Multigrid Acceleration of the Horn-Schunck Algorithm for the Optical Flow Problem

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Overview

- Introduction and Related Works
- Optical Flow Constraints
- Regularization
- Horn Schunck Algorithm
- Multigrid Scheme
- A Simple Illustration
- Variational Multigrid
- Experimental Results

Introduction and Related Works

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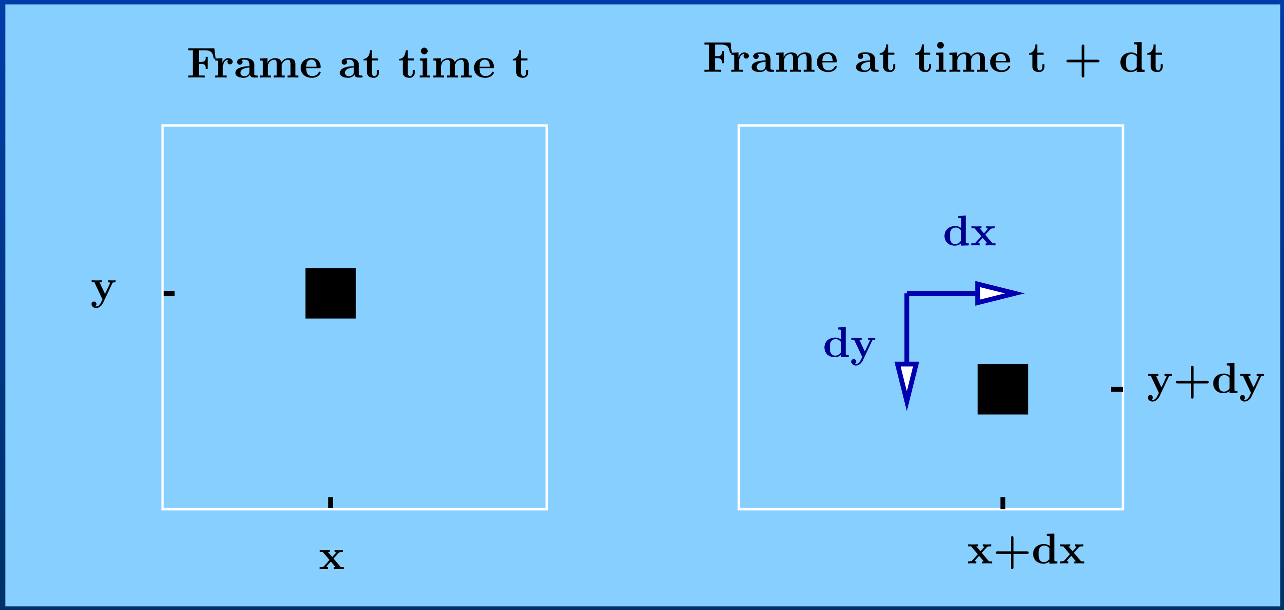

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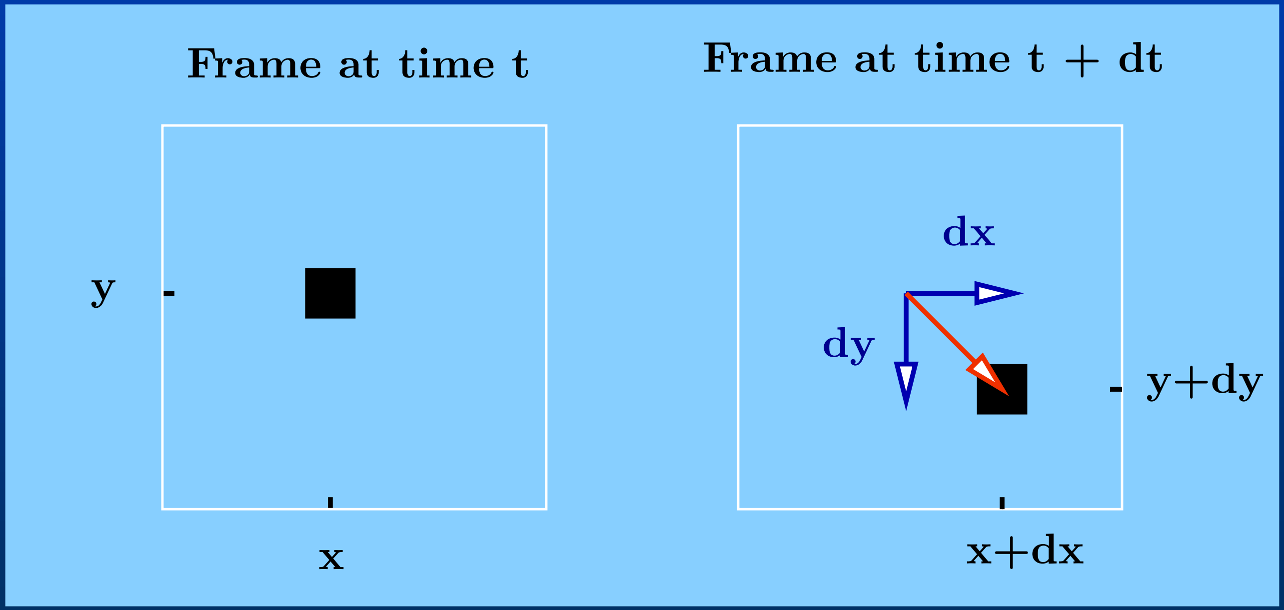

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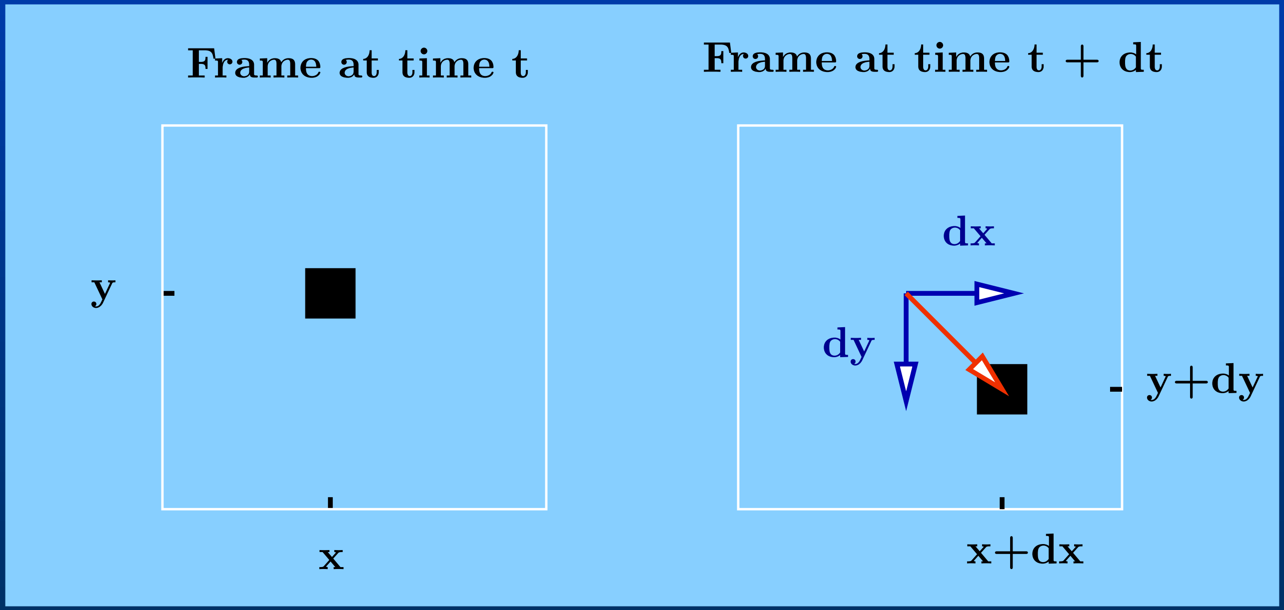

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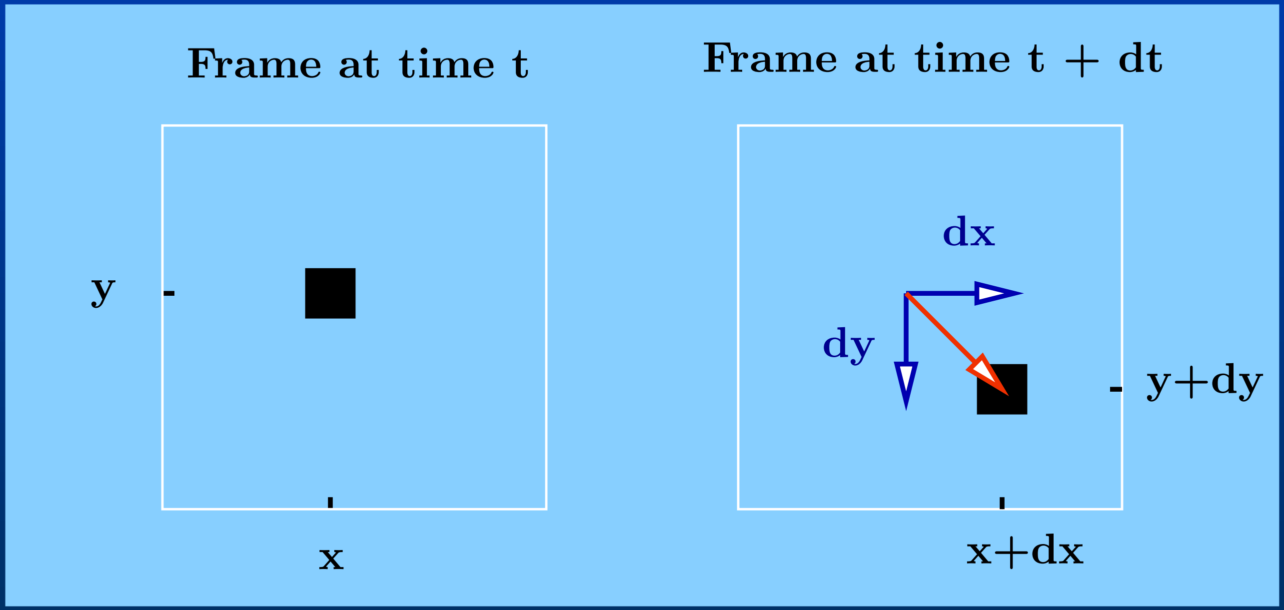

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- An approximation of the 2D-motion
- Optical Flow $\neq$ Motion

Introduction and Related Works

- Term originates with James Gibson in 1979
- Quadratic smoothness $\leftrightarrow$ Horn–Schunck (1981)
- Registration technique with local constraints $\leftrightarrow$ Lucas–Kanade (1981)
- Oriented smoothness $\leftrightarrow$ Nagel–Enkelmann (1983–86)
- Multigrid relaxation $\leftrightarrow$ Terzopolous (1986)
- Performance evaluation of popular algorithms $\leftrightarrow$ Barron–Fleet–Beauchemin (1994)
- General anisotropic smoothness $\leftrightarrow$ Weickert (1996)
- Optimal control framework $\leftrightarrow$ Borzi–Ito–Kunisch (2002)

Optical Flow Constraints

- $I(x,y,t)$: The image intensity of the pixel (x,y) at time t.
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Taylor Expansion $\Longrightarrow$

$$\boxed{I_x u + I_y v + I_t = 0}$$

The optical flow constraint equation (OFCE)

Optical Flow Constraints

An equivalent form of the (OFCE) :

$$\vec{\nabla} I . \vec{w} = -I_t \;\; \Rightarrow \;\; \vec{D} I . (\vec{w}, 1) = 0$$

where

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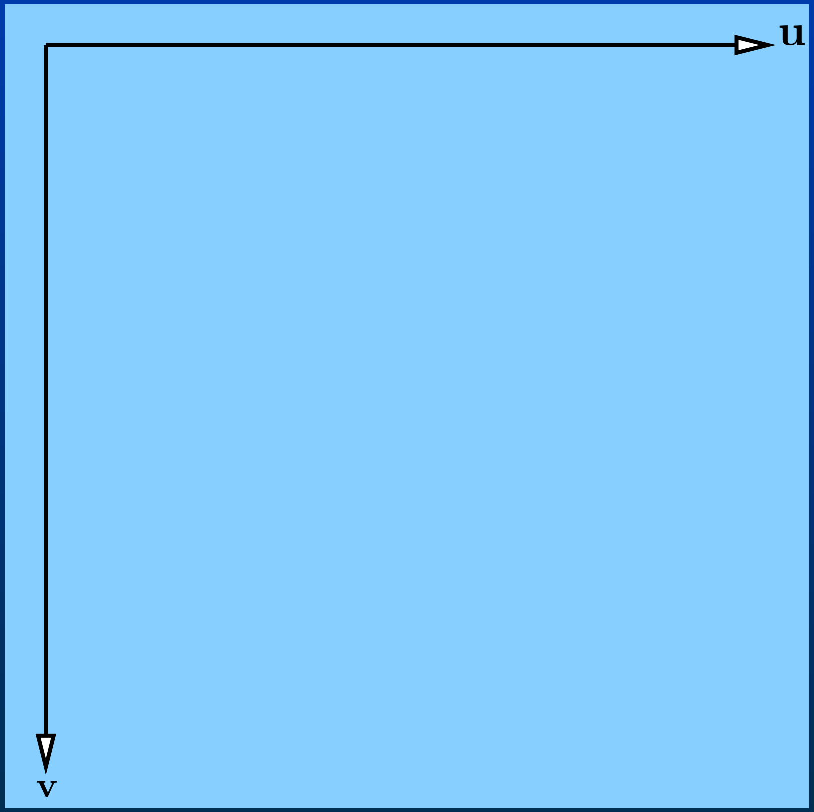

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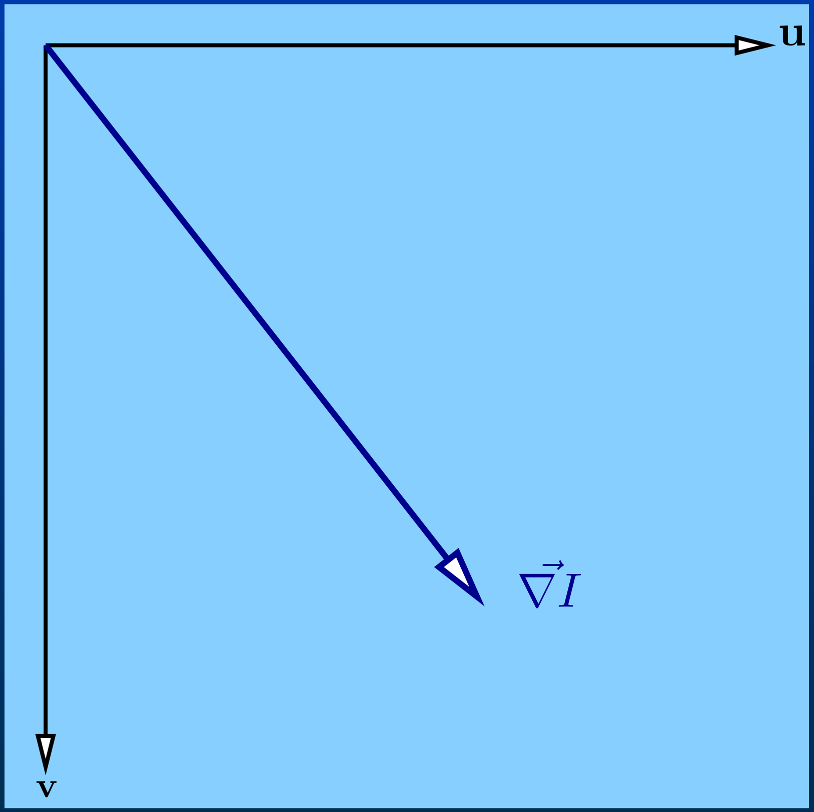

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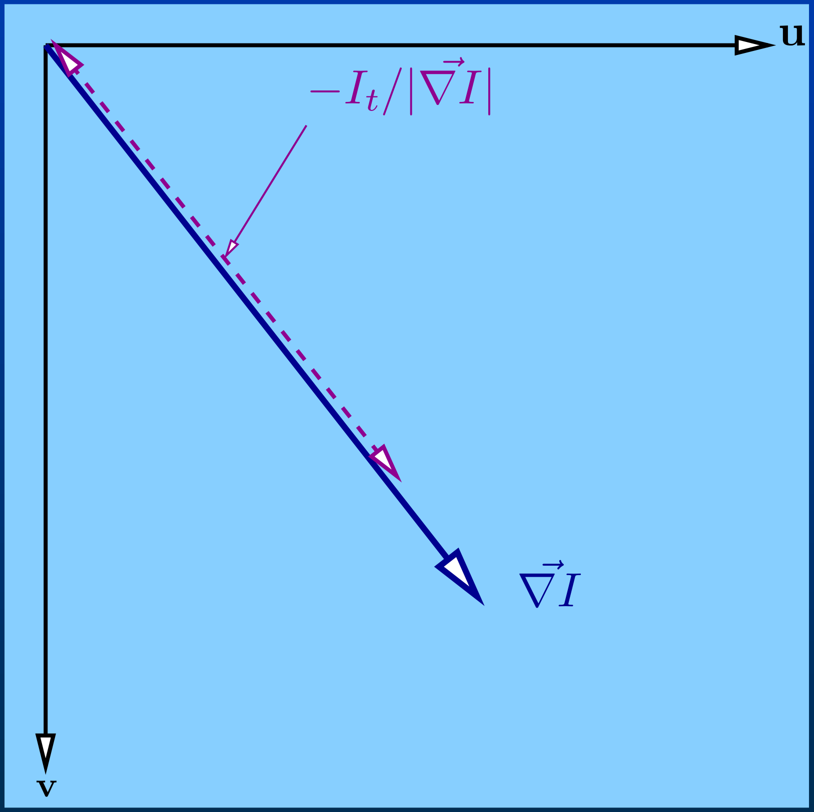

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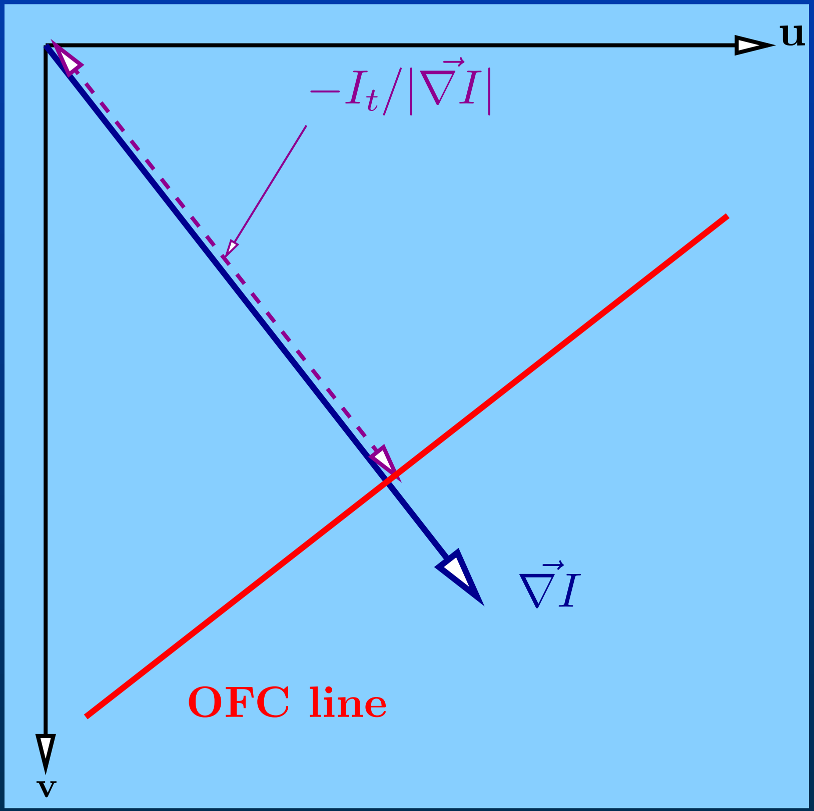

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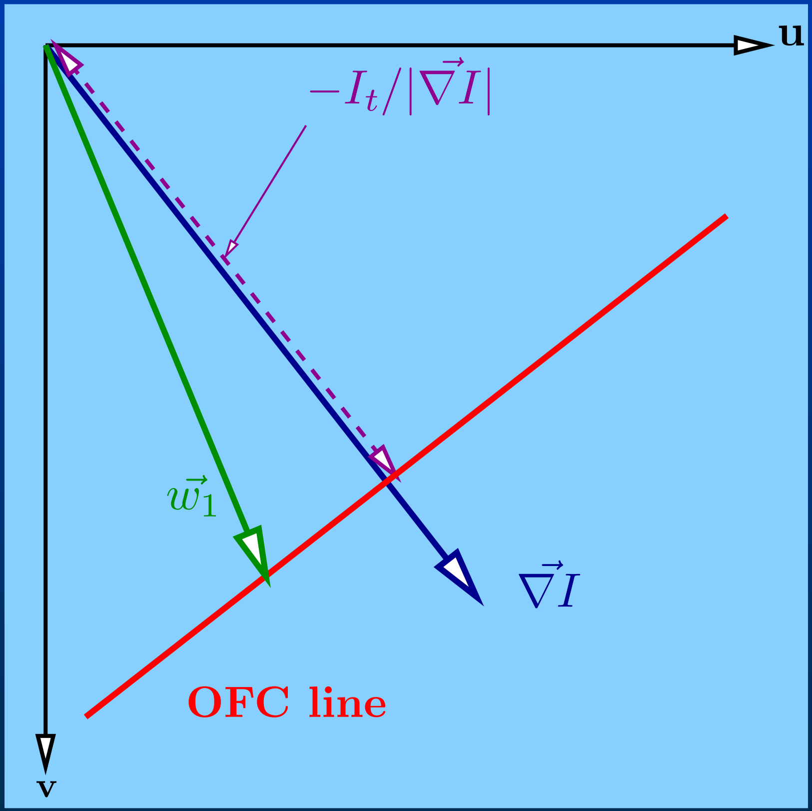

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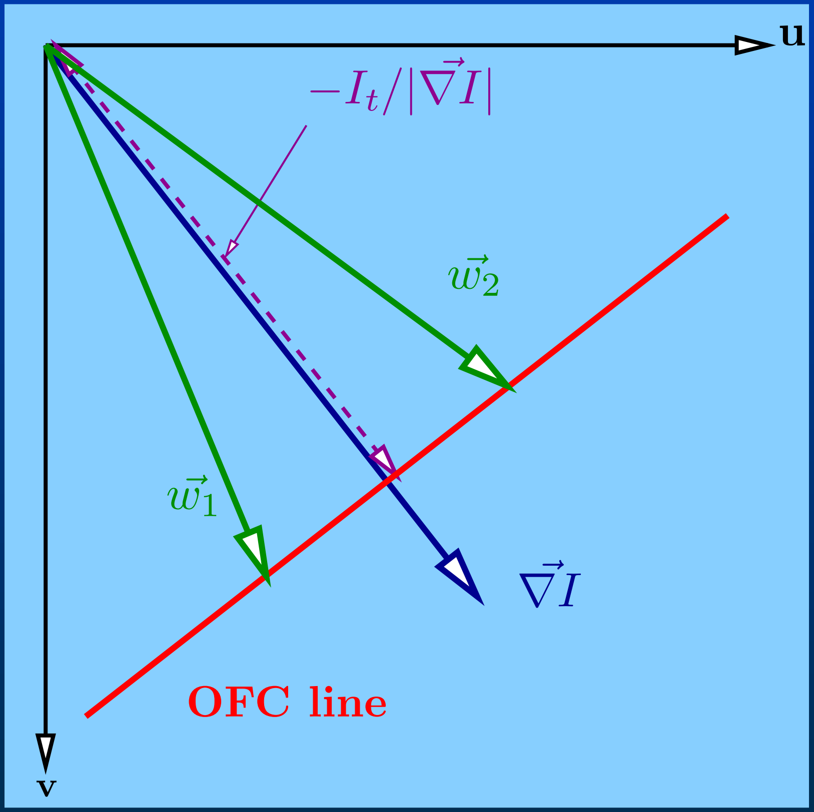

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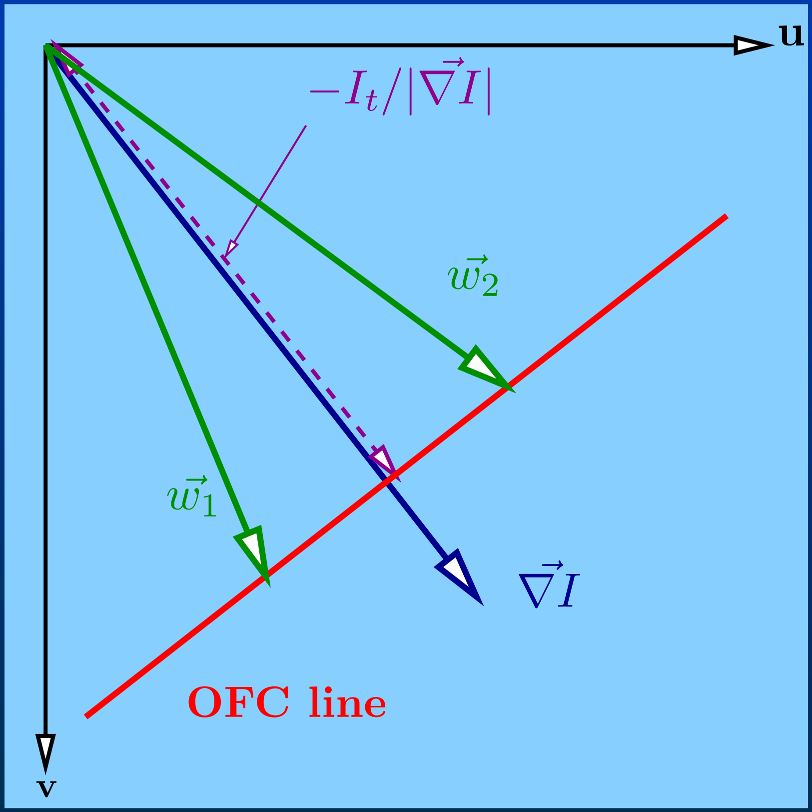

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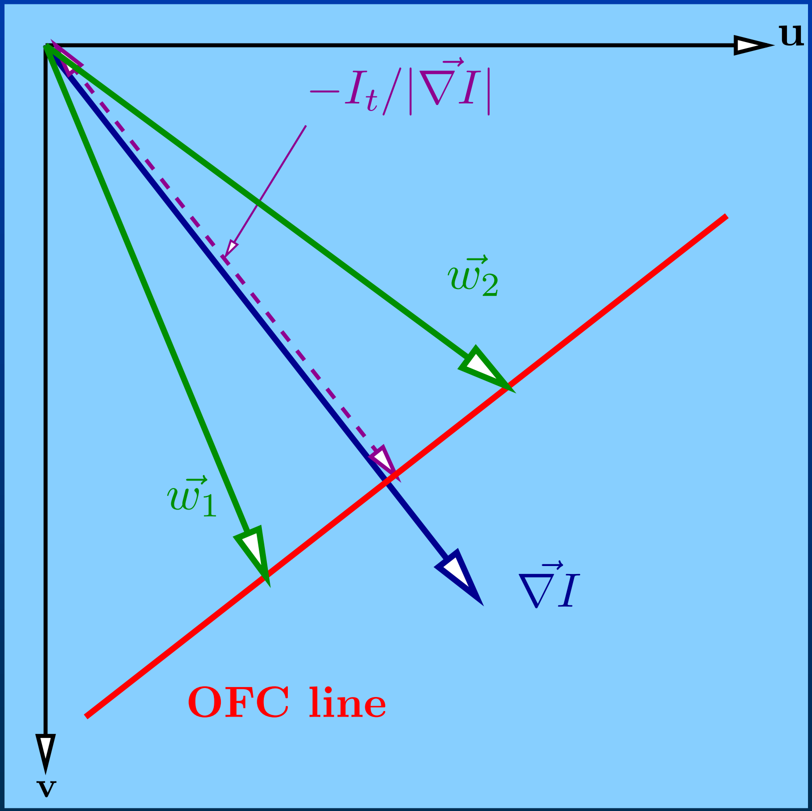

We can only calculate the normal component of the velocity $\vec{w}$ and not the tangent flow $\longrightarrow$ The aperture problem.

Regularization

The (OFCE) is replaced by

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The method for solving $(\mathbf{P})$ will depend on the choice of E_r.

Horn-Schunck Algorithm

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We discretize the Laplacien Δ by the standard 5 point stencil

$$\begin{pmatrix} & 1 & \\ 1 & -4 & 1 \\ & 1 & \end{pmatrix}$$

and use $\Delta w = \bar{w} - w$ where $\bar{w}$ is the average of the neighbors.

Horn-Schunck Algorithm

Spatial and Temporal Image Derivatives Masks

Horn-Schunck Algorithm

Spatial and Temporal Image Derivatives Masks

$$M_x = \frac{1}{4}\begin{pmatrix} -1 & 1 \\ -1 & 1 \end{pmatrix} \quad M_y = \frac{1}{4}\begin{pmatrix} 1 & 1 \\ -1 & -1 \end{pmatrix} \quad M_t = \frac{1}{4}\begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$$

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$$I_x = M_x * (I_1 + I_2) \qquad I_y = M_y * (I_1 + I_2) \qquad I_t = M_t * (I_2 - I_1)$$

Coupled Gauss-Seidel relaxation

Horn-Schunck Algorithm

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Coupled Gauss-Seidel relaxation

$$u^{k+1} = \vec{u}^k - I_x \frac{I_x \vec{u}^k + I_y \vec{v}^k + I_t}{\alpha + I_x^2 + I_y^2}$$

$$v^{k+1} = \vec{v}^k - I_y \frac{I_x \vec{u}^k + I_y \vec{v}^k + I_t}{\alpha + I_x^2 + I_y^2}$$

Multigrid Scheme

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- Discretization coarse grid approximation (DCA approach)

A Simple Illustration

- Intensity value :

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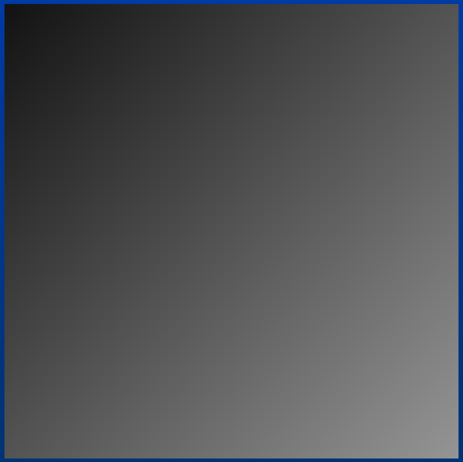

A Simple Illustration

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- Corresponding system of PDE's :

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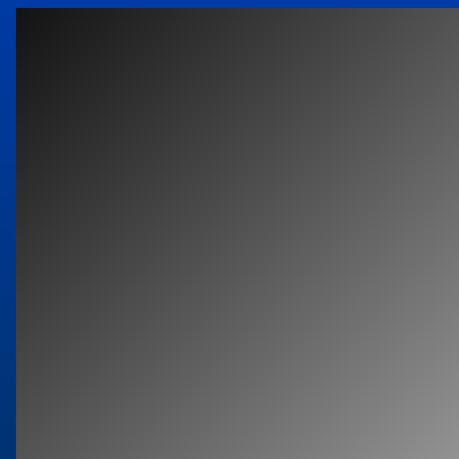

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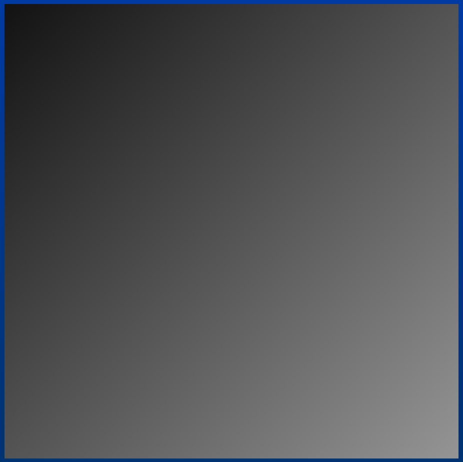

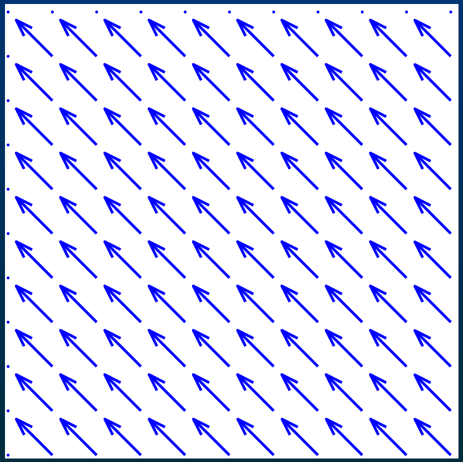

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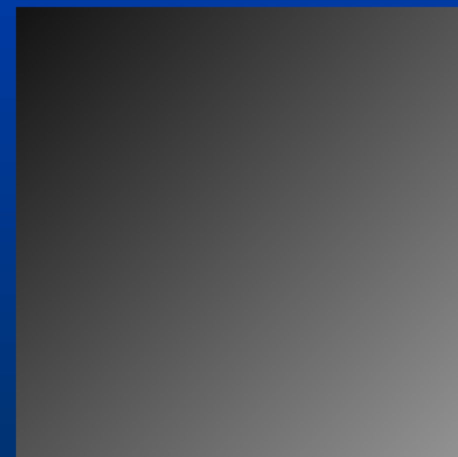
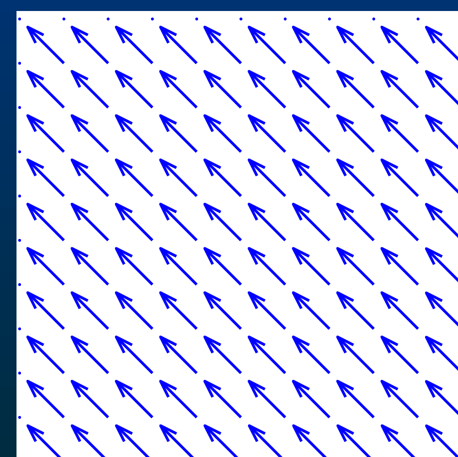
$\alpha = 1$ and $u_0 \neq v_0$	
Method	Convergence rate
Horn-Schunck	0.998
V(1,0)	0.370
V(1,1)	0.183
V(2,1)	0.116
V(3,3)	0.056





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$$L \begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} f \\ g \end{pmatrix}$$

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$$f = -I_x I_t \quad , \quad g = -I_y I_t$$

$$L = L_d + L_r \quad , \quad L_r = \begin{pmatrix} -\alpha\Delta & 0 \\ 0 & -\alpha\Delta \end{pmatrix}$$

and L_d is a 2x2 block diagonal matrix with entries $\begin{pmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{pmatrix}$

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L_d (positive semi-definite) + L_r (positive definite)

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L_d (positive semi-definite) + L_r (positive definite) = L (positive definite).

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An optimal coarse grid correction $I_H^h w_H$ of w_h is characterized by

$$((I_H^h)^T L_h I_H^h) w_H = (I_H^h)^T (F - L_h w_h)$$

Variational Multigrid

The CGO is chosen then as follows

$$L_H = I_h^H L_h I_H^h \quad \text{and} \quad I_h^H = (I_H^h)^T$$

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For our system, we get

$$\begin{aligned} L_H &= \begin{pmatrix} R & 0 \\ 0 & R \end{pmatrix} \begin{pmatrix} L_h^1 & L_h^2 \\ L_h^2 & L_h^3 \end{pmatrix} \begin{pmatrix} P & 0 \\ 0 & P \end{pmatrix} \\ &= \begin{pmatrix} RL_h^1P & RL_h^2P \\ RL_h^2P & RL_h^3P \end{pmatrix} \end{aligned}$$

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READ FRAMES

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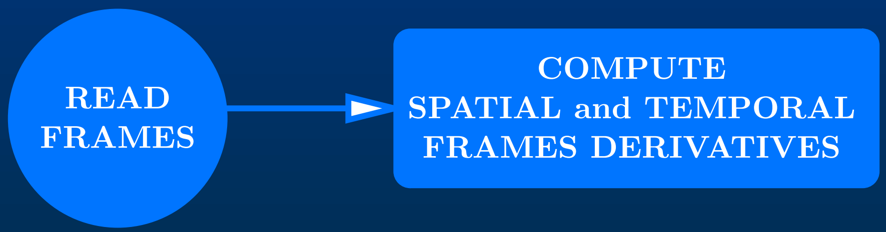

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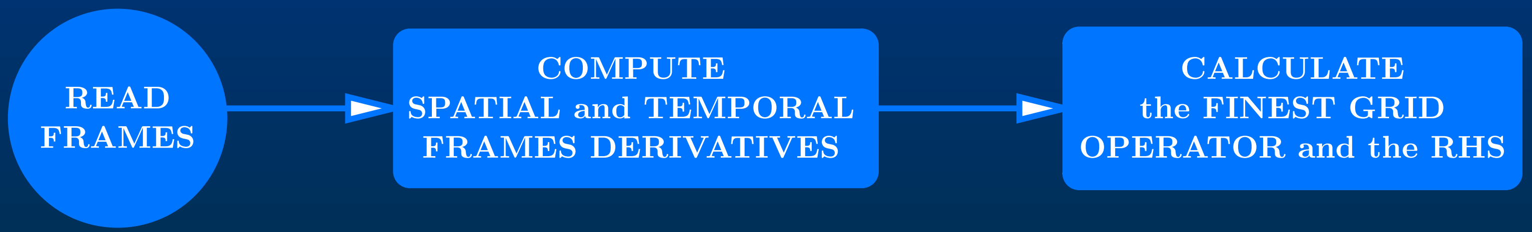

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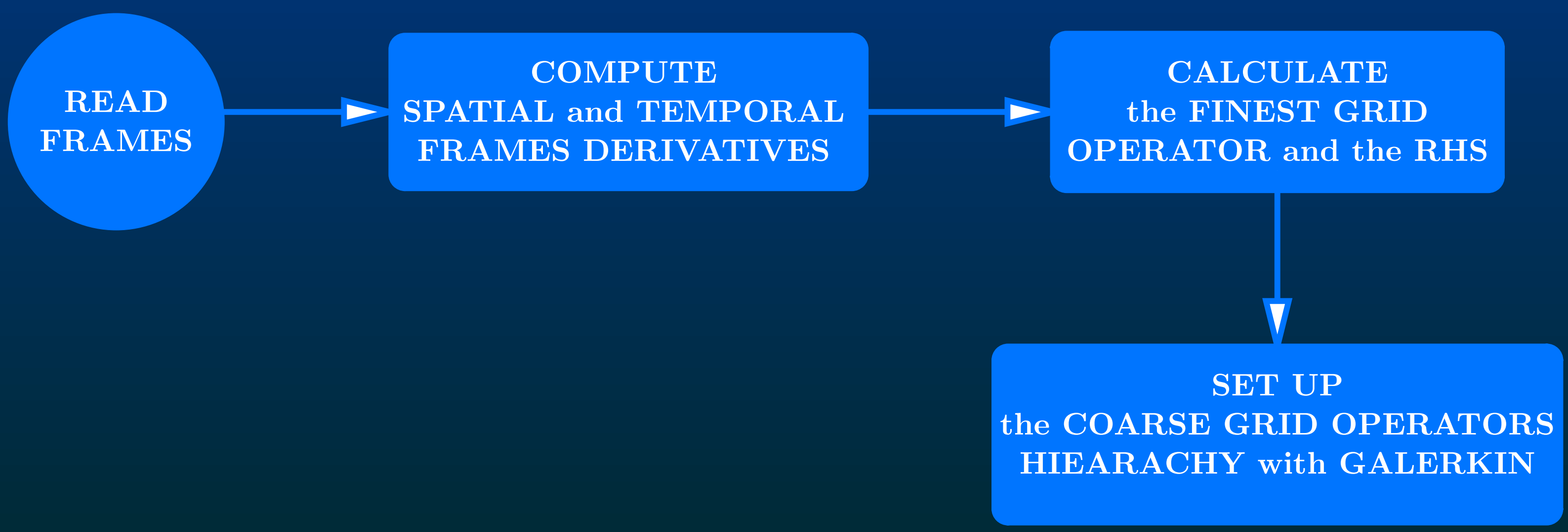

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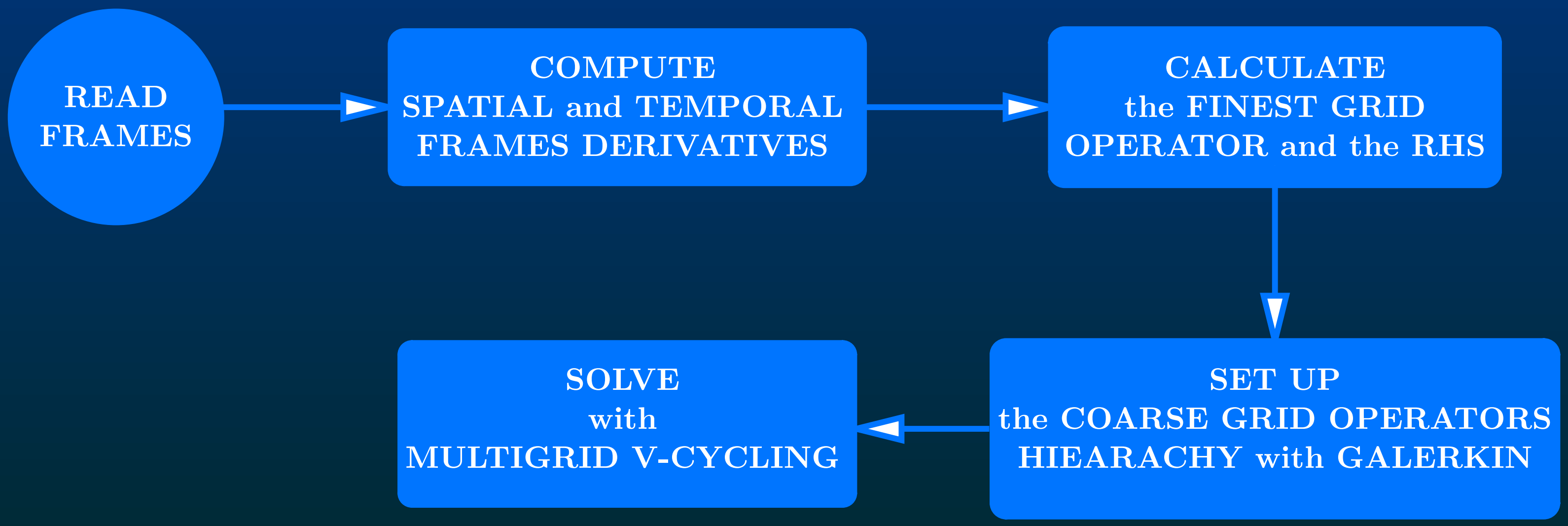
  - ▷ Vertex-centered grid and standard coarsening
  - ▷ Coupled lexicographic point Gauss-Seidel smoother
  - ▷ Full weighting and bilinear interpolation
  - ▷ **Galerkin coarse grid approximation (GCA approach)**
- The General Scheme



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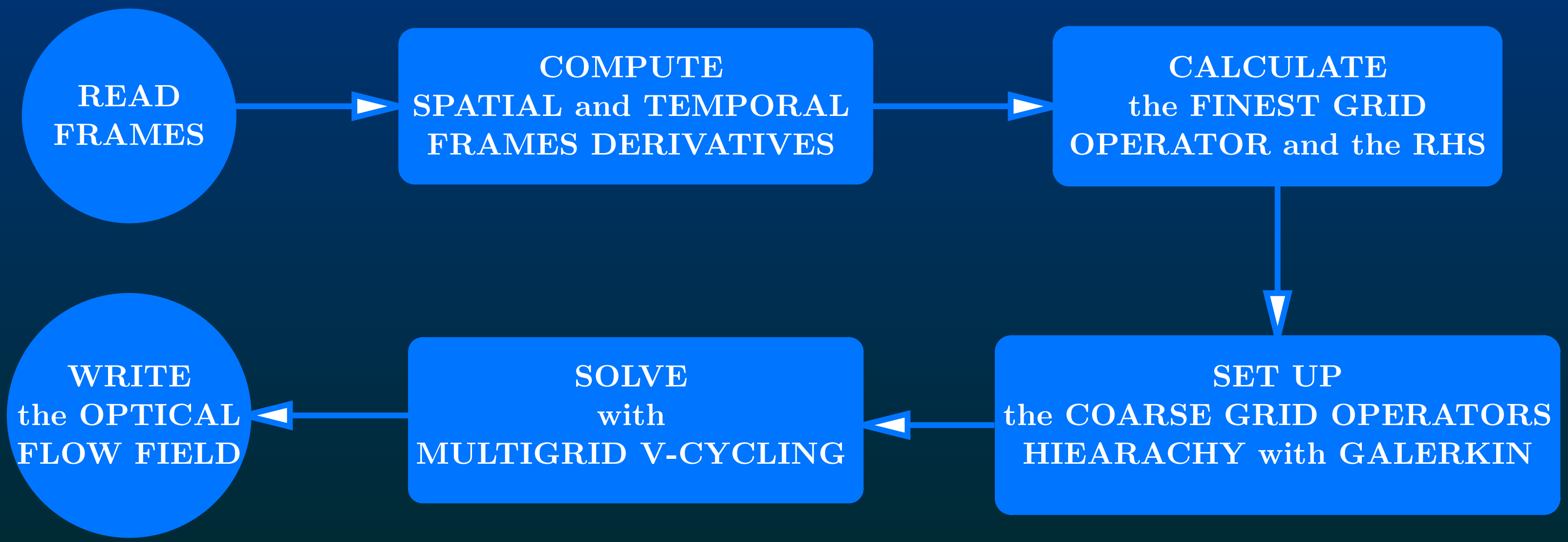

Experimental Results

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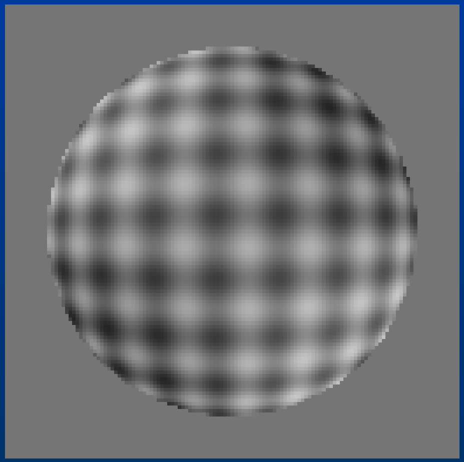

A rotating sphere (128x128)

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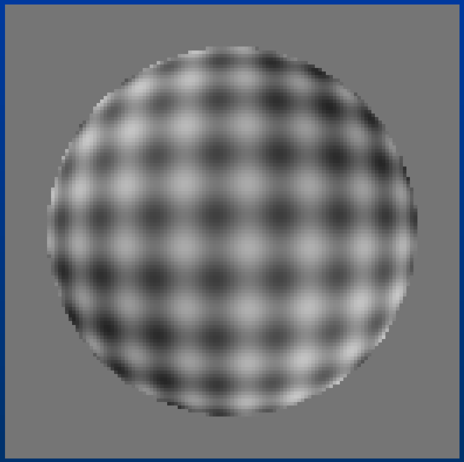

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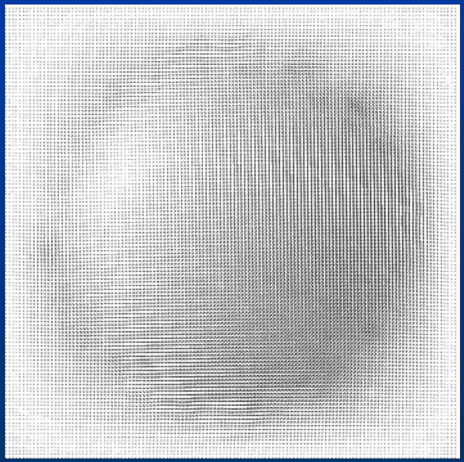

the flow field

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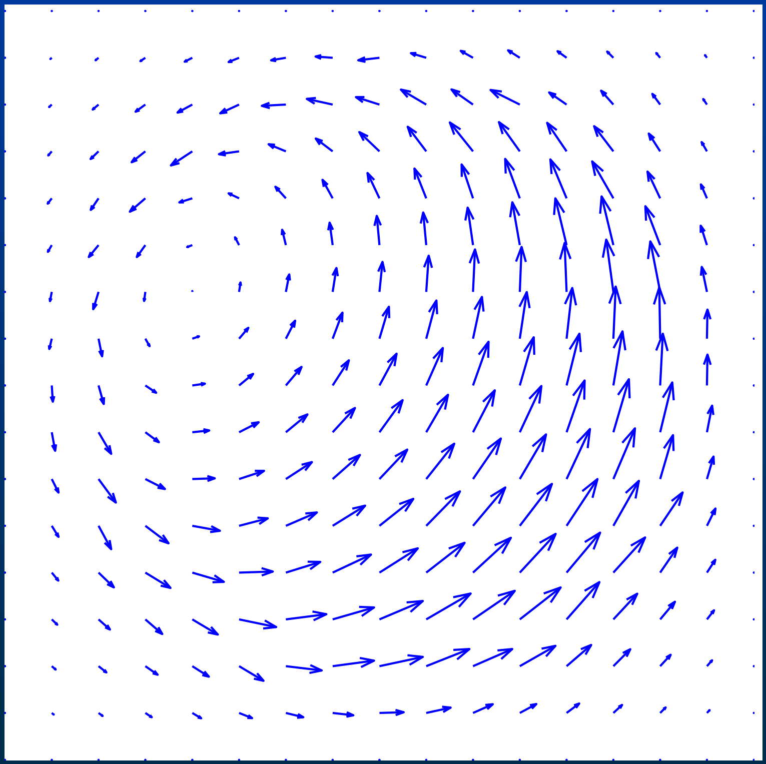

the flow field after scaling

Experimental Results

The marble sequence (512x512)

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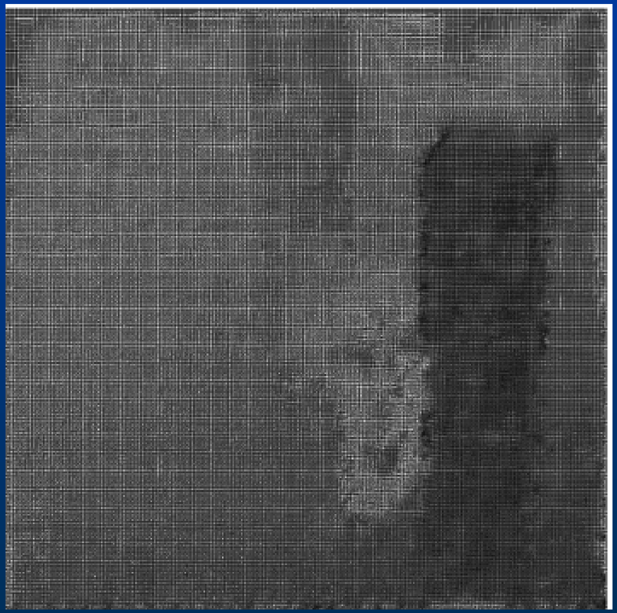

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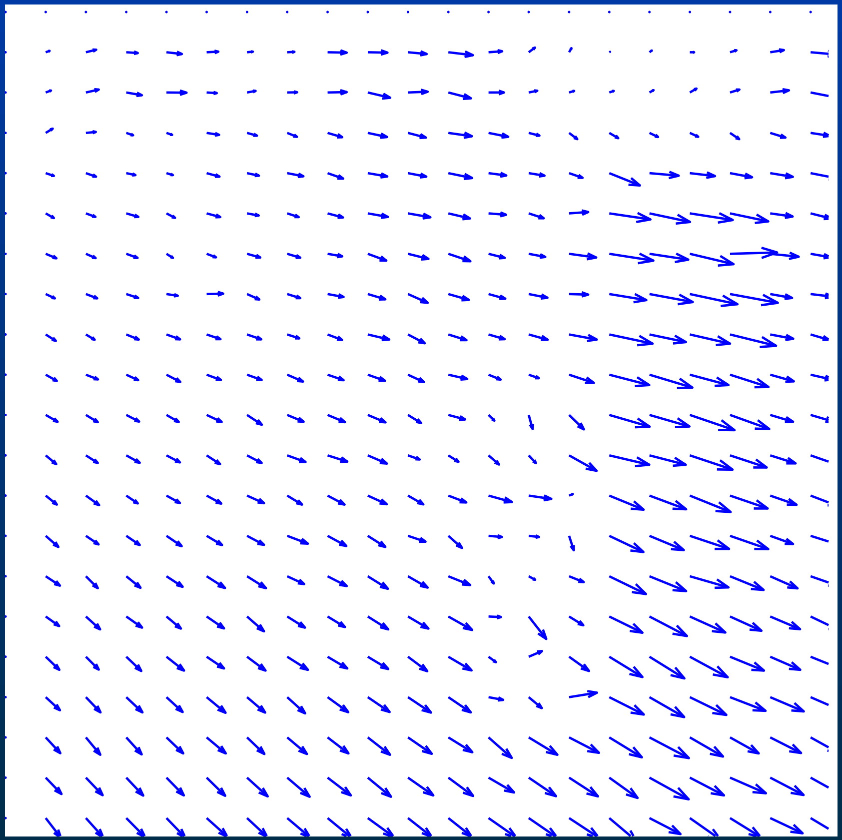

the flow field after scaling

Experimental Results

The Hamburg taxi sequence (256x190)

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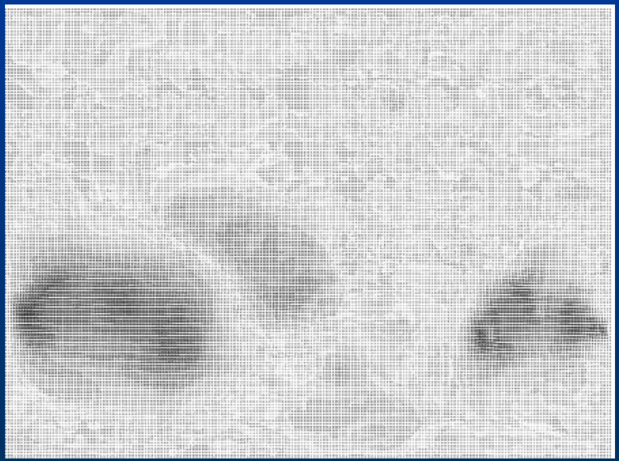

the flow field

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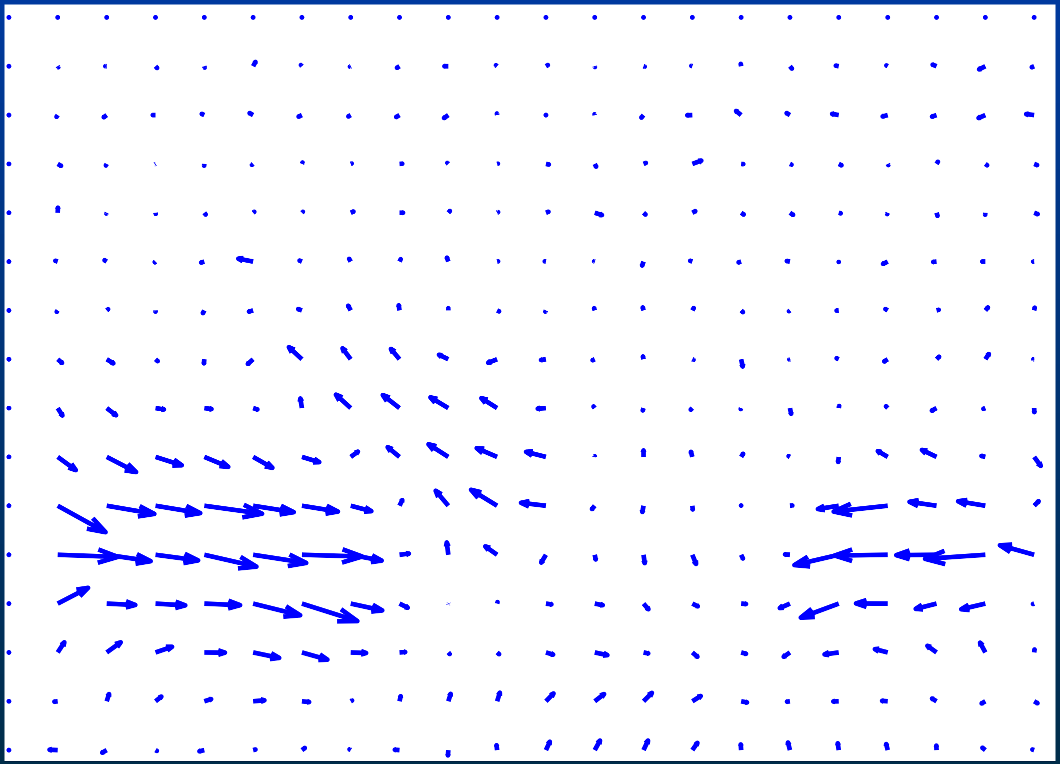

the flow field after scaling

Experimental Results

$\alpha = 5$ *and* $u_0 = v_0 = 0$ on P4 2.4GHz						
	Sphere		Marble		Taxi	
	ρ	CPU	ρ	CPU	ρ	CPU
Horn-Schunck	0.98	3.9	0.98	106	0.98	20.8
VMG V(2,1)	0.15	1.1	0.43	23.8	0.45	4.3

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– Galerkin leads to high memory costs
$\Rightarrow$ search for better representation of the CGOs

Future work

- Application in medicine imaging
- Consider other regularization (e.g. by Nagel, Weickert ...)

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PLEASE WAKE UP!

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THANKS FOR YOUR ATTENTION