Introduction	Random Excitation	Parametric Optimization	Conclusion

Random Excitation by Optimized Pulse Inversion in Contrast Harmonic Imaging

Sébastien Ménigot and Jean-Marc Girault



Université François Rabelais de Tours Inserm U930 - *Imaging and Brain* Team 5 - *Imaging and Ultrasound* Tours, France

April 26th, 2012



/ 20

April 26th, 2012

Introduction	Random Excitation	Parametric Optimization	Conclusions
Outline			

- Ultrasound Contrast Imaging
- Pulse Inversion Imaging
- Problematic

Random Excitation

- Principle
- Simulation Model
- Results for linear system
- Results for nonlinear pulse inversion imaging system

3 Parametric Optimization

- Implementation
- Results

Introduction	Random Excitation	Parametric Optimization	Conclusions

Random Excitation

Parametric Optimization

Conclusions

Ultrasound Contrast Imaging

Ultrasound Contrast Imaging

Contrast Agents

- Injection of contrast agents ⇒ perfusion imaging
- Encapsulated microbubbles: mean diameter between 1 to 10 μ m
- High nonlinear behavior





Ménigot & Girault (Tours, France)

April 26th, 2012 **©0**€0

Random Excitation

Parametric Optimization

Conclusions

Ultrasound Contrast Imaging

Ultrasound Contrast Imaging

Contrast Agents

- Injection of contrast agents ⇒ perfusion imaging
- Encapsulated microbubbles: mean diameter between 1 to 10 μ m

• High nonlinear behavior





Ménigot & Girault (Tours, France)

Random Excitation

Parametric Optimization

Conclusions

Ultrasound Contrast Imaging

Ultrasound Contrast Imaging

Contrast Agents

- Injection of contrast agents ⇒ perfusion imaging
- Encapsulated microbubbles: mean diameter between 1 to 10 μ m
- High nonlinear behavior





Random Excitation

Parametric Optimization

Conclusions

Ultrasound Contrast Imaging

Ultrasound Contrast Imaging

Contrast Agents

- Injection of contrast agents ⇒ perfusion imaging
- Encapsulated microbubbles: mean diameter between 1 to 10 μ m
- High nonlinear behavior





Contrast to Tissue Ratio

$$CTR = \frac{E_{microbubbles}}{E_{tissue}}$$

Ménigot & Girault (Tours, France)

April 26th, 2012

Introduction	Random Excitation	Parametric Optimization	Conclusions
••••			
Ultrasound Contrast Imaging			

Ultrasound Contrast Imaging



 $CTR = \frac{E_{microbubbles}}{E_{tissue}}$





Ménigot & Girault (Tours, France)

Contrast to Tissue Ratio

Random Excitation

April 26th, 2012 ©000

Introduction	Random Excitation	Parametric Optimization	Conclusions
0000			
Ultrasound Contrast Imaging			

Ultrasound Contrast Imaging



Ménigot & Girault (Tours, France)







Ménigot & Girault (Tours, France)

April 26th, 2012 @080



 Introduction
 Random Excitation
 Parametric Optimization
 Conclusions

 0000
 0000
 0000
 0000
 0000

 Pulse Inversion Imaging
 Pulse Inversion Imaging
 Pulse Inversion Method
 Pulse Inversion Method



Random Excitation

Parametric Optimization

Conclusions

Problematic

What is the best command to optimize the criterion?



Introduction	Random Excitation	Parametric Optimization	Conclusions

Ménigot & Girault (Tours, France)

Random Excitation

April 26th, 2012 ©000

Random Excitation

Parametric Optimization

Conclusions

Principle

Principle of Random Excitation



Principle of Implementation

• Find the input signal x(t) of the pulse inversion imaging system

Optimize the CTR

3 Random search by Monte-Carlo method

Ménigot & Girault (Tours, France)

9 / 20

(日) (同) (三) (三)

Random Excitation

Parametric Optimization

Conclusions

Principle

Principle of Random Excitation



Principle of Implementation

• Find the input signal x(t) of the pulse inversion imaging system

Optimize the CTR

Random search by Monte-Carlo method

Ménigot & Girault (Tours, France)

9 / 20

(日) (同) (三) (三)

Random Excitation 0000

Parametric Optimization

Conclusions

Principle

Principle of Random Excitation



Principle of Implementation

- Find the input signal x(t) of the pulse inversion imaging system
- 2 Optimize the CTR
- Random search by Monte-Carlo method 3

_ ∢ ≣ →

Random Excitation 0000

Parametric Optimization

Conclusions

Principle

Principle of Random Excitation



Principle of Implementation

- Find the input signal x(t) of the pulse inversion imaging system
- 2 Optimize the CTR
- Random search by Monte-Carlo method 3

_ ∢ ≣ →

Introduction	Random Excitation ○●○○○	Parametric Optimization	Conclusions
Simulation Model			
Simulation	Model		

Simulation Properties

• Transducer centred at $f_c = 3 \text{ MHz}$

Microbubble

- Free simulation software Bubblesim [Hoff, 2001]
- Modified Rayleigh-Plesset Equation
- Diameter: 2.5 μ m
- Shell thickness: 1 nm
- Resonance Frequency: 3.1 MHz
- Tissue : Rayleigh diffusion

@ • • • •

Introduction	Random Excitation	Parametric Optimization	Conclusions
Simulation Model			
Simulation Mo	odel		

Simulation Properties

- Transducer centred at $f_c = 3 \text{ MHz}$
- Microbubble
 - Free simulation software Bubblesim [Hoff, 2001]
 - Modified Rayleigh-Plesset Equation
 - Diameter: 2.5 μ m
 - Shell thickness: 1 nm
 - Resonance Frequency: 3.1 MHz

• Tissue : Rayleigh diffusion

Introduction	Random Excitation	Parametric Optimization	Conclusions
Simulation Model			
Simulation Mo	odel		

Simulation Properties

- Transducer centred at $f_c = 3 \text{ MHz}$
- Microbubble
 - Free simulation software Bubblesim [Hoff, 2001]
 - Modified Rayleigh-Plesset Equation
 - Diameter: 2.5 μ m
 - Shell thickness: 1 nm
 - Resonance Frequency: 3.1 MHz
- Tissue : Rayleigh diffusion

Random Excitation 00000

Parametric Optimization

Conclusions

Results for linear system

Results for linear system: Optimization of microbubble

power



Ménigot & Girault (Tours, France)

Random Excitation

Random Excitation 00000

Parametric Optimization

Conclusions

Results for nonlinear pulse inversion imaging system

Results for nonlinear pulse inversion imaging system



Ménigot & Girault (Tours, France)

April 26th, 2012

Random Excitation ○○○○● Parametric Optimization

Conclusions

13 / 20

Results for nonlinear pulse inversion imaging system

Results for nonlinear pulse inversion imaging system



$$f_{opt} = 2.5 \text{ MHz}$$

CTR = 30.4 dB

Random Excitation

Parametric Optimization

Conclusions

Results for nonlinear pulse inversion imaging system

Results for nonlinear pulse inversion imaging system



0000

Random Excitation

Parametric Optimization

Conclusions

Parametric Optimization

Ménigot & Girault (Tours, France)

Random Excitation

April 26th, 2012 @080

< ∃ >

14 / 20

< 17 ▶

Random Excitation

Parametric Optimization

Conclusions

Implementation

Implementation of the Parametric Optimization



Setting of Iterative Optimization

- ① Choice of the Cost Function $J(\theta)$
- 2 Choice of the parameters heta
- 3 Choice of the optimization algorithm

Ménigot & Girault (Tours, France)

Random Excitation

April 26th, 2012

@ØØ@

Random Excitation

Parametric Optimization

Conclusions

Implementation

Implementation of the Parametric Optimization



Setting of Iterative Optimization

- Choice of the Cost Function $J(\theta)$
- 2 Choice of the parameters heta
- Choice of the optimization algorithm

Ménigot & Girault (Tours, France)

Random Excitation

April 26th, 2012

@ØØ@

Random Excitation

Parametric Optimization

Conclusions

Implementation

Implementation of the Parametric Optimization



Setting of Iterative Optimization

- **O** Choice of the Cost Function $J(\theta)$
- **2** Choice of the parameters θ

Choice of the optimization algorithm

Ménigot & Girault (Tours, France)

Random Excitation

April 26th, 2012

@ØØ@

Random Excitation

Parametric Optimization

Conclusions

Implementation

Implementation of the Parametric Optimization



Setting of Iterative Optimization

- **O** Choice of the Cost Function $J(\theta)$
- 2 Choice of the parameters θ
- Ochoice of the optimization algorithm

Ménigot & Girault (Tours, France)

Random Excitation

April 26th, 2012

@ØØ@

Random Excitation

Parametric Optimization

April 26th, 2012

@ØØ@

15 / 20

Conclusions

Implementation

Implementation of the Parametric Optimization



Setting of Iterative Optimization

- **Q** Choice of the Cost Function $J(\theta) \rightarrow CTR$
- 2 Choice of the parameters θ
- S Choice of the optimization algorithm

Ménigot & Girault (Tours, France)

Random Excitation

Random Excitation

Parametric Optimization ○●○○ Conclusions

16 / 20

Implementation

Implementation of the Parametric Optimization

Optimization Setting

Maximization of the CTR

Input signal described by autoregressive model

$$\hat{x}(t) = \sum_{i=0}^{M-1} h_1(i) x(t-i)$$



Random Excitation

Parametric Optimization ○●○○ Conclusions

16 / 20

Implementation

Implementation of the Parametric Optimization

Optimization Setting

- Maximization of the CTR
- Input signal described by autoregressive model

$$\hat{x}(t) = \sum_{i=0}^{M-1} h_1(i) x(t-i)$$

Solution Neider-Mead's Algorithm based on simplex

Random Excitation

Parametric Optimization ○●○○ Conclusions

16 / 20

Implementation

Implementation of the Parametric Optimization

Optimization Setting

Maximization of the CTR

Input signal described by nonlinear autoregressive model (NAR)

$$\hat{x}(t) = \sum_{i=0}^{M-1} h_1(i) x(t-i) + \sum_{i=0}^{M-1} \sum_{j=i}^{M} h_2(i,j) x(t-i) x(t-j) + \cdots$$

Nelder-Mead's Algorithm based on simplex

Random Excitation

Parametric Optimization ○●○○ Conclusions

16 / 20

Implementation

Implementation of the Parametric Optimization

Optimization Setting

Maximization of the CTR

Input signal described by nonlinear autoregressive model (NAR)

$$\hat{x}(t) = \sum_{i=0}^{M-1} h_1(i) x(t-i) \\ + \sum_{i=0}^{M-1} \sum_{j=i}^{M} h_2(i,j) x(t-i) x(t-j) + \cdots$$

Order K = 3 and memory $M = 3 \Rightarrow 19$ parameters

3 Nelder-Mead's Algorithm based on simplex

Random Excitation

Parametric Optimization ○●○○ Conclusions

16 / 20

Implementation

Implementation of the Parametric Optimization

Optimization Setting

Maximization of the CTR

Input signal described by nonlinear autoregressive model (NAR)

$$\hat{x}(t) = \sum_{i=0}^{M-1} h_1(i) x(t-i) + \sum_{i=0}^{M-1} \sum_{j=i}^{M} h_2(i,j) x(t-i) x(t-j) + \cdots$$

Order K = 3 and memory $M = 3 \Rightarrow 19$ parameters Drawback: what is the signal x(t) ?

Nelder-Mead's Algorithm based on simplex

Random Excitation

Parametric Optimization ○●○○ Conclusions

16 / 20

Implementation

Implementation of the Parametric Optimization

Optimization Setting

Maximization of the CTR

Input signal described by nonlinear autoregressive model (NAR)

$$\hat{x}(t) = \sum_{i=0}^{M-1} h_1(i) x(t-i) + \sum_{i=0}^{M-1} \sum_{j=i}^{M} h_2(i,j) x(t-i) x(t-j) + \cdots$$

Order K = 3 and memory $M = 3 \Rightarrow 19$ parameters Drawback: what is the signal x(t)? \Rightarrow Optimal Input Signal obtained randomly

Random Excitation

Parametric Optimization ○●○○ Conclusions

16 / 20

Implementation

Implementation of the Parametric Optimization

Optimization Setting

Maximization of the CTR

2 Input signal described by nonlinear autoregressive model (NAR)

$$\hat{x}(t) = \sum_{i=0}^{M-1} h_1(i) x(t-i) + \sum_{i=0}^{M-1} \sum_{j=i}^{M} h_2(i,j) x(t-i) x(t-j) + \cdots$$

Order K = 3 and memory $M = 3 \Rightarrow 19$ parameters Drawback: what is the signal x(t)? \Rightarrow Optimal Input Signal obtained randomly

Nelder-Mead's Algorithm based on simplex

Introduction	Random Excitation	Parametric Optimiza ○○●○	tion Conclusions
Results			
Results v	vith Parametric Op	otimization	
	Pulse	Random	Random with
			Parametric
		(Optimization
CTR	30.4 dB	31.4 dB	

Ménigot & Girault (Tours, France)

Random Excitation

 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 ▲ □ ▶
 <t

∃ 990

Introduction 0000 Results	Random Excitation	Parametric Optimi ○○●○	zation Con	iclusions
Results with F	Parametric Opt	imization		
	Pulse	Random	Random with Parametric	
			Optimization	-
CTR	30.4 dB	31.4 dB	31.5 dB	

Introduction 0000 Results	Random Excitation	Parametric Optim ○○●○	zation	Conclusions
Results with F	Parametric Opt	imization		
			<u> </u>	
	Pulse	Random	Random wi Parametric	th
			Optimization	
CTR	30.4 dB	31.4 dB	31.5 dB	

Introduction	Random Excitation	Parametric Optimization	Conclusions
Results			
Comparison			

		Random	Random with Parametric Optimization
CTR	30.5 dB		
N _{test}	15		

◆□▶ ◆□▶ ◆臣▶ ◆臣▶ 三臣 - 釣�(♡

Introduction	Random Excitation	Parametric Optimization	Conclusions
		0000	
Results			
Comparison			

	Ra	ndom	Random with Parametric Optimization
CTR	30.5 dB	31.3 dB	
N _{test}	15	2165	

◆□▶ ◆□▶ ◆臣▶ ◆臣▶ 三臣 - 釣�(♡

Introduction	Random Excitation	Parametric Optimization	Conclusions
		000	
Results			
Comparison			

	Rando	om	Random with Parametric Optimization
CTR	30.5 dB		31.3 dB
N _{test}	15		258

◆□ ▶ ◆□ ▶ ◆三 ▶ ◆三 ▶ ● ● ● ● ●

Introduction	Random Excitation	Parametric Optimization ○○○●	Conclusions
Results			
Comparison			

	Rai	ndom	Random with Parametric Optimization
CTR	30.5 dB	31.3 dB	31.3 dB
N _{test}	15	2165	258

◆□ ▶ ◆□ ▶ ◆三 ▶ ◆三 ▶ ● ● ● ● ●

Introduction	Random Excitation	Parametric Optimization	Conclusions

Conclusion & Prospects

Ménigot & Girault (Tours, France)

Random Excitation

April 26th, 2012 ©000

Random Excitation

Parametric Optimization

Conclusions

20 / 20

Conclusion & Prospects

Know the optimal shape of the optimal command

- Random process without a priori knowledge of the medium
- Suboptimal excitation by combination between random process and parametric optimization
- Decrease test number
- Prospects:
 - Analysis the optimal excitation
 - Find the optimal command by metaheuristic

Introd	uction
0000	

Parametric Optimization

Conclusions

20 / 20

- Know the optimal shape of the optimal command
- Random process without a priori knowledge of the medium
- Suboptimal excitation by combination between random process and parametric optimization
- Decrease test number
- Prospects:
 - Analysis the optimal excitation
 - Find the optimal command by metaheuristic

Introd	uction
0000	

Parametric Optimization

Conclusions

20 / 20

- Know the optimal shape of the optimal command
- Random process without a priori knowledge of the medium
- Suboptimal excitation by combination between random process and parametric optimization
- Decrease test number
- Prospects:
 - Analysis the optimal excitation
 - Find the optimal command by metaheuristic

Introduction	
0000	

Parametric Optimization

Conclusions

20 / 20

- Know the optimal shape of the optimal command
- Random process without a priori knowledge of the medium
- Suboptimal excitation by combination between random process and parametric optimization
- Decrease test number
- Prospects:
 - Analysis the optimal excitation
 - Find the optimal command by metaheuristic

Introduction	
0000	

Parametric Optimization

Conclusions

20 / 20

- Know the optimal shape of the optimal command
- Random process without a priori knowledge of the medium
- Suboptimal excitation by combination between random process and parametric optimization
- Decrease test number
- Prospects:
 - Analysis the optimal excitation
 - Find the optimal command by metaheuristic

Introd	uction
0000	

Parametric Optimization

Conclusions

20 / 20

- Know the optimal shape of the optimal command
- Random process without a priori knowledge of the medium
- Suboptimal excitation by combination between random process and parametric optimization
- Decrease test number
- Prospects:
 - Analysis the optimal excitation
 - Find the optimal command by metaheuristic

Random Excitation

Parametric Optimization

Conclusions

Conclusion & Prospects

Thank you for your attention

sebastien.menigot@univ-tours.fr jean-marc.girault@univ-tours.fr







April 26th, 2012



Institut national de la santé et de la recherche médicale

@080

20 / 20

Random Excitation