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A hybrid classifier committee for analysing asymmetry features in breast thermograms

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ABSTRACT

Breast cancer is the most commonly occurring form of cancer in women. While mammography is the standard modality for diagnosis, thermal imaging provides an interesting alternative as it can identify tumors of smaller size and hence lead to earlier detection. In this paper, we present an approach to analysing breast thermograms based on image features and a hybrid multiple classifier system. The employed image features provide indications of asymmetry between left and right breast regions that are encountered when a tumor is locally recruiting blood vessels on one side, leading to a change in the captured temperature distribution. The presented multiple classifier system is based on a hybridisation of three computational intelligence techniques: neural networks or support vector machines as base classifiers, a neural fuser to combine the individual classifiers, and a fuzzy measure for assessing the diversity of the ensemble and removal of individual classifiers from the ensemble. In addition, we address the problem of class imbalance that often occurs in medical data analysis, by training base classifiers on balanced object subspaces. Our experimental evaluation, on a large dataset of about 150 breast thermograms, convincingly shows our approach not only to provide excellent classification accuracy and sensitivity but also to outperform both canonical classification approaches as well as other classifier ensembles designed for imbalanced datasets.

1. Introduction

Breast cancer is the most commonly occurring form of cancer in women and accounts for about 30% of all cases [3]. While the standard modality to detect breast cancer is mammography, thermal imaging provides an interesting alternative [4,20]. Thermography uses cameras with sensitivities in the thermal infrared to capture a picture of the temperature distribution of the human body or parts thereof. In contrast to other modalities such as mammography, it is a non-invasive, non-contact, passive and radiation-free technique. The radiance from human skin is a function of the surface temperature which in turn is influenced by the level of blood perfusion in the skin. Thermal imaging is hence well suited to pick up changes in blood perfusion which might occur due to inflammation, angiogenesis or other causes [22]. Asymmetrical temperature distributions as well as hot or cold spots are known to be strong indicators of an underlying dysfunction [38].

Importantly, it has been shown that thermography has advantages over mammography when detecting tumors in early stages or in dense tissue. Early detection is crucial as it provides significantly higher chances of survival [18] and in this respect infrared imaging outperforms the standard method of mammography. While mammography can detect tumors only once they exceed a certain size, smaller tumors can be identified using thermography due to the high metabolic activity of cancer cells which leads to an increase in local temperature that can be picked up in the infrared. The average tumor size undetected by mammography is 1.66 cm compared to only 1.28 cm by thermography [24].

While diagnosis is typically performed manually by experts, there is a high demand for automated methods in order to provide an objective decision that can also be used as a second, unbiased, opinion.

Several such computer aided diagnostic (CAD) approaches have been presented in the literature. In [33], an attempt based on asymmetry analysis is presented where, following segmentation based on edge detection and the Hough transform, Bezier histograms are generated and compared to identify cancer cases. In [36], some basic statistical features are extracted and fed to a complementary learning fuzzy neural network (CLFNN) for diagnosis. [37] proposes morphological analysis of "localised temperature increase"

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amplitudes in thermograms to detect tumors. A series of image features from the breast regions were extracted in [35] and subsequently analysed by a fuzzy classification method. The approach in [7] is based on transforming the thermogram into a representation derived from independent component analysis, thresholding and correlating the obtained channels to locate tumor areas. In [1], texture features and support vector machine classifiers are employed, while in [31] wavelet and texture descriptors are employed in combination with several classification algorithms.

In this paper, we present an effective approach to analysing breast thermograms for cancer diagnosis. As cancer tumors recruit local blood vessels, this will lead to a change in the temperature pattern of the affected area. We therefore derive a set of image features that describe possible asymmetries between the bilateral breast regions to capture this effect. These features are then used in a pattern classification stage for which we employ a multiple classifier system. Multiple classifier systems (MCSs), ensemble classifiers or classifier committees, perform classification not based on a single algorithm but based on a joint decision of a pool of classifiers [29]. MCSs are considered one of the most promising trends in pattern recognition [41], being able to outperform single-model approaches when it comes to accuracy [13], robustness [27] or effective implementations [12]. They have also proven themselves as an effective tool for medical decision support systems, with numerous reports describing their superior performance over standard machine learning methods for tasks such as tumor malignancy grading [21], cytological image analysis [16] or microarray analysis [32] amongst many others.

Our ensemble classifier is based on a hybridisation of three computational intelligence techniques. As base classifiers we employ neural networks or support vector machines. The individual classifiers are combined using an fuser implemented as a one-layer perceptron neural network. Finally, we remove redundant classifiers through an ensemble diversity measure based on fuzziness using an energy approach. Importantly, we also address the problem of class imbalance that often occurs in medical data analysis and might lead to biased decision making. We do this by training the individual base classifiers on balanced data subsets, thus eliminating any unfavourable class distribution.

The main contributions of our presented work are as follows:

- a hybrid decision support system, applied to the challenging task of breast cancer detection on a large dataset of thermograms;
- a novel classifier ensemble, dedicated to imbalanced classification;
- a method for generating base classifiers on the basis of object bags, consisting of the entire minority class and an equal number of randomly sampled objects from the majority class, to counter the unfavourable class distribution;
- a method for promoting best classifiers from the pool to boost minority class recognition rate, based on a novel diversity measure and a trained neural fuser.

Our experimental results, on a dataset of about 150 breast thermograms, show convincingly that our proposed approach works well and gives excellent classification performance. Moreover, it is shown to statistically outperform canonical classifiers and recent classifier ensembles that are also dedicated to imbalanced classification, as well as to give clearly improved performance compared to prior published approaches on the same dataset.

The remainder of the paper is organised as follows. In Section 2, we describe the set of image features we extract from the breast thermograms. Our classification approach is presented in Section 3, while experimental results are given in Section 4. Section 5 concludes the paper.

2. Thermogram asymmetry features

As has been shown [33], an effective approach to automatically detect cancer cases is to study the symmetry between left and right breast regions in the captures thermograms. In the case of cancer presence, the tumor will locally recruit blood vessels resulting in hot spots and a change in vascular pattern, and hence an asymmetry between the temperature distributions of the two breasts. On the other hand, symmetry typically identifies healthy subjects.

We follow this approach and segment (manually) the areas corresponding to the left and right breast from thermograms taken in frontal view. Once segmented, image features then need to be derived that can be employed in a decision making stage [8]. For this, we convert the breast regions to a polar co-ordinate representation to simplify the calculation of several of the features that we employ. A set of image features are then calculated to provide indications of symmetry between the regions of interest (i.e. the two breast areas) [35].

The simplest feature to describe the temperature distribution captured in thermograms is to calculate its statistical mean. As we are interested in symmetry features, we calculate the mean for both breasts and use the absolute difference between the two. Similarly, we calculate the standard temperature deviation and use the absolute difference as a feature. Furthermore, we employ the absolute differences of the median temperature and the 90-percentile.

Image moments [17] are defined as

$$m_{pq} = \sum_{y=0}^{M-1}\sum_{x=0}^{N-1} x^p y^q g(x, y), \tag{1}$$

where x and y define the pixel location and N and M the image size. We utilise moments m_{01} and m_{10} which essentially describe the centre of gravity of the breast regions, as well as the distance (both in x and y direction) of the centre of gravity from the geometrical centre of the breast. For all four features we calculate the absolute differences of the values between left and right breast.

Histograms record the frequencies of certain temperature ranges of the thermograms. We construct normalised histograms for both regions of interest (i.e. left and right breast) and use the cross-correlation between the two histograms as a feature. From the difference histogram (i.e. the difference between the two histograms) we compute the absolute value of its maximum, the number of bins exceeding a certain threshold (0.01 in our experiments), the number of zero crossings, energy and the difference of the positive and negative parts of the histogram.

Co-occurrence matrices have been widely used in texture recognition tasks [19] and can be defined as

$$\gamma^{(k)}_{T_i,T_j}(I) = \mathrm{PR}_{p_1 \in I_{T_i}, p_2 \in I}[p_2 \in I_{T_j}, |p_1 - p_2| = k], \tag{2}$$

with

$$|p_1 - p_2| = \max\{|x_1 - x_2|, |y_1 - y_2|\}, \tag{3}$$

where T_i and T_j denote two temperature values and (x_k, y_k) denote pixel locations. In other words, given a temperature T_i in the thermogram, γ gives the probability that a pixel at distance k away is of temperature T_j. In order to arrive at an indication of asymmetry between the two sides we adopted this concept and use the cross co-occurrence matrix [44] defined as

$$\gamma^{(k)}_{T_i,T_j}(I(1), I(2)) = \mathrm{PR}_{p_1 \in I(1)_{T_i}, p_2 \in I(2)}[p_2 \in I(2)_{T_j}, |p_1 - p_2| = k], \tag{4}$$