A Swarm Intelligence Method for Feature Tracking

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Outline

1. Introduction
2. Feature tracking as a search problem.
3. Stochastic Diffusion Search (SDS).
4. SDS and feature tracking in sat images.
5. Conclusion and plans for the future.

1. Introduction – why this project?

- Research project started “the other way around”.
- We started with Stochastic Diffusion Search
  - a search technique in the Swarm Intelligence family.
- We were looking for a challenging real-life application.
  - SDS used in feature tracking in other areas.
  - AMVs a familiar problem.
- We decided to explore the potential of SDS to address feature tracking in AMV derivation.

2. Feature tracking as a search problem

- Operations: usually template matching methods
  - A box (e.g. 20*20 pixels) in image 1 is selected as a template.
  - We look for its best match within a search area in image 2.
  - This is done for a number of templates in image 1.
- Objective function defines how good a match is:
  - Distance / similarity between radiance vectors.
  - Euclidean distance – min is optimal.
  - Cross correlation – max is optimal.
- Computationally expensive, reliable.
- But also other methods, e.g. optical flow.

2. Feature tracking as a search problem

- Feature tracking as an optimisation problem:
  - We look for the optimal values of an objective (real valued) function within the search space.
- If the search space is 2-dim, we can visualize the objective function as a landscape
  - error landscape – we look for the min, as with ED
  - fitness landscape – we look for the max, as with CC.
  - Landscape example - ED for MSG WV 6.2 μm
- We can turn to generic search techniques.

2. Feature tracking as a search problem

- Exhaustive search
  - reliable, can be computationally expensive.
- Gradient descent/ascent (smooth surfaces)
  - cheaper when possible but can get stuck in suboptimal locations.
- Random search
  - generate locations randomly, keep the best.
- Genetic algorithms – population based
  - best locations retained,
  - then recombined to generate new locations.
- Swarm Intelligence – population based
  - Problem solving abilities of the system emerge from simple individual behaviour.

3. Stochastic Diffusion Search (SDS)

- Key characteristic of SDS: objective function must be decomposable into microfeatures.
- We start with a collective of simple agents.
- Agents' behaviour. Each agent
  - has a location in search space (hypothesis),
  - is able to evaluate a microfeature of the objective function (e.g. one pixel),
  - is said to be active if evaluation positive,
  - can communicate location and activity with other agents,
  - can change location in two ways: random selection / copied from other.

3. Stochastic Diffusion Search - pseudoalgorithm

1 - All agents select hypothesis, randomly

2 - Loop (until golden brown)

  # Test phase – **loop on all agents**

    * Each agent selects and evaluates a micro-feature.

    * If OK, agent is said to be active, otherwise inactive.

  # Diffusion of information – **loop on inactive agents**

    * Each agent selects randomly another agent.

    * If agent contacted is active, its hypothesis is copied, otherwise a new hypothesis is randomly selected.

End loop

3. Stochastic Diffusion Search (SDS)

- Illustration – the restaurant example (Mark Bishop).
- A group of delegates attending a conference have the task of finding the best restaurant in town (tough!).
- Each delegate chooses a restaurant randomly.
- And tests one dish (not the whole menu).
- The following morning, delegates chat about restaurants.
- Those happy with their restaurant return in the evening.
- Those unhappy with their restaurant contact randomly another delegate and
  - Copy the restaurant if the contacted delegate is happy.
  - Choose a random restaurant in town otherwise.

3. Stochastic Diffusion Search (SDS)

- SDS is simple and robust.
- It can be extended to exploit any knowledge of the error surface.
- How do we get the best location?
  - The score of a location is the % of microfeatures that return positive evaluation.
  - Locations with high scores attract agents.
  - Eventually, agents cluster around the best location(s).
- SDS suitable in problems where objective function
  - is computationally expensive,
  - can be decomposed into microfeatures.

4. SDS and feature tracking in sat images

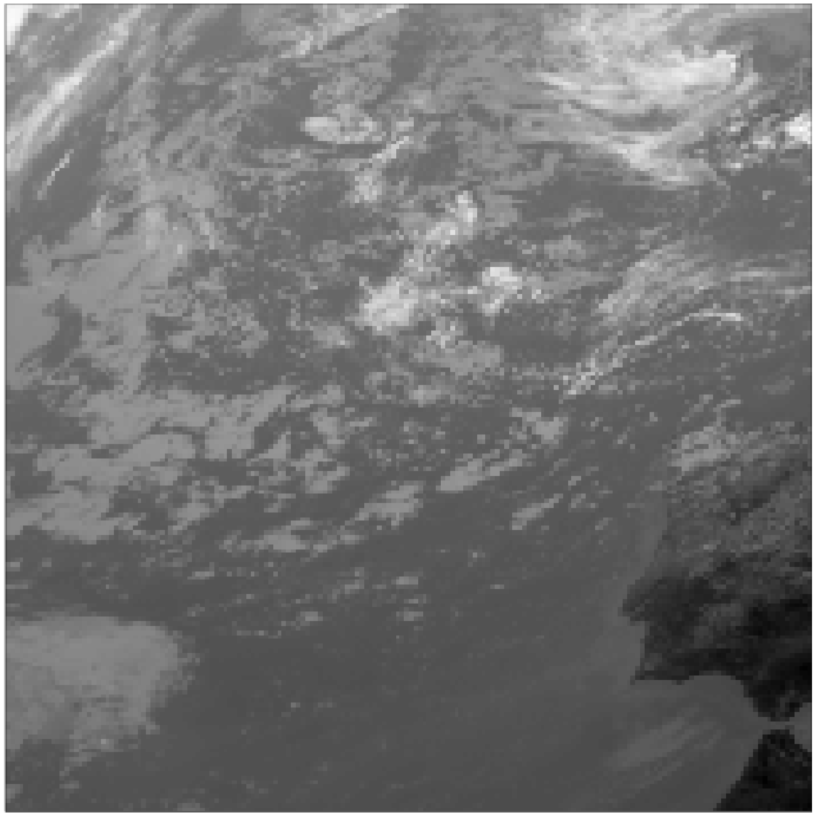
- Definition of objective function a key issue
  - For representing the suitability of a location.
  - Also for convergence. Objective function: many are possible.
- Two functions considered. Micro-feature evaluation defined as:
  1. Random selection of pixel in template (i). Eval is positive if
     - $| R(i) – R'(i) | < \varepsilon$.
  2. Random selection of two pixels in template (j and k). Eval is positive if
     - $Sign (R(j) – R(k)) = Sign (R'(j) – R'(k))$

4. SDS and feature tracking in sat images

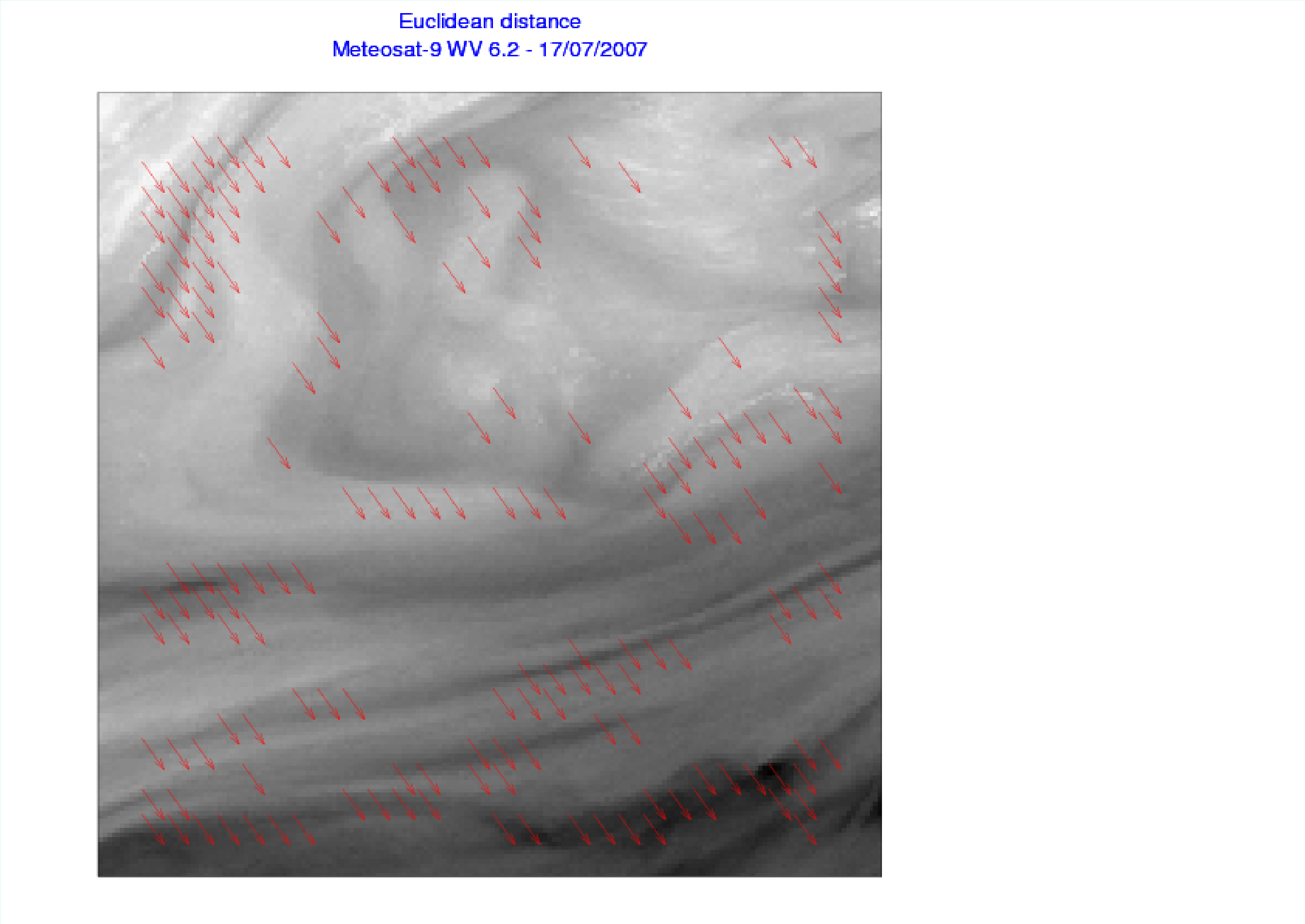
- Started with WV 6.2 μm.
  - To avoid coastlines, multilayer scenes.
- Artificial sequence, “known” displacement:
  - Not realistic – there is a unique perfect match
  - But we know the “truth” – useful to spot flaws in the system.
- Real sequence:
  - Evaluation: consistency (spatial, temporal).
  - Good template selection essential – error landscapes can be very different. (Now: contrast 48, std dev 8).

4 - Area

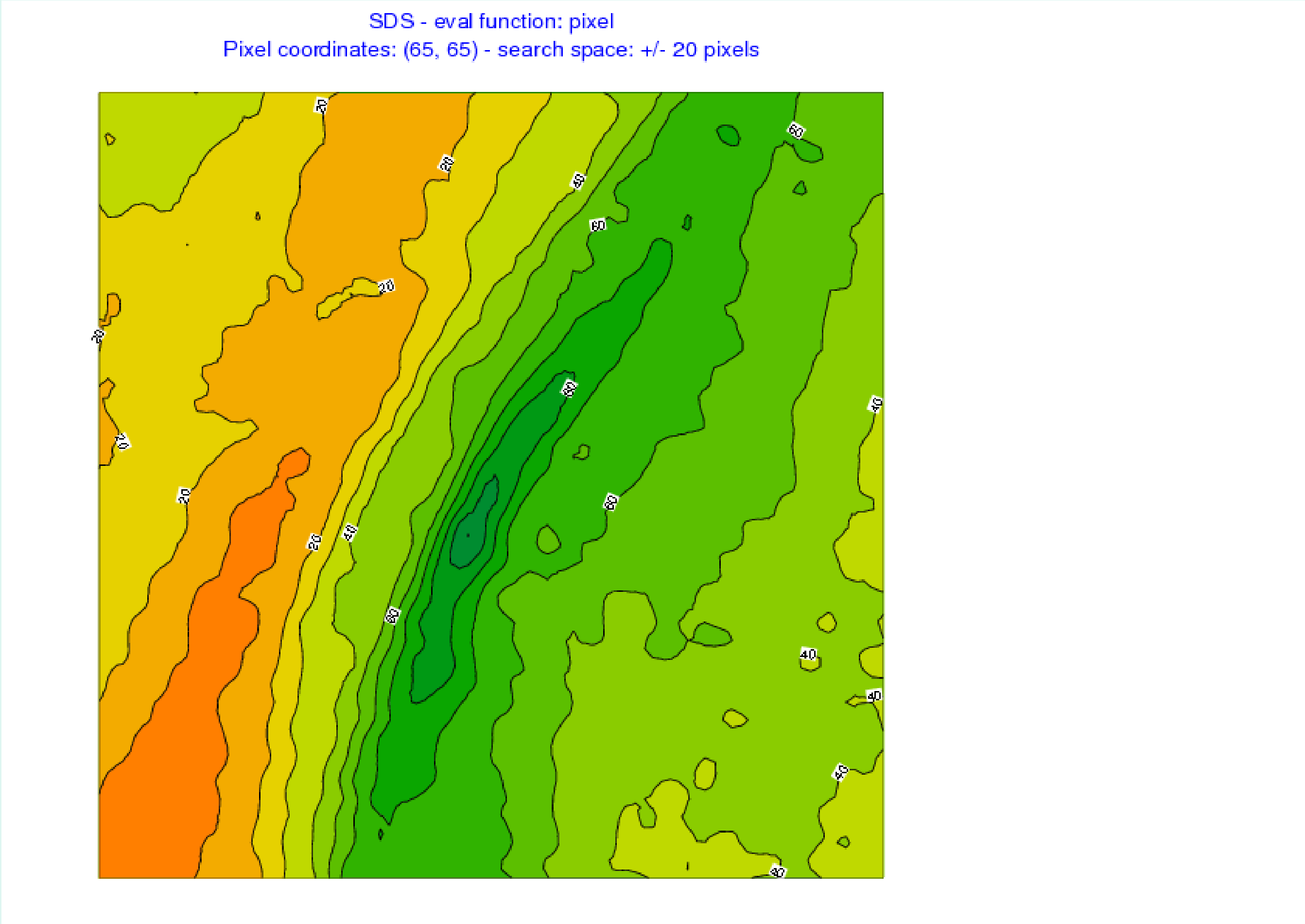
Meteosat-9 IR 10.8 - 17/07/2007



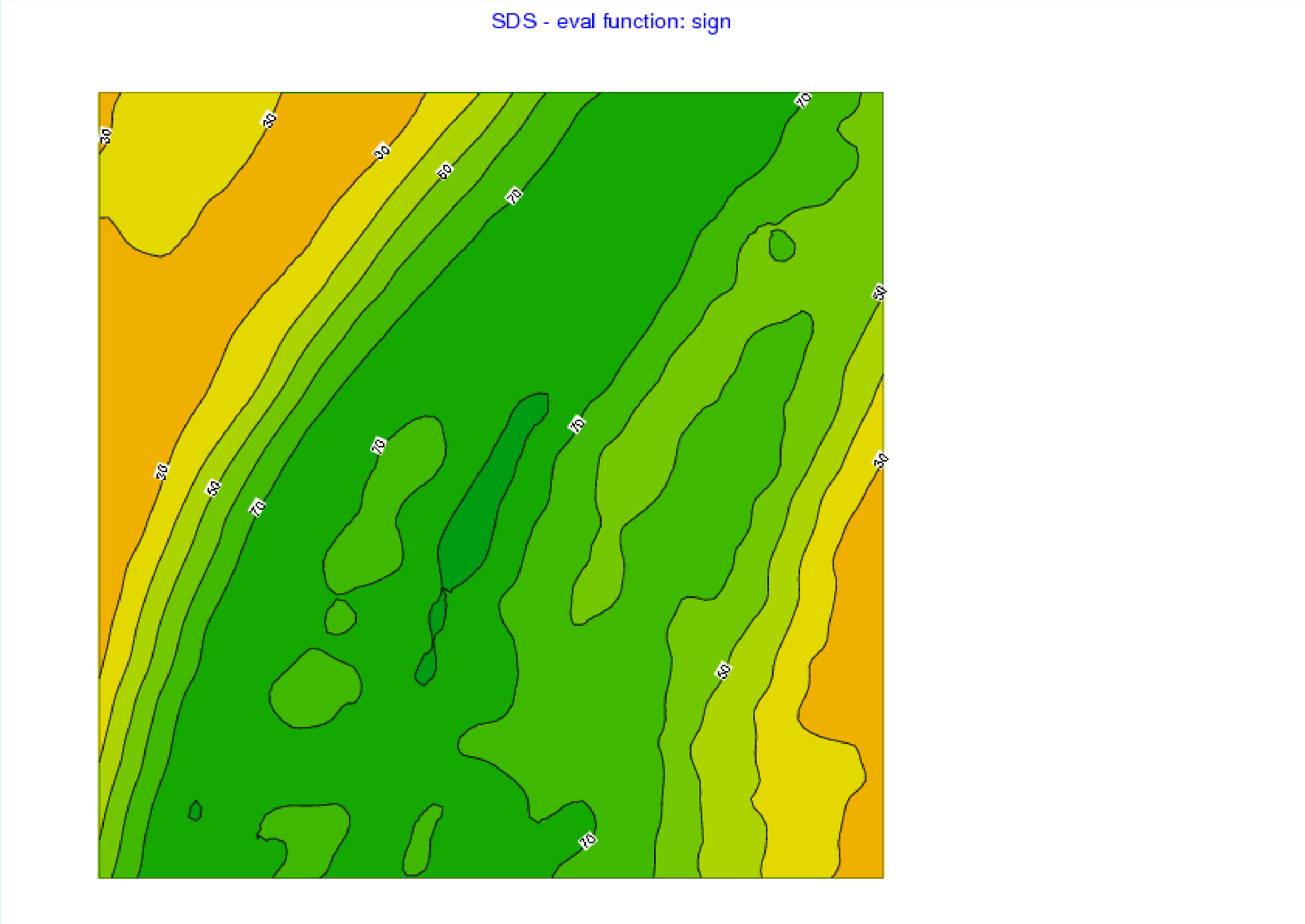
4. Template selection



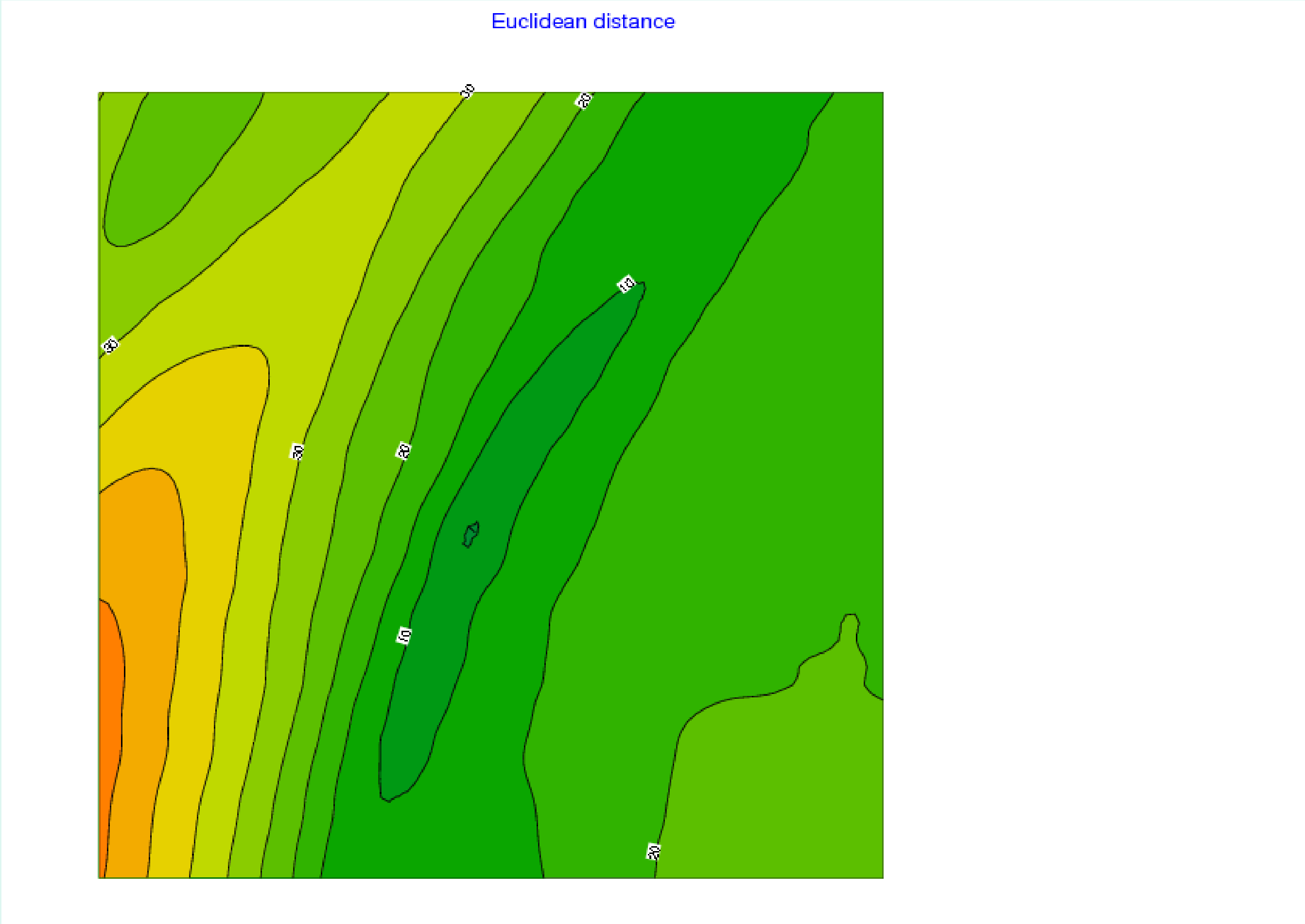
4 – Landscapes



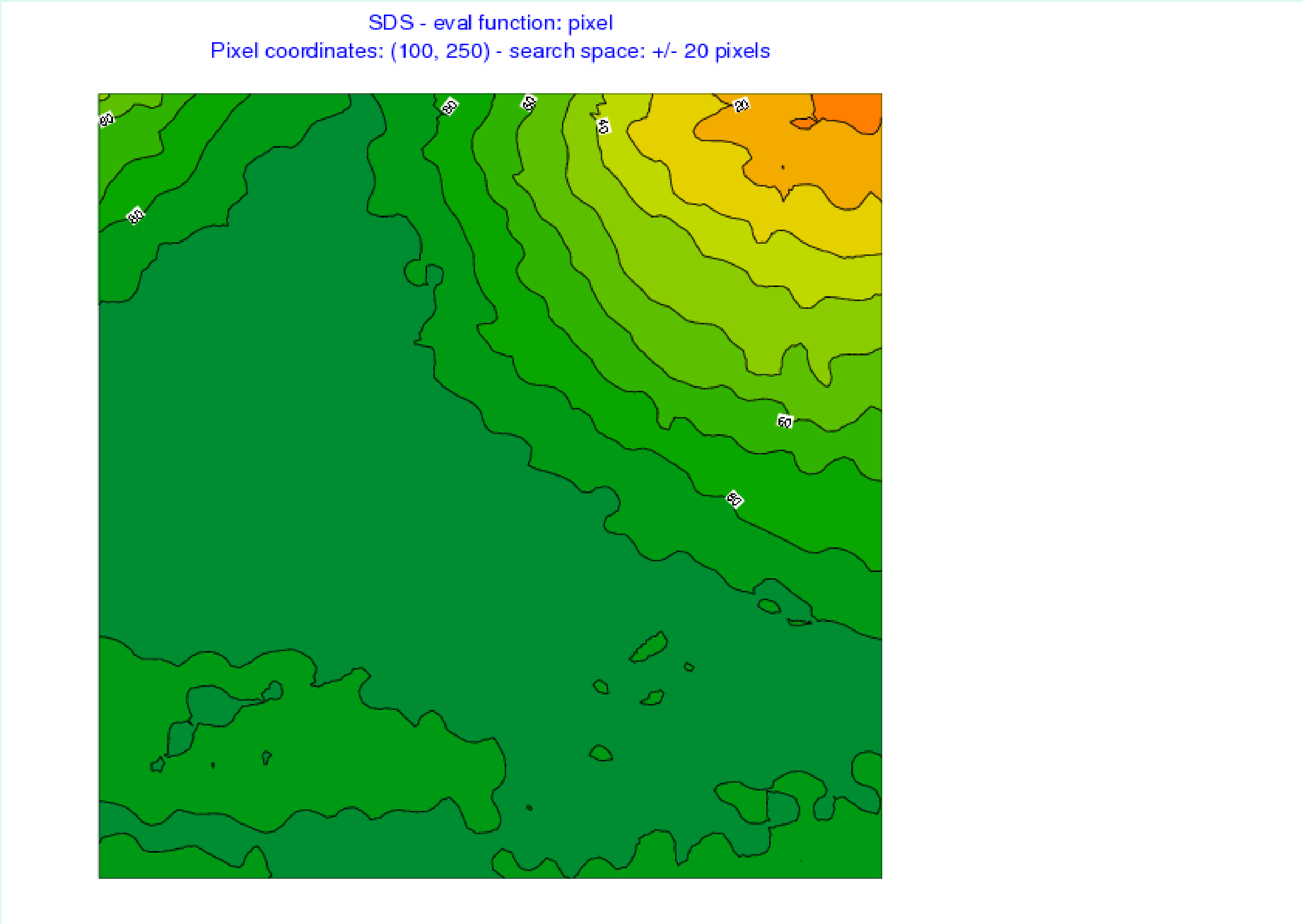
4 – Landscapes



4 – Landscapes



4 – Flat landscape



4 – Flat landscape

4 – Flat landscape

5. Conclusions

- SDS seems a potentially useful framework.
- More questions than answers.
- Key issues:
  - When is the best solution to the minimisation problem likely to yield a good estimate of displacement?
    - Mainly related to the template - not part of this research – advice welcomed!
  - Objective function to measure similarity / distance:
    - Can make a difference in computational efficiency.
    - Able to find the best solution (with good templates)
    - Representation of the radiance field.

5. Conclusions – plans for the future

- Explore different representations and related objective functions
  - E.g. Fourier or wavelets expansion.
- Explore extension of SDS – search space is smooth.
- Consider also rotation and/or deformation.
  - Search space would be 3 (or 4 or 5) dimensional.
  - SDS is a general framework, extension OK.
  - Increasing computer power and comp savings could be used in more complex search space.
  - Could improve the quality of the calculated vectors.

Thank you
for your attention!

Notes

- All data: Meteosat-9, 17 July 2007 ~ 10 UTC
- Images 500*500 pixels.

Notes – ED – from real seq.