From medical image to automatic medical report generation

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We present a novel method for automatic breast radiology report generation from image data. We formalize this problem as learning to map a set of diverse image measurements to a set of discrete semantic descriptor values that represent the standard radiology lexicon. We use a structured learning framework to model individual semantic descriptors and their relationships. The parameters of the learned model are efficiently learned based on a training set of images using the structured support vector machine (SVM). The output report for a new image is generated in the form of a set of radiological lexicon descriptors. If the proposed method is used in a computer aided diagnosis (CAD) system, radiologists should be able to easily understand the diagnosis decision of the system since the system output is the standard radiological lexicon used to make a diagnosis. We applied the method to breast imaging modalities, sonography, and mammography. Our experiments indicate that our method generalizes better than competing approaches. Although the proposed method is tested for breast imaging report generation, it should be useful in general doctors' practice, wherein there is a predefined set of medical descriptors to be acquired by a doctor during image investigation.

vocabulary

Introduction

Worldwide, breast cancer is one of the most frequently diagnosed cancers in women, and it is the second leading cause of death for women. A great deal of effort has been devoted to improving breast cancer diagnosis. In particular, in many countries large-scale screening programs have been instituted to facilitate early cancer detection. Moreover, due to the relatively high rate of misdetection, many screening programs require either two independent human readers or a single human reader supported by an automated computer aided diagnosis (CAD) tool [1, 2].

The above requirements have spawned a massive amount of research in the development of effective CAD tools. The end result of the mammography screening is a report filled out by a radiologist (reader) that summarizes the severity of the findings. If a CAD system has been used, a human reader in his report should also address findings from the CAD system.

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Typical CAD detection algorithms calculate image features to identify suspicious regions. Based on these regions, the goal of the next stage, namely the CAD systems, is to make a prediction of whether a finding is malignant or benign. Such a decision is often not accompanied with guidance about practical and nuanced interpretations. This is in contrast to a human (reader) who must provide an extensive report regarding the mammography findings that support his assessment. Therefore, CAD systems are often thought of as "black boxes" whose diagnosis decision is not at all clear to their users, namely, to radiologists. Another criticism of CAD systems is that they are often set to work with very low rates of misdetection, which results in relatively high rates of false alarms. Subsequently, this increases the burden of reporting on the human reader who must account also for unexplained findings detected by the CAD system.

In order to mitigate these problems, we propose a CAD system that uses semantic image interpretation that mimics a human's image analysis. This approach offers a number of important advantages. For example, the use of automatically

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extracted semantic image descriptors decreases the labor in a normally laborious reporting process. These semantic descriptors are then introduced into automated case reporting, yielding a faster and more coherent reporting system.

Reasoniing

As for another advantage, note that providing a lucid presentation of the reasons for a given image interpretation would promote a physician's trust in the performance of the automated system, since it interacts with the physician in the standard radiological lexicon. For example, a physician would know that system classified a given tumor as benign due to its "sharp edges" and "parallel to skin orientation."

The physician would be able to weigh these features relative to, say, "inhomogeneous tumor structure." Therefore, this approach would allow setting the system parameters to match a physician's individual preferences. Indeed, today, the user can control only system trade-offs between sensitivity and specificity. In the semantic system, it would be possible to also control the relative impact of each feature.

As another advantage, consider that the semantic approach can also facilitate the combination of image and clinical features, ensuring improved overall performance.

Adopting the aforementioned semantic approach poses its own set of problems. The foremost is the choice of semantic descriptors. It is important that such a semantic system would be able to interact with a human reader using the standard radiological lexicon.

The need for standardized terminology is not new; it arises in mammography reporting by human readers even without a CAD system being used. For that reason, the American College of Radiology [3] developed the Breast Imaging Reporting and Data System (BI-RADS) that standardized the assessment and reporting of breast lesions. Both lesion description and management recommendations have become more consistent with use of the BI-RADS. By making auditing easier, the BI-RADS categorization of reports has also facilitated quality assurance practices. Accordingly, the BI-RADS became a feature of paramount importance in classification of tumors in breast imaging. However, since the BI-RADS focuses on evaluation of the tumor malignancy, it is insufficient to express the entire richness of information necessary for effective diagnosis and reporting.

The main contributions of this work are as follows: 1) a novel, discriminative method for automatic radiological report generation, which is medically sound and based on the standard radiological terminology; 2) a new model for semantic description of radiological findings, which captures semantic feature relationships; and 3) in the mode of diagnosis, the proposed method solves one of the major complaints of radiologists regarding CAD systems, namely, the lack of explanation for the CAD system decision process. Our system can actually "explain" to radiologist why a particular diagnosis is made, using the standard radiological language. Note that computer-aided diagnosis systems are often referred to as CADx in the literature (so as to contrast this with computer-aided detection, CADe); however, we will use the term CAD instead of CADx in the remainder of this paper.

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The rest of the paper is organized as follows. First, we summarize related work. Second, we introduce the proposed method for semantic based CAD and reporting systems. Then, we show an application of our method to sonography and mammography data, and provide a quantitative evaluation of its performance. We summarize the proposed approach and discuss future directions in the final section.

Related work

Typical CAD systems use various image features for the benign-or-malignant diagnosis, which, essentially, is a binary classification problem. The features usually include histograms of intensity values, texture descriptors, and others (see [4, 5] for an extensive overview of such methods). Semantic descriptors have been primarily used in content based information retrieval (CBIR) for automatic retrieval of similar cases. In [6] the BI-RADS lexicon is used to extract texture characteristics associated with image regions obtained from a human reader mammography reports. The method searches similar regions by automatically computing the Mahalanobis distance of feature vectors that describe the main shape and texture characteristics of the selected regions. Wei et al. [7] present a content-based mammogram retrieval system, which employs a query example to search for similar mammograms in the database. In this system, the mammographic lesions are interpreted on the basis of their medical characteristics specified in the BI-RADS lexicon. Then it employs a hierarchical similarity measure based on a distance weighting function; each medical feature is considered independently. Finally, it employs a machine learning approach to retrieve similar cases.

Another use of semantic descriptors was proposed in [8, 9], wherein the goal is to extend the classification to specific disease classes (in contrast to usual benign-or-malignant classification traditionally used in CADs). The authors introduce a Bayesian network that models the probabilistic relationships between breast diseases, mammographic findings, and patient risk factors to provide a disease specific classification. In order to simplify the model, the semantic terms are assumed to be conditionally independent. This however, ignores dependencies among the semantic terms as we show in the next sections.

The proposed method

A schematic depiction of the proposed approach is shown in **Figure 1**. In the following subsections, we describe the main modules of our system. The main emphasis of this paper is the report generation by estimating the mapping from visual features to semantic values. Therefore, we do not

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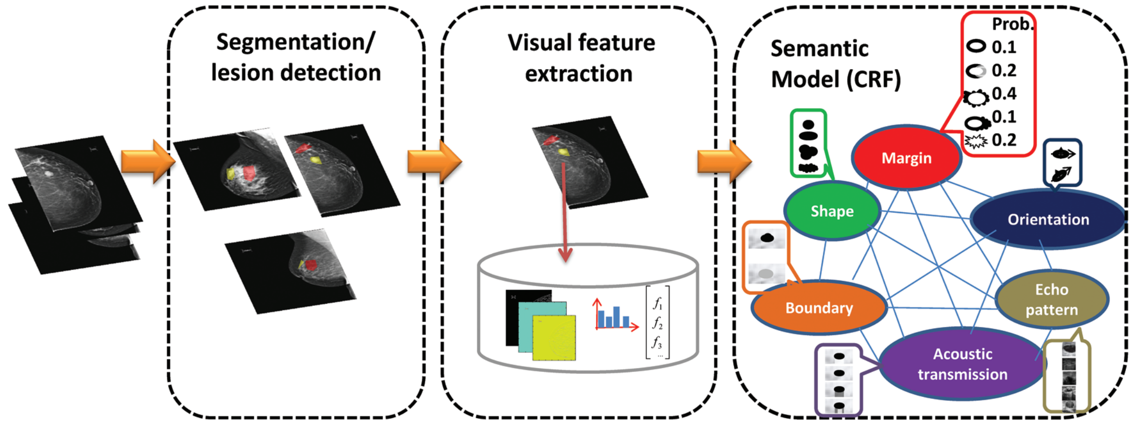

Figure 1

System workflow. The first module involves automatic or semiautomatic lesion detection. The second module involves an image features extractor. The third module involves the semantic layer that provides a final, well-explained decision. (CRF: Conditional Random Field).

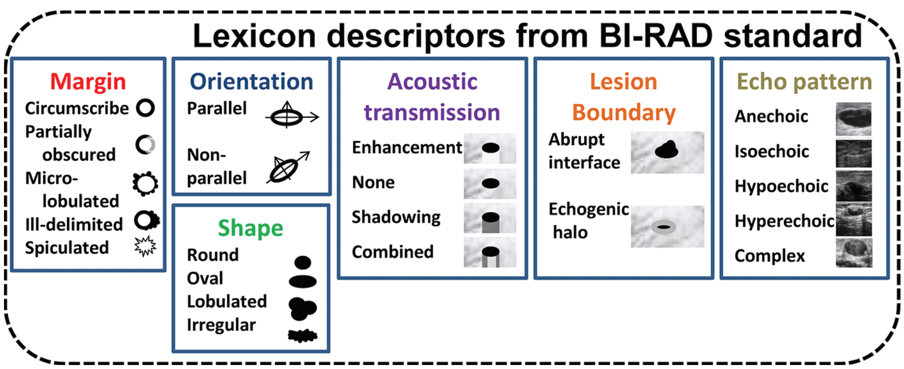

Figure 2

Semantic features used in the proposed system.

provide a description of the first module, the lesion detection, since a specific detection method, either automatic or semiautomatic, is less important and is beyond the scope of this paper. In our implementation, we used a semiautomatic detection method wherein a radiologist marked a seed point inside of a lesion. We then applied an active contour-type region growing method to obtain the lesion boundaries.

Semantic descriptors and corresponding image measurements

Given a region of interest (ROI) (i.e., a lesion), the following characteristics are examined by radiologists. Following the standard radiology lexicon for sonography images, the semantic descriptors are 1) shape, 2) margin, 3) orientation, 4) acoustic transmission (posterior enhancement/shadowing), 5) lesion boundaries, and 6) echo pattern. A graphical depiction of these semantic descriptors is given in **Figure 2**. For mammography, the semantic descriptors are 1) shape, 2) margin, and 3) density. The above characteristics are complex semantic descriptors. We build a diverse set of image measurements related to the above semantic descriptors, and describe each one of them quantitatively. These measurements are used in the calculation of informative features used in the model. In the following, we describe the semantic descriptors and explain how various related image measurements are obtained.

Shape and orientation

The shape of the mass is the most important characteristic examined by radiologists. Malignant tumors tend to have more *irregular* and *lobular* shapes. To find this, we calculate different quantities such as the area of the mass, its aspect ratio, and the curvature along the mass boundaries. Additional shape features are calculated by fitting an ellipse to the borders of a mass. These features include the following: the ellipse orientation, the ratio between the minor and the major axes, and various distances (L_1 norm, the maximal distance, etc.) between the mass border and the ellipse.

Margin and boundary

Sharp margins may indicate a benign tumor, while *smooth* margins may indicate a malignant one. To assess the sharpness of the boundaries, we divide the mass into eight sectors of 45 degrees and calculate several measures of sharpness of the boundary in each sector.

Acoustic transmission

The posterior (signal) enhancement of the mass is an important characteristic to consider when assessing the risk of malignancy. Strong *enhancement* and *edge shadowing* are common in benign masses (such as cysts), while *posterior shadowing* is common in malignant tumors. In order to assess the level of the posterior enhancement or shadowing, we automatically detect the area behind the mass, and calculate ratios of the median intensities and intensity variances inside its different segments.

Echo pattern

Another important characteristic of masses examined by doctors is their *echogenicity* compared to the fat tissue. High values may indicate malignancy; the *echogenicity* and mass *uniformity* are useful for diagnosis of specific types of tumors. In order to quantify these features, we use various heuristics to recognize the fat tissue, which is located on the upper side of the sonography images. We then compare the histogram of the lesion interior values to the one of the fat tissue.

Additional measurements: Intensity and texture

To describe the texture content of the ROI, we compute the local entropy at three different scales. We also compute two normalized intensity histograms of the inner and the outer (next to the boundary) areas of the ROI.

All of the above measurements are combined into the feature vector for learning learn the model parameters and to make the inference as described below.

Structured learning formulation for report generation

We define the problem of report generation as learning to map a set of various image measurements to the set of semantic descriptor values. An image finding, or a lesion, is represented by a predefined set of m semantic descriptors. The report generated from an image i is an assignment $\mathbf{y}_i = [y_{i,1}, \ldots, y_{i,m}]$where each jth semantic descriptor $y_{\cdot,j}$ can assume one of the possible discrete values $Y_j \in \{1, \ldots, V_j\}$ corresponding to the radiological lexicon described above. The energy function of the above assignment for a given image i is a sum of unary and pairwise terms:

$$\sum_{j=1}^{m} \mathbf{u}_1^t \phi_1(y_{ij}, X_i) + \sum_{j,k \in S} \mathbf{u}_2^t \phi_2(y_{ij}, y_{ik}, X_i) + \sum_{j=1}^{m} \mathbf{u}_3^t \phi_3(y_{ij}) \quad (1)$$

where S is the set of all possible pairs of semantic descriptors, and ϕ_1, ϕ_2, and ϕ_3 are unary, pairwise, and cardinality potentials respectively, defined below. The unary potentials describe the characteristics of the semantic descriptors; the pairwise potentials describe the relationships between the semantic descriptors, and capture the likelihood of semantic descriptors to jointly have particular values; cardinality potentials count the number of appearances in the training set of a particular value Y_j for each one of the descriptors divided by corresponding total number of training examples of Y_j. The unary potentials are defined as

$$\phi_{1,j}(y_{ij} = Y_j, \mathbf{X}_i; \theta_{1,j}) \sim P_{Y_j} \doteq \Pr(y_{ij} = Y_j | \mathbf{X}_i; \theta_{1,j}) \quad (2)$$

where $\mathbf{X}_i$ is, in general, a set of various image measurements that implicitly related to semantic descriptor values. Further, $\phi_{1,j}$ are the jth feature model parameters. Intuitively, each channel component can be considered as a predictor of a semantic descriptor $y_{\cdot,j}$ based on a full or partial set of the image measurements $\mathbf{X}_i$. The model parameters $\mathbf{u}_1$, $\mathbf{u}_2$, $\mathbf{u}_3$ are learned during the classifiers' training. For that purpose, we use multiclass SVM (support vector machine) classifiers whose output scores approximate the above probabilities P_{Y_j} (We obtained slightly worse results while using proper probability estimates by a logistic regression classifier, as compared to the SVM-based one).

Similarly to the unary potentials, we define the pairwise potentials:

$$\phi_{2,j,k}(y_{ij} = Y_j, y_{ik} = Y_k, \mathbf{X}_i; \theta_{2,j}) \sim P_{Y_j,Y_k} \doteq \Pr(y_{ij} = Y_j, y_{ik} = Y_k | \mathbf{X}_i; \theta_{2,j}) \quad (3)$$

Cardinality potential $\phi_3(y_{ij})$ is a vector of probabilities of appearances of each one of the particular values Y_j for each one of the descriptors, and of their joint probabilities of appearances.

In the model above, the number of model parameters and of required training examples are intractable. Therefore, we simplify the model and replace the above probabilities with the normalized number of appearances of corresponding pairs of feature values.

Learning and inference

We learn the model parameters using a structured SVM formulation instead of maximum likelihood. Given N training examples, the model parameters $\mathbf{u} = [\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3]$

in (1) are learned by optimizing the regularized large-margin objective [10]:

$$\hat{\mathbf{u}} = \arg\min_{\mathbf{u},\xi\geq 0} \frac{1}{2}\|\mathbf{u}\|^2 + C\xi$$
$$\text{s.t. } \frac{1}{N}\sum_{i=0}^{N} \max_{\bar{\mathbf{y}}_i\in \mathrm{Y}} \left[\Delta\left(\bar{\mathbf{y}}_i, \mathbf{y}_i^*\right) - \langle \mathbf{u}, \psi(I_i, \bar{\mathbf{y}}_i)\rangle + \langle \mathbf{u}, \psi(I_i, \mathbf{y}_i)\rangle\right] \leq \xi \tag{4}$$

where for a report with m semantic descriptors, we combine all the potential values into a single vector ψ,

$$\psi(\bar{\mathbf{y}}_i, \mathbf{X}_i) = \begin{bmatrix} \sum_{j=1}^{m} \phi_1(\bar{y}_{ij}, \mathbf{X}_{ij}) \\ \sum_{j,k\in S} \phi_2(\bar{y}_{ij}, \bar{y}_{ik}, \mathbf{X}_{ij}, \mathbf{X}_{ik}) \\ \sum_{j=1}^{m} \phi_3(\bar{y}_{ij}) \end{bmatrix} \tag{5}$$

The task loss

$$\Delta\left(\bar{\mathbf{y}}_i, \mathbf{y}_i^*\right) = \frac{\sum_{j=1}^{m} w_j \mathbf{I}\left(\bar{y}_{ij} \neq \mathbf{y}_{ij}^*\right)}{\sum_{j=1}^{m} w_j} \tag{6}$$

is calculated as a normalized weighted Hamming loss with the weights w_j defined (or learned in advance) by the relative importance of descriptors $y_{\cdot,j}$ in the diagnosis process, and I is the indicator function that equals 1 whenever the predicted value $\bar{y}_{ij}$ is different from the ground truth $\mathbf{y}_{ij}^*$.

Given the model parameters learned as described above, the inference goal is, for a new image, to find the best assignment whose semantic values result in the lowest task loss. This is achieved by solving

$$\hat{\mathbf{y}}_i = \arg\min_{\bar{\mathbf{y}}_{i\in \mathrm{Y}}} \left\langle \hat{\mathbf{u}}, \psi(\bar{\mathbf{y}}_i, \mathbf{X}_{ij})\right\rangle \tag{7}$$

We obtain the approximate solution of the above problem by using a message-passing algorithm proposed in [11].

After semantic descriptor values are estimated, and a radiological report is generated, they can be used also to make a diagnosis decision. In this task, the semantic descriptors are features in a standard binary (malignant-or-benign) or a multiclass (specific disease) classification problem. This classification task can be performed by any known classification method, for example, by a logistic regression. Notice also that the formulation of the structured learning problem (1) is similar to the Conditional Random Field (CRF) modeling [12] used in various tasks such as object segmentation and natural language processing.

Experiments

We used collections of 408 sonography images and of 203 mammography images; they contain a nearly equal number of benign and malignant cases. Each image is accompanied with a confirmed diagnosis, BI-RADS value, and radiological lexicon descriptor values. For each modality, we performed 10 random subsampling experiments by dividing the whole set of cases into training and testing sets of approximately two thirds and one third of the overall number of cases, respectively. Both training and testing sets contain equal amount of benign and malignant cases. The ROI from where the visual features are calculated is obtained by a semiautomatic active contour-type lesion boundary detection method. We compared our method with the somewhat competing approaches of Narvaez et al. [6] and Wei et al. [7], which are essentially k-nearest neighbors (KNN) approaches, and of Burnside et al. [8] and Rubin et al. [9], which perform each semantic descriptor estimation independently using a classifier. The performance measure we used is the Hamming loss defined in (6) with equal weights, averaged over the testing set of images, and over the 10 random subsampling experiments. The results of our experiments are summarized in **Table 1**. Clearly, our method outperforms the competing approaches. We attribute this to our more sophisticated model that captures the relationships between different semantic descriptors.

An example of typical input and of the corresponding automatically generated output of the proposed system are shown in **Figure 3**.

Table 1 Comparative results of the semantic descriptors estimation using competing methods. The hamming loss (6) is used as the quality measure (a value of 1 corresponds to perfect prediction).

Method	*Hamming loss (6), sonography set*	*Hamming loss (6), mammography set*
[6, 7]	0.58	0.52
[8, 9]	0.65	0.61
Ours	0.71	0.64

Conclusions

We presented a novel discriminative method for automatic radiological report generation using a structured learning model for semantic description of radiological findings. The method is expected to save time for radiologist practitioners by making the process of report filling automatic or semiautomatic. In the mode of the computer aided diagnosis, the proposed method addresses one of the major complaints of radiologists, namely, the lack of intelligibility of the CAD decision process. Our system can "explain" to a radiologist why a particular diagnosis is made, using the standard radiological lexicon. The main obstacle in making such a system completely automatic is the lesion detection module, since the accuracy of feature calculation is

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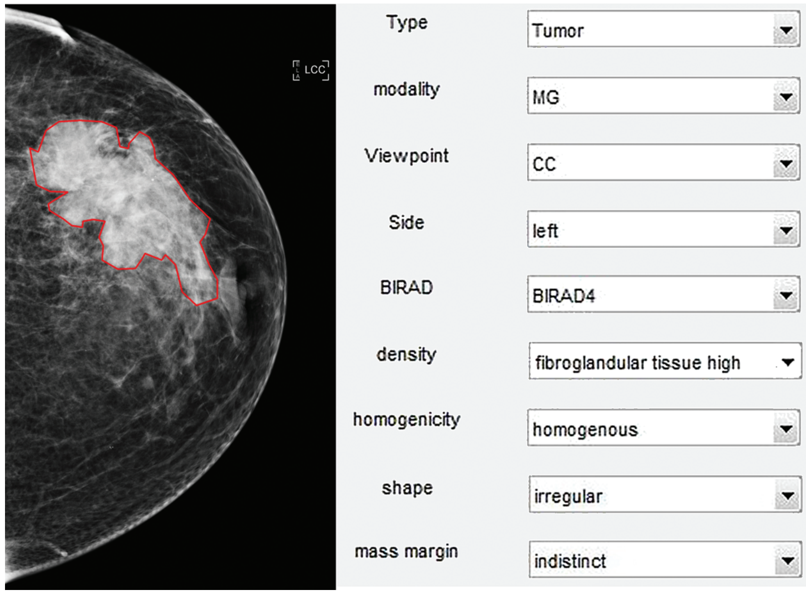

Figure 3

An example of typical input with semiautomatically detected lesion boundaries (left), and the corresponding automatically generated output of the proposed system (right).

greatly dependent on it. We therefore plan to investigate dependable lesion-detection methods, along with improving image feature measurements, which will make our system less sensitive to the detection errors and will provide more accurate results.

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