Analysis and modeling techniques for ultrasonic tissue characterization

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Tutor: Prof. Guido Masetti

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1. **Context**

   Tissue Characterization for Ultrasound Diagnostic
   
   Problem: limits of TRUS-guided biopsy
   
   Tools: ultrasound image processing
   
   State of the art

2. **Main contributions in image analysis**

   Deconvolution as pre-processing step

3. **Main contributions in image modelling**

   Continuous-time model for ultrasound signals
   
   CT parameters for tissue characterization

4. **Clinical Application**

   Ground truth collection
   
   Real-time Computer-Aided Biopsy

5. **Conclusions**
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Tissue characterization for diagnostic ultrasound

- Biomedical image to monitor inner physiological systems to early diagnose potential disease
- **Image analysis** to capture features correlated to the pathological state of the tissue and invisible to human eye
- **Image modeling** provides mathematical descriptors of measured signals correlated to tissue state
- Computer-aided Diagnosis to improve reliability of physician judgement

**Specific context:** Improvement of standard prostate biopsy protocol
Tissue characterization for diagnostic ultrasound

- Biomedical image to **monitor** inner physiological systems to early **diagnose** potential disease
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- Computer-aided Diagnosis to improve reliability of physician judgement
- **Specific context**: Improvement of standard prostate biopsy protocol
Limits of standard prostate biopsy protocol

- Transrectal ultrasound (TRUS)-guided prostate biopsy
- Systematic sampling of high cancer incidence areas (PZ)
- Variable tumour appearance at TRUS $\Rightarrow$ non lesion-directed biopsy
- Positive biopsy rate: 20-25% $\Rightarrow$ $ppv = P(U\ core|U\ patient)$
- Detection rate over patients: 80-85% $\Rightarrow$ $1 - (1 - ppv)^{N_{cores}}$
- Low efficiency and high number of unnecessary biopsies

**Figure:** double sextant biopsy protocol
Why ultrasound processing to improve biopsy?

**Problem:** improve efficiency of standard biopsy protocol

**Solution:** ultrasonic tissue characterization for lesion-directed biopsy

- Advantages of US technology: real-time, non-invasive, cheap (vs. MRI, CT)
- US machine in all health institutions
- World healthcare market target: affordable medical equipment for developing countries
- Boost performance of cost-effective devices
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The story so far...

Figure: Tissue characterization procedure
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State of the art methods:

<table>
<thead>
<tr>
<th>Work</th>
<th>Ground Truth</th>
<th>Technique</th>
<th>Results %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># patients</td>
<td>Features</td>
<td>SE</td>
</tr>
<tr>
<td>[Huynen et al., 1994]</td>
<td>51</td>
<td>Textural</td>
<td>80</td>
</tr>
<tr>
<td>[Houston et al., 1995]</td>
<td>25</td>
<td>Textural</td>
<td>73</td>
</tr>
<tr>
<td>[Schmitz et al., 1999]</td>
<td>33</td>
<td>Multi</td>
<td>82</td>
</tr>
<tr>
<td>[Scheipers et al., 2003]</td>
<td>100</td>
<td>Multi</td>
<td>-</td>
</tr>
<tr>
<td>[Feleppa et al., 2004]</td>
<td>200</td>
<td>Spectral</td>
<td>-</td>
</tr>
<tr>
<td>[Llobet et al., 2007]</td>
<td>300</td>
<td>Textural</td>
<td>68</td>
</tr>
<tr>
<td>[Mohamed et al., 2008]</td>
<td>20</td>
<td>Multi</td>
<td>83.3</td>
</tr>
<tr>
<td>[Han et al., 2008]</td>
<td>51</td>
<td>Multi</td>
<td>92</td>
</tr>
<tr>
<td>HistoScanning™ [2009]</td>
<td>29</td>
<td>Multi??</td>
<td>95</td>
</tr>
</tbody>
</table>
The story so far...

Figure: Tissue characterization procedure

Limits of published methods:

- Small ground truth database
- Low accuracy performances
- No real-time methods
- No medical feedback
- Inappropriate to clinical employment
Main contributions roadmap

- **Image Analysis**
  - Deconvolution as pre-processing step
  - Non linear multi-feature approach

- **Image Modeling**
  - Continuous-time model of ultrasound signal
  - New ultrasonic features for tissue characterization

- **Clinical Application**
  - Large medical ground-truth collection
  - Real time detection tool to improve biopsy efficiency
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Modified scheme for tissue characterization

- Deconvolution as preprocessing step
- Increase diagnostic significance of ultrasonic features
- Reduce system-dependent effects
- Traditional role of deconvolution: improve visual quality (subjective!)
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Deconvolution to recover Tissue Response

Problem:
- **Convolution model:** $z[k] = x[k] \ast h[k] + n[k]$ with $x = \Sigma s$
- **$\Sigma$:** coherent reflection, macroscopic interactions, mean value of diffused field.
- **$s$:** incoherent reflections, interactions smaller than wavelength, random fluctuations of diffused field.

Solution:
- Blind adaptive deconvolution approach
- Advantages: simplicity, low computational cost, variable PSF
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Improvement in lesion detection due to Deconvolution

Benignant case

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<tr>
<th></th>
<th>No Preprocessing</th>
<th>Deconvolution</th>
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<tbody>
<tr>
<td>SE</td>
<td>0.69 ± 0.06</td>
<td>0.75 ± 0.09</td>
</tr>
<tr>
<td>SP</td>
<td>0.94 ± 0.02</td>
<td>0.93 ± 0.01</td>
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<tr>
<td>Acc</td>
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<tr>
<td>Az</td>
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**Improvement in lesion detection due to Deconvolution**

**Malignant case**

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Continuous-time model for ultrasound signals

- Continuous-time Auto Regressive Moving Average (CARMA)
- Continuous-model for ultrasound signal
- Identification of continuous model from sampled data
- New mathematical formulation of CARMA model based on exponential B-splines\(^1\)
- Autocorrelation of \(z(t)\) can be derived exactly by interpolation of discrete samples through appropriate exponential B-splines

\(^1\)[Unser and Blu, 2005]
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New approach to CARMA identification

State of the art identification methods:

- Approximated sampling process
- Valid for high sampling frequency: no deal with aliasing

Proposed a new estimator for CARMA processes:

- Maximum-likelihood estimator
- Exploit interpolation by exponential B-splines
- Incorporate sampling process in problem formulation
- No a priori assumption on digital data nor sampling interval
- Several minima of likelihood function
- Correct solution in global minimum
- Multi-band approach to optimization
- Good estimates also in aliasing conditions
Simulation results

- Performances of algorithm for CARMA identification on simulated signals.
- Comparison with an approach based on polynomial splines\(^2\)
- CAR(2): \(\Phi(s) = \frac{1}{s^2 + 0.4s + 49.04} = \frac{\sigma^2}{s^2 + a_0s + a_1}\)

\[^2\text{[Gillberg and Ljung, 2009]}\]
Simulation results

- Performances of algorithm for CARMA identification on simulated signals.
- Comparison with an approach based on polynomial splines

\[ \Phi(s) = \frac{s+3}{s^2+2s+26} = \frac{s+b_0}{s^2+a_0s+a_1} \]

\[ a_0 \]

\[ a_1 \]

\[ b_0 \]

\[ ^2[Gillberg and Ljung, 2009] \]
CARMA parameters for tissue characterization

- Study: comparison between ARMA and CARMA parameters for tissue typing
- Tissue-mimicking phantoms with different particles concentration
- ARMA\((4, 3)\) vs. CARMA\((4, 2)\) parameters
- Performances as ability in capturing information about scatterers concentration

Table: Rate of misclassification\(^1\)CARMA, \(^2\)ARMA.

<table>
<thead>
<tr>
<th>Classes</th>
<th>Features for classification</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration</td>
<td>poles</td>
<td>zeroes</td>
<td>all parameters</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(a^1) (c^2)</td>
<td>(b^1) (d^2)</td>
<td>((a, b)^{1}) ((c, d)^2)</td>
<td></td>
</tr>
<tr>
<td>[0.5%, 0.75%]</td>
<td>0.010 0.037</td>
<td>0.016 0.021</td>
<td>0.010 0.011</td>
<td></td>
</tr>
<tr>
<td>[0.5%, 0.75%, 3%]</td>
<td>0.012 0.034</td>
<td>0.009 0.027</td>
<td>0.013 0.016</td>
<td></td>
</tr>
<tr>
<td>[0.5%, 0.75%, 3%, 6%]</td>
<td>0.122 0.118</td>
<td>0.159 0.260</td>
<td>0.067 0.105</td>
<td></td>
</tr>
<tr>
<td>[0.5%, 0.75%, 3%, 6%, 12%]</td>
<td>0.133 0.127</td>
<td>0.275 0.366</td>
<td>0.088 0.126</td>
<td></td>
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Ground truth database

- Collaboration with dep. Urology of S. Orsola Hospital in Bologna since Nov. ’09
- Recorded about 8-12 US video sequences for each patient
- More recorded info: PSA value, DRE result, patient history
- Histopathological analysis: % of tumour and Gleason score
- Up to now: about 1000 US videos for 120 patients

<table>
<thead>
<tr>
<th>code</th>
<th># cores</th>
<th>Description</th>
<th>Label</th>
</tr>
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<tbody>
<tr>
<td>M</td>
<td>18</td>
<td>% tumour ≥ 70%</td>
<td>Malignant</td>
</tr>
<tr>
<td>UM</td>
<td>46</td>
<td>% tumour &lt; 70%</td>
<td>Unknown</td>
</tr>
<tr>
<td>BB</td>
<td>179</td>
<td>Benignant tissue(^1)</td>
<td>Benignant</td>
</tr>
<tr>
<td>BM</td>
<td>120</td>
<td>Benignant tissue(^2)</td>
<td>Benignant</td>
</tr>
<tr>
<td>U</td>
<td>40</td>
<td>Precancerous lesions</td>
<td>Unknown</td>
</tr>
<tr>
<td>TOT</td>
<td>403</td>
<td>42 patients (22 pathological)</td>
<td></td>
</tr>
</tbody>
</table>

\(^1\) from healthy patient  
\(^2\) from unhealthy patient
real-time Computer-Aided Biopsy

- Malignancy risk map to guide biopsy
- Statistical and textural features
- Motion tracking to reduce computational-time
- Parallel processing on CUDA™ enabled graphic card
- Classifier trained on ground-truth to maximize core-based PPV
- 100% median sensitivity and 39% PPV at 30 fps
- Same diagnostic value of standard protocol $\Rightarrow 1 - (1 - ppv)^N_{\text{cores}}$
- Cores reduction from 8-12 to 7 deemed feasible
Conclusions

- Deconvolution as pre-processing step in ultrasonic tissue characterization
- Continuous-time model for ultrasound signal
- CARMA parameters to type scatterers concentrations
- Clinical study to improve standard prostate biopsy protocol

Further Developments

- Study of CARMA parameters on in vivo images
- Real-time deconvolution for clinical applications
- Improvement of classification task by semi-supervised methods
- Clinical trial for computer-aided biopsy tool validation
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Thank you for your attention!

http://mas.deis.unibo.it/
Publications

- **2011 (under revision)**
  IEEE Transactions on Signal Processing
  H. Kirshner, S. Maggio, M. Unser.
  *On Continuous-Domain ARMA Modeling*

- **2011 (under revision)**
  Proceedings ISBI 2011
  S. Maggio, M. Alessandrini, N. Speciale, O. Bernard, D. Vray, O. Basset, M. Unser.
  *Continuous-domain ARMA modeling for ultrasound tissue characterization*

- **2011 (under revision)**
  IEEE Transactions on Ultrasonics, Ferr., and Freq. Control
  *An expectation maximization framework for improved tissue response characterization*

- **2011 May**
  Proceedings SampTA 2011
  H. Kirshner, S. Maggio, M. Unser.
  *Maximum-Likelihood Identification of Sampled Gaussian Processes*

- **2011 February**
  SPIE Medical Imaging
  *An expectation maximization framework for an improved tissue characterization using ultrasounds*

- **2010 November**
  17 Congresso Nazionale SIEUN
  *A retrospective study to reduce prostate biopsy cores by a real time interactive tool*

- **2010 October**
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  N. Testoni, S. Maggio, F. Galluzzo, L. De Marchi, N. Speciale.
  *rtCAB: a tool for reducing unnecessary prostate biopsy cores*

- **2010 August**
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  S. Maggio, H. Kirshner, M. Unser
  *Continuous-time AR model identification: does sampling rate really matter?*

- **2010 February**
  IEEE Transactions on Medical Imaging
  S. Maggio, A. Palladini, L. De Marchi, M. Alessandrini, N. Speciale, G. Masetti
  *Predictive deconvolution and hybrid feature Selection for Computer-Aided Detection of prostate cancer*

- **2009 March**
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  *Computer aided detection of prostate cancer based on GDA and predictive deconvolution*

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  *Ultrasound Images Enhancement by means of Deconvolution Algorithms in the Wavelet Domain*

- **2005 September**
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  S. Maggio, N. Testoni, L. De Marchi, N. Speciale, G. Masetti
  *Wavelet-based Deconvolution Algorithms Applied to Ultrasound Images*
Ultrasonic tissue-type imaging (tti) for planning treatment of prostate cancer.
*Proceedings of SPIE*, 5373(223).

Frequency-domain identification of continuous-time arma models from sampled data.
*Automatica*, 45:1371–1378.

Computer-aided prostate cancer detection using texture features and clinical features in ultrasound image.

Prostate ultrasound image analysis: Localization of cancer lesions to assist biopsy.

Analysis of ultrasonographic prostate images for the detection of prostatic carcinoma: the automated urologic diagnostic expert system.

Computer-aided detection of prostate cancer.

Ultrasonic multifeature tissue characterization for prostate diagnostics.
Tissue-characterization of the prostate using radio frequency ultrasonic signals.

Cardinal exponential splines: Part i - theory and filtering algorithms.