

# Visualization of uncertain scalar data fields using color scales and perceptually adapted noise

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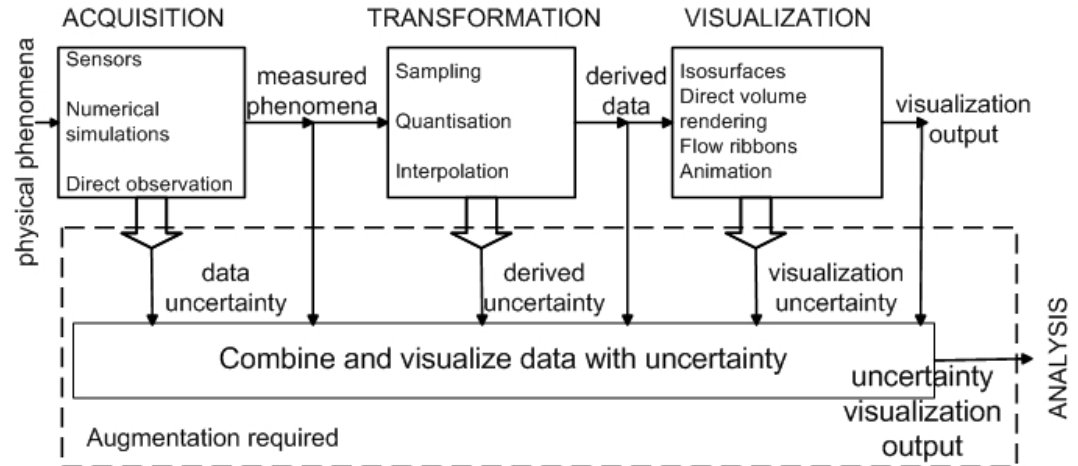


**edf**  
R&D

# Uncertain data visualization

Scientific data always contains **uncertainty** introduced by...

- **Data acquisition** : sensors and models are never perfect
- **Data transformation** : some treatments may reduce data quality
- **Post-processing** : visualization techniques do not perfectly depict all of the available data
- **User interaction** : users make mistakes due to lack of experience, fatigue, cognitive bias, ...



*Riveiro et al. 2007*

- Visualization goal : better data understanding through visual exploration
  - How to exploit the uncertainty information to achieve better visualization ?

# Uncertain data visualization

We focus on :

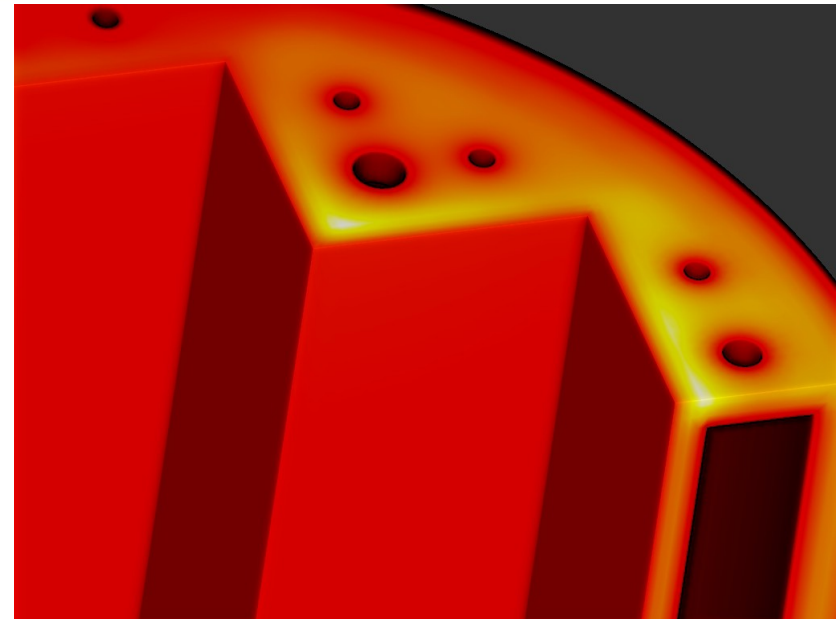
- **Scalar data** defined on a **2D manifold** domain

- Example : surface extracted from 3D FEM simulation for industrial applications
- Usually visualized using **colormaps**

High temperatures

Low temperatures

Colormap



*Thermal simulation result for internal elements of nuclear reactor*

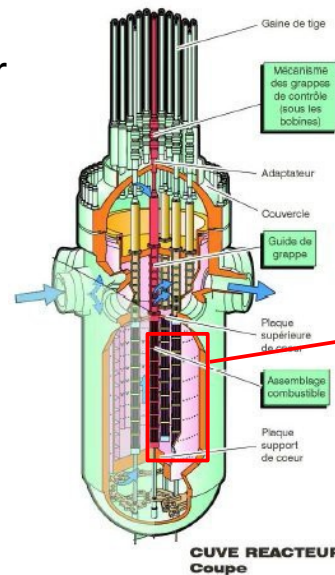
- Where a **quantitative uncertainty information** is known
  - Something like an error, accuracy, variance, ...
  - For probabilistic simulation (Monte-Carlo methods) : descriptive statistics (standard deviation, etc.)

# Uncertain scalar data visualization : our dataset

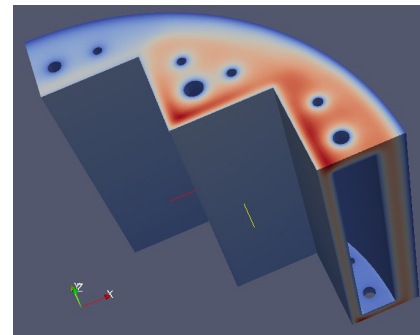
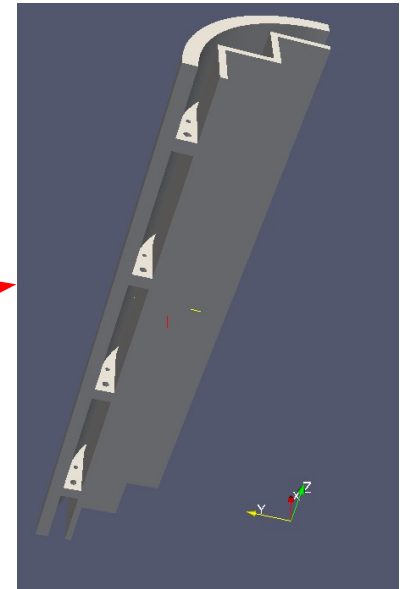
Our test case :

- Simulated dataset from the nuclear industry
- Structural **internal elements from a nuclear reactor**
  - Heated by radiation
  - Cooled by water
- **Solid thermal simulation** (SYRTHES) on moderate size 3D mesh (~1M cells) ; steady state
- Radiation data is uncertain  $\Rightarrow$  **Monte Carlo simulation**, 3000 runs
- Output : **3000 temperature values** per cell
  - We compute **mean value** and **standard deviation**

*Nuclear reactor*



*3D mesh*



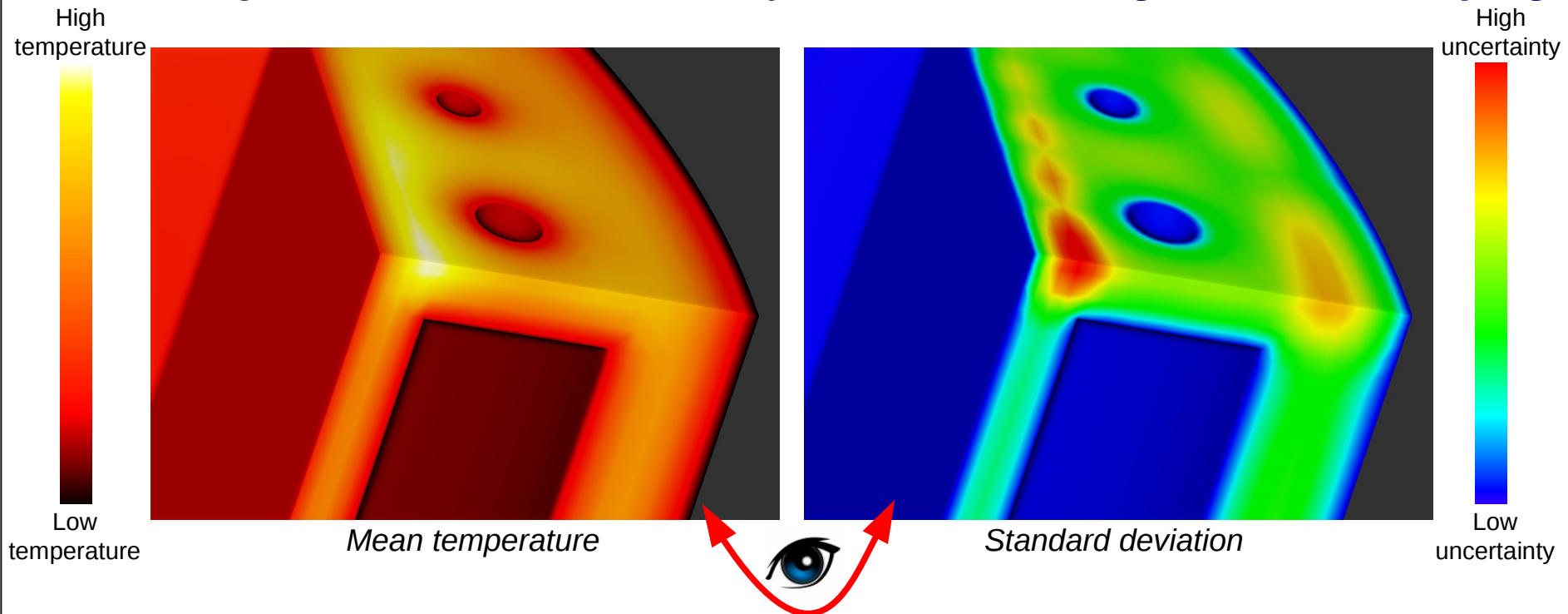
**SYRTHES**  
Thermal simulation  
code

*Thermal simulation and data*



# Uncertain scalar data visualization : previous work

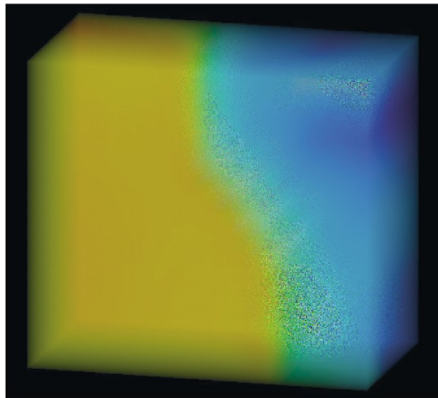
- Showing value data and uncertainty data on **two images** is **not satisfying** :



- Involves attentional shifts and **eye saccades** between two images
- Saccadic eye movement **does not allow for an effective integration** of spatial information (O'Reagan, 1983 ; Irwin 1991)

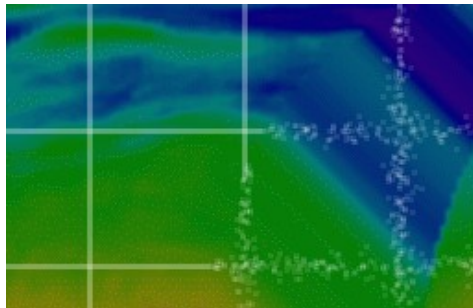
# Uncertain scalar data visualization : previous work

- **Visual noise** intuitively conveys the concepts of **uncertainty and fuzziness**



*Djurcilov, 2007*

*Binary noise added to DVR images*



*Cedilnik, 2000*

*Noisy gratings on 2D scalar data*

- In large and complex 3D scenes, quickly produces **visual clutter** and can **mask the data**

- For a static dataset, **animation** and motion is a **free visual variable**
- Can be used to show the possible values **without masking the data**



*Lundström, 2007*

*Animation for uncertain DVR medical data*

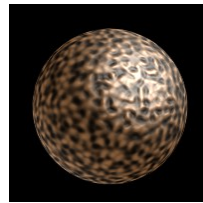
- Must be **used with care** :
  - If too salient : captures attention
  - If not salient enough : invisible

# Uncertainty visualization using colormaps and animated noise

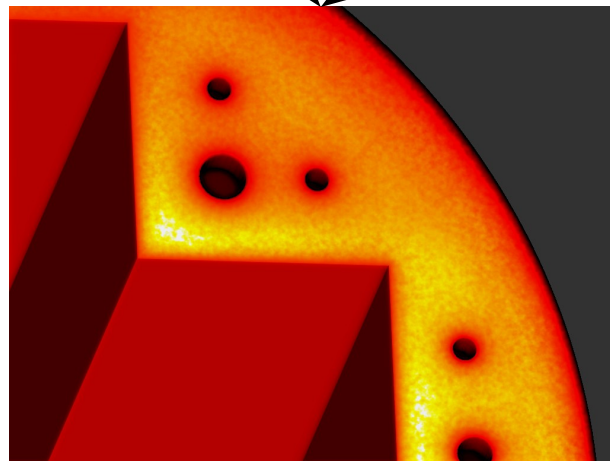
Colormap



Perlin noise



(Perlin, 2002)



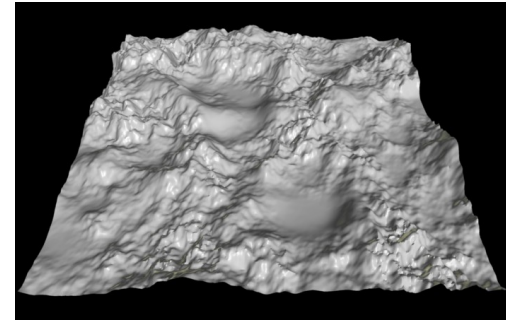
Uncertain data visualization

Our approach :

- **Perturbing the input to colormap** according to uncertainty
- Using an **animated procedural noise function**
- Visual mapping : high uncertainty  $\Leftrightarrow$  strong noise
- Choosing noise parameters according to **perceptual criteria**

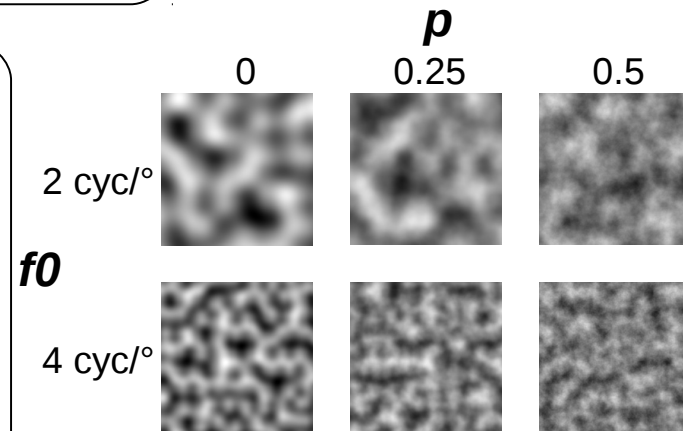
# Perlin noise

- Proposed by Ken Perlin in 1985 ; improved in 2002
- Algorithm generating **random procedural textures** using spline interpolation between random gradients on a square lattice
- Commonly used in computer graphics for natural phenomenoms simulation
- Arbitrary number of dimensions (2D, 3D, 3D+t, ...)



2D Perlin noise used as digital elevation model to generate a 3D landscape image

- Controlled by two **parameters** :
  - Base frequency  **$f_0$**  (cyc/°) :
    - global **scaling factor** ; controls the lattice size (high  $f_0 \Leftrightarrow$  small scale)
  - Persistence  **$p$**  (dimensionless ; usually in  $[0;1[$  ) :
    - determines the weight of **higher frequency features**



Various examples of 2D Perlin noise



# Uncertainty visualization using colormaps and animated noise

- **4D Perlin noise** (3D space + time)
  - Animated noise
  - $n(x,y,z,t)$
- **Scalar data field**  $V(x,y,z)$
- **Uncertainty**  $U(x,y,z)$  about the data
- Classic 1D **colormap**

## Classic visualization (no uncertainty)

$$V(x,y,z) = v$$



## Uncertain data visualization with animated noise

$$U(x,y,z) = u$$

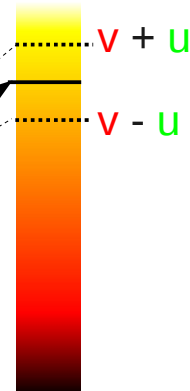
$$n(x,y,z,t)$$

in  $[-1 ; 1]$

$$u * n(x,y,z,t)$$

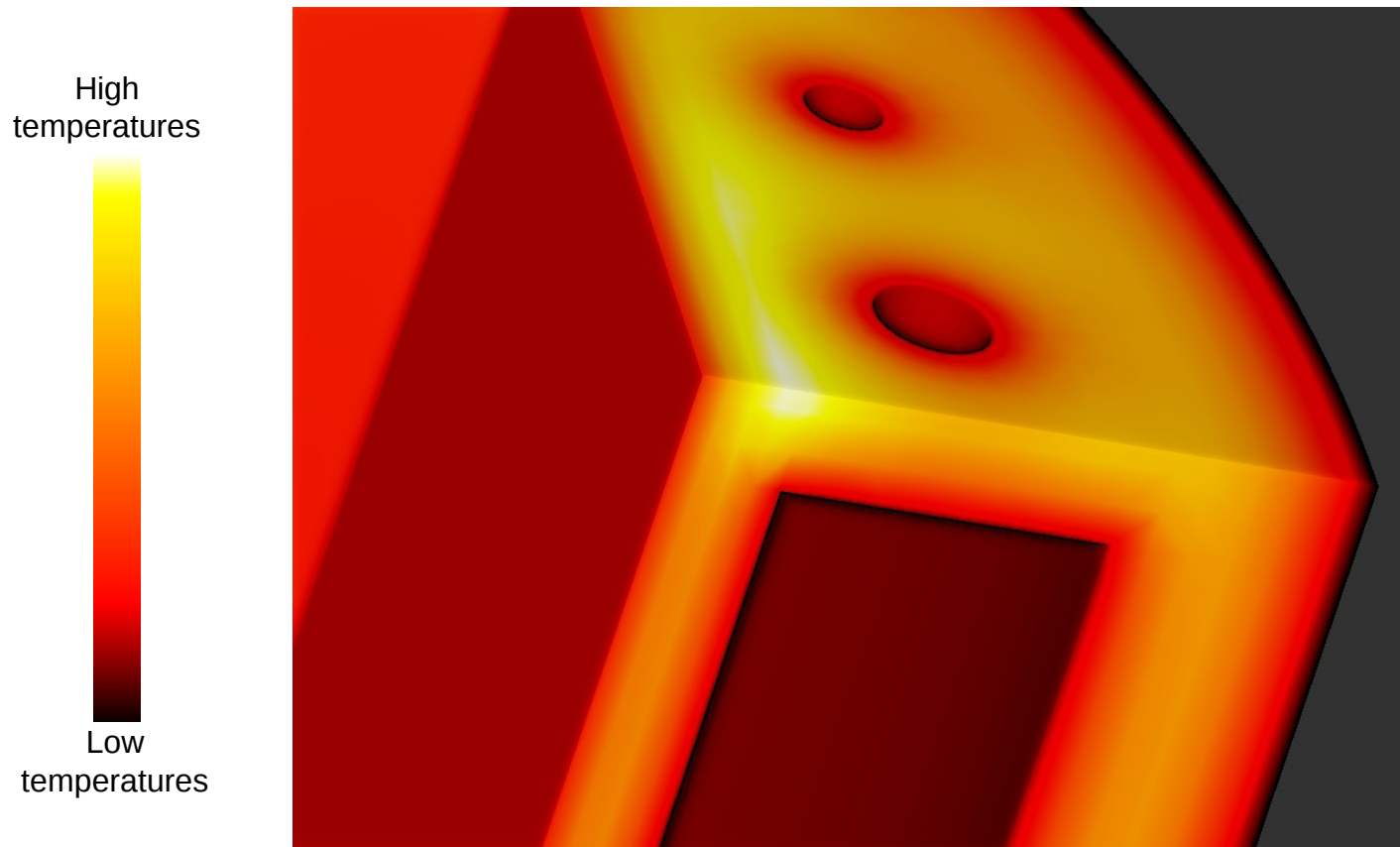
$$V(x,y,z) = v$$

$$v + u * n(x,y,z,t)$$



# Example : solid thermal diffusion simulation

Thermal diffusion in an internal nuclear reactor element, computed w. Monte-Carlo method



Classic visualization : mean temperature

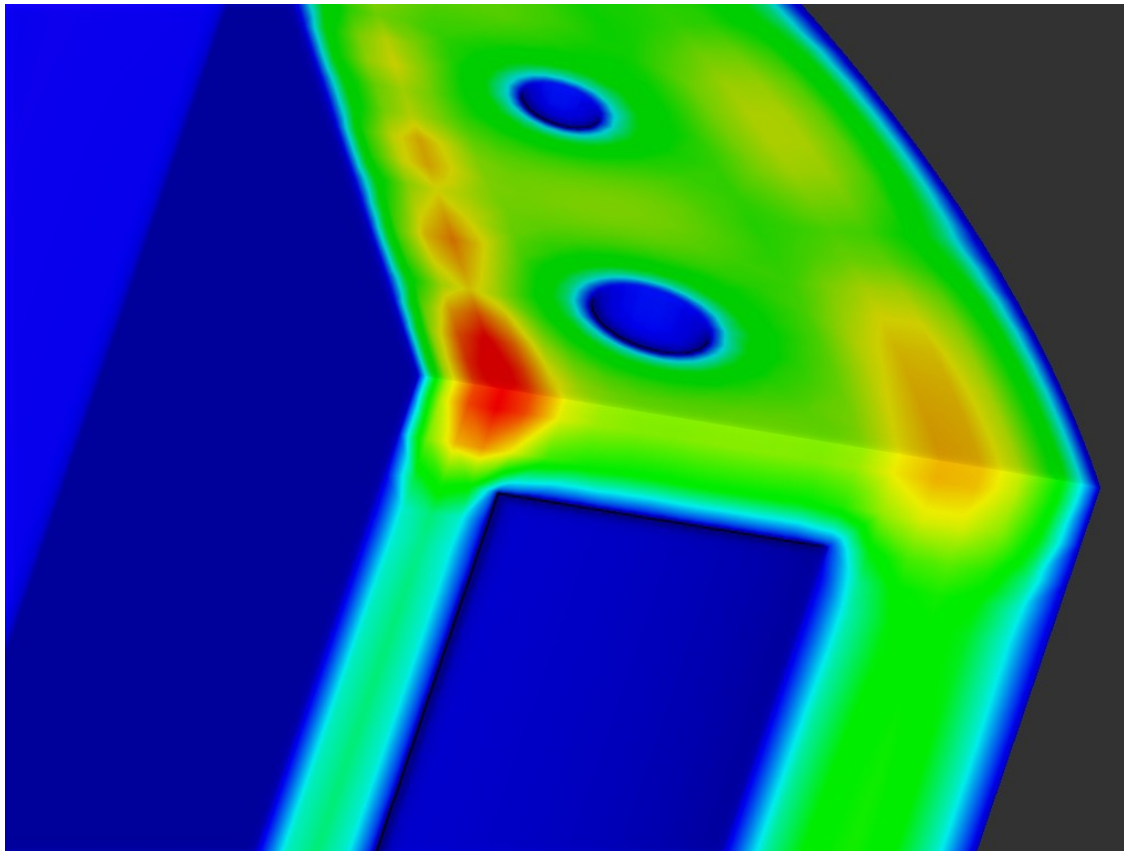
# Example : solid thermal diffusion simulation

Thermal diffusion in an internal nuclear reactor element, computed w. Monte-Carlo method

High uncertainty



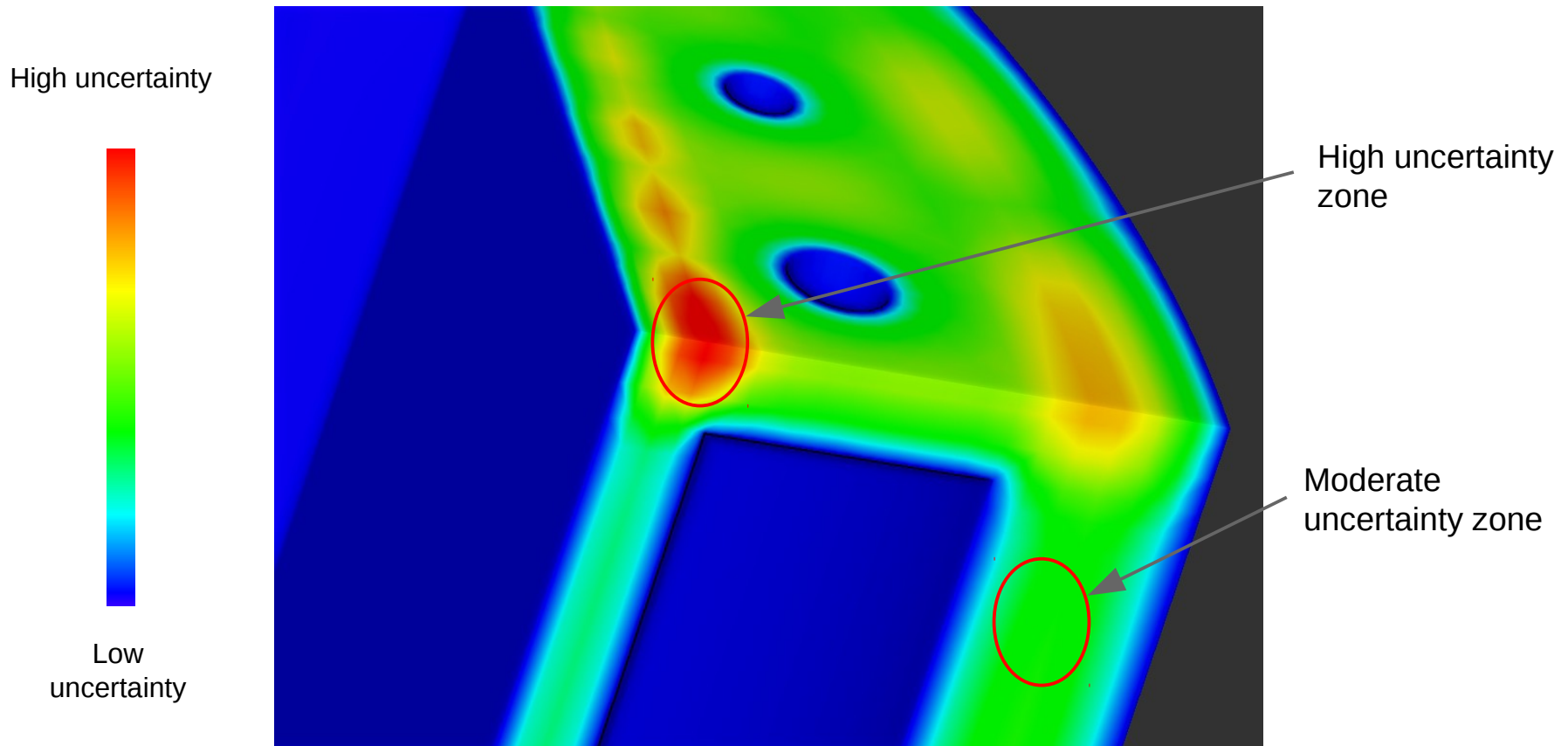
Low  
uncertainty



Classic visualization : standard deviation of temperature

# Example : solid thermal diffusion simulation

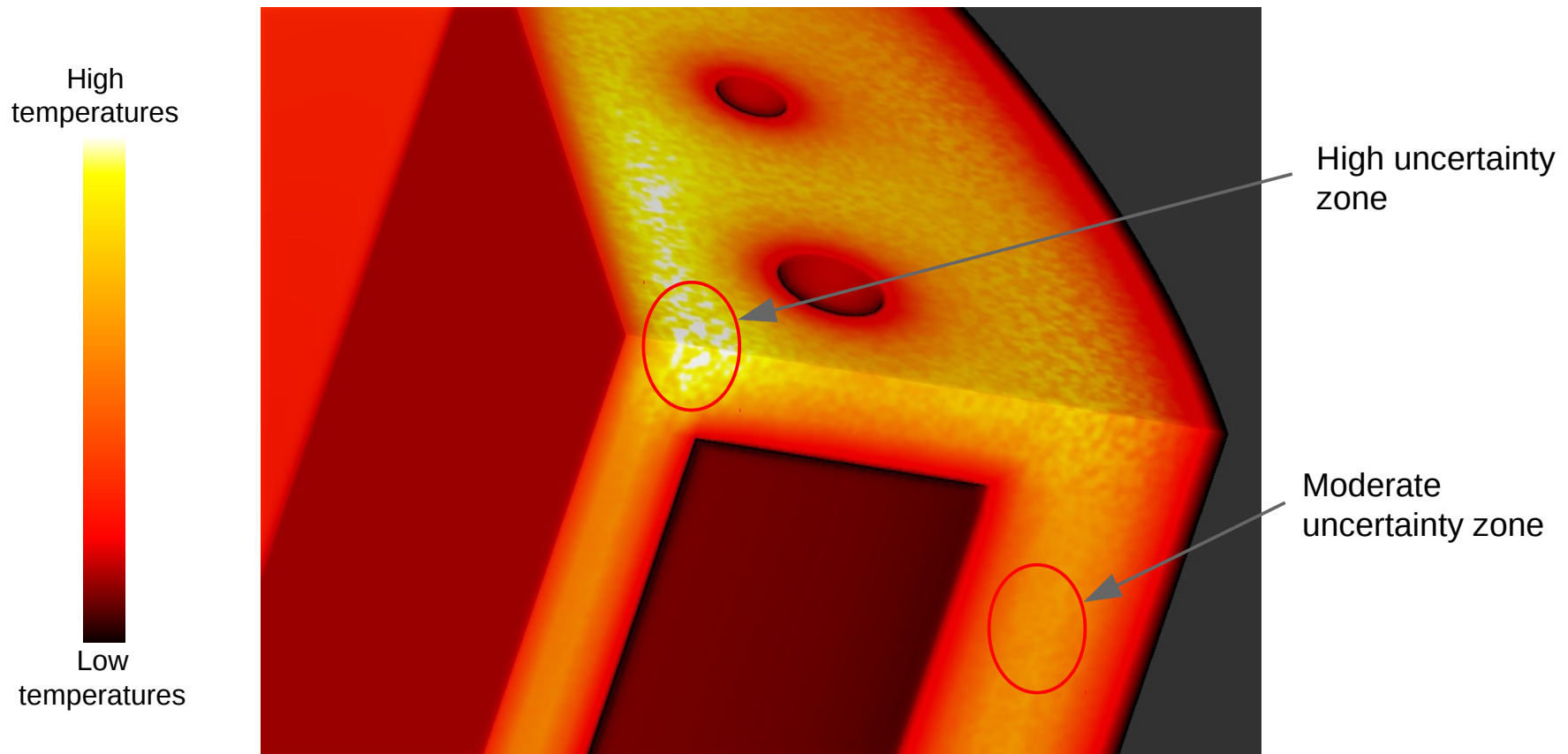
Thermal diffusion in an internal nuclear reactor element, computed w. Monte-Carlo method



Classic visualization : standard deviation of temperature

# Example : solid thermal diffusion simulation

Thermal diffusion in an internal nuclear reactor element, computed w. Monte-Carlo method

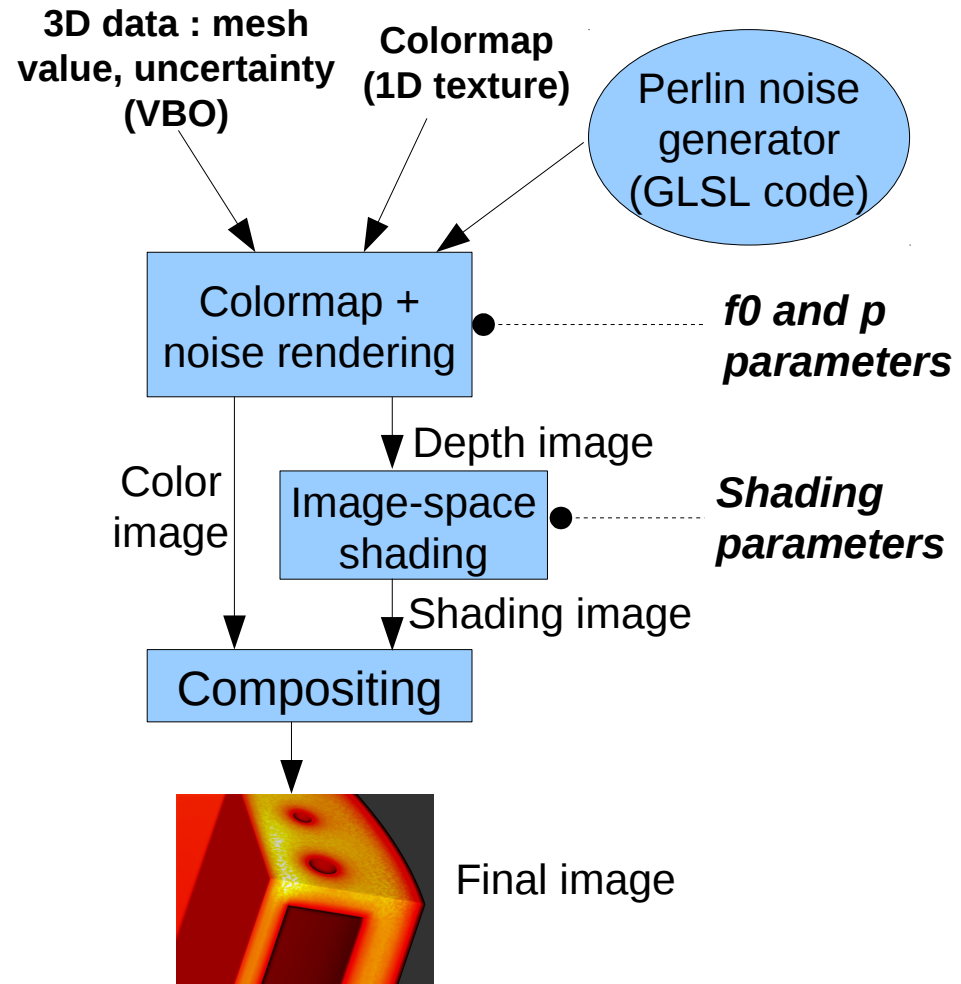


Our method : noise-based uncertain data visualization



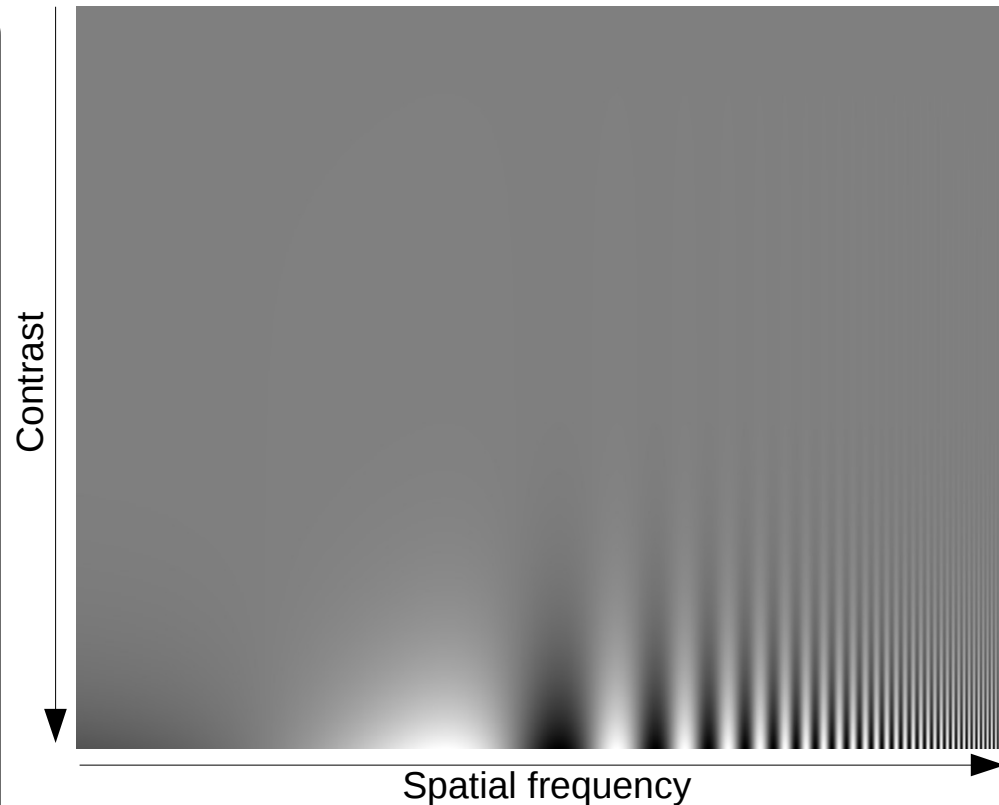
# Technical implementation

- Technique **entirely implemented on GPU** using GLSL
  - Builds on the **Perlin noise shader** by Gustavson (2004)
  - Highly portable
  - Several optimizations and precomputations → **realtime rendering**
- Use of an **image-space shading technique** such as
  - Screen-space Phong
  - EyeDome Lighting (Boucheny, 2009)



# Perceptual issues

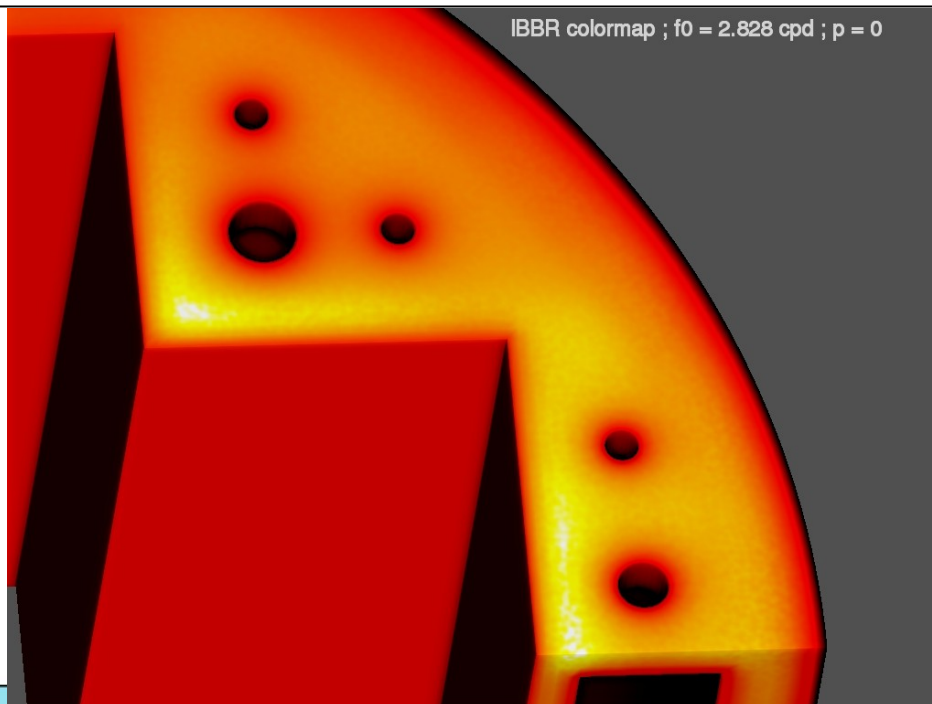
- **Contrast** of the noise patterns varies with the uncertainty data
- Detection of the noise by the human visual system depends on both contrast and **spatial (and temporal) frequencies** !
- The **contrast sensitivity function** :
  - Contrast threshold for stimulus detection varies with spatial frequencies
  - For sine wave gratings : maximum around 4-5 cyc/°
  - For Perlin noise : ???



Contrast sensitivity function for sine-wave gratings : maximum sensitivity is achieved for medium spatial frequencies (4-5 cyc/°)

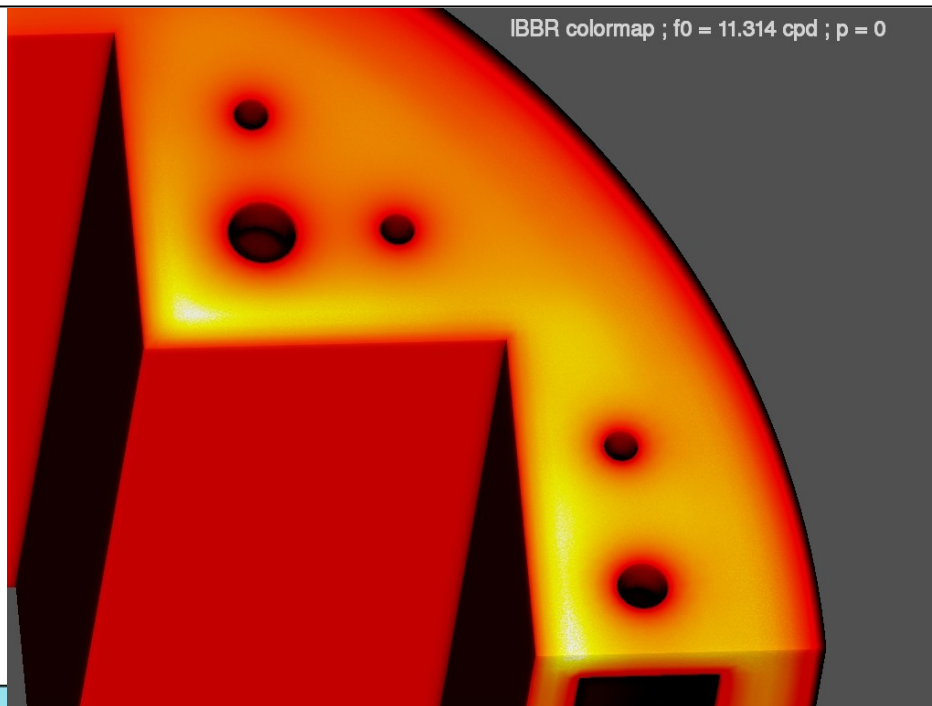
# Perceptual issues

- The **parameters of Perlin noise** (base frequency and persistence) directly impact the noise pattern's spatial spectrum
  - For a given uncertainty value, depending on these parameters, uncertainty **may be visible...**



# Perceptual issues

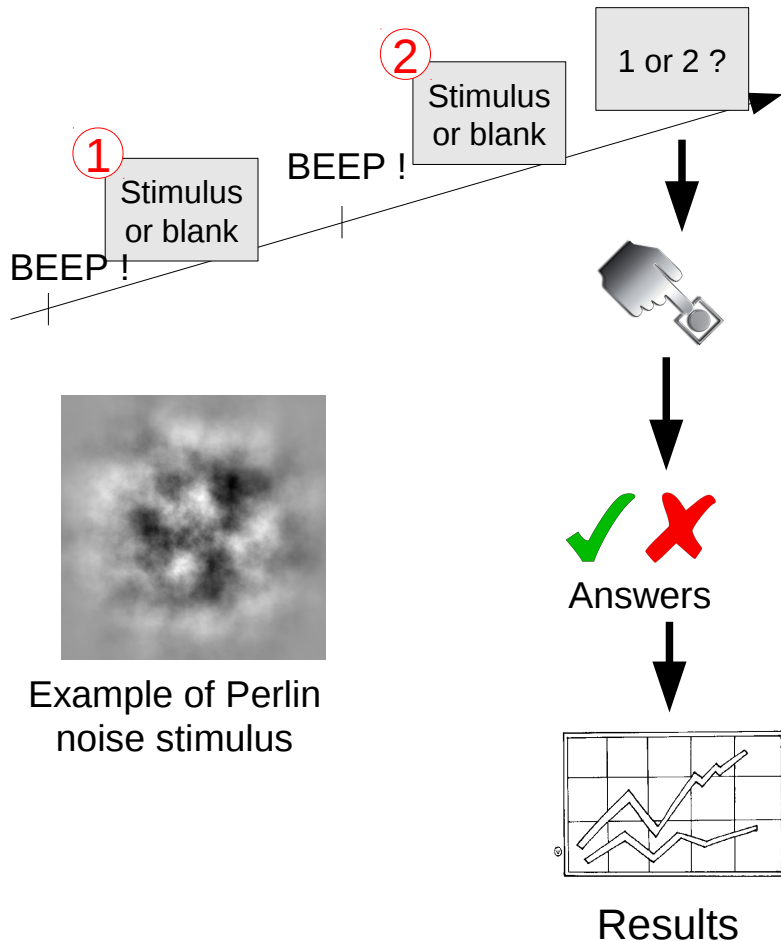
- The **parameters of Perlin noise** (base frequency and persistence) directly impact the noise pattern's spatial spectrum
  - For a given uncertainty value, depending on these parameters, uncertainty **may be visible...**



... or **may not** !

→ We need to study **contrast sensitivity for Perlin noise patterns**

# Perceptual evaluation of contrast sensitivity for Perlin noise

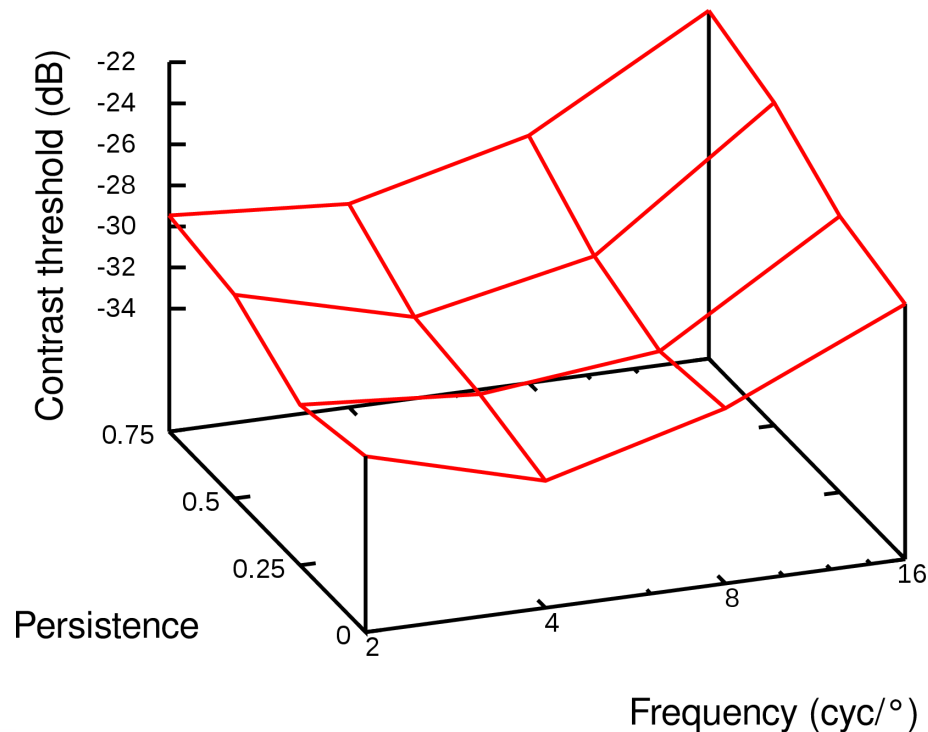


- Psychophysical methodology
- Goal : measure the average contrast sensitivity thresholds for 16 Perlin noise parameter values :
  - $f_0$  in  $[2 ; 4 ; 8 ; 16]$  cyc/°
  - $p$  in  $[0 ; 0,25 ; 0,5 ; 0,75]$
- 2IFC paradigm : temporal two-alternative forced choice
- Psi method (Kontsevich & Tyler, 99) used to minimize the number of trials



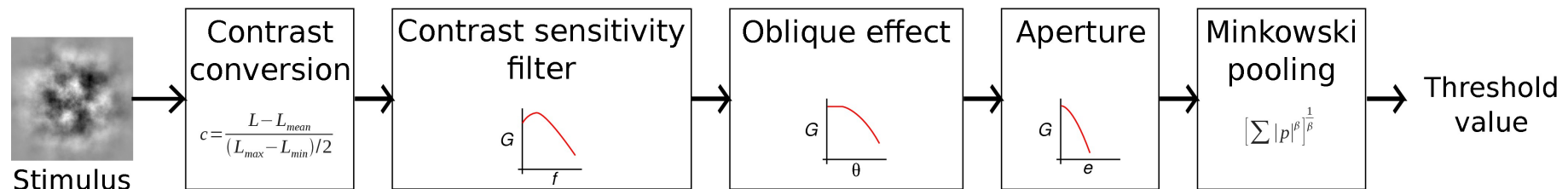
# Perceptual evaluation of Perlin noise : results

- 8 subjects ; we study the mean threshold values
- On  $f0$  : maximum sensitivity for  $f0 = 4 \text{ cyc/}^\circ$
- On  $p$  : sensitivity decreases with  $p$



# Computational model of contrast sensitivity

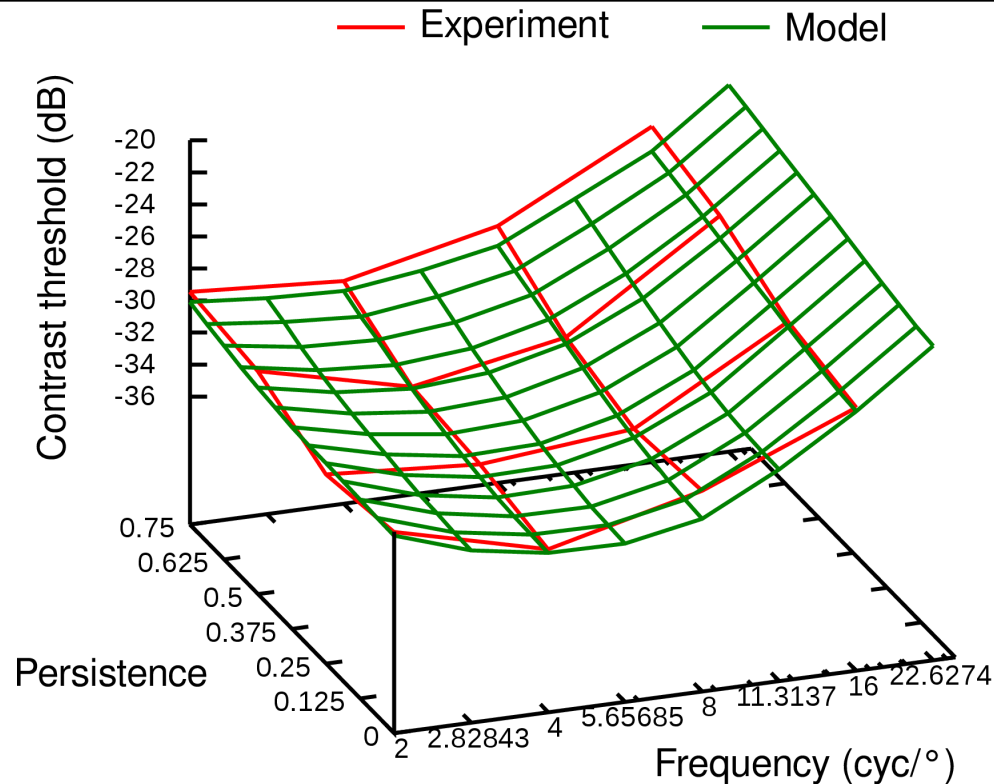
- Watson & Ahumada (2005) developed a **computational model of contrast sensitivity**, which can predict the average threshold for any luminance stimulus
- 8 model parameters, which are fit using the ModelFest database, which contains thresholds values for 44 luminance stimuli



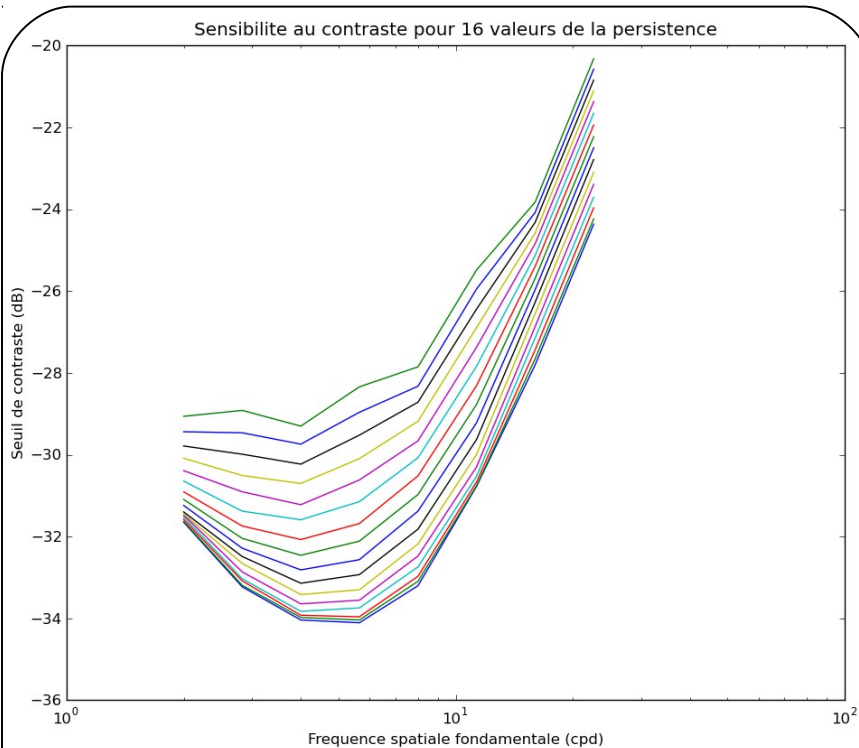
- We entirely **implemented and ran this model** on our stimuli and **compared its predictions** to the experimental results

# Perceptual evaluation of Perlin noise : model

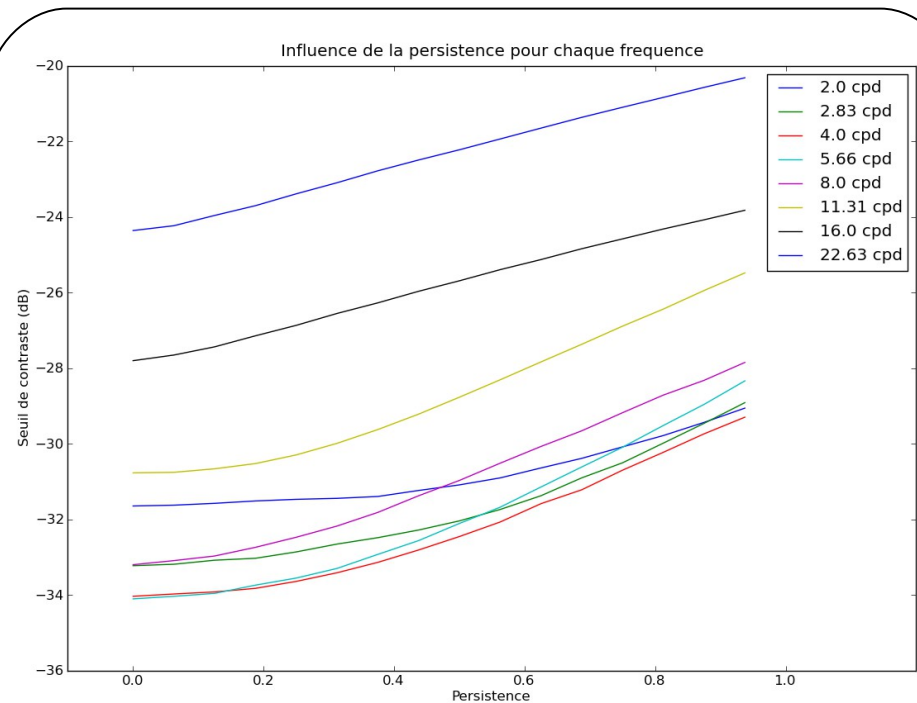
- **Excellent fit** between this model and our results (maximum difference 1dB)
- **Validates** our experimental data
- We can use the simulated data to **extend our perceptual work**



# Perceptual evaluation of Perlin noise : results analysis



Sensitivity is **maximal for f0 around 4-5 cycles/°** and decreases for lower and higher values

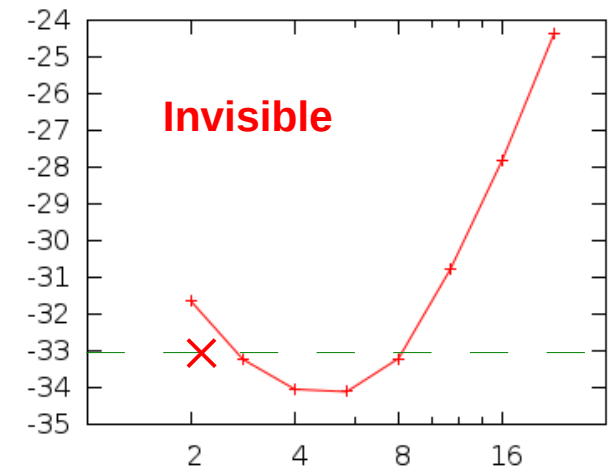


Sensitivity **decreases** with persistence

# Application of psychophysical data : base frequency

$p = 0$

$f_0 = 2$

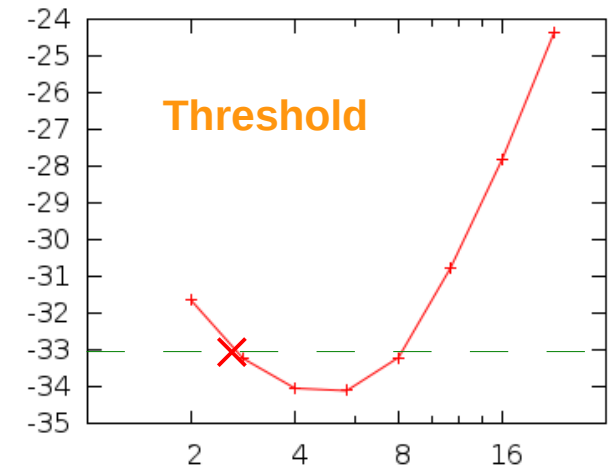




# Application of psychophysical data : base frequency

$p = 0$

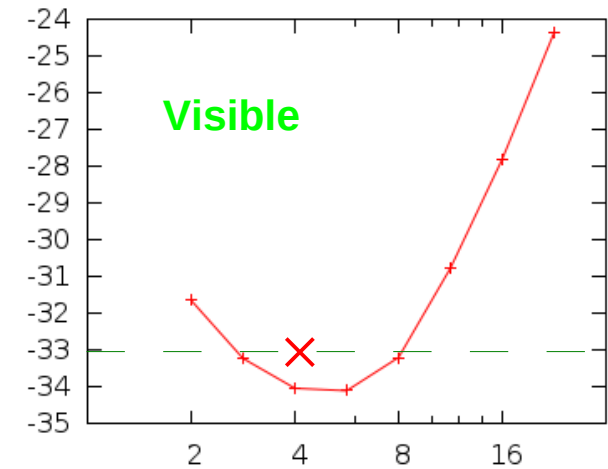
$f_0 = 2,82$



# Application of psychophysical data : base frequency

$p = 0$

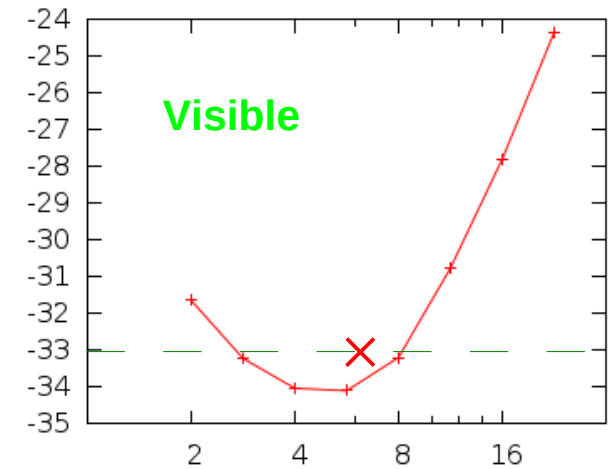
$f_0 = 4$



# Application of psychophysical data : base frequency

$p = 0$

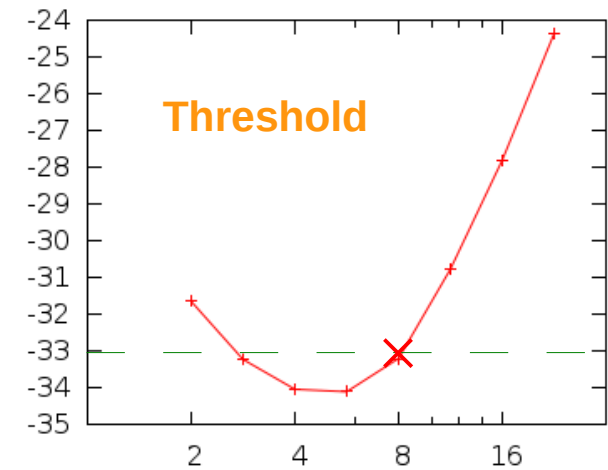
$f_0 = 5,65$



# Application of psychophysical data : base frequency

$p = 0$

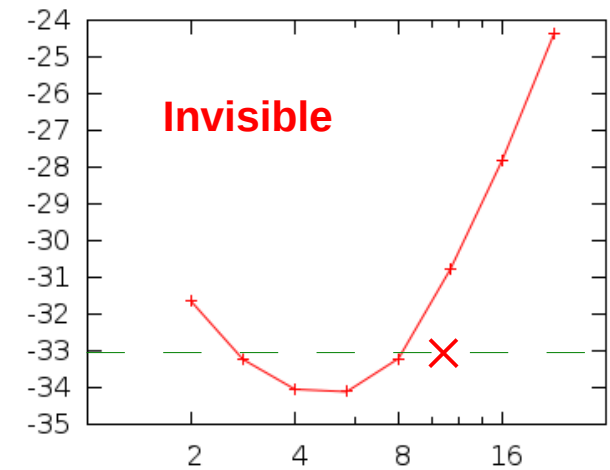
$f_0 = 8$



# Application of psychophysical data : base frequency

$p = 0$

$f_0 = 11,31$

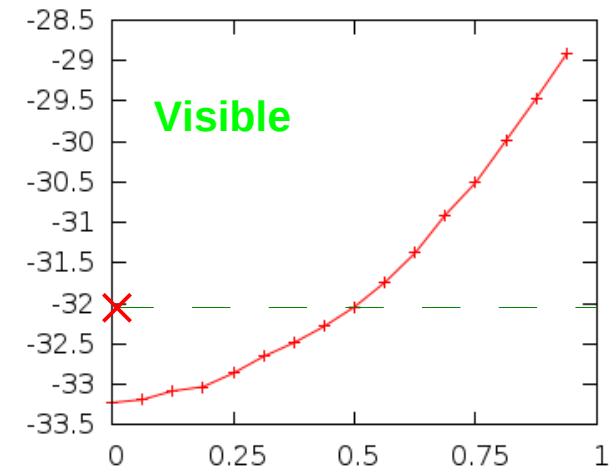
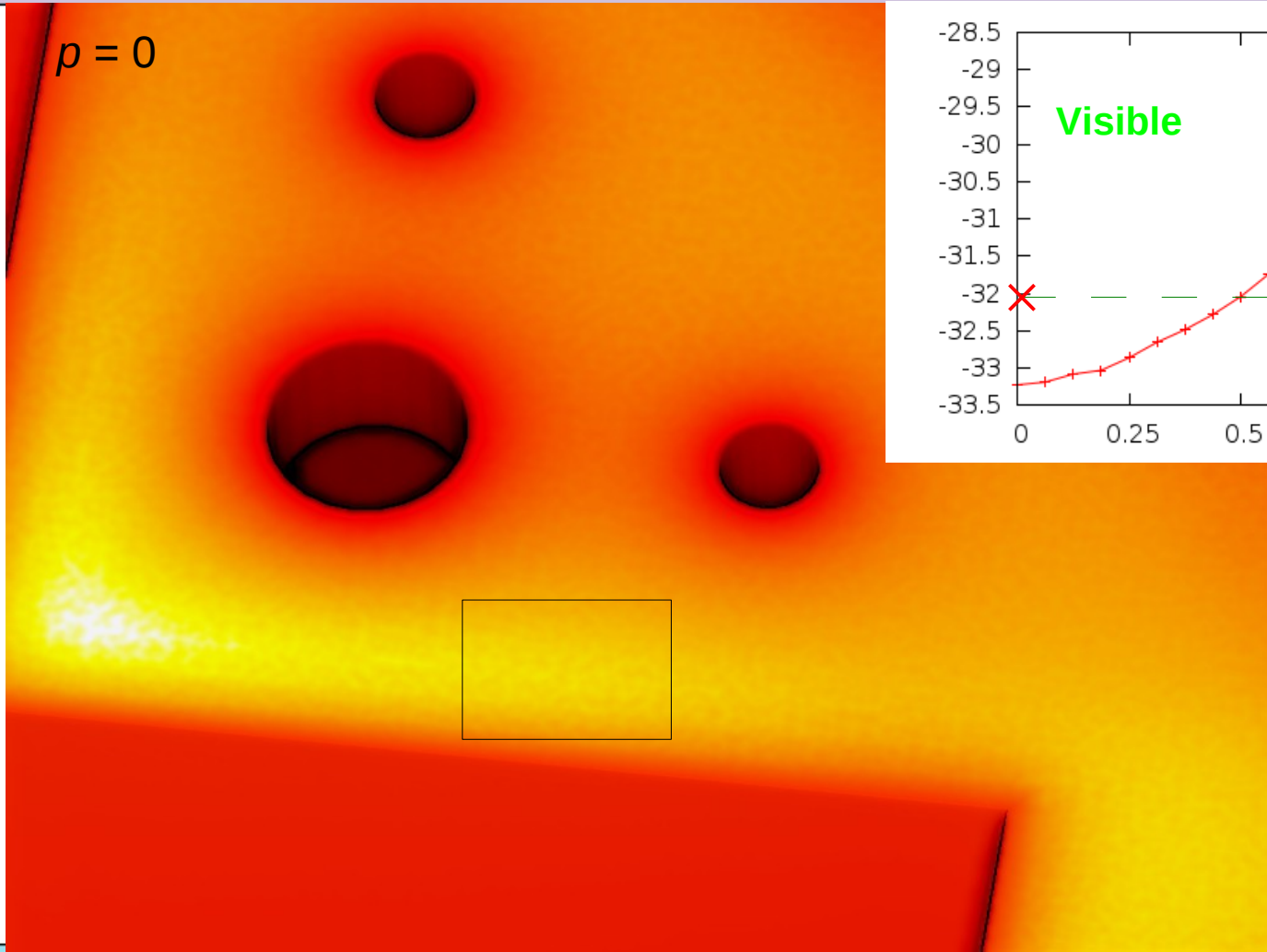




# Application of psychophysical data : persistence

$f0 = 4$

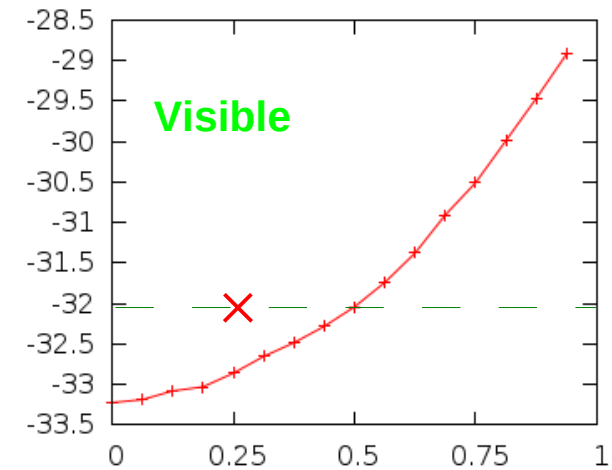
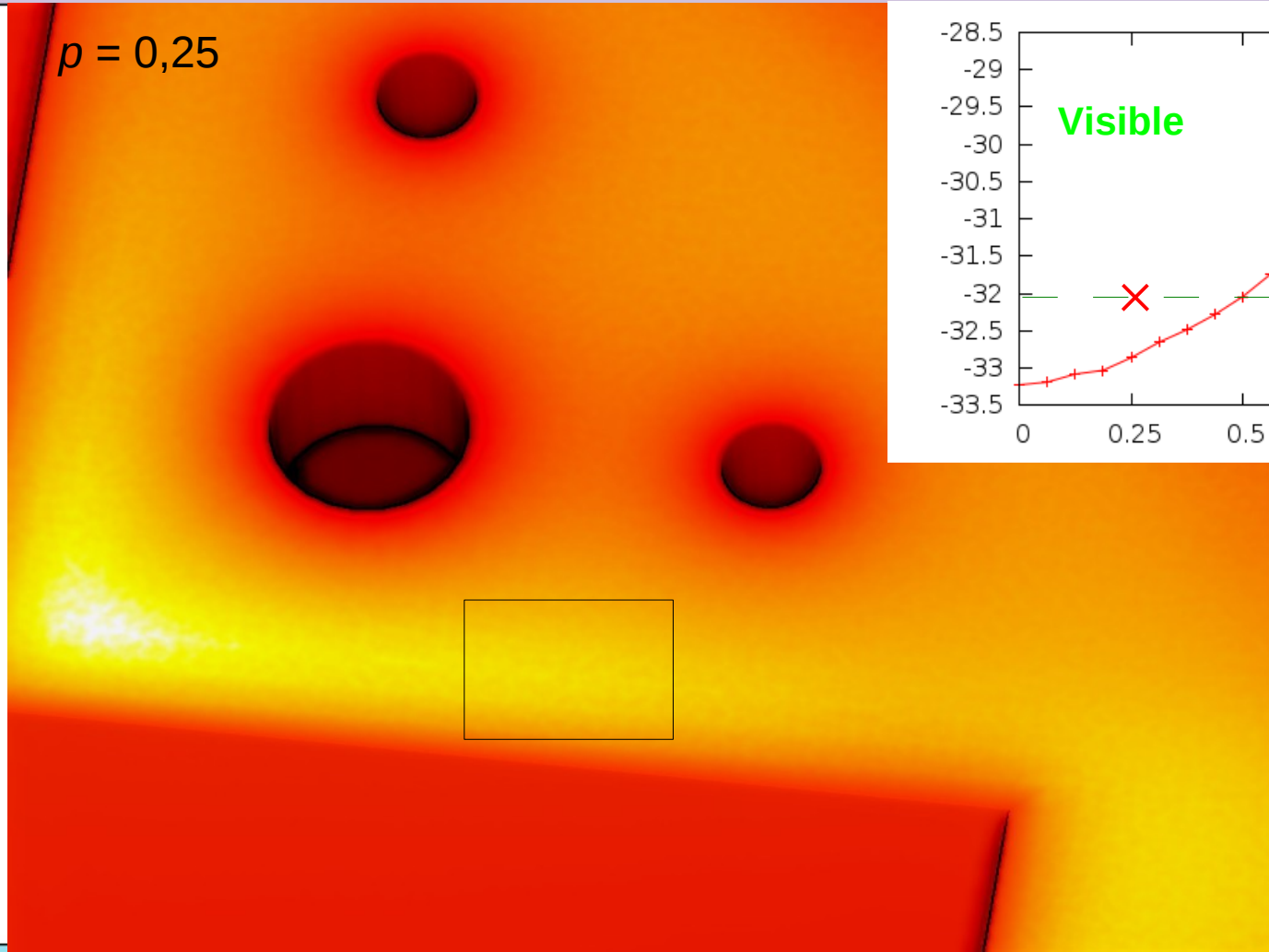
$p = 0$



# Application of psychophysical data : persistence

$f0 = 4$

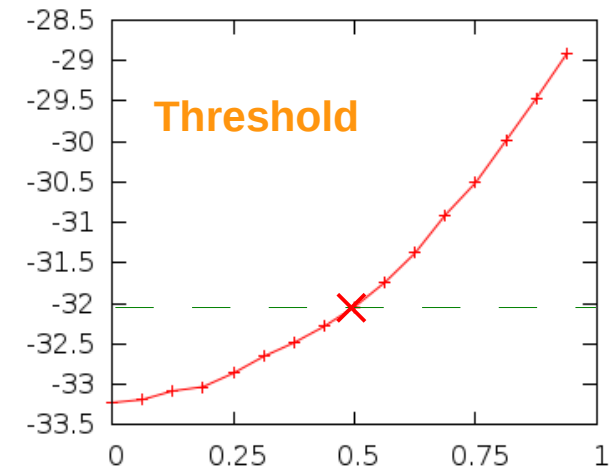
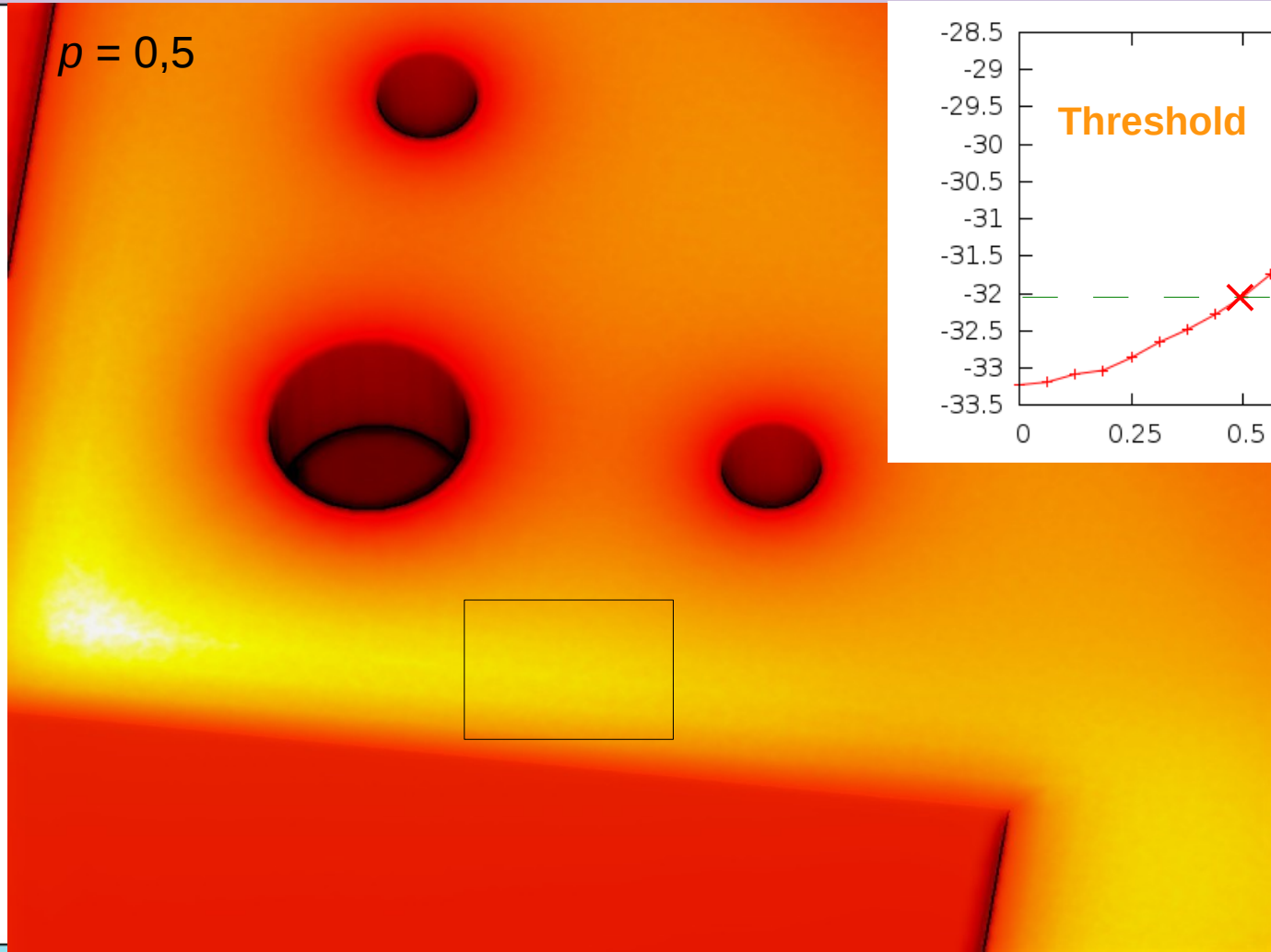
$p = 0,25$



# Application of psychophysical data : persistence

$f0 = 4$

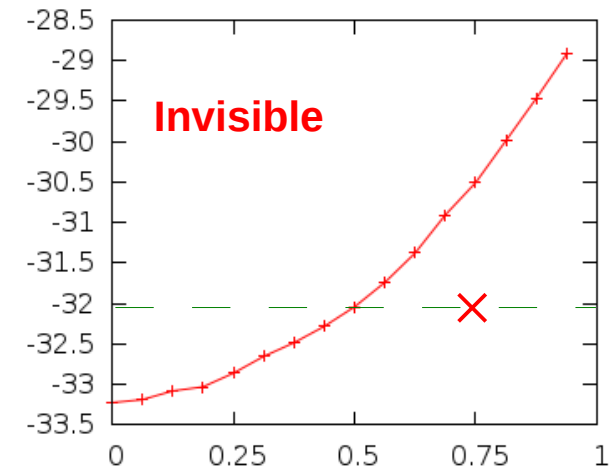
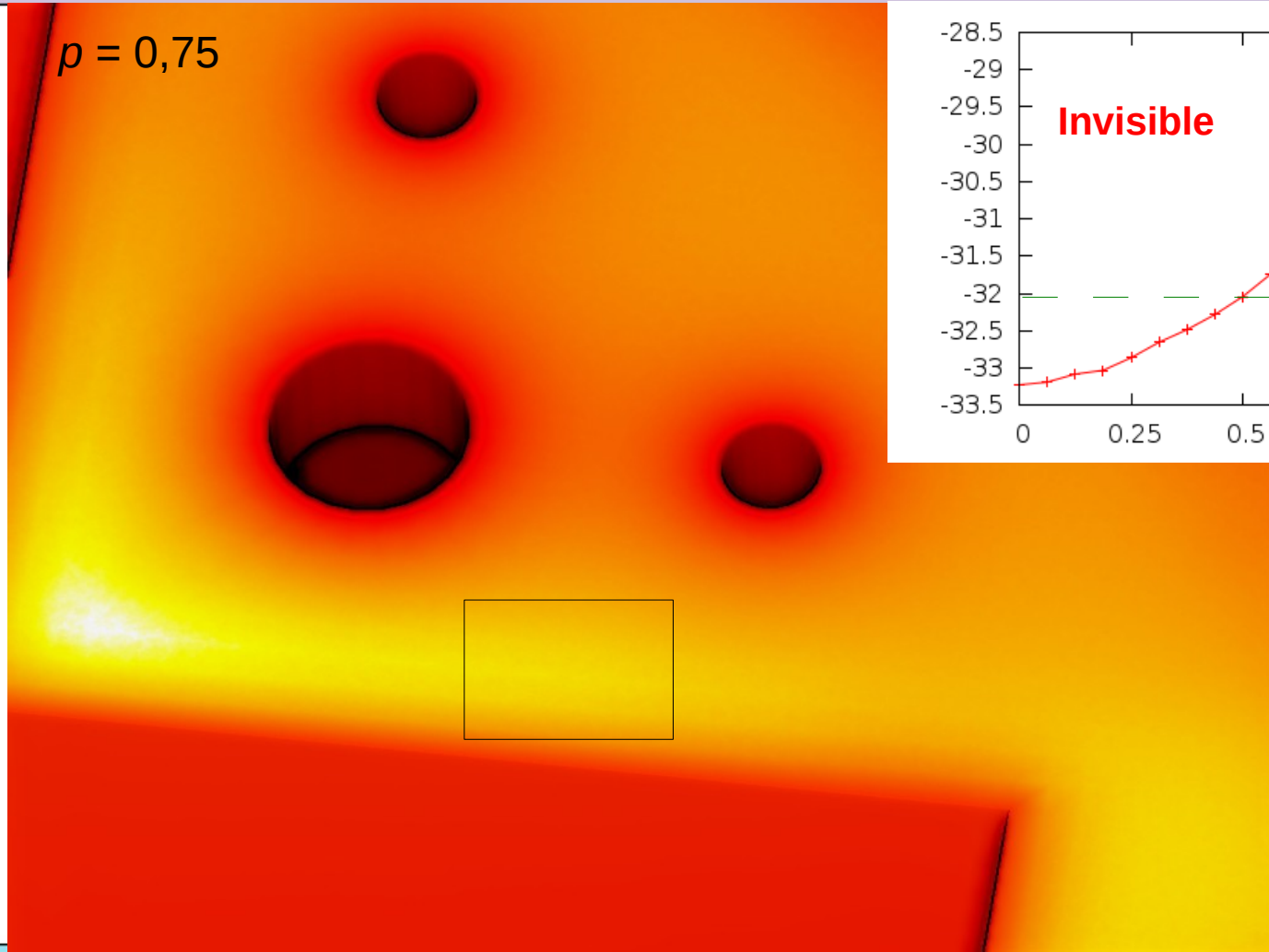
$p = 0,5$



# Application of psychophysical data : persistence

$f0 = 4$

$p = 0,75$

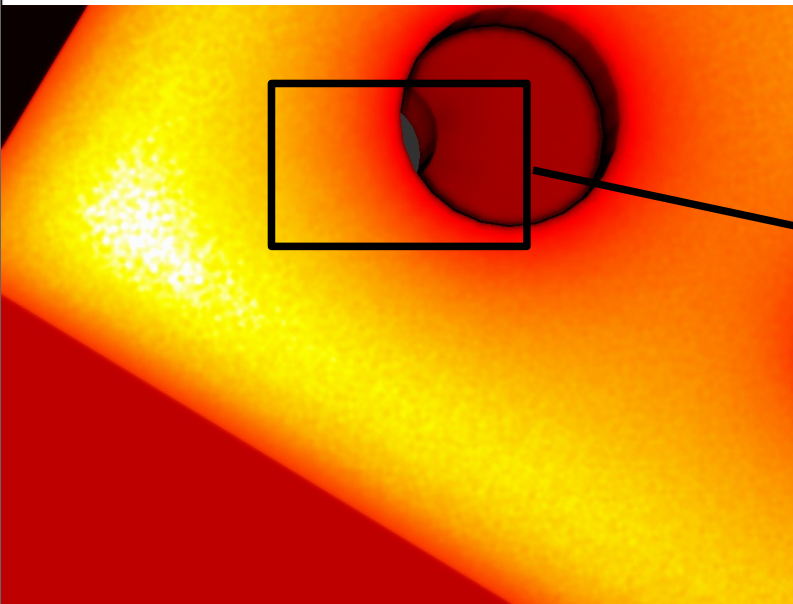


# Zoom adaptation of spatial frequency

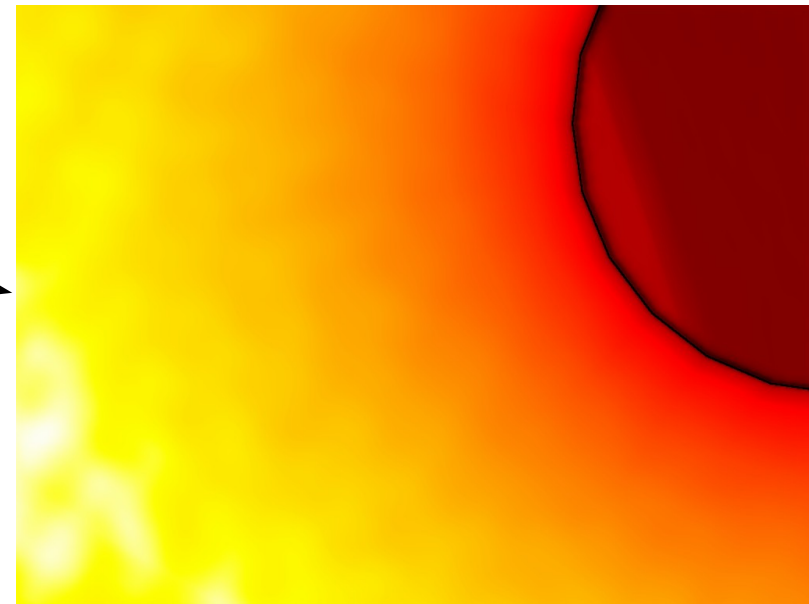
- We often want to explore the data using **interactive visualization**
  - Free exploration of the 3D scene : translations, rotations and zoom
- The noise pattern's spectral features depend on :
  - The **noise parameters** ( $f_0, p$ ) ;
  - The screen size, resolution and viewing distance.
  - The distance to the visualized object on the 3D scene (**zoom level**) ;
- We need to deal with **all of these factors** to control the final rendering
  - Parameters : studied in our psychophysical work
  - Screen and viewing distance are constant  $\Rightarrow$  configuration options in our demonstration software
  - Zoom level : must be taken into account

# Zoom adaptation of spatial frequency

- Example : automatic adaptation of the  $f_0$  parameter to the zoom level
  - Without adaptation, a user zooming towards a scene detail changes the noise spatial frequency and, thus, its visibility :



Overview

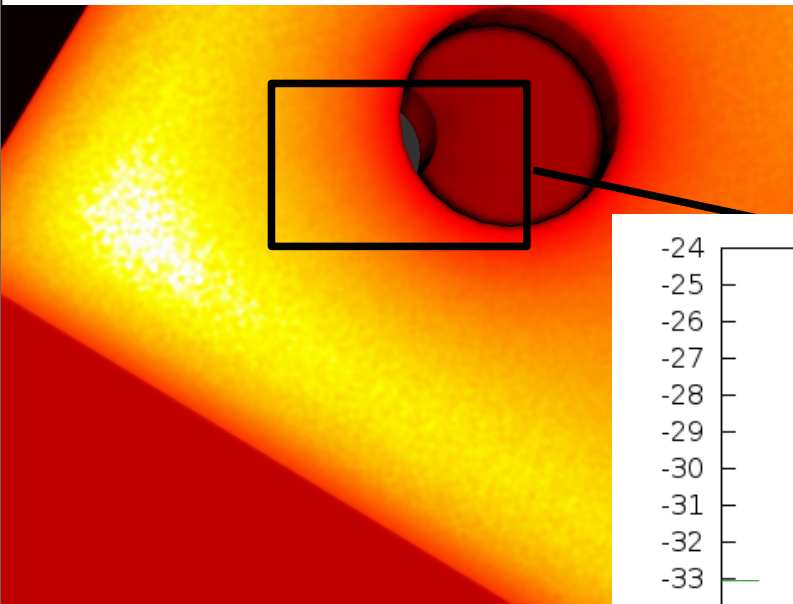


Detail

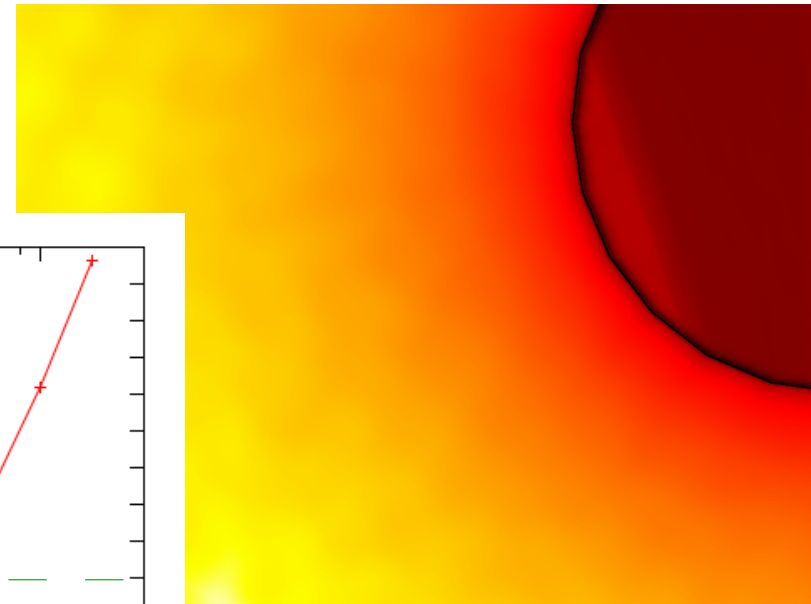
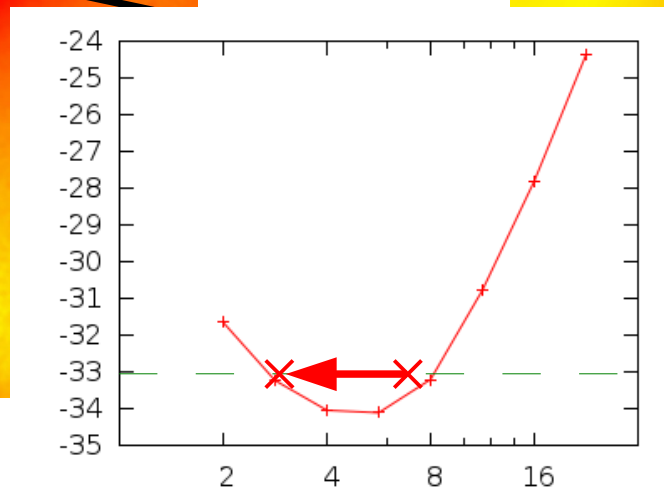


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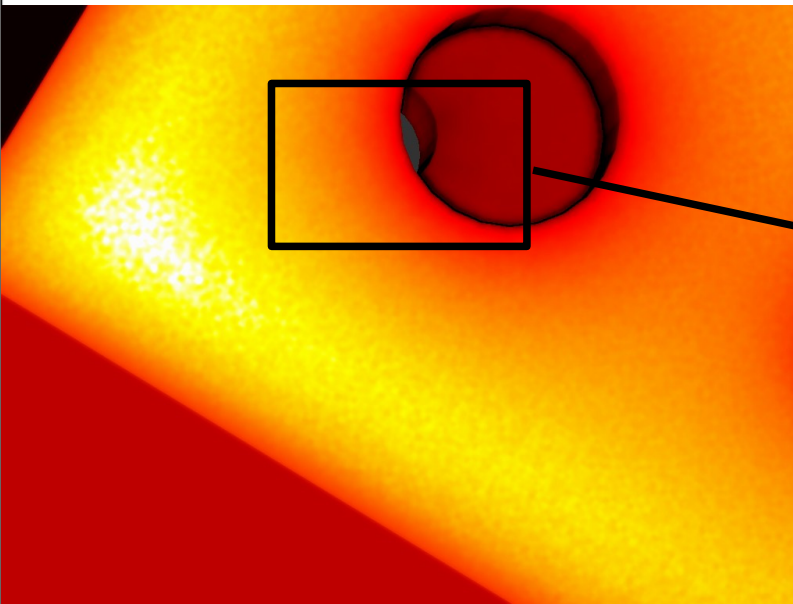


Detail

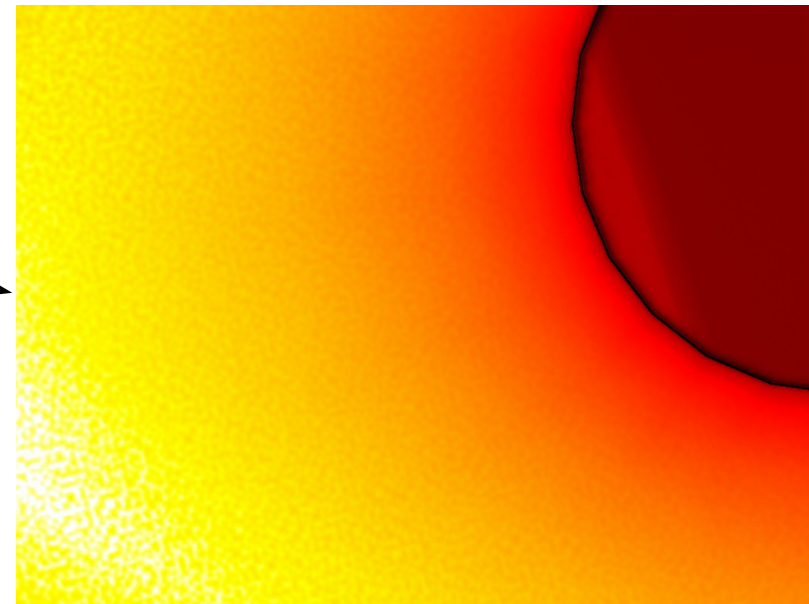


# Zoom adaptation of spatial frequency

- Example : automatic adaptation of the  $f_0$  parameter to the zoom level
  - With adaptation, the perceived spatial frequencies remain constant during the scene exploration



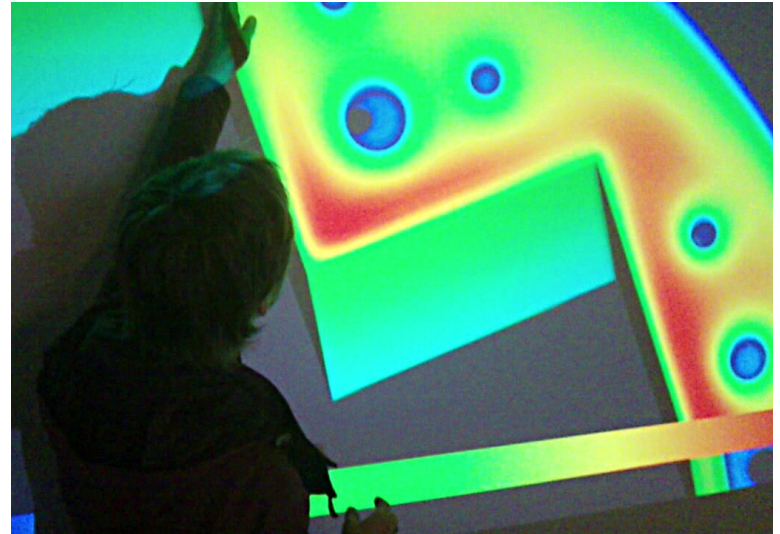
Overview



Detail

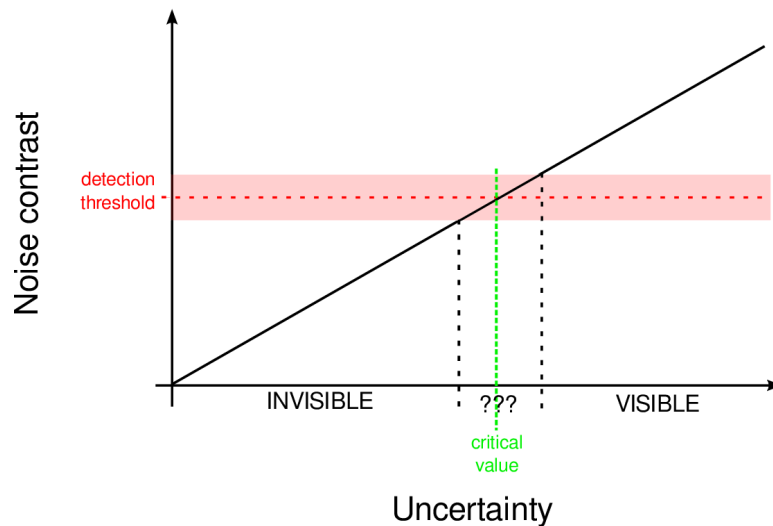
# User feedback

- We presented our technique to **3 research engineers** from EDF R&D
  - Experts in thermal simulation ; considerable experience in visualizing 3D temperature data using colormaps
- Positive feedback :
  - Mapping uncertainty to noise is **efficient and intuitive**
  - High uncertainty zones pop out
  - Mean temperature value visualization is **not disrupted**
- Critical feedback :
  - The quantitative uncertainty value **cannot be accurately assessed**
    - Very difficult to compare the uncertainty level between two points
    - Shows **where** the uncertainty is, **not how high** it is

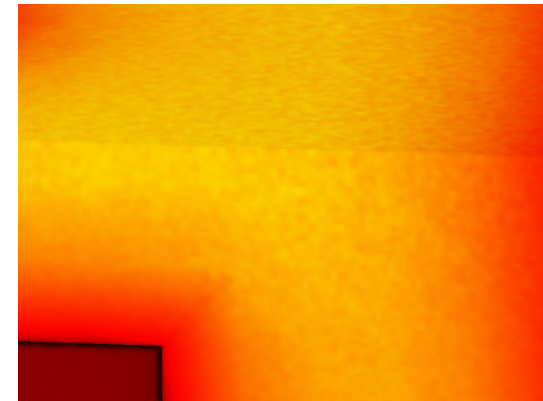


# Uncertainty threshold visualization

- The technique should thus be used to **highlight regions of interest**
  - Zones where the uncertainty is **above a given critical value**
- This critical value should be mapped to the **perceptual detection threshold**
- But noise perception at threshold is random and user-dependent

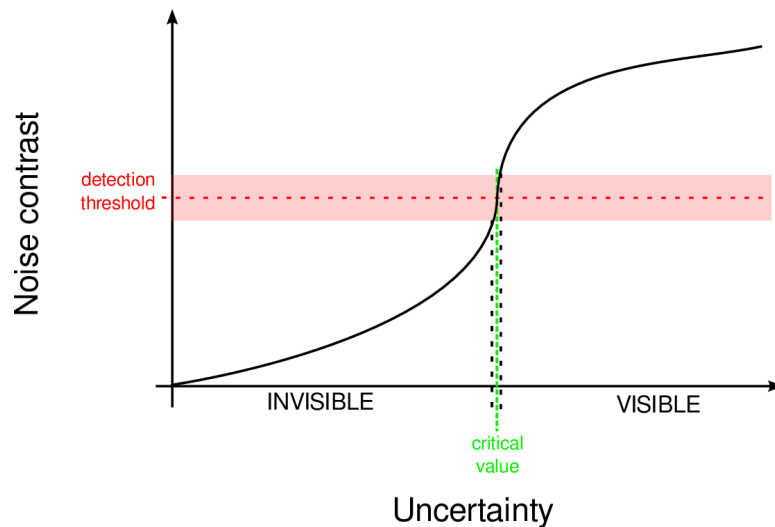


*Linear mapping of uncertainty to noise contrast : the borders of the region of interest are not well defined*

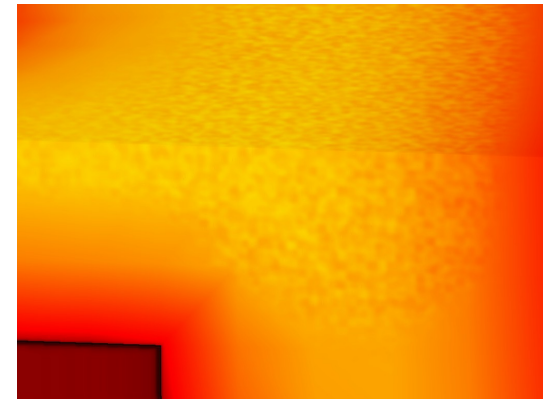


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- The technique should thus be used to **highlight regions of interest**
  - Zones where the uncertainty is **above a given critical value**
- This critical value should be mapped to the **perceptual detection threshold**
- But noise perception at threshold is random and user-dependent
- Solution : use a **nonlinear transfer function** to limit the influence of the threshold area



*S-shaped transfer function : the limit between the visible and invisible zones is sharper*



# Conclusion

- We put forward a method to see and understand **uncertain scalar data**, which :
  - Displays the **primary data** in a straightforward and simple way ;
  - Conveys an **information about the level of (un)certainty** of this data ;
  - Is **perceptually controlled** and **easy to implement**.
- We would like to do research in :
  - The influence of **hue variations** and the colormap choice ;
  - The influence of **temporal contrast** and the choice of time frequency ;
  - The application of this method to **other datasets and visualization types**.



**Thank you for your  
undivided attention !**

