# Transport with congestion, weak flows and degenerate elliptic PDE's

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# Outline

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- ② Minimal flow formulation
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### A continuous congestion model

Discrete congested network model: G = (N, A) finite oriented and connected graph,  $P \subset N \times N$  (sources/dest.),  $\gamma_{s,d} \geq 0$  mass to be sent from s to d,  $C_{s,d}$  (nonempty) set of simple paths connecting s to d ( $(s,d) \in P$ ) and C their union. Travelling time functions(congestion), for  $a \in A$   $w \mapsto t_a(w)$  ( $w \geq 0$  flow on arc a),  $t_a$  nonnegative, nondecreasing.

Cost of a path  $r \in C$  given the flows  $(w_a)_{a \in A}$ :

$$T_w(r) := \sum_{a \in r} t_a(w_a)$$

Unknown: arc flows  $(w_a)_{a\in A}$  and mass travelling on each road  $(h_r)_{r\in C}$ , constraints:

$$\gamma_{s,d} = \sum_{r \in C_{s,d}} h_r, \ w_a = \sum_{r \ni a} h_r, \ w_a \ge 0, h_r \ge 0. \tag{1}$$

Pbm: what is a long-term steady state or equilibrium flow-configuration?

Wardrop: used paths have to be shortest paths, given the flow configuration (similar to Nash equilibrium).

Wardrop equilibrium (1952):  $(w_a)_{a \in A}$ ,  $(h_r)_{r \in C}$  satisfying (1) such that,  $\forall (s, d) \in P$ ,  $\forall r \in C_{s,d}$ , if  $h_r > 0$ , then:

$$T_w(r) = \min\{T_w(r'), r' \in C_{s,d}\}$$

Beckman, McGuire, Winsten (1956) noticed that  $(w_a)_{a \in A}$ ,  $(h_r)_{r \in C}$  is a Wardrop equilibrium iff it minimizes

$$C(w) := \sum_{a \in A} \int_0^{w_a} t_a$$

subject to (1).

Continuous model: Given  $\Omega$  some bounded open and connected subset of  $\mathbb{R}^d$  and probability measures  $\mu_0$  and  $\mu_1$  on  $\overline{\Omega}$  (or a transport plan  $\pi$  that is a joint probability on  $\overline{\Omega} \times \overline{\Omega}$ ) one looks for a probability measure Q on  $C([0,1],\overline{\Omega})$  concentrated on absolutely continuous curves such that

$$e_0 \sharp Q = \mu_0, \ e_1 \sharp Q = \mu_1 \text{ or } (e_0, e_1) \sharp Q = \pi, \text{ with } e_t(\gamma) = \gamma(t)$$

that is an equilibrium i.e. (in a sense to be made precise) such that Q is supported by geodesics for a metric  $\xi_Q$  depending on Q itself (congestion).

Intensity of traffic  $i_Q \in \mathcal{M}(\overline{\Omega})$ , defined by

$$\int \varphi di_Q := \int_{C([0,1],\overline{\Omega})} \left( \int_0^1 \varphi(\gamma(t)) |\dot{\gamma}(t)| dt \right) dQ(\gamma)$$

for all  $\varphi \in C(\overline{\Omega}, \mathbb{R}_+)$ . Congestion effect:

$$\xi_Q(x) := g(i_Q(x)), \text{ for } i_Q \ll \mathcal{L}^d \text{ (+}\infty \text{ otherwise)}.$$

for a given increasing function  $g: \mathbb{R}_+ \to \mathbb{R}_+$ . Denote by  $\mathcal{Q}(\mu_0, \mu_1)$  (resp.  $\mathcal{Q}(\pi)$ ) the set of probabilities Q such that  $(e_0 \sharp Q, e_1 \sharp Q) = (\mu_0, \mu_1)$  (resp.  $(e_0, e_1) \sharp Q = \pi$ ).

Consider then

$$\inf_{Q \in \mathcal{Q}(\mu_0, \mu_1)} \int_{\Omega} H(i_Q(x)) dx \tag{2}$$

where H' = g, H(0) = 0.

Under the assumptions:

- H is strictly convex and increasing on  $\mathbb{R}_+$  with H(0) = 0,
- there exists p > 1, and positive constants a and b such that  $az^p \leq H(z) \leq b(z^p + 1)$  for all  $z \in \mathbb{R}_+$ ,
- the following set

$$Q^{p}(\mu_{0}, \mu_{1}) := \{ Q \in Q(\mu_{0}, \mu_{1}) : i_{Q} \in L^{p} \}$$
 (3)

is nonempty,

then (2) has a solution (and the optimal  $i_Q$  is unique).

Not easy to check a priori that  $Q^p(\mu_0, \mu_1) \neq \emptyset$ , but

- it holds whenever  $\mu_0$  and  $\mu_1$  are  $L^p$  (De Pascale, Pratelli),
- it holds for  $\mu_0$  and  $\mu_1$  have finite support, d=2 and p<2,
- also when  $\overline{\Omega} = [0,1]^2$  and  $\mu_0$  and  $\mu_1$  are respectively the one-dimensional Hausdorff measures of the vertical sides of the square.

In dimension 2,  $Q^2(\mu_0, \mu_1) = \emptyset$  as soon as  $\mu_0 - \mu_1 \notin H^{1'}$ . Indeed associate to every  $Q \in Q(\mu_0, \mu_1)$  the vector-measure  $\sigma_Q$  defined by,  $\forall X \in C(\overline{\Omega}, \mathbb{R}^2)$ :

$$\int_{\overline{\Omega}} X(x) d\sigma_Q(x) = \int_{C([0,1],\overline{\Omega})} \left( \int_0^1 X(\gamma(t)) \cdot \dot{\gamma}(t) dt \right) dQ(\gamma).$$

It is easy to check:

$$\operatorname{div}(\sigma_Q) = \mu_0 - \mu_1$$
, and  $|\sigma_Q| \le i_Q$ .

Hence, if  $\mu_0 - \mu_1 \notin H^{1\prime}$  there is no  $L^2$ , vector-field with divergence  $\mu_0 - \mu_1$ .

**Link with equilibria** Further assume that H is differentiable with  $H'(z) \leq C(1+z^{p-1})$  and p < d/(d-1) i.e. q := p' > d. Geodesic distance :  $\xi \in C(\overline{\Omega}), \xi \geq 0, x, y$  in  $\overline{\Omega}^2$ :

$$c_{\xi}(x,y) := \inf_{\gamma : \gamma(0) = x, \gamma(1) = y} \int_{0}^{1} \xi(\gamma(t)) |\dot{\gamma}(t)| dt$$

for  $\xi$  only  $L^q$ ,  $\xi \geq 0$ :

$$\overline{c}_{\xi}(x,y) = \sup \{c(x,y) : c \in \mathcal{A}(\xi)\},$$

where

$$\mathcal{A}(\xi) = \left\{ \lim_{n} c_{\xi_n} \text{ in } C^0 : (\xi_n)_n \in C^0(\overline{\Omega}), \, \xi_n \ge 0, \, \xi_n \to \xi \text{ in } L^q \right\}.$$

(well defined and Hölder continuous by the Sobolev imbeddings).

Other characterizations of  $\overline{c}_{\xi}$ :

$$\overline{c}_{\xi} = \lim_{\varepsilon} c_{\rho_{\varepsilon} \star \xi}$$

also  $\overline{c}_{\xi}(x,.)$  is the viscosity solution (i.e. largest a.e. subsolution) of the eikonal equation

$$|\nabla u| = \xi, \ u(x) = 0.$$

For  $\xi \in C(\overline{\Omega})$ ,  $\xi \geq 0$  and  $\gamma$  an absolutely continuous curve, set

$$L_{\xi}(\gamma) := \int_{0}^{1} \xi(\gamma(t)) |\dot{\gamma}(t)| dt$$

for  $Q \in \mathcal{Q}^p(\mu_0, \mu_1)$ ,  $\xi \in L^q$ ,  $\xi \geq 0$ , and  $(\xi_n)_n \geq 0$ , continuous,  $\xi_n \to \xi$  in  $L^q$ , then  $(L_{\xi_n})_n$  converges strongly in  $L^1(C, Q)$  to some limit which is independent of the approximating sequence  $(\xi_n)_n$  and which will again be denoted  $L_{\xi}$ .

**Theorem 1** Let  $\overline{Q} \in \mathcal{Q}^p(\mu_0, \mu_1)$  with  $\overline{Q} := \overline{p} \otimes \overline{\pi}$  (with  $\overline{\pi} \in \Pi(\mu_0, \mu_1)$ ), and set  $\overline{\xi} := H'(i_{\overline{Q}})$ , then  $\overline{Q}$  solves (2) iff:

1.  $\overline{\pi}$  solves the Monge-Kantorovich problem:

$$\inf_{\pi \in \Pi(\mu_0, \mu_1)} \int_{\overline{\Omega} \times \overline{\Omega}} \overline{c}_{\overline{\xi}}(x, y) d\pi(x, y), \tag{4}$$

2. for  $\overline{Q}$ -a.e.  $\gamma$ , one has:

$$L_{\overline{\xi}}(\gamma) = \overline{c}_{\overline{\xi}}(\gamma(0), \gamma(1)). \tag{5}$$

The second condition is the Wardrop equilibrium condition.

Variant: the transportation plan  $\pi$  is prescribed, then one has a similar variational characterization by considering

$$\inf_{Q \in \mathcal{Q}(\pi)} \int_{\Omega} H(i_Q(x)) dx.$$

#### Minimal flow formulation

For  $Q \in \mathcal{Q}^p(\mu_0, \mu_1)$  define as before every the vector-measure  $\sigma_Q$  defined by,  $\forall X \in C(\overline{\Omega}, \mathbb{R}^d)$ :

$$\int_{\overline{\Omega}} X(x) d\sigma_Q(x) = \int_{C([0,1],\overline{\Omega})} \left( \int_0^1 X(\gamma(t)) \cdot \dot{\gamma}(t) dt \right) dQ(\gamma)$$

which is a kind of vectorial traffic intensity.

It is easy to check:

$$\operatorname{div}(\sigma_Q) = \mu_0 - \mu_1, \ \sigma_Q \cdot n = 0, \ \text{and} \ |\sigma_Q| \le i_Q.$$

Since H is increasing, it proves that the value of the scalar problem (2) is larger than that of the minimal flow problem (setting:  $\mathcal{H}(\sigma) = H(|\sigma|)$ ):

$$\inf_{\sigma \in L^p(\Omega, \mathbb{R}^d) : \operatorname{div}(\sigma) = \mu_0 - \mu_1} \int_{\Omega} \mathcal{H}(\sigma(x)) dx \tag{6}$$

Conversely, if  $\sigma$  is a minimizer of (6) and  $Q \in \mathcal{Q}^p(\mu_0, \mu_1)$  is such that  $i_Q = |\sigma|$  then Q solves the scalar problem (2) (i.e. is an equilibrium).

Heuristic construction (assuming  $\sigma$  Lipschitz,  $\mu_0$ ,  $\mu_1$  Lipschitz densities  $\geq c > 0$ ). Consider (as in Moser, Dacorogna-Moser and more recently Evans and Gangbo) the ODE

$$\dot{X}(t,x) = \frac{\sigma(X(t,x))}{(1-t)\mu_0(X(t,x)) + t\mu_1(X(t,x))}, \ X(0,x) = x.$$

and define  $\overline{Q}$  by

$$\overline{Q} = \delta_{X(.,x)} \otimes \mu_0$$

Set  $\mu_t = (1 - t)\mu_0 + t\mu_1$  and

$$v(t,x) = \frac{\sigma(x)}{\mu_t(x)}$$

then by construction  $\mu_t$  solves the continuity equation:

$$\partial_t \mu_t + \operatorname{div}(\mu_t v) = 0$$

By construction  $e_0 \sharp \overline{Q} = \mu_0$  and because of the continuity equation,  $X(t,.)\sharp \mu_0 = \mu_t = (1-t)\mu_0 + t\mu_1$ . In particular the image of  $\mu_0$  by the flow at time 1, X(1,.) is  $\mu_1$ , which proves that  $e_1 \sharp \overline{Q} = \mu_1$  hence  $\overline{Q} \in \mathcal{Q}(\mu_0, \mu_1)$ . Moreover for every test-function  $\varphi$ :

$$\int_{\Omega} \varphi di_{\overline{Q}} = \int_{\Omega} \int_{0}^{1} \varphi(X(t,x)) |v(t,X(t,x))| dt d\mu_{0}(x)$$

$$= \int_{0}^{1} \int_{\Omega} \varphi(x) |v(t,x)| \mu_{t}(x) dx dt$$

$$= \int_{\Omega} \varphi(x) |\sigma(x)| dx$$

so that  $i_{\overline{Q}} = |\sigma|$  and then  $\overline{Q}$  is optimal.

The previous argument works as soon as  $\sigma \in W^{1,\infty}$ . By duality, the solution of (6) is  $\sigma = \nabla \mathcal{H}^*(\nabla u)$  where  $\mathcal{H}^*$  is the Legendre transform of  $\mathcal{H}$  and u solves the PDE:

$$\begin{cases} \operatorname{div}\nabla \mathcal{H}^*(\nabla u) &= \mu_0 - \mu_1, & \text{in } \Omega, \\ \nabla \mathcal{H}^*(\nabla u) \cdot \nu &= 0, & \text{on } \partial \Omega, \end{cases}$$
 (7)

Let us recall that H' = g where g is the congestion function, natural to have g(0) > 0: the metric is positive even if there is no traffic, so that the radial function  $\mathcal{H}$  is not differentiable at 0 and then its subdifferential at 0 contains a ball. By duality, this implies  $\nabla \mathcal{H}^* = 0$  on this ball which makes (7) very degenerate. A reasonable model of congestion is  $g(t) = \lambda + t^{p-1}$  for  $t \geq 0$ , with p > 1 and  $\lambda > 0$ , so that

$$\mathcal{H}(\sigma) = \frac{1}{p} |\sigma|^p + \lambda |\sigma|, \ \mathcal{H}^*(z) = \frac{1}{q} (|z| - \lambda)_+^q, \text{ with } q = \frac{p}{p-1}.$$
 (8)

For a general vector field  $\mathbf{v}$  under very mild assumptions, the most general meaning that we can give to the flow of  $\mathbf{v}$  is in terms of the so-called *superposition principle* (Ambrosio-Crippa), the continuity equation:

$$\partial_t \mu_t + \operatorname{div}(\mathbf{v}\mu_t) = 0, \tag{9}$$

**Définition 1** Let Q be concentrated on the integral curves of  $\mathbf{v}$ , in the sense that

$$\int_{C([0,1];\overline{\Omega})} \left| \gamma(t) - \gamma(0) - \int_0^t \mathbf{v}(s, \gamma(s)) \, ds \right| \, dQ(\gamma) = 0. \tag{10}$$

If we define the curve of measures  $\mu_t^Q$  through

$$\int_{\overline{\Omega}} \varphi(x) \ d\mu_t^Q(x) := \int_{C([0,1];\overline{\Omega})} \varphi(\gamma(t)) \ dQ(\gamma) \ \text{for every } \varphi \in C(\overline{\Omega}),$$
(11)

then this curve  $\mu_t^Q$  is called superposition solution of (9).

Theorem 2 (Superposition principle) Let  $\mu_t$  be a positive measure-valued solution of the continuity equation

$$\frac{\partial}{\partial t}\mu_t + \operatorname{div}(\mathbf{v}\mu_t) = 0,$$

with the vector field **v** satisfying the following condition

$$\int_0^1 \int_{\overline{\Omega}} \frac{|\mathbf{v}(t,x)|}{1+|x|} d\mu_t(x) dt < +\infty, \tag{12}$$

then  $\mu_t$  is a superposition solution.

One can still relate (6) and (2) under quite weak assumptions thanks to the superposition principle (Ambrosio-Crippa), assume that  $\mu_0$  and  $\mu_1$  have  $L^p$  densities bounded from below by a positive constant, define  $\sigma$ ,  $\mu_t$  as before and  $\hat{\sigma} = \sigma/\mu_t$ . Since

$$\frac{\partial}{\partial t}\mu_t + \operatorname{div}(\widehat{\sigma}\mu_t) = 0,$$

with initial datum  $\mu_0$ . By the superposition principle,  $\mu_t$  is a superposition solution:  $\mu_t = \mu_t^Q$  with  $Q \in \mathcal{Q}^p(\mu_0, \mu_1)$  and  $i_Q = |\sigma|$  so that Q solves (2). In particular the values of (6) and (2) coincide.

To sum up, we have seen how to construct an optimal Q for

$$\inf_{Q \in \mathcal{Q}(\mu_0, \mu_1)} \int_{\Omega} H(i_Q(x)) dx$$

using the flow of the ODE

$$\dot{\gamma}(t) = \widehat{\sigma}(t, \gamma(t)), \ \widehat{\sigma}(t, x) = \frac{\sigma(t, x)}{(1 - t)\mu_0(x) + t\mu_1(x)}$$

and  $\sigma = \nabla \mathcal{H}^*(\nabla u)$  with

$$\operatorname{div} \nabla \mathcal{H}^*(\nabla u) = \mu_0 - \mu_1, \text{ in } \Omega, \ \nabla \mathcal{H}^*(\nabla u) \cdot \nu = 0, \text{ on } \partial \Omega.$$

- Cauchy Lipschitz case : requires  $\sigma$  to be Lipschitz, not realistic in traffic congestion models,
- in the general case, using supeposition solutions of the continuity equation: not really satisfactory, the regularity of the curves charged by Q is quite poor, no flow, no group property...

Assume  $\Omega$  Lipschiz,  $\mu_0$ ,  $\mu_1$  have Lipschitz densities  $\geq c > 0$ . Intermediate approach: DiPerna-Lions theory. Requires  $\widehat{\sigma}$  to have Sobolev regularity and an  $L^{\infty}$  bound on

$$\operatorname{div}(\widehat{\sigma}) = \frac{\operatorname{div}(\sigma)}{\mu_t} - \frac{1}{\mu_t^2} \nabla \mu_t \cdot \sigma = \frac{\mu_0 - \mu_1}{\mu_t} - \frac{1}{\mu_t^2} \nabla \mu_t \cdot \sigma.$$

The issue then becomes proving Sobolev regularity and an  $L^{\infty}$  bound on  $\sigma$ .

## Regularity

Aim: prove Sobolev and  $L^{\infty}$  estimates for the optimizer  $\sigma$  of (6) under the following assumptions:

- (i)  $\mu_i = f_i \mathcal{L}^d$ , with  $f_i \in \text{Lip }(\Omega)$  and  $f_i \geq c > 0$ , for i = 0, 1;
- (ii)  $\Omega$  open connected bounded subset of  $\mathbb{R}^d$  having Lipschitz boundary.

in the case where the congestion takes the form

$$\mathcal{H}(\sigma) = \frac{1}{p} |\sigma|^p + |\sigma|, \ \mathcal{H}^*(z) = \frac{1}{q} (|z| - 1)_+^q, \text{ with } q = \frac{p}{p-1}$$
 (13)

with  $q \geq 2$ .

so that the optimal  $\sigma$  is

$$\sigma = \left( |\nabla u| - 1 \right)_{+}^{q-1} \frac{\nabla u}{|\nabla u|}.$$

where u solves the very degenerate PDE:

$$\operatorname{div}\left(\left(|\nabla u|-1\right)_{+}^{q-1}\frac{\nabla u}{|\nabla u|}\right) = f = f_0 - f_1,\tag{14}$$

with Neumann boundary condition

$$\left(|\nabla u| - 1\right)_{+}^{q-1} \frac{\nabla u}{|\nabla u|} \cdot \nu = 0.$$

Note that there is no uniqueness for u but there is for  $\sigma$ .

Setting

$$G(z) = |\nabla \mathcal{H}^*(z)|^{\frac{p}{2}} \frac{z}{|z|} = (|z| - 1)_+^{\frac{q}{2}} \frac{z}{|z|}, \ z \in \mathbb{R}^d$$

using

$$\left(\nabla \mathcal{H}^*(z) - \nabla \mathcal{H}^*(w)\right) \cdot (z - w) \ge \frac{4}{q^2} \left| G(z) - G(w) \right|^2,$$

and

$$|\nabla \mathcal{H}^*(z) - \nabla \mathcal{H}^*(w)|$$

$$\leq (q-1)\left(|G(z)|^{\frac{q-2}{q}} + |G(w)|^{\frac{q-2}{q}}\right)|G(z) - G(w)|$$

together with arguments originally due to Bojarski and Iwaniec for the p-laplacian, we first get:

**Theorem 3**  $\mathcal{G} \in W^{1,2}(\Omega)$ , where the function  $\mathcal{G}$  is defined by

$$\mathcal{G}(x) := G(\nabla u(x)) = (|\nabla u(x)| - 1)_{+}^{\frac{q}{2}} \frac{\nabla u(x)}{|\nabla u(x)|}, \ x \in \Omega.$$
 (15)

#### Corollary 1

$$\sigma = \nabla \mathcal{H}^*(\nabla u) = |\mathcal{G}|^{\frac{q-2}{q}} \mathcal{G} \in W^{1,r}(\Omega), \tag{16}$$

for suitable exponents r = r(d, q) given by

$$r(d,q) = \begin{cases} 2, & \text{if } d = q = 2, \\ any \ value < 2, & \text{if } d = 2, \ q > 2, \\ \frac{dq}{(d-1)q+2-d}, & \text{if } d > 2. \end{cases}$$

Regularizing (14) and using the fact that convex transforms of derivatives of the solution are subsolutions (in fact we use  $(\partial_1 u - 2)_+^r$  of an elliptic PDE and using a bootstrap argument, we can prove the following:

**Theorem 4** If u solves (14), then u is globally Lipschitz on  $\Omega$ .

This enables us to define a flow à la DiPerna-Lions for the ODE related to the traffic congestion problem.

## Other formulations, numerical approximation

Here we consider the case where the transport plan  $\gamma$  is fixed (so that the equivalence with the minimal flow problem does not hold any more). Recall that our study of equilibria relies on the following convex optimization problem:

$$(\mathcal{P})\inf\left\{\int_{\Omega}H(x,i_{Q}(x))dx:Q\in\mathcal{Q}(\gamma)\right\}$$
 (17)

We will also assume here that d = 2 and q > 2 i.e. p < 2.

For every  $x \in \Omega$  and  $\xi \geq 0$ , let us define

$$H^*(x,\xi) := \sup\{\xi i - H(x,i), i \ge 0\}, \ \xi_0(x) := g(x,0).$$

Let us now define the functional

$$J(\xi) = \int_{\Omega} H^*(x, \xi(x)) dx - \int_{\overline{\Omega} \times \overline{\Omega}} \overline{c}_{\xi}(x, y) d\gamma(x, y)$$
 (18)

and consider:

$$(\mathcal{P}^*) \sup \{-J(\xi) : \xi \in L^q, \xi \ge \xi_0\}$$
 (19)

**Theorem 5** If the domain of (P) is nonempty, then

$$\min(\mathcal{P}) = \max(\mathcal{P}^*) \tag{20}$$

and  $\xi \in L^q$  solves  $(\mathcal{P}^*)$  if and only if  $\xi = \xi_Q$  for some  $Q \in \mathcal{Q}(\gamma)$  solving  $(\mathcal{P})$ .

In the sequel, we will numerically approximate the unique equilibrium metric  $\xi_Q$  by a descent method on  $(\mathcal{P}^*)$ . One can recover the corresponding equilibrium intensity  $i_Q$  by inverting the relation  $\xi(x) = g(x, i_Q(x))$ .

#### Discretization

Start with the dual formulation

$$\inf_{\xi \in L^q, \ \xi \ge \xi_0 = g(.,0)} J(\xi) = \int_{\Omega} H^*(x, \xi(x)) dx - W(\xi)$$

to compute the optimal metric  $\xi = \partial_i H(x, i_Q(x))$ . Case of a fixed (discrete) transport plan  $\gamma = \sum \gamma_{\alpha\beta} \delta_{(S_\alpha, T_\beta)}$ :

$$W(\xi) := \sum \gamma_{\alpha\beta} c_{\xi}(S_{\alpha}, T_{\beta}).$$

Where  $c_{\xi}(S,.)$  is the *viscosity* solution (or largest  $W^{1,q}$  a.e. subsolution) of the Eikonal equation

$$\|\nabla \mathcal{U}\| = \xi; \quad \mathcal{U}_{\xi}(S) = 0 \tag{21}$$

(and we assume that q > 2 so that the domain of the primal is nonempty).

Space discretization, mesh size h, consistent (Souganidis, Barles-Souganidis, Rouy-Tourin) discretization of the Eikonal equation:

$$\left(\frac{\max\{(\mathcal{U}_{i,j} - \mathcal{U}_{i-1,j}), (\mathcal{U}_{i,j} - \mathcal{U}_{i+1,j}), 0\}}{h_x}\right)^2 + \left(\frac{\max\{(\mathcal{U}_{i,j} - \mathcal{U}_{i,j-1}), (\mathcal{U}_{i,j} - \mathcal{U}_{i,j+1}), 0\}}{h_y}\right)^2 = (\xi_{i,j})^2.$$

can be solved efficiently by Sethian's Fast Marching Method. Notation :  $c_{\xi}^{h}(S,T)$ , discrete functional

$$J^{h}(\xi) = h^{2} \sum_{i,j} H^{*}(i,j;\xi_{i,j}) - \sum_{r,s} c_{\xi}^{h}(S_{\alpha}, T_{\beta}) \gamma_{\alpha,\beta},$$

Note that each  $J^h$  is convex.

#### $\Gamma$ -convergence:

**Theorem 6** The sequence of functionals  $J^h$   $\Gamma$ -converges with respect to the weak  $L^q$  convergence to the limit functional J. Moreover, as the sequence  $(J^h)_h$  is equi-coercive and every functional, J included, is strictly convex, (strong) convergence of the unique minimizers and of the values of the minima is guaranteed.

Solving the discrete problem by a subgradient descent method,  $J^h$  involves a differentiable part and a convex homogenous one. Problem: compute at each iteration a subgradient of the second part. Not straightforward but possible recursively by a method that uses the same recursivity as the FMM. We call this method the Fast Subgradient Marching Method, it enables to compute efficiently  $(N^2 \log(N))$  a supergradient of the (discrete) geodesic distance with respect to the values of the metric on a grid. See the problem as an optimization problem over metrics.

There are several other applications of this strategy to compute by FMM a supergradient of distances with respect to metrics: inverse problems in travel-time tomography for instance. Optimal design of obstacles to prevent mass transfer or the invasion of an army (Buttazzo):

$$\max_{\xi} \sum \alpha_i \overline{c}_{\xi}(x_i, y_i)$$

subject to  $\underline{\xi} \leq \underline{\xi} \leq \overline{\xi}$  and

$$\int \xi = \lambda.$$