## Optimisation of Computer Algebra Techniques Application for Rician Data Analysis

## Tatiana Yakovleva

Federal Research Center "Computer Science and Control" of the Russian Academy of Sciences Moscow, Russia

# Abstract

The paper presents a mathematical research directed on the optimization of the computer-algebra methods' application for solving the task of stochastic data analysis. Within the conducted theoretical investigation <u>a</u> few mathematical techniques of the statistical data analysis have been elaborated which allow essential simplifying of the task solution by *computer algebra methods.* The developed two-parameter approach to data analysis is efficiently applicable to a wide spectrum of scientific and applied tasks, in which a signal to be analyzed is described by the Rice statistical model.

#### Optimization of computer algebra techniques' application for twoparameter analysis of stochastic data:

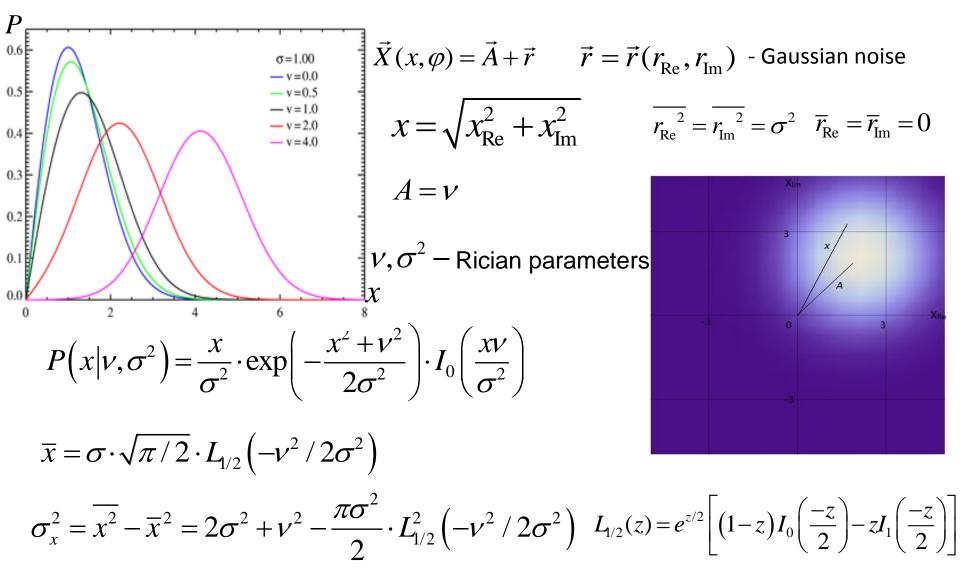
- Two-parameter Rician signals analysis provides joint computing of both the informative and the noise signal's components (in contrast to non-realistic one-parameter approximation) and is in demand in applications implying operation in a real time mode.
- The subject of the research: simplification (optimization) of the algorithms of the Rician parameters joint computing.
- The compute-intensive task of <u>solving the system of two nonlinear equations</u> with two variables was reduced to solving just one equation for one variable.
- The possibility was proved of joint computing of both the signal and noise parameters without additional computations if compared with one-parameter approximation.
- The elaborated techniques may be applied in <u>data processing</u> systems <u>with the</u> <u>priority of operation in a real time mode</u>.

*The Rice statistical distribution* characterizes <u>a value</u> <u>of an amplitude</u>, or envelope of the complex signal composed as <u>a sum of the sought-for initial signal and a</u> <u>Gaussian noise.</u>

The fields of application:

- magnetic-resonance visualization,
- radio signals reception and processing,
- radar signals analysis,
- analysis of the sonar signals,
- optical medium's properties measurements, etc.

## The Rice distribution properties



# Formulation of the problem of random Rician value two-parameter analysis

Initially determined complex value with amplitude  $\nu$  is distorted by a Gaussian noise of dispersion  $\sigma^2$ ,

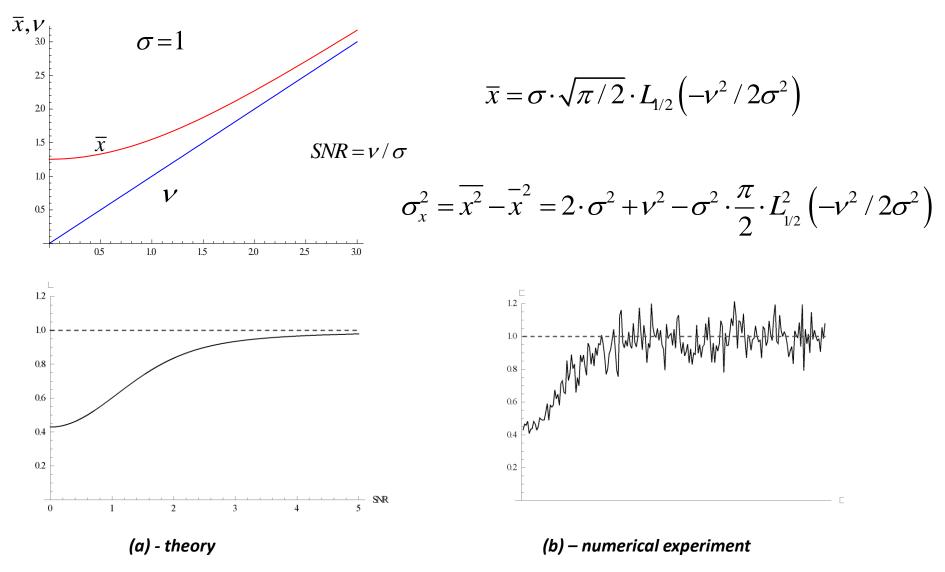
Amplitude  $x = \sqrt{x_{Re}^2 + x_{Im}^2}$  of the resulting signal obeys the Rice statistical distribution with parameters V and  $\sigma^2$ .

 $x_{
m Re}$  ,  $x_{
m Im}~$  – independent Gaussian values with dispersion  $\sigma^2$ 

$$P(x|\nu,\sigma^2) = \frac{x}{\sigma^2} \cdot \exp\left(-\frac{x^2 + \nu^2}{2\sigma^2}\right) \cdot I_0\left(\frac{x\nu}{\sigma^2}\right)$$

**The task** consists in <u>reconstruction of useful (informative) signal</u> V against the noise background <u>by joint computing the both Rician parameters</u> on the basis of measurements of the summary signal  $X_i$  (i = 1, ..., n), without any a priory assumptions concerning value of  $\sigma^2$ .

### Nonlinear properties of the Rice distribution



#### THE LIKELIHOOD FUNCTION OF THE RICE STATISTICAL DISTRIBUTION

V - a sough-for amplitude of un-noised signal X;

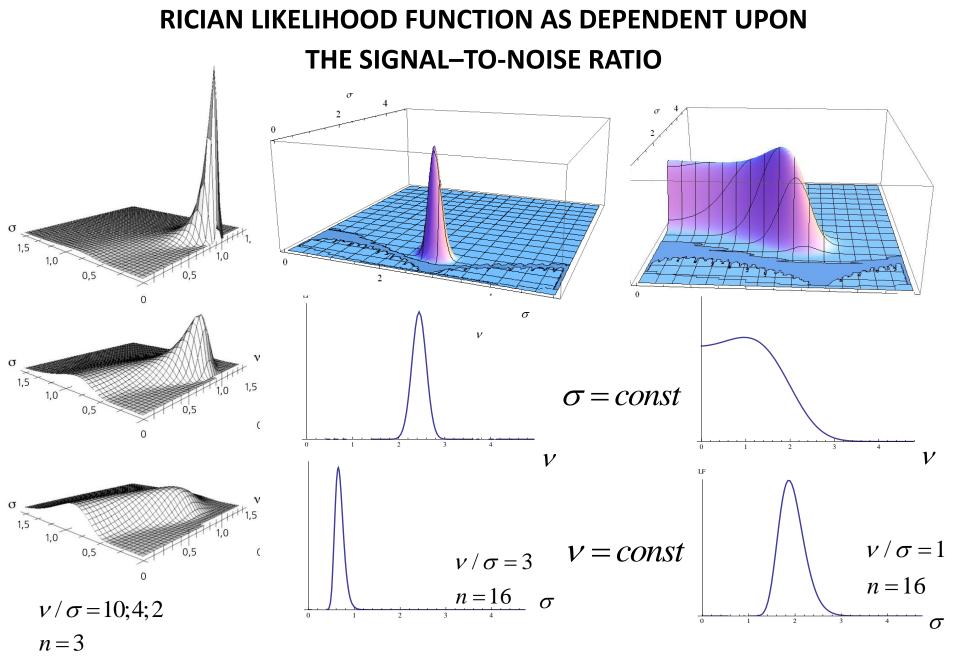
 $\sigma^2$ - a dispersion of the Gaussian noise distorting components  $x_{
m Re}$  and  $x_{
m Im}$ 

of signal 
$$x = \sqrt{x_{\text{Re}}^2 + x_{\text{Im}}^2}$$
  
 $P(x|\nu, \sigma^2) = \frac{x}{\sigma^2} \cdot \exp\left(-\frac{x^2 + \nu^2}{2\sigma^2}\right) \cdot I_0\left(\frac{x\nu}{\sigma^2}\right)$ 

The likelihood function (i.e. a joint probability density function of the events

resulting in 
$$x = x_i$$
 ( $i = 1, ..., n$ ),

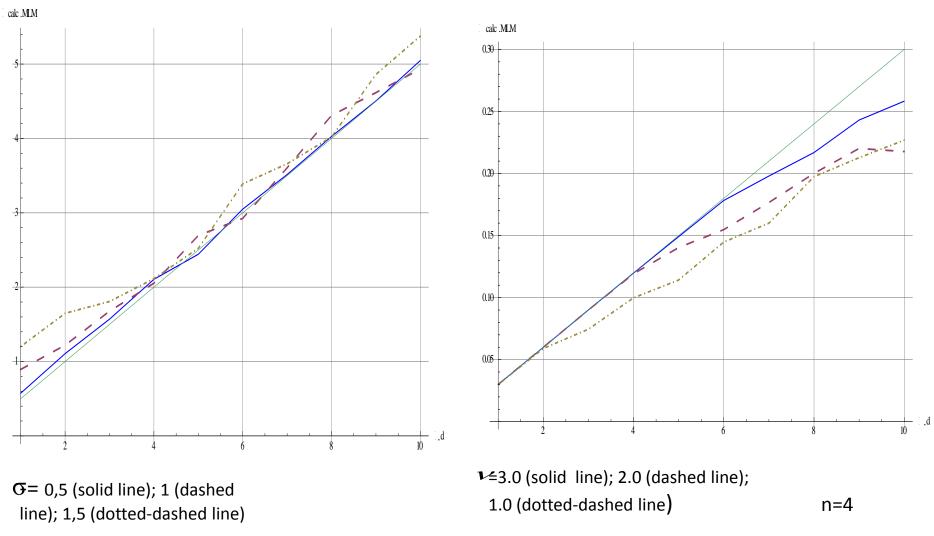
$$L\left(\overrightarrow{x}|\nu,\sigma^{2}\right) = \prod_{i=1}^{n} P\left(x_{i}|\nu,\sigma\right) = \prod_{i=1}^{n} \frac{x_{i}}{\sigma^{2}} \cdot \exp\left(-\frac{x_{i}^{2}+\nu^{2}}{2\sigma^{2}}\right) \cdot I_{0}\left(\frac{x_{i}\nu}{\sigma^{2}}\right)$$
$$\ln L\left(\overrightarrow{x}|\nu,\sigma^{2}\right) = \sum_{i=1}^{n} \ln P\left(x_{i}|\nu,\sigma\right) = \sum_{i=1}^{n} \left\{-2 \cdot \ln \sigma - \frac{x_{i}^{2}+\nu^{2}}{2 \cdot \sigma^{2}} + \ln I_{0}\left(\frac{x_{i}\nu}{\sigma^{2}}\right)\right\}$$



#### **TWO-PARAMETER COMBINED ML-MM METHOD**

 $v, \sigma^2$  – Rician parameters  $v, \sigma^{2} - \text{Rician parameters}$   $\sum_{i=1}^{n} \frac{\partial}{\partial v} \ln I_{0} \left( \frac{x_{i}v}{\sigma^{2}} \right) - \frac{n \cdot v}{\sigma^{2}} = 0 \qquad \frac{1}{\sigma^{2}} \sum_{i=1}^{n} x_{i} \cdot \frac{I_{1} \left( \frac{x_{i}v}{\sigma^{2}} \right)}{I_{0} \left( \frac{x_{i}v}{\sigma^{2}} \right)} - \frac{n \cdot v}{\sigma^{2}} = 0$  $r = \frac{V^2}{2\sigma^2}$  $\bar{x} = \sigma \cdot \sqrt{\pi/2} \cdot L_{1/2} \left( -\nu^2/2\sigma^2 \right)$  $\begin{cases} v = \frac{1}{n} \sum_{i=1}^{n} x_i \cdot \tilde{I}\left(\frac{x_i \cdot v}{\sigma^2}\right) \\ \frac{1}{n} \sum_{i=1}^{n} x_i = \sigma \sqrt{\frac{\pi}{2}} \cdot L_{1/2}\left(-\frac{v^2}{2\sigma^2}\right) \implies 2\sqrt{r/\pi} \cdot \frac{\langle x \rangle}{L_{1/2}\left(-r\right)} = \frac{1}{n} \sum_{i=1}^{n} x_i \tilde{I}\left(\frac{x_i \sqrt{\pi \cdot r}}{\langle x \rangle} L_{1/2}\left(-r\right)\right) \end{cases}$  $L_q(z)$  - the Laguerre polynomial  $\sigma = \frac{\langle x \rangle}{\sqrt{\pi/2} \cdot L_{1/2}(-r)}$   $v = \sqrt{2\sigma^2 r}$ 

#### **Computer simulation results for ML-MM method**

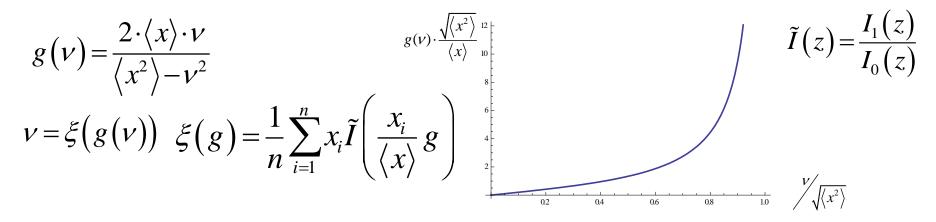


#### MAXIMUM LIKELIHOOD (ML) TECHNIQUE FOR SOLVING THE TASK OF TWO-PARAMETER RICIAN DATA ANALYSIS

The key ML equations' system for parameters  $\,\mathcal{V}$  and  $\,\sigma^2$ :

$$\begin{cases} \frac{\partial}{\partial \nu} \ln L\left(\overrightarrow{x} \middle| \nu, \sigma^2\right) = 0 \quad \left\{ \nu = \frac{1}{n} \sum_{i=1}^n x_i \cdot \tilde{I}\left(\frac{x_i \nu}{\sigma^2}\right) \\ \frac{\partial}{\partial \sigma} \ln L\left(\overrightarrow{x} \middle| \nu, \sigma^2\right) = 0 \quad \left\{ \sigma^2 = \frac{1}{2 \cdot n} \sum_{i=1}^n (x_i^2 + \nu^2) - \frac{\nu}{n} \sum_{i=1}^n x_i \cdot \tilde{I}\left(\frac{x_i \nu}{\sigma^2}\right) \\ \sigma^2 = \frac{1}{2 \cdot n} \left\{ \sigma^2 = \frac{1}{2 \cdot n} \left\{ \sqrt{\frac{\nu}{2} + \nu^2} \right\} - \frac{\nu}{n} \sum_{i=1}^n x_i \cdot \tilde{I}\left(\frac{x_i \nu}{\sigma^2}\right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right) \\ \sigma^2 = \frac{1}{2} \cdot \left( \sqrt{\frac{\nu}{2} + \nu^2} \right)$$

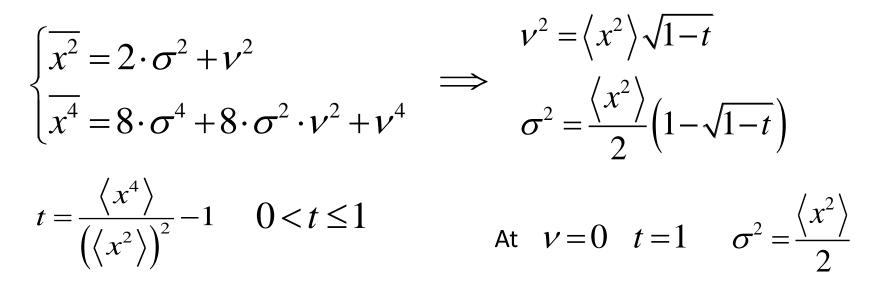
#### THEOREM: Solution of the ML equation' system exists and is a unique one



## Variants of the Method of Moments at solving the Task of Twoparameter Analysis of Rician Data

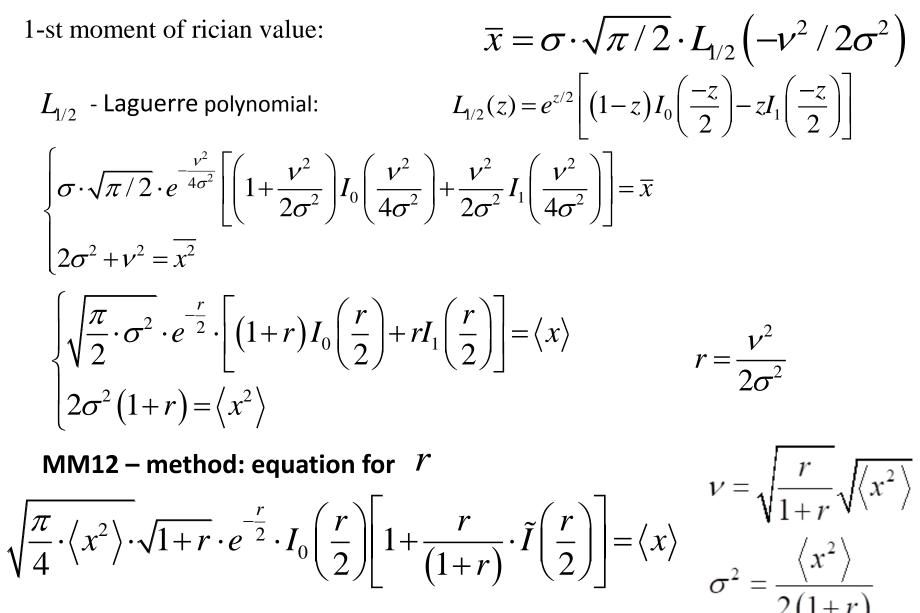
- 1. The method of lower even-numbered moments (MM24);
- 2. The method of lower moments (MM12).

#### **Two-parameter method MM24**



Семинар по Компьютерной алгебре Апрель 2023, Москва

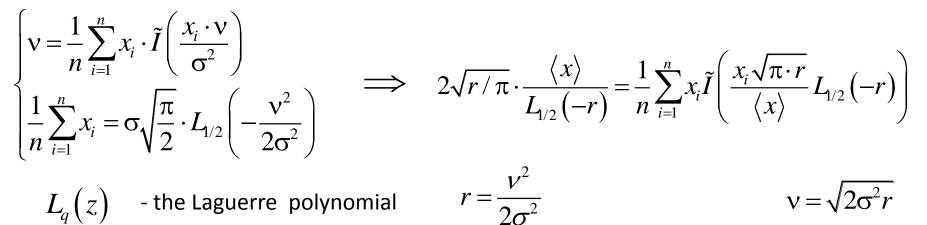
#### **Two-parameter method MM12**



Семинар по Компьютерной алгебре Апрель 2023, Москва

#### **TWO-PARAMETER COMBINED ML-MM METHOD**

 $\nu, \sigma^2$  – Rician parameters



#### **TWO-PARAMETER METHOD OF MOMENTS MM13**

$$\overline{x} = \sigma \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{1}{2}} \left( -\frac{v^2}{2\sigma^2} \right),$$
  

$$\overline{x^3} = 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$\sigma = \langle x \rangle \sqrt{\frac{2}{\pi}} / {}_1F_1 \left( -\frac{1}{2}; 1; -r \right)$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \cdot L_{\frac{3}{2}} \left( -\frac{v^2}{2\sigma^2} \right).$$
  

$$x^3 - 3 \cdot \sigma^3 \cdot \sqrt{\frac{\pi}{2}} \left( -\frac{v^2}{2\sigma$$

Семинар по Компьютерной алгебре Апрель 2023, Москва

## Conclusion

- The mathematical methods have been developed <u>to optimize the computer</u> <u>algebra techniques for solving the two-parameter task of the both signal and</u> <u>noise parameters joint computing</u> at stochastic data analysis, namely:
- ✓ The compute-intensive task of <u>solving the system of two essentially nonlinear</u> <u>equations with two sought-for variables has been mathematically reduced to</u> <u>solving just one equation for one unknown variable</u>;
- ✓ The possibility of <u>computing the both sought-for parameters by computer</u> <u>algebra techniques without any additional calculative capacities if compared</u> <u>with the traditional one-parameter approximation</u> has been ensured;
- Decreasing the needed calculative resources for the task under consideration allows applying the elaborated techniques in information technologies and data processing systems with priority of operation in a real-time mode.
- The presented research has revealed that <u>improvement of the computer</u> <u>algebra's mathematical means for simplifying the symbolic computation is an</u> <u>important and a quite solvable task.</u>

Thank you very much for your

attention