Feature Saliency Analysis for Perceptual Similarity of Clustered Microcalcifications

Juan Wang and Yongyi Yang

Medical Imaging Research Center
Department of Electrical & Computer Engineering
Illinois Institute of Technology

MIRC MEDICAL IMAGING RESEARCH CENTER

ILLINOIS INSTITUTE OF TECHNOLOGY
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Background: Breast cancer and MCs

- Breast cancer is the most frequently diagnosed non-skin cancer in women in US.
- One important early sign of breast cancer in mammograms is the appearance of clustered MCs.
- MCs are calcium deposits of very small dimensions which appear as a group of granular bright spots in a mammogram.
- Great effort has been made in development of computed-aided diagnosis (CADx) methods for lesions with clustered MCs.

A mammogram with clustered MCs (left) and a magnified view of the area with clustered MCs (right).
Background: Content-based image retrieval (CBIR)

- We investigate the use of content-based image retrieval (CBIR) as a diagnostic aid for lesions with cluster MCs.
- The goal is to assist radiologists by presenting them with a set of images similar to the one being evaluated along with their known pathology.
Background: Motivation of study

• Challenge of CBIR approach: the retrieved images need to be *perceptually similar* to the lesion under consideration

• Solution: we developed a supervised-learning algorithm to model the perceptual similarity from expert readers based on their ratings of sample image pairs.

• Our previous research\[1\] found:
  – In spite of the great variability among the individual readers, the average similarity ratings from a group of readers could achieve a high level of consistency and agreement in retrieval of similar images;
  – Perceptually similar cases also tend to be similar in their underlying pathology and image features of clustered MCs

• Purpose of this study: to identify which features contribute the most to the similarity ratings in the reader’s interpretation of MC lesions.

Method: Perceptual similarity from reader study

- We made use of a set of similarity scores from five radiologists on 1000 pairs of mammogram lesions with clustered MCs;
- The image pairs were scored on a scale from 0 (most dissimilar) to 10 (most similar) based on the visual appearance of the clustered MCs in each pair;
- The image pairs were formed from a dataset of 365 mammogram images from 222 cases;
- The similarity scores from each reader were transformed into z-scores, and then the scores from all readers were averaged for each pair for future analysis.

Histogram of similarity scores on 1,000 image pairs
Method: Features for characterizing clustered MCs

- It is unknown a priori which features were relevant to the reader’s judgment of similarity
- Consider two categories of quantitative features for clustered MCs as following:

<table>
<thead>
<tr>
<th>Clustering features</th>
<th>MC features</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 area of the cluster</td>
<td>1 size of the MC</td>
</tr>
<tr>
<td>2 compactness of the cluster</td>
<td>2 eccentricity of the MC</td>
</tr>
<tr>
<td>3 eccentricity of the cluster</td>
<td>3 mean of the intensity values of the MC</td>
</tr>
<tr>
<td>4 rotation invariant moment $I_1$ of the cluster</td>
<td>4 standard deviation of the intensity values of the MC</td>
</tr>
<tr>
<td>5 Fourier descriptor II of the cluster</td>
<td>5 effective thickness of the MC</td>
</tr>
<tr>
<td>6 moment measure $F_3' - F_1'$ of the cluster</td>
<td>6 effective volume of the MC</td>
</tr>
<tr>
<td>7 number of MCs in the cluster</td>
<td>7 rotation invariant moment $I_1$ of the MC</td>
</tr>
<tr>
<td>8 density of MCs in the cluster</td>
<td>8 the 4th order central moment of the MC</td>
</tr>
<tr>
<td>9 cluster scatterness</td>
<td>9 mean intensity of a $11 \times 11$</td>
</tr>
<tr>
<td>10-11 cluster roughness $R_1$ and $R_2$</td>
<td>10 image window centered at the MC</td>
</tr>
</tbody>
</table>
Method: Similarity modeling

- **Purpose:** model the following relationship:
  \[ y = f(x) \]
  perceptual similarity level
  image features of image pair

- **Image features of image pair:**
  - **Representation:**
    \[ x_j = \left| x_j^{(1)} - x_j^{(2)} \right| / \left( x_j^{(1)} + x_j^{(2)} \right) \]
    j-th feature of the 1st image in the pair
    j-th feature of the 2nd image in the pair
  - **Properties:**
    - Invariant to the particular ordering of the two images in the pair;
    - The image pairs are considered to be more similar when they have more MCs if the feature difference is same;
    - Values in range [0,1].
Method: Support vector regression (SVR)

- Linear model:
  \[ f(x) = w^T x + b \]
  - unknown parameters, determined from training

- Formulation:
  \[ \min J(w, \xi) = \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{N} \gamma_i (\xi_i + \xi_i^*) \]
  - to control the trade-off between model complexity and model error
  - weight factor of each sample
  - \( \xi_i, \xi_i^* \geq 0, i = 1, \cdots, N \)
  - \( \epsilon \)-insensitive cost

- The resulting model by applying kernel function \( K(\cdot, \cdot) \)
  \[ f(x) = \sum_{k=1}^{N_s} (\alpha_k - \alpha_k^*) K(x, s_k) + b \]
  - support vector
  - Lagrange multipliers associated with the constraint in formulation
Method: Feature saliency analysis

- Feature saliency of a feature:
  - sensitivity of the similarity model output to change in the feature value;
  - calculated as partial-derivatives of the similarity model to the feature at the mean value of the feature.

- Feature saliency of i-th feature derived from SVR:
  \[
  \beta_i = \left. \frac{\partial f(x)}{\partial x_i} \right|_{x=x} = \left. \sum_{k=1}^{N_s} (\alpha_k - \alpha_k^*) \frac{\partial K(x,s_k)}{\partial x_i} \right|_{x=x} \\
  \text{mean of } x
  \]

- For the Gaussian RBF kernel parameter, \( K(x,s) = \exp\left(-\|x - s\|^2/2\sigma^2\right) \) is the kernel width

  \[
  \beta_i = \frac{1}{\sigma^2} \left. \sum_{k=1}^{N_s} (\bar{x}_i - s_{k,i})(\alpha_k - \alpha_k^*) \exp\left(-\|x - s_k\|^2/2\sigma^2\right) \right|_{x=x} 
  \]
Method: Feature selection and model optimization

- Case-based leave-one-out (LOO) for feature selection and SVR model training.
- Shrinkage LASSO algorithm was applied for feature selection in each case-based LOO repetition, and a voting scheme was used to determine the final set of features.
- In the end, both the parameters and features to use for the SVR model were determined by case-based LOO.
Results: Feature selection

- Selection features are rather stable among different repetitions;
- Indicating that readers are consistent in terms of image features used for judging the similarity between different MC lesions;
- The parameters for SVR model were determined as: $\varepsilon = 0.5$, $C = 1$, and $\sigma = 4$.

Frequency of selection of features by LOO procedure
Results: Feature saliency

- Among 9 selected features, there are three geometric clustering features and six MC image features;
- Indicating that the readers have considered both the individual MCs and their cluster as a whole in their scoring;
- The most important clustering and MC features are density of MCs in the cluster and average effective volume of MCs in the cluster.

Saliency of 9 selected features in the SVR model
Results: MDS embedding

- Neighboring cases in MDS plot tend to have MC clusters similar in size and shape, which is consistent with the selected size and Fourier descriptor II of the cluster in saliency results;
- Neighbor cases in MDS plot tend to have MCs similar in size, shape and contrast; this is consistent with the selected MCs features in saliency results.

MDS embedding of perceptually similar cases in the dataset, wherein cancer and benign cases are represented by “red dots” and “blue squares”, respectively. The spatial distribution patterns of clustered MCs are shown for some sample cases, where the spatial locations of MCs are indicated by “green plus signs”.
Conclusion

• We investigated quantitatively how perceptually similar cases are related to each other in their image features through machine learning and feature saliency analysis.

• The relevant features are consistent in radiologists’ similarity ratings among different MC lesions, including both geometric clustering features and MC features.

• In the future, we plan to study the utility of these identified features in a CBIR system.
Thanks!