Fast global matching via energy pyramid

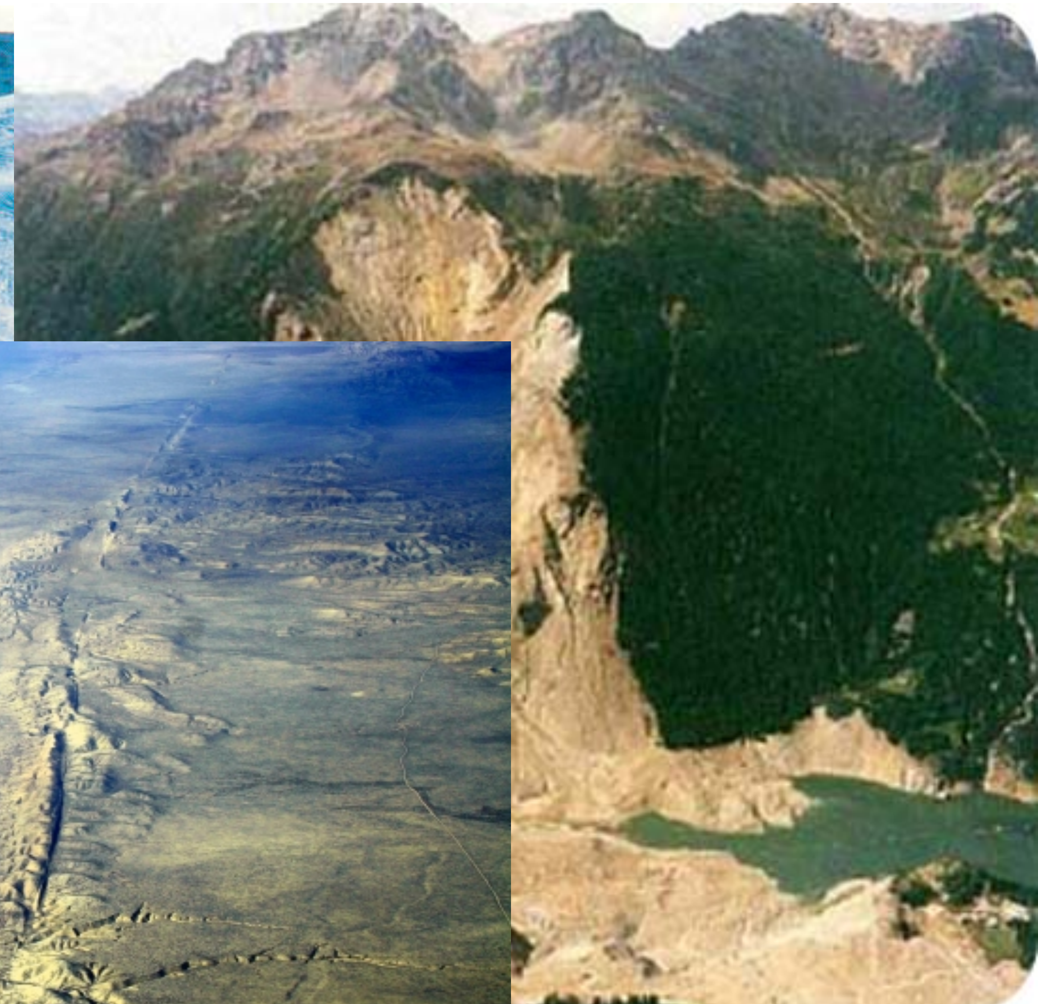
7/17/2014

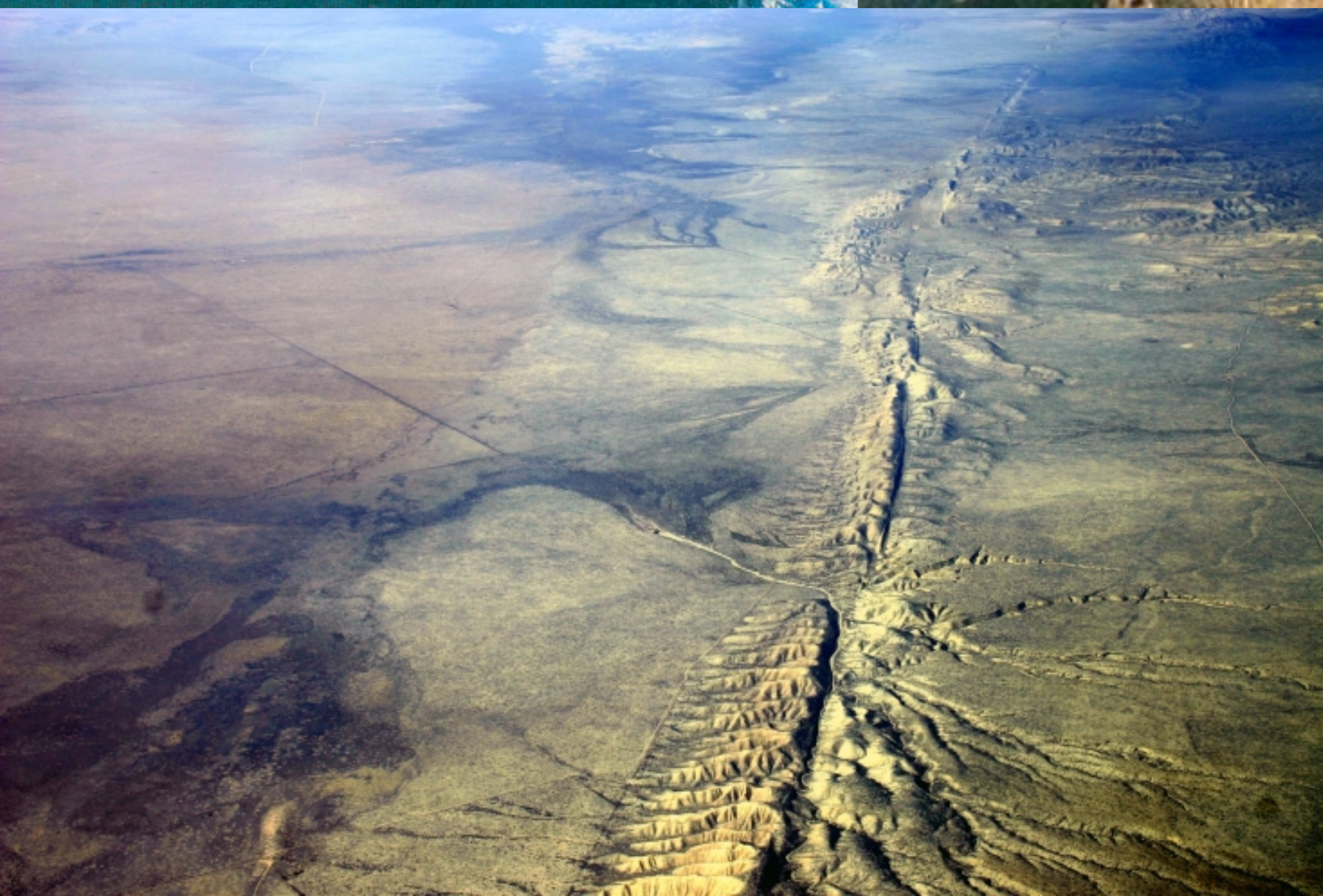
B. Conejo
(bconejo@caltech.edu)
with S. Leprince, F. Ayoub & JP. Avouac (GPS, Caltech)
And P.Monasse & N.Komodakis (LIGM, Paris-Est)

USGS science for a changing world
THOR Terrestrial Hazard Observation and Reporting
Gordon and Betty Moore Foundation
California Institute of Technology 1891
IMAGINE Université Paris-Est École des Ponts ParisTech CSTB
Keck Institute for Space Studies
Caltech www.caltech.edu

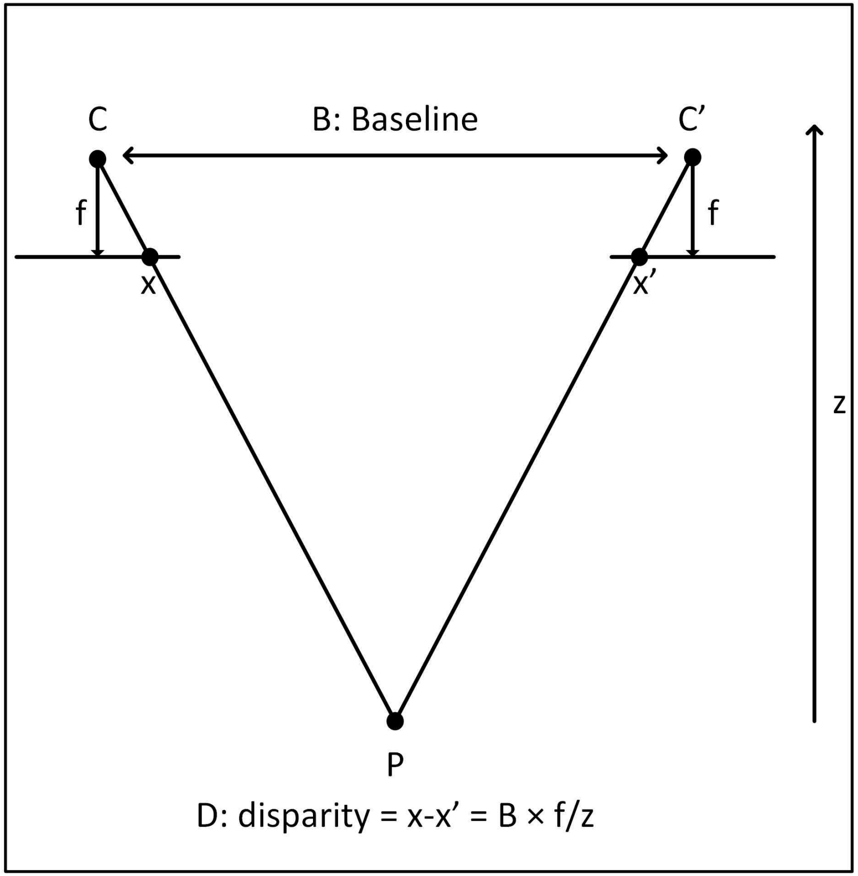
Motivation:

Some matching problems:

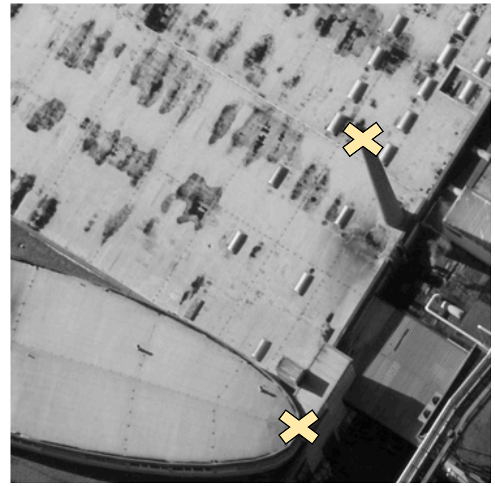


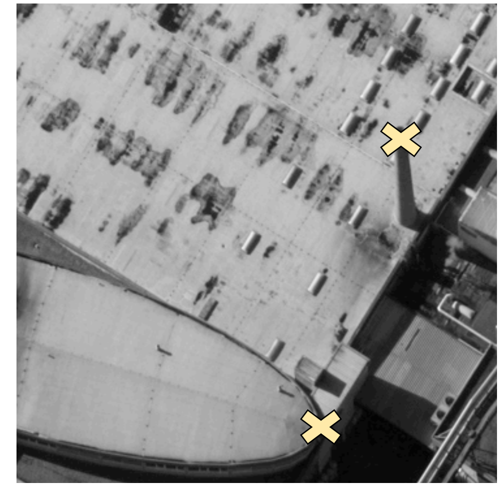


Classic stereo-imaging setup



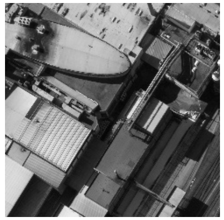
Disparity is inversely proportional to depth!



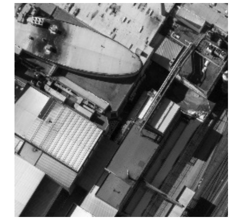


Modeling: bayesian approach

Given a stereo-pair of images (I_r,I_t) how to retrieve the most probable disparity map d^*?



$$I_r \xrightarrow{d} I_t$$



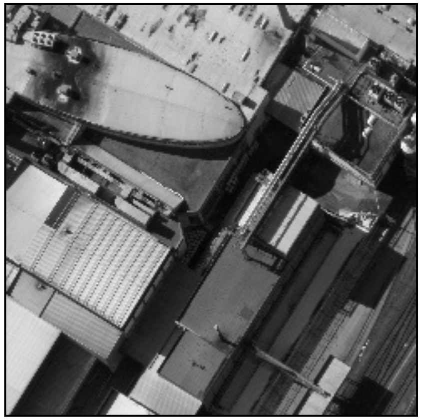
In term of probability, we need to estimate the Maximum A Posteriori (MAP) of:

$$P(d|I_r, I_t) = \underbrace{P_M(d|I_r, I_t)}_{\text{Matching: encourages similarity}}\underbrace{P_R(d|I_r)}_{\text{Regularization: priors on disparity}}.$$

Gibbs measure relates probability density function to energy:

$$P(X = x) = \frac{1}{\underbrace{Z}_{\text{Normalizing constant}}} \exp(\underbrace{-E(x)}_{\text{Energy of configuration } x}))$$

Modeling: continuous Conditional Random Field (CRF)



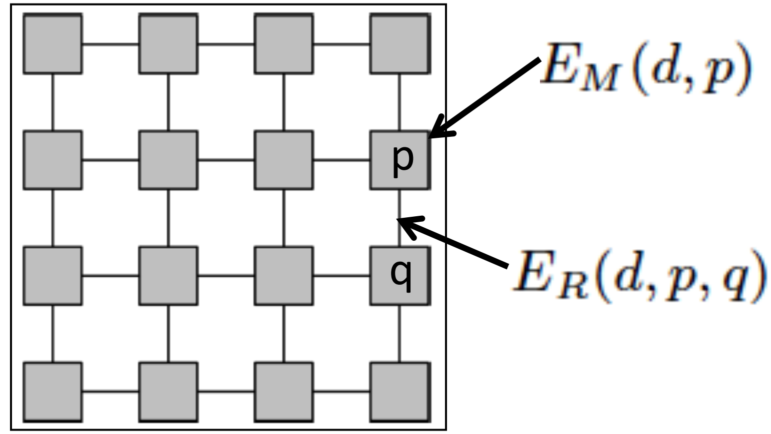


Image and its associated graph $G = (\mathcal{V}, \mathcal{E})$

From the Gibbs measure we relates probabilities to the energies (*E_M , E_R , E*):

$$E_M(d,p) = \rho(I_r, I_t \circ (id + d(p))).$$ → Similarity criteria (L_1, L_2, ZNCC, ...)

$$E_R(d,p,q)) = w(p,q)\|d(p) - d(q)\|_1$$ → Enforces piecewise constant prior

$w(p,q)$ → Modulates the importance of prior

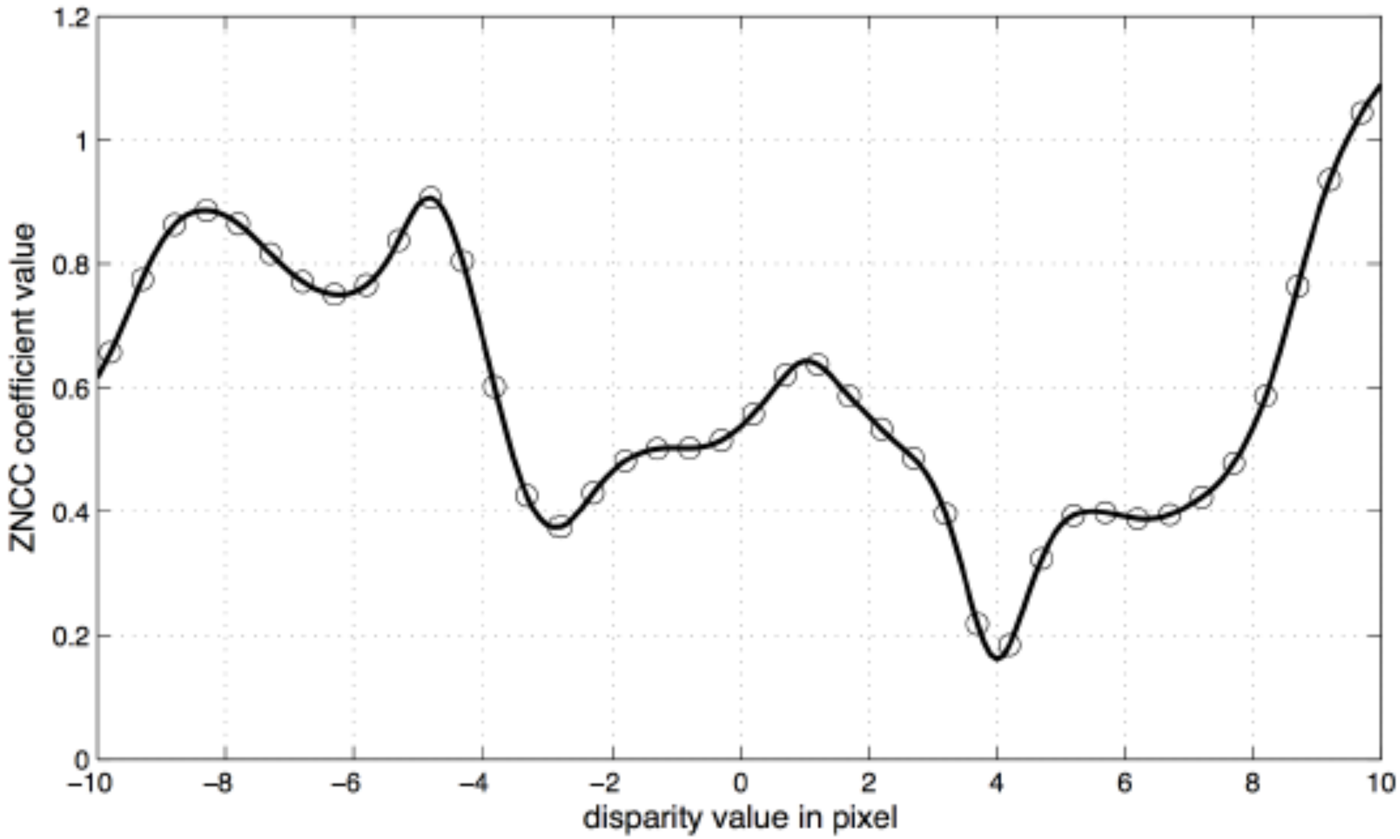
$$E(d) = \sum_{p \in \mathcal{V}} E_M(d,p) + \sum_{pq \in \mathcal{E}} E_R(d,p,q).$$ → First order Conditional Random Field (CRF)

Modeling: non-convexity

We need to globally solve a continuous CRF over all possible disparity maps (D):

$$d^* = \min_{d \in D} E(d).$$

However, this is a non-convex problem: variational approaches will not work!



Non-convexity of a matching terms w.r.t. the disparity

Multi-scale:

Solution: Restrict *d* to take value in a finite discrete set, i.e., the “search space”.

This leads to globally optimize a first order discrete CRF (still NP-Hard) :

- Message passing (quadratic w.r.t search space): Loopy BP, TRW-S, DD-MRF, …
- Making move (linear w.r.t search space) : α-exp, β-swap, Fast-PD, …

We work with large images (30,000 by 30,000) and we have large disparity range (-300,300). A direct approach is inefficient (even impossible) and unnecessary!

Locally the disparity range is “small”.

We can use a multi-scale approach:

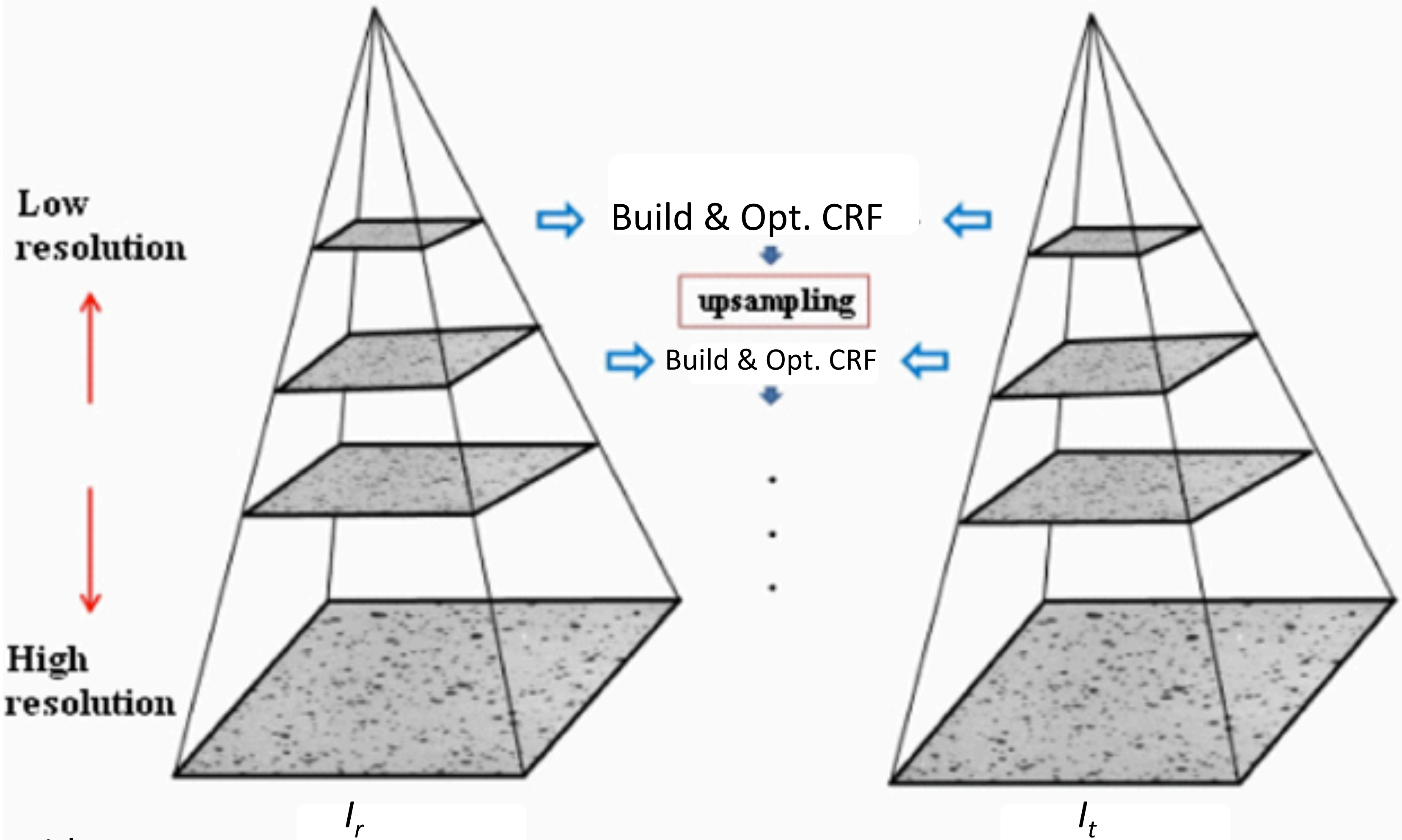
- Coarsest scales: “large” disparities with low spatial frequencies (natural topography).

- Finest scales: “small” disparities with high spatial frequencies (man made objects).

Two multi-scale schemes exist:

- Image pyramid (classic).
- Energy pyramid (ours).

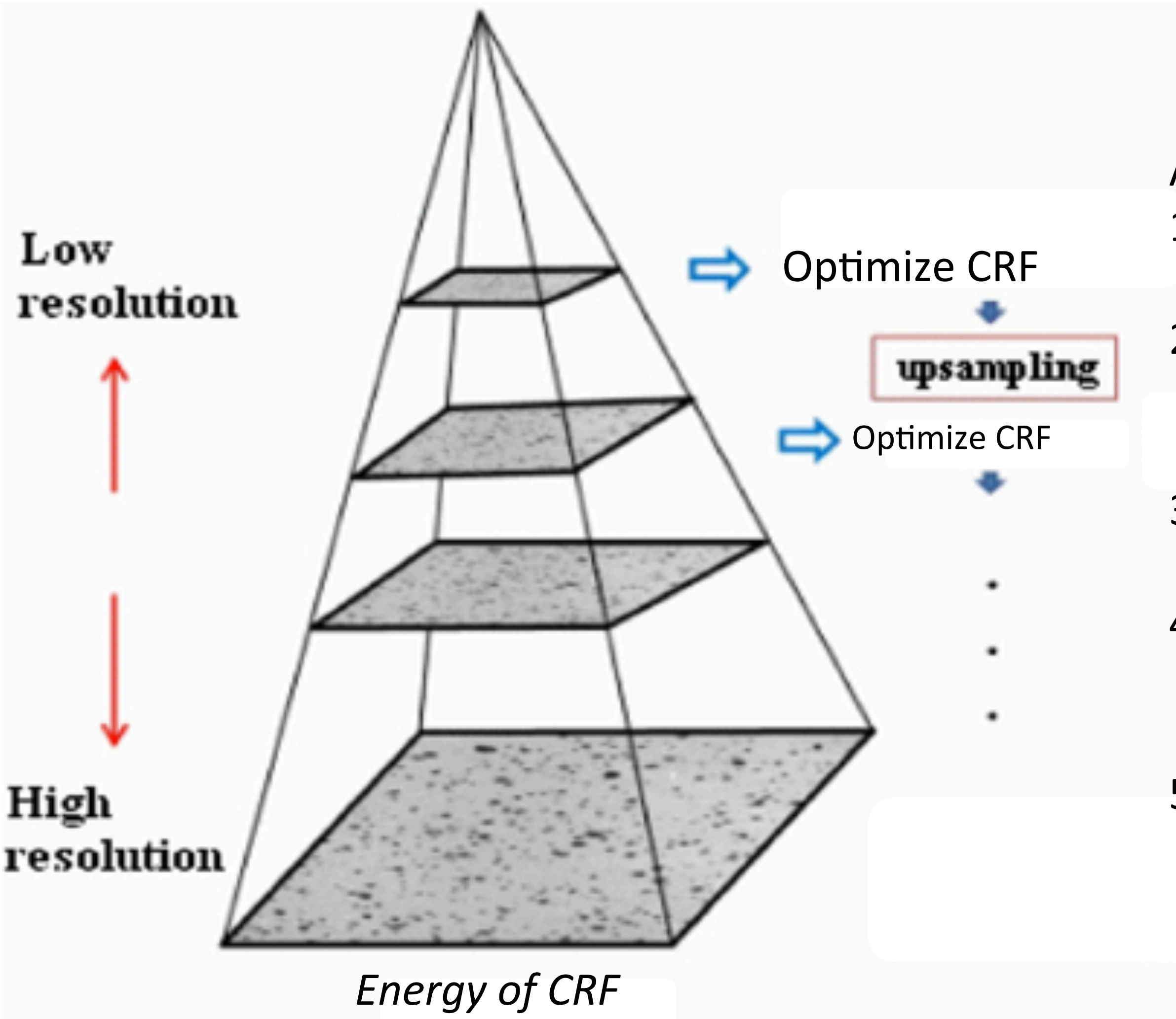
Multi-scale: Image Pyramid



Algorithm

1) Build pyramid of image for each image by iterative downsampling
2) Compute and optimize CRF at coarsest scale
3) Define new search space around current solution
4) Repeat (2-3) until finest scale

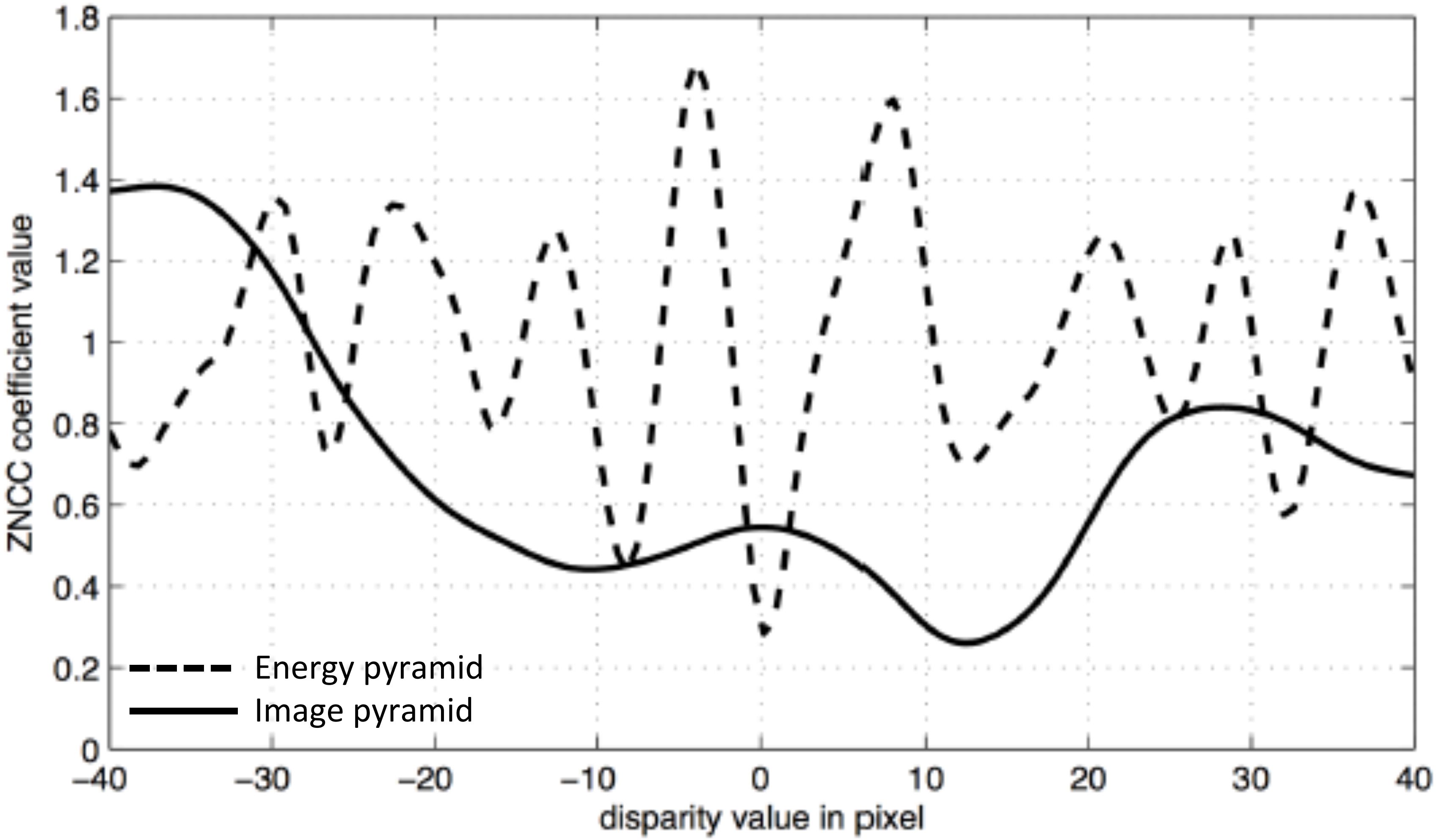
Multi-scale: Energy Pyramid



Algorithm:

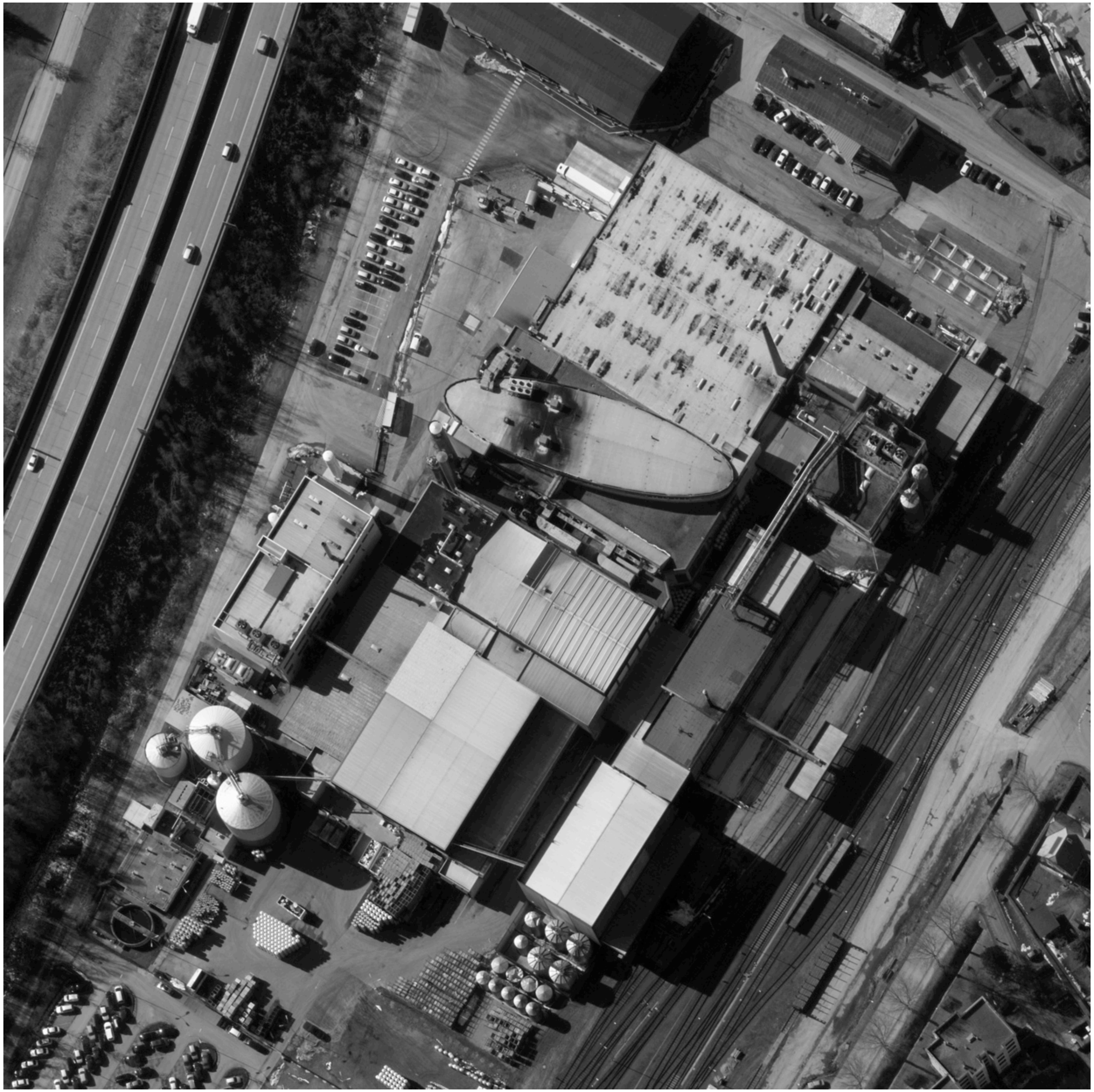
1) Compute CRF at finest scale
2) Build energy pyramid by iterative downsampling
3) Optimize CRF at coarsest scale
4) Define new search space around current solution
5) Repeat (3-4) until finest scale

The image pyramid yields a smoothed representation of the energy and destroys local minimums:

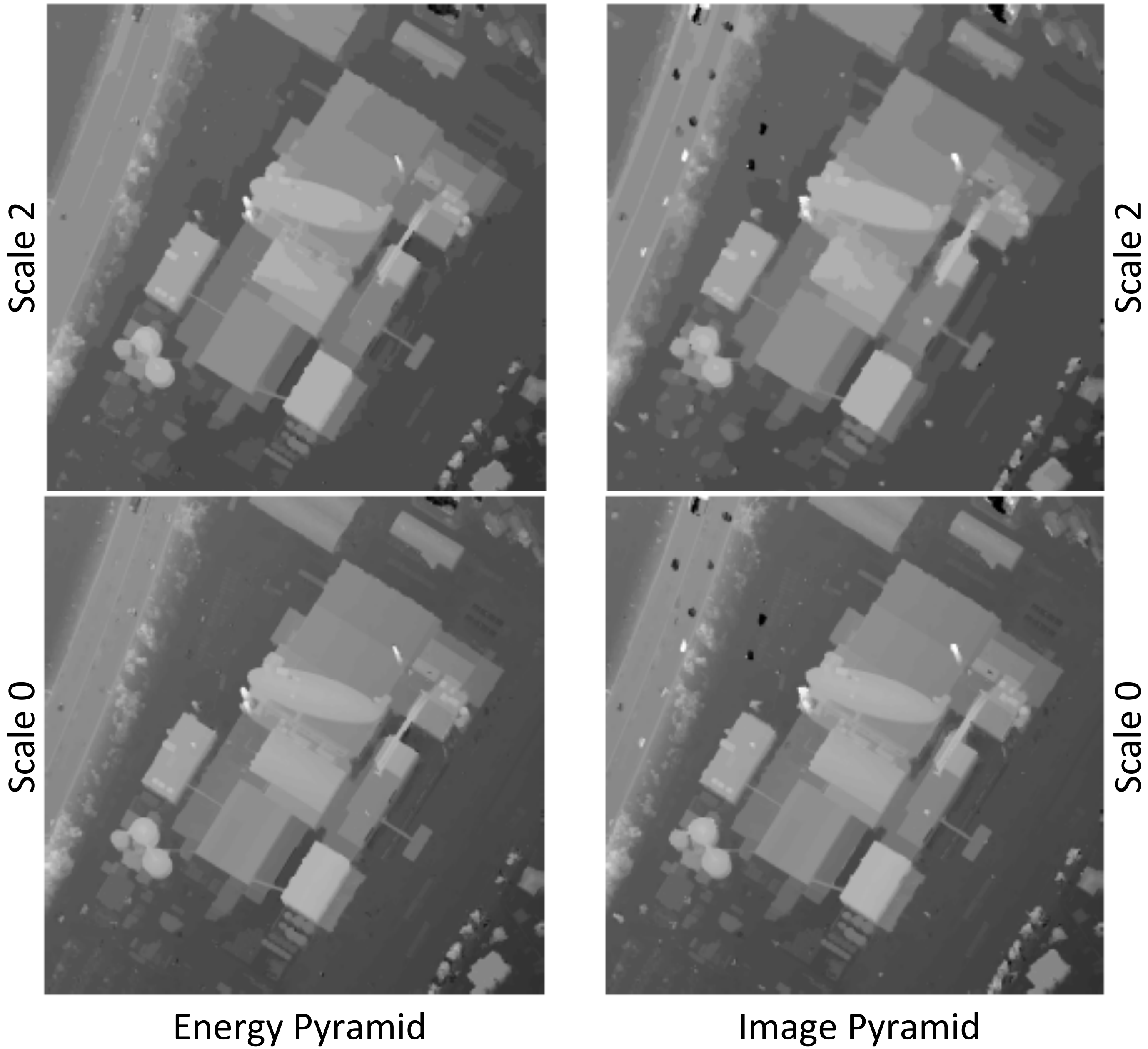


Matching terms at a coarse scale

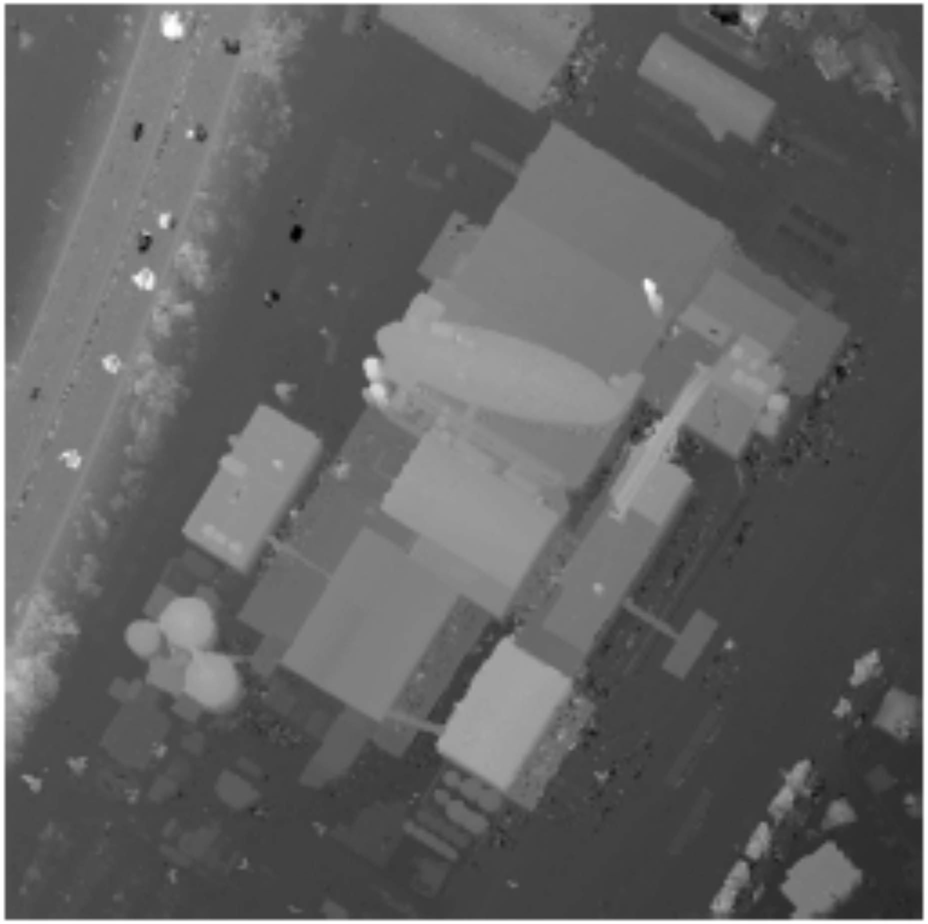
Stereo-imaging in urban context:



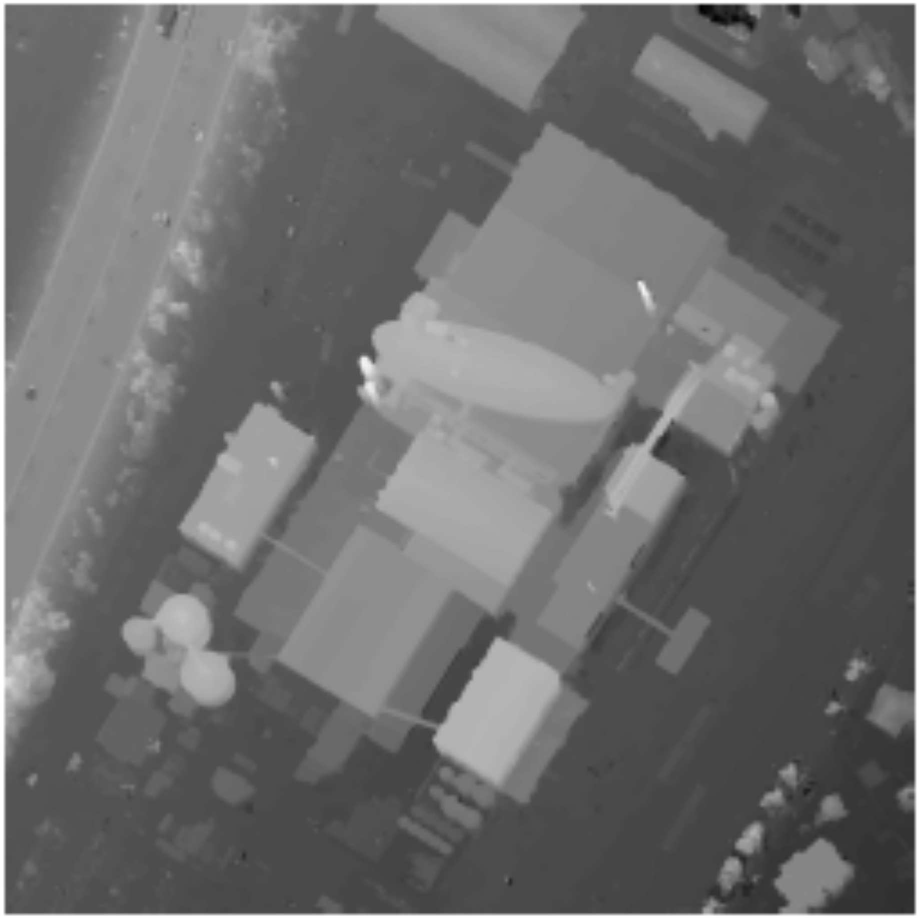
Energy Pyramid vs Image Pyramid



Micmac vs Energy Pyramid



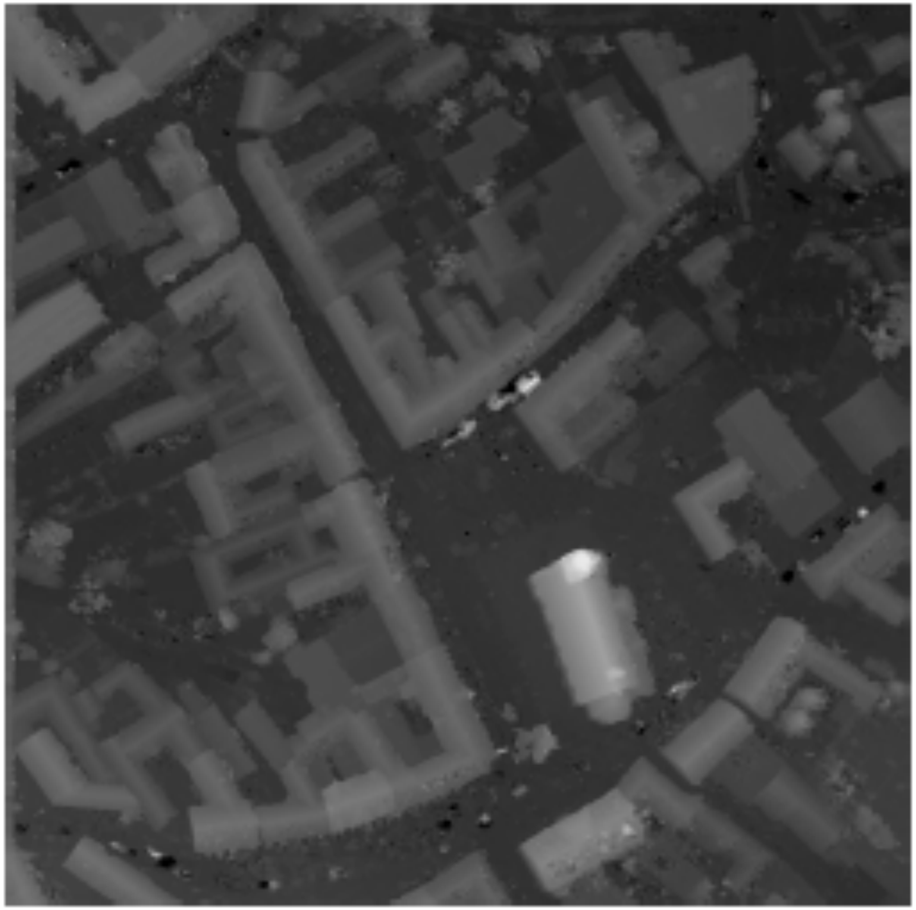
Micmac



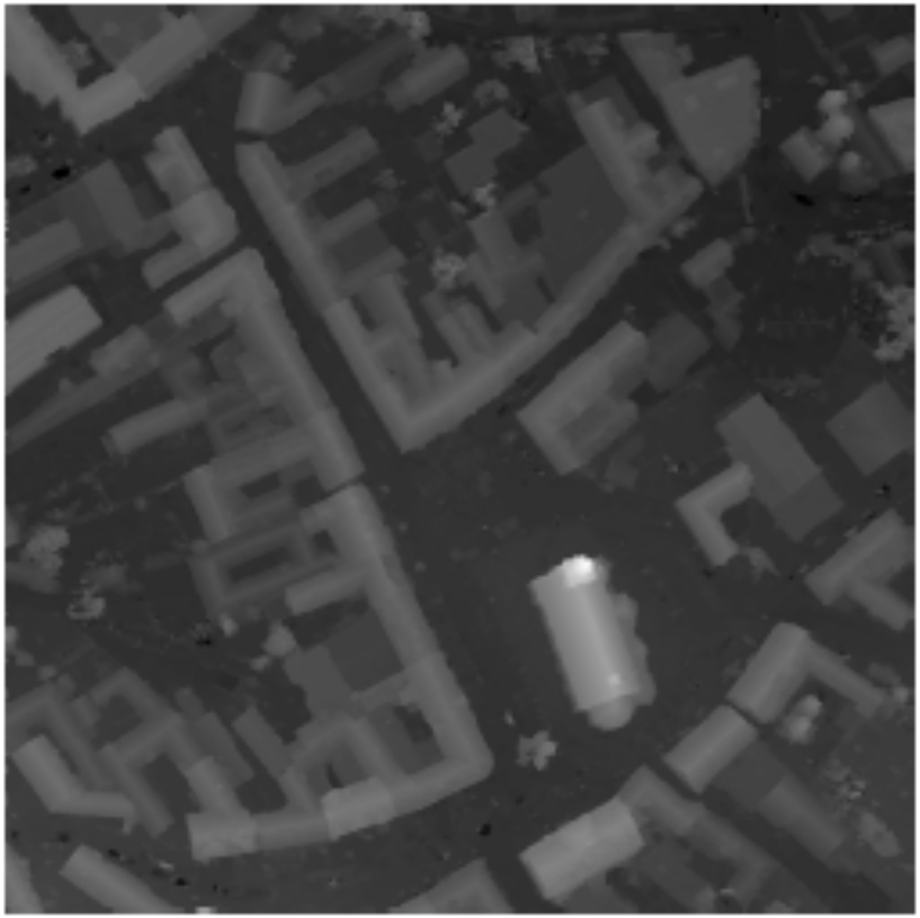
GM-EP
(Energy Pyramid)

Stereo-imaging in urban context:

Micmac vs Energy Pyramid



Micmac



GM-EP
(Energy Pyramid)

Conclusion & Future work:

Key points:

- A versatile matching model efficiently optimized with state of the art discrete optimization technique.

- Energy pyramid yields a better representation of the energy.

Future work:

- Modeling:
    - Impact of images' noise,
    - Symmetry w.r.t. the images,
    - Occlusions ,
    - CRF parameters (unary terms, weights of CRF, distance function).

- Optimization
    - Auto definition of the search-space,
    - Multigrid instead of multiscale,
    - Parallelization for shared and distributed memory architectures.


THANK
YOU
GRACIAS
ARIGATO
SHUKURIA
DANKSCHEEN
BİYAN
SHUKRIA
TINGKI
TASHAKKUR ATU
YAQHANYELAY
CHALTU
NUHUN
SNACHALHUYA
SPASSIBO
YUSPAGARATAM
WABEEJA
MAITEKA
HUI
SUKSAMA
EKHMET
DHANYABAAD
ANIHA
ATTO
MEHRBANI
GRAZIE
MAAKE
KOMAPSUMNIDA
SANCO
MERSI
SPASIBO
DENKAUJA
NENACHALHYA
UNALCHÉESH
GUI
HATUR
EKOJU
SIKOMO
MAKETAI
MERASTAWHY
GAEJTHO
LAH
TAVTAPUCH
MEDAWAGSE
GOZAIMASHITA
EFCHARISTO
AGUYJE
FAKAAUE
BAIIKA
JUSPAXAR
PALDIES
BOLZÏN
MERCI
MINMONCHAR