen et al 2002). Though the contours of lesions can be extracted automatically, selection of the training set, time-consuming nature of the training process and dependence of segmentation performance on the database are the limiting factors.

The active contour or snake model (Kass et al 1987) has been used by researchers for detecting the ROI’s edge. Here, the contour is actively modified through minimization of the associated energy which has two components, namely internal and external energy. The external energy derived from the features of the image is used to extract the contour of the ROI, whereas the internal energy derived from the contour model is used to control the contour’s shape. The snake model has been employed widely for detection of ROIs in sonograms (Madabhushi & Metaxas 2003). Level set method was explored to improve the snake-based segmentation of sonograms (Sarti et al 2005). Though the active contour method could handle ROIs whose boundaries are of any shape, it cannot be applied on the entire image but only on the ROIs. Yet another disadvantage is that it is time consuming.

For characterizing sonographic breast lesions, model-based features are also useful in addition to textural and morphological features. These features are related to the echo that is back scattered from the breast tissue. However, the difficulty in developing a suitable model for echo simulation and
estimation of model parameters, limit the use of these features. Certain other features, which are based on the empirical classification criteria of the radiologists and do not actually have numerical expressions, have also been employed; most of these features, known as descriptive features, are included in the BI-RADS. Other features like patient’s age and family disease history have also proved to be useful in sonographic CADx systems (Cheng et al 2010).

Stepwise feature selection has been employed to determine the most significant sonographic features for classification (Horsch et al 2002b). PCA has also been widely employed by researchers for optimizing the sonographic feature vector (Huang et al 2004). Template matching, LDA, logistic regression, ANN and SVM are the variety of techniques used for classification (Huang et al 2004, Horsch et al 2002a, Sehgal et al 2004, Joo et al 2004, Huang et al 2006).

In order to improve the accuracy of classification, sonograms are increasingly used by radiologists as an important adjunct to mammogram images. It is also reported in some studies that the sensitivity and specificity achieved by radiologists in the diagnosis of breast cancer are higher when both these modalities are used rather than using either modality separately (Berg et al 2006). Sonography is particularly useful in diagnosis of palpable masses and in cases where mammograms are inconclusive (Rahbar et al 1999).

Few researchers have explored computer aided analysis of sonogram and mammogram images in combination for classification of breast lesions. The performance of observers in classifying lesions with and without the aid of CADx systems has been analyzed by Horsch et al (2006). In this work, two independent CADx systems based on sonogram and mammogram images are developed. Both the systems employed an automatic segmentation
of lesions, using manually indicated lesion center as the starting point; segmentation was followed by automatic feature extraction. The features extracted from the mammographic lesion included gray level in the lesion neighborhood, texture, shape, margin sharpness and spiculation. The sonogram features included posterior acoustic behavior, texture, shape and margin. Following feature extraction, each CADx system employed a Bayesian neural network to determine the probability of malignancy of the lesion. The performance of the observers, measured in terms of AUC, partial area under the curve (pAUC) and sensitivity, improved due to the multimodal CADx system’s aid. In the above said work, computerized fusion techniques have not been attempted to combine information from the two modalities; instead, it has been demonstrated that the interpretation of human observers improved when they combined the decisions from the two unimodal (single modality) CADx systems. This work suggests that if the human observer is replaced by a computerized algorithm for information fusion, an improvement over the unimodal systems could be achieved. This improvement can be expected to be better than that achieved by human observers, due to objective nature of computer aided analysis.

Jesneck et al (2006) have proposed a CADx system that is used to combine sonographic and mammographic features of lesions so as to classify them as benign or malignant. Mammographic features included size, shape, density, calcification and architectural distortion associated features and comparison with prior findings. Sonographic features including texture, shape, orientation, margin, posterior acoustics, echogenicity, calcification and cystic component related features, vascularity and patient history features were extracted. The mammographic and sonographic features are subjected to feature fusion based on concatenation and used for lesion classification. Both LDA and ANN are employed for classification. In terms of AUC, there was no
significant performance difference between the two classifiers; also, their performance was observed to match that of the radiologists only. In this work, information fusion has been implemented in a computerized framework, unlike the previous study (Horsch et al 2006). However, the fusion scheme considered in this work yields a performance which is only comparable to that of the radiologists. Further, the fusion-based scheme has been compared with that of human radiologists’ performance only and not with unimodal scheme. This results in the lack of a comparison platform between unimodal and bimodal schemes (fusion-based schemes involving two modalities) and hence the merits of information fusion could not be verified.

Jesneck et al (2007) employed decision fusion using the product rule to combine the two modalities. The features extracted from either modality are the same as in the above-mentioned work (Jesneck et al 2006). The classifier employed in each of the unimodal schemes is the naive Bayesian classifier. Following this, two variants of decision fusion based on product rule are performed. One of the variants (DF-A) optimized the AUC and the other (DF-B) optimized the normalized partial area under the curve (pAUC). Further, the feature fusion schemes using LDA and ANN classifiers employed in the previous work (Jesneck et al 2007) were compared with these schemes. It has been reported that the DF-A scheme has outperformed both the feature fusion schemes in terms of both AUC and pAUC, while the DF-P scheme resulted in a performance equivalent to those of the two schemes. Performance comparison with unimodal schemes has not been reported in this work also.

2.2 SUMMARY AND PROBLEM STATEMENT

Information fusion has been largely explored in CADe and CADx systems for breast cancer diagnosis. Several fusion techniques that operate at feature level as well as decision level have been used for deriving useful
information from multiple sources. In few studies (Horsch et al 2006, Jesneck et al 2006, Jesneck et al 2007), it has been reported that the performance of the fusion-based computer aided detection/diagnosis (CAD) systems have resulted in a performance that is better than or at least equivalent to that achieved by radiologists. However, since most of the studies have not attempted performance comparison between fusion-based schemes and those that rely only on a single information source, the use of information fusion in a CAD framework is not properly justified in these studies. Few reported results (Gupta et al 2006a, Wu et al 2007) in which this comparison has been included have demonstrated an improved performance due to the use of fusion. An important observation is evident from the specific case of CADx systems based on ipsilateral information fusion (Gupta et al 2006a, Gupta et al 2006b); application of the same fusion techniques in two different studies on ipsilateral CADx systems that involve different datasets has not resulted in consistent results. More precisely, while all the fusion schemes that have been considered have outperformed both single-view systems in one of the cases, this is not true for the other case. In the latter case, most of the fusion schemes have achieved an improved performance when compared to one of the single-view systems only.

The sub-optimal performance of these fusion schemes and their dependence on the nature of the data involved could be reasoned out as follows: feature fusion could derive highly discriminative information from the complex relations between correlated sources; on the other hand, decision fusion could perform better discrimination by combining decisions of statistically independent information sources. Thus, when the sources are neither strictly correlated nor strictly independent, these fusion strategies are not optimal. This also explains the reason for the difference in performance of the fusion schemes for different dataset combinations governed by varying
interrelationships. Thus, an arbitrary choice of a fusion scheme for combining information sources is associated with a risk of degraded performance when compared to systems based on the individual sources.

2.3 OBJECTIVES OF THE RESEARCH

The sub-optimal nature of fusion schemes employed in state-of-the-art fusion-based systems necessitates a proposal for transforming the datasets, which makes them ideal for a given fusion technique, given that feature fusion and decision fusion are beneficial for correlated and independent sources, respectively. In other words, the motivation is towards processing the datasets corresponding to the sources to be fused, so as to capture the relationship between them, which would make subsequent fusion effective. A scheme so developed should be validated against schemes that do not involve fusion (schemes based on single information source) as well as schemes based on various benchmark fusion strategies, to check for its optimality. It is worth emphasizing here that the focus of the proposals in the succeeding chapters (Chapter 3, Chapter 4 and Chapter 5) is the fusion module and its optimality in combining information from multiple information sources so as to improve the breast cancer diagnostic performance. Therefore, in each of these studies, a proper and fair validation of the usefulness of the proposed fusion scheme can be achieved by comparing its performance with other schemes under identical conditions (the same database, the same subset of cases from a given database and same techniques implemented in other modules of the CAD system used for validation). Due to difference in the above mentioned respects among various state-of-the-art systems, a direct comparison with the results of state-of-the-art fusion-based systems is not fair.

In addition to comparison with single-source and other fusion-based schemes, the proposed scheme should also be validated with different
performance metrics and databases for verification of its consistency. Validation in all these respects is essential for ensuring robustness of the scheme and would increase its reliability in breast cancer diagnostic tasks.

### 2.4 RESEARCH HYPOTHESIS

Canonical correlation analysis (CCA) is a statistical technique that transforms two multivariate datasets such that the correlation between them is maximized. Thus, the application of CCA prior to fusion of two information sources, namely unilateral and bilateral mammographic information for false positive reduction and ipsilateral mammographic information for mass classification (both targeting the screening phase), is expected to optimize feature fusion. The implementation details of these ideas have been discussed in Chapter 3 and Chapter 4, respectively.

Further, in combining information from three information sources, i.e., sonograms and mammograms (both MLO and CC views) for mass classification targeting the diagnostic (post-screening) phase, a hybrid fusion scheme realized as an extension of the CCA-based feature fusion is expected to yield an improved performance. The proposed extension is to first apply CCA-based feature fusion to fuse sonographic information with information pertaining to either mammographic view for exploiting the correlated information among the sources. When this stage is followed by decision fusion to fuse the local decisions of the two CCA-based subsystems, statistically independent information could as well be exploited. This work has been discussed in Chapter 5.