Development of Computer-Aided Detection of Breast Lesion Using Gabor-Wavelet BASED Features in Mammographic Images

Bardia Yousefi, Hua-Nong Ting, Seyed Mostafa Mirhassani, Mohammad Mehdi Hosseini
Department of Biomedical Engineering, University of Malaya
50603 Kuala Lumpur, Malaysia
Outline of Presentation

• Introduction
• Methodology
• Experimental Results
• Conclusion

1. Source: MeVis Medical Company
Introduction

1. 8% of women during their lifetime,

2. Second Cause of Death,

3. Early detection can reduce more than 40% of the death rate,

4. The earlier detection of symptom helps to provide better treatment,

5. We need:
   - Accurate,
   - re-liable diagnosis,
   - distinguish tumors,
   - System must produce both false positive (FP) rate and false negative (FN) rate low.

Scope and Significance of The Study

1. Picture from: website of University of Zagreb
2. source: CYCLINE Development gourp;
What is CAD? Why CAD?

- Reading mammography image needs well-trained and skilled radiologists.
- Even in well-trained human experts, there is a high inter-observer disparity rate.
CAD

What is CAD? Why CAD?

• Reading mammography image needs **well-trained and skilled radiologists**

• Even in well-trained human experts, there is a high **inter-observer disparity rate**,
CAD system for detecting and classifying of breast cancer. Adopted from (Cheng et al., 2010).
Literature Review

• Features Categories
  – **Texture features** (Mencattini & et, 2010)
  – **Morphological features** (Drukker, et al., 2008)
  – **Model-Based features** (Tsui, et al., 2010)
  – **Descriptive features** (Cho, et al., 2006; Cheng et al., 2010).

• Classifier
  – **Linear Classifier** (Garra, et al., 1993; Giger, et al., 2007)
  – **ANN**(Artificial Neural Network) (Suzuki, Zhang, & Xu, 2010; Chen, et al., 2000)
  – **BNN**(Bayesian Neural Network) (Drukker, et al., 2004; Drukker, et al., 2006)
  – **Decision tree** (Cheng, et al., 2006; Chen, et al., 2002)
  – **Template Matching** (Kuo, et al., 2002)
  – **Fuzzy** (Tsui, et al., 2010; Cheng et al., 2010).
Problem Statement
There are very good but complex and hybrid techniques. e.g:
- **Sensitivity** problem;
- **Poor performance, adaptability** *(Linear classifier)*;
- **Long Training time, need construct model** *(ANN or BNN)*;
- Supervised learning *(data should be labeled)* *(SVM)*;
- **Need large database** *(Template Matching)*; *(Cheng, et al., 2010)*
Still needs more research in its area.

Objectives and Hypothesis

```
Input
  └── Gabor Filtering
      └── Bayesian Classifier
          └── Detection of Lesions
```
Methodology

The Sequential (1-D) Gabor Filter

\[ g(t) = ke^{-j\theta} \omega(at)s(t) \]

\[
\begin{align*}
\omega(t) &= e^{-\pi t^2} \\
s(t) &= e^{j(2\pi f_0 t)}
\end{align*}
\]

\[ e^{j\theta} s(t) e^{j(2\pi f_0 t + \theta)} = (\sin(2\pi f_0 + \theta), j \cos(2\pi f_0 + \theta)) \]

\[
\begin{align*}
g_r(t) &= \omega(t) \sin(2\pi f_0 + \theta) \\
g_i(t) &= \omega(t) \cos(2\pi f_0 + \theta)
\end{align*}
\]

Fourier transform

\[
\hat{g}(f) = k e^{j\theta} \int_{-\infty}^{\infty} e^{-j2\pi ft} \omega(at)s(t)dt = k e^{j\theta} \int_{-\infty}^{\infty} e^{-j2\pi(f-f_0)t} \omega(at)dt = \frac{k}{a} e^{j\theta} \hat{\omega}(\frac{f-f_0}{a})
\]

Source From: (Movellan, 2005)
The Sequential (2-D) Gabor Filter

Carrier

\[ g(x, y) = s(x, y)\omega_r(x, y) \]

Envelope

Compound Sinusoid Carrier

\[ s(x, y) = \exp(j(2\pi(u_0x + v_0y) + P)) \]

\[ \text{Re}(s(x, y)) = \cos(2\pi(u_0x + v_0y) + P) \]

\[ \text{Im}(s(x, y)) = \sin(2\pi(u_0x + v_0y) + P) \]

\[ F_0 = \sqrt{u_0^2 + v_0^2} \quad \omega_0 = \tan^{-1}\left(\frac{u_0}{v_0}\right) \quad u_0 = F_0 \cos \omega_0 \]

\[ v_0 = F_0 \sin \omega_0 \]

Complex Sinusoid:

\[ s(x, y) = \exp(j(2\pi F_0 (x \cos \omega_0 + y \sin \omega_0) + P)) \]

Gaussian Envelope

\[ \omega_r(x, y) = K \exp(-\pi(a^2(x-x_0)^2 + b^2(y-y_0)^2)) \]

\[ (x-x_0)_r = (x-x_0)\cos \theta + (y-y_0)\sin \theta \]

\[ (y-y_0)_r = -(x-x_0)\sin \theta + (y-y_0)\cos \theta \]

Adopted From: (Movellan, 2005)
\[ g(x, y) = K \exp(-\pi(a^2(x - x_0)^2 + b^2(y - y_0)^2))\exp(j(2\pi(u_0 x + v_0 y) + P)) \]

**Polar Coordinates:**

\[ g(x, y) = K \exp(-\pi(a^2(x - x_0)^2 + b^2(y - y_0)^2))\exp(j(2\pi F_0 (x \cos \omega_0 + y \sin \omega_0) + P)) \]

\[ \hat{g}(u, v) = \frac{K}{ab} \exp(j(-2\pi(x_0 (u - u_0) + y_0 (v - v_0) + P))\exp\left(-\pi\left(\frac{u - u_0}{a^2} + \frac{v - v_0}{b^2}\right)\right) \]
Input

Gabor

Gabor Outcome

Picture From: Modular toolkit for Data Processing
\[ I(x, y) \quad \text{Input image} \]

\[ I_g(x, y) = I(x, y) * g(x, y) \quad \text{Features after applying Gabor filter} \]

Bayesian Classifier

\[
\begin{align*}
\begin{cases}
C_l & S(C_{\text{lesions}}) \\
C_{nl} & S(C_{\text{non-lesions}})
\end{cases}
\Rightarrow
\begin{cases}
C_{\text{lesions}} & \text{if } P(C_l \mid \lambda) > P(C_{nl} \mid \lambda) \\
C_{\text{non-lesions}} & \text{O.W}
\end{cases}
\end{align*}
\]

Lesions Class: \( S(C_{\text{lesions}}) \Rightarrow P(C_l \mid \lambda) > P(C_{nl} \mid \lambda) \) \quad \forall \ x, y \in I_g(x, y) \Rightarrow \{x, y \mid S(C_{\text{lesions}}) \subseteq I_g(x, y)\}

Non-Lesions Class: \( S(C_{\text{non-lesions}}) \Rightarrow P(C_l \mid \lambda) < P(C_{nl} \mid \lambda) \) 

\[ \forall x, y \in I_g(x, y) \Rightarrow \{x, y \mid S(C_{\text{non-lesions}}) \subseteq I_g(x, y)\} \]

Experimental Results

**Dataset**
- 40 Cases:
  - 10 cases are normal with no sign of breast cancer;
  - 30 are breast cancer patients.
- 5500×2600 pixels to 3960×1800 pixels (Resize Images was 3500×1750 pixels)
- Each case has four LJPG images.
- Each image is 11MB.

**Simulation**
- CPU 2.26GHz, 6MB Cache, 2GB
- MATLAB R2009b (version)
Introduction

Methodology

Experimental Results

Conclusion

Input

Gabor Outcome

After Bayesian Classifier
**Methodology**

<table>
<thead>
<tr>
<th>(Discriminating ratio in Bayesian Classifier) ( \lambda )</th>
<th>Number of the Results have Noise</th>
<th>Number of the Results have Miss-classification</th>
<th>Accuracy</th>
<th>Total Images</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>3</td>
<td>1</td>
<td>97.5</td>
<td>160</td>
</tr>
<tr>
<td>0.03</td>
<td>3</td>
<td>1</td>
<td>97.5</td>
<td>160</td>
</tr>
<tr>
<td>0.05</td>
<td>2</td>
<td>3</td>
<td>96.8</td>
<td>160</td>
</tr>
<tr>
<td>0.08</td>
<td>0</td>
<td>4</td>
<td>97.5</td>
<td>160</td>
</tr>
<tr>
<td>0.10</td>
<td>0</td>
<td>8</td>
<td>95</td>
<td>160</td>
</tr>
</tbody>
</table>

**Accuracy** = \( \frac{\text{Number of Detection} - (\text{Number of results having Noise} + \text{Number of Missclassification})}{\text{Total Number of Dataset}} \)

<table>
<thead>
<tr>
<th>Methods</th>
<th>Accuracy for Detection of Breast Lesions (in percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FNN (Naghibi, et al., 2010)</td>
<td>98.5</td>
</tr>
<tr>
<td>HFNN (Naghibi, et al., 2010)</td>
<td>99.04</td>
</tr>
<tr>
<td>Kohnan NN (Asad, et al., 2011)</td>
<td>80</td>
</tr>
<tr>
<td>Our Proposed Approach</td>
<td>97.5</td>
</tr>
</tbody>
</table>
The proposed method has been applied to our dataset which comprise of 30 cases of breast cancer and 10 cases normal. It includes 160 mammographic images. The results indicate the accuracy of 97.5 percent for diagnosing the breast cancer.
REFERENCES


REFERENCES


• Naghibi, S., Teshnehlab, M., & Shoorehdeli, M. A. (November 2010). Breast Cancer Detection by using Hierarchical Fuzzy Neural System with EKF Trainer. 17th Iranian Conference of Biomedical Engineering (ICBME2010), (pp. 1-4). Isfahan : IEEE.


thank you