Lost at See

Using Random Walks for Scale Spaces in Sea Surface Satellite Image Analysis

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Data Science Association
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Satellite Imagery used for Sea Surface observation

Figure : 239 + 162 victims of airplane accident overseas

Satellite Imagery used for Sea Surface observation

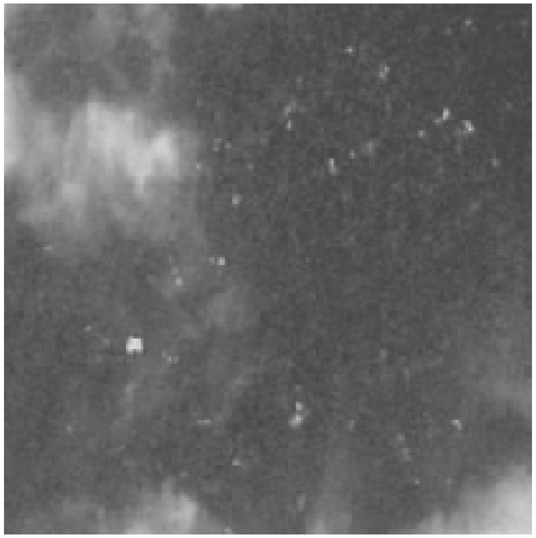

Figure : Satellite image shown in the News Media in the course of the search for flight MH370

Satellite sea surface imagery: Clouds, wavecrests, and ... objects?

Satellite Imagery used for Sea Surface observation

Figure : Image from sample gallery of Skytruth (Copyright Google 2007).

What are the statistical properties of ‘natural ocean pictures’?
How do objects appear ‘untypical’ in these statistics?

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Figure : Image from Texas Equusearch (found Sep. 2013): Possibly the 'Niña', lost at sea since June 2013

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- about 2.5 Million 500$\times$500 Pixel images $\simeq$ 1 month (1 sec/pic of size 500 x 500 pixels)

Scale Spaces

- Space of images $S : D \to \mathbb{R}$
  (e.g. $D = (\epsilon\mathbb{Z})^2 \bigcap [0,1]^2$, and $R = \{0, \ldots, 255\}$
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- Typical Applications: Scale-Detection, Feature-Recognition, Edge-Detection, Image-Registration, Object-Classification

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- $\Phi_t[g](x) \;=\; \mathbb{E}_x[g(X_t)]$ where X_t is a diffusion, so

$$\Phi_t[g](x) = \int_\Omega g(y)K(x,y,t)dy$$

where $K(x,y,t) \neq K(x-y,0,t)$, so this Scale Space **doesn't** have translational invariance (not a convolution). (see Leo Grady: 'Random Walks for Image Segmentation', IEEE Tr. PAMI, 2006)

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- This is a *linear* Scale-Space. Advantage over Non-linear: *Fast* and Predictable

Properties of Scale Spaces

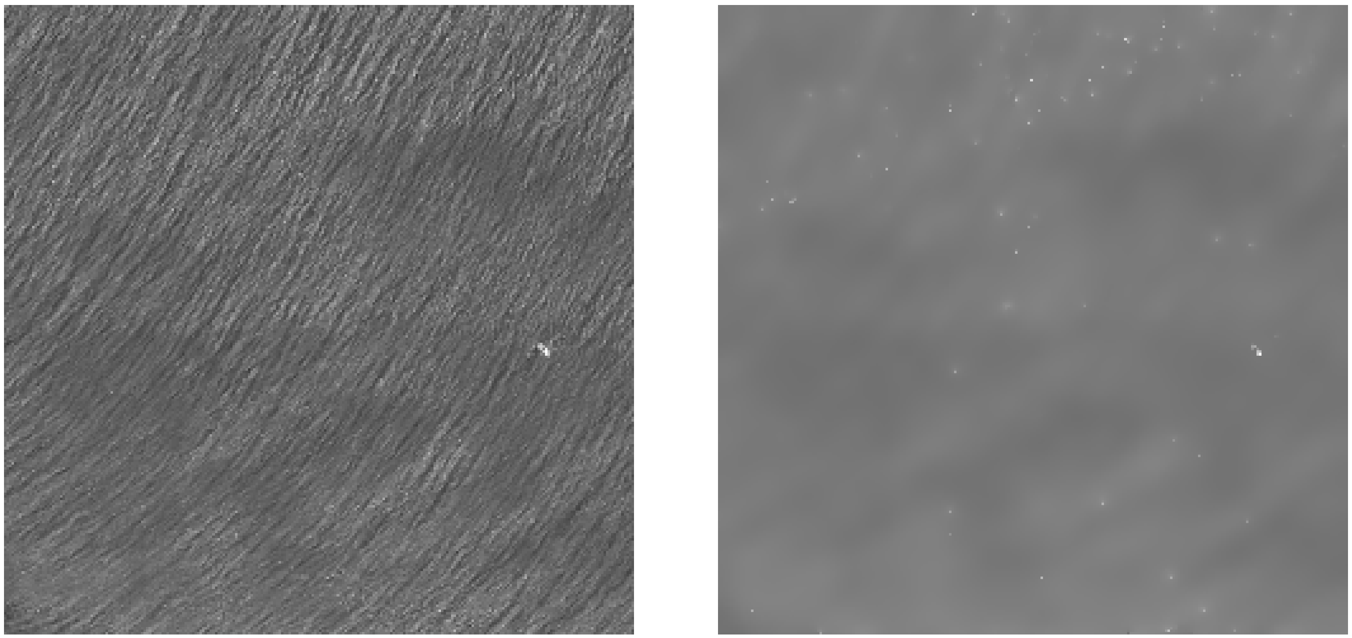

Figure : San Francisco at Golden Gate Bridge (Sample of Digital Globe): Power of the Random Walk Smoothing Filter

- Smoothing removes clouds and 'homogeneous texture'

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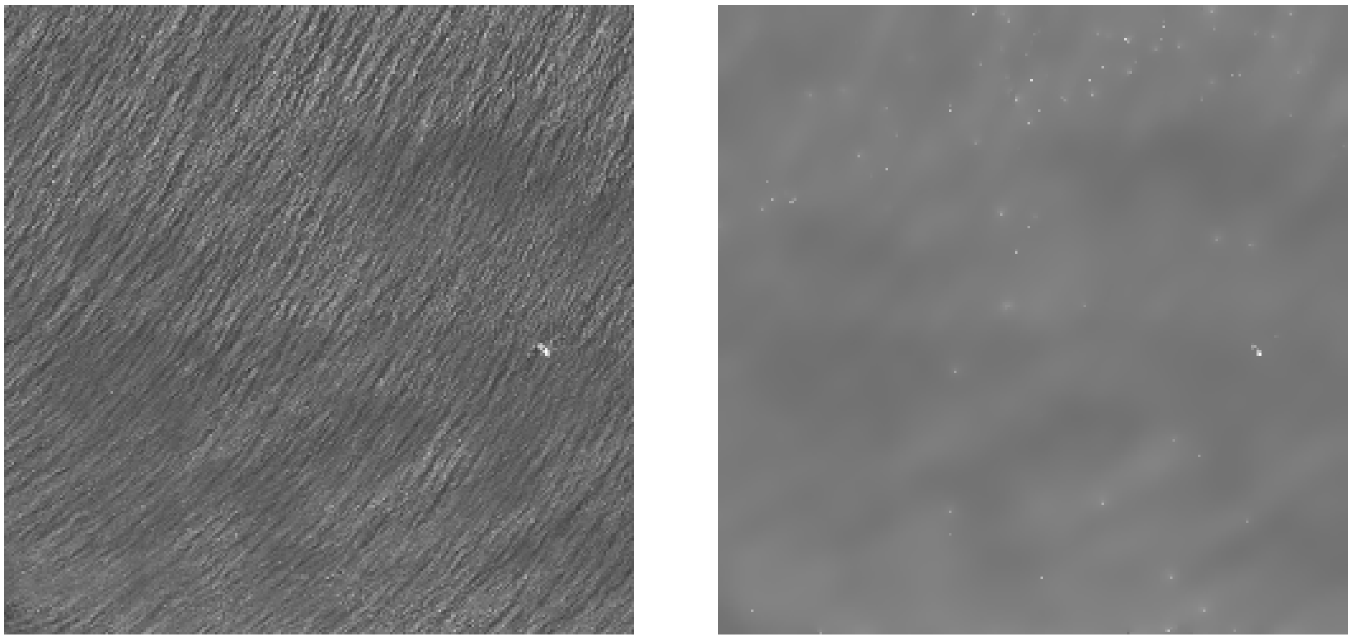

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- Smoothing removes clouds and 'homogeneous texture'
- However: Parameters chosen carefully – will not work for other parts of image

Two scale spaces for edge-preserving smoothing

Figure : GIMP's 'Selective Gaussian Blurr' (top row) and Random Walk Smoothing (bottom row). Original: Left Column. Random Walk is the 'Delayed Random Walk' after 2, 3 and 4 steps, with threshold of 20 greyvalues out of 256. Gaussian blurr with comparable removal of noise sooner deteriorates fine detail.

Wavelet-coefficients

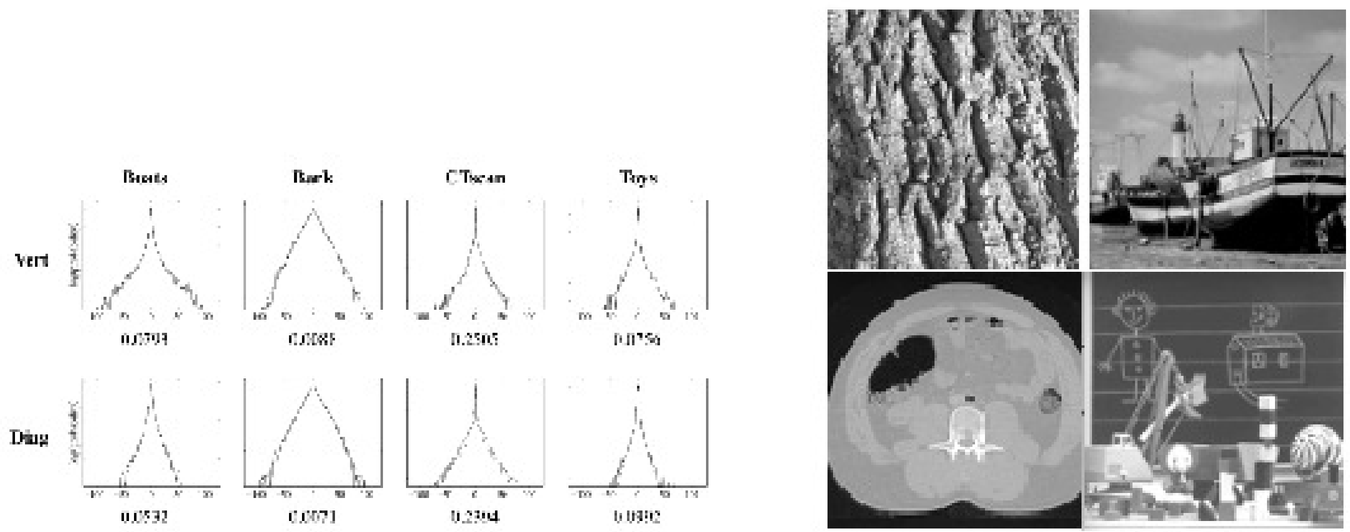

Figure : **Left:** From Buccigrossi, Simoncelli: 'Image Compression via Joint Statistical Characterization in the Wavelet Domain': Measured Distribution of discrete Gradient (= coefficient of First Sub-band) $g(x+1) - g(x)$: Natural Images have usually a wider Peak... **Right:** The Images 'Bark', 'Boats', 'CTScan', and 'Toys'

Quantization of picture: Work on Bitplanes alone

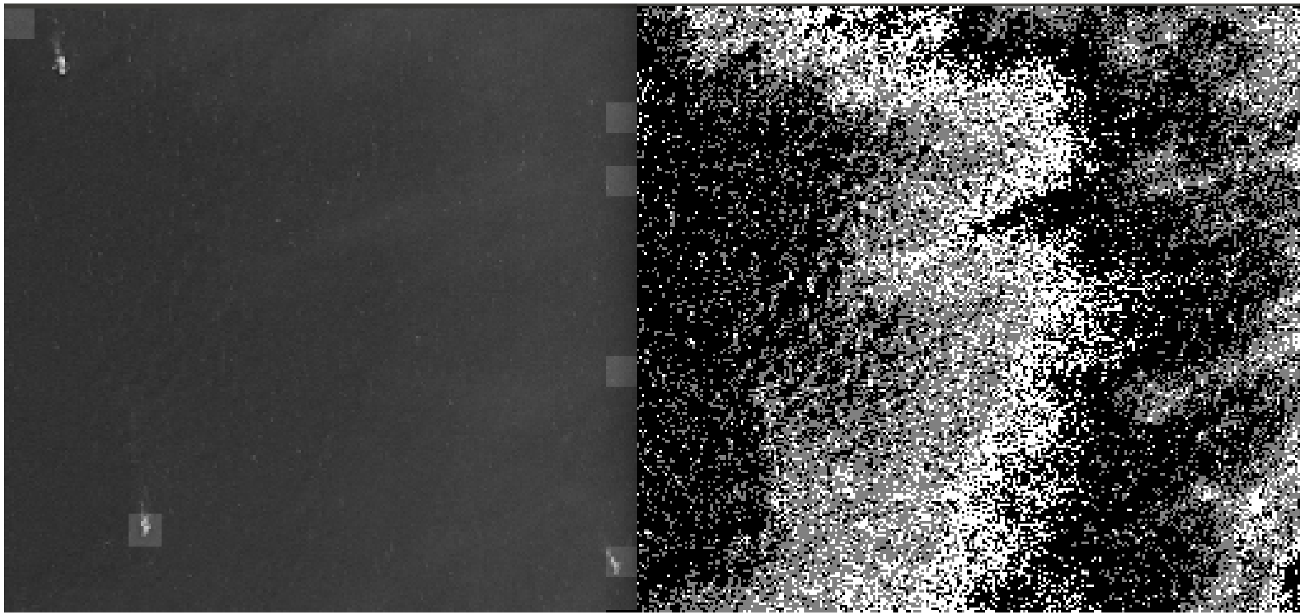

Figure : Solution: Look at quantized picture, and take gradient then. This increases the focus on parts in which the large gradients belong to object0-boundaries (due to repetition)

Example for an object to be reviewed by naked eye

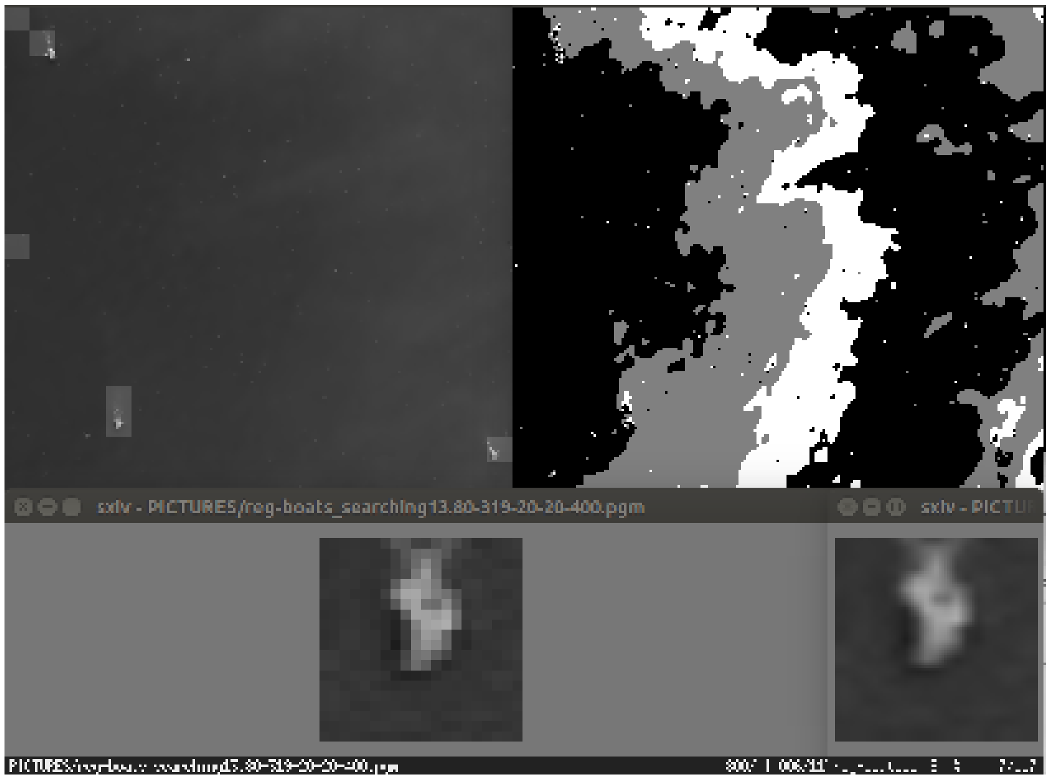

Figure : If also blurring of Random Walk Scale Space is applied, then weight of least significant bits is reduced in smoothed areas.

Flight MH370

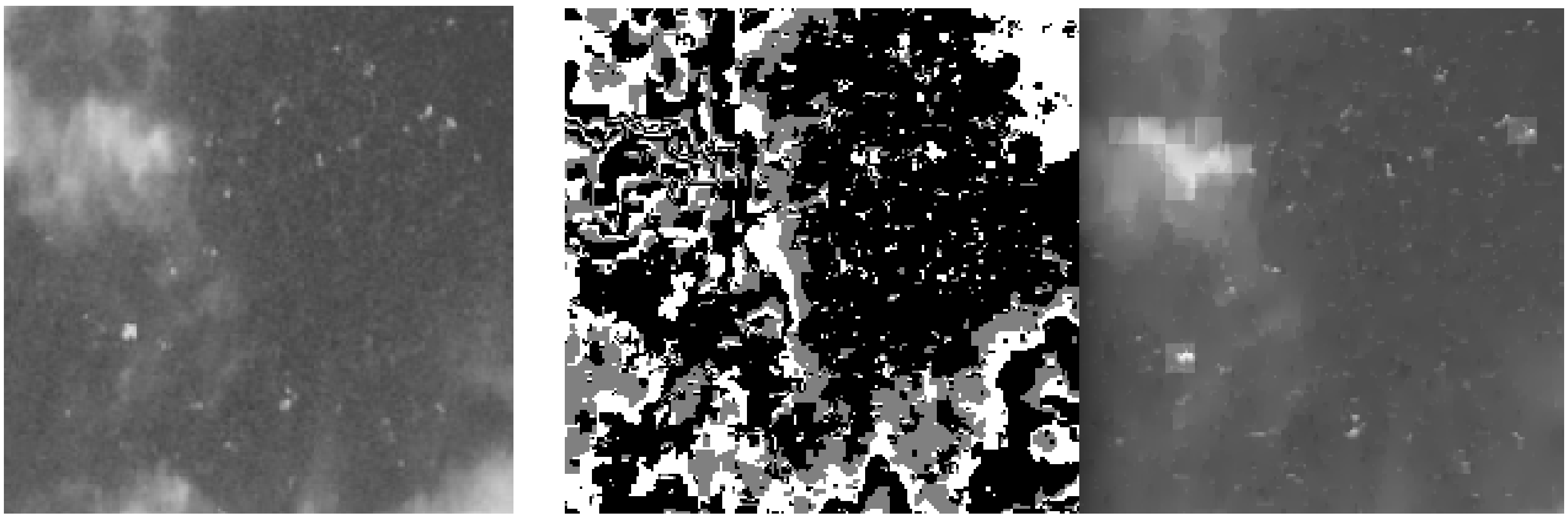

Figure : This Picture released in the course of search for flight MH370: Quantization and smoothing allow detecting 'unusual' spots as regions of high gradients.

The Niña

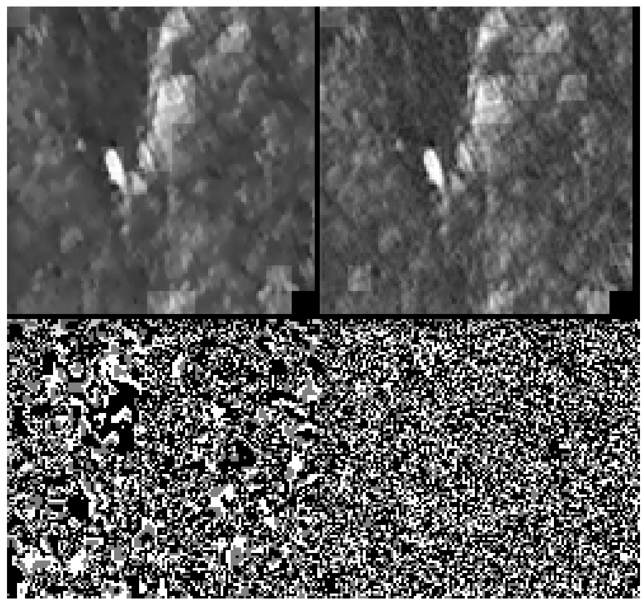

Figure : On Oct 15, 2013, Media (e.g.Dayly Mail.com) reported Texas EquuSearch found satellite image well fitting the 'Nina' at -28.784317, 164.45064., a boat and its crew of 7 lossed at sea since June 2013.

The Nina

Figure : *We will continue to scan the satellite data to find more evidence of what happened to the Crew of the Niña!*