SAR-SIFT Algorithm

There are four main steps involved in SAR-SIFT algorithm

1)Keypoint Detection

2)Orientation Assignment

3)Descriptor Assignment

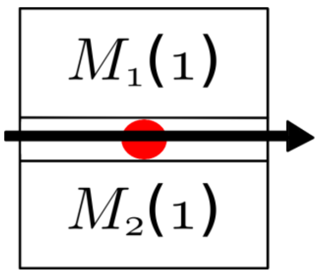
4)Keypoint Matching

Here in SAR-SIFT algorithm we define a new gradient function known as gradient ratio approach for computing above mentioned steps,

Gradient Ratio approach:

Many works on edge detection have underlined the problem of using gradient by difference on SAR images. Traditional approaches in edge detection consist in thresholding the gradient magnitude. For SAR images, this leads to higher false alarm rates in homogeneous areas of high reflectivity than in the ones of low reflectivity. The classical gradient by difference is thus not a constant false alarm rate operator. Statistical studies have shown that the use of ratio is more suitable to multiplicative noise than the use of difference. Several edge detectors using ratio have been introduced in order to obtain a constant false alarm rate on SAR images

The Ratio of Average (ROA) consists in computing the ratio of local means on opposite sides of the studied pixel along one direction i



(a) Scheme of the ratio of local means for the first direction.

$$R_i = \frac{M_1(i)}{M_2(i)}.$$

The ratio R_i is then normalized:

$$T_i = \max\left(R_i, \frac{1}{R_i}\right).$$

The gradient magnitude and orientation are defined respectively as

$$D_n^1 = \max_i(T_i)$$
$$D_t^1 = (\operatorname{argmax}_i(T_i) - 1) \times \frac{\pi}{4}$$

Edges may then be obtained by thresholding the gradient magnitude.

Those operators have been designed for edge detection and provide a good estimate of the gradient magnitude.

The Ratio of Exponentially Weighted Averages (ROEWA) is an improvement of the ROA for a multi-edge context, obtained by computing exponential weighted local means

$$M_{1,\alpha}(1) = \int_{x=\mathrm{R}} \int_{y=\mathrm{R}^+} I(a+x, b+y) \times e^{-\frac{|x|+\alpha|y|}{\alpha}}$$
$$M_{2,\alpha}(1) = \int_{x=\mathrm{R}} \int_{y=\mathrm{R}^-} I(a+x, b+y) \times e^{-\frac{|x|+\alpha|y|}{\alpha}}$$

Where α is the weighted parameter

$$R_{i,\alpha} = \frac{M_{1,\alpha}(i)}{M_{2,\alpha}(i)}$$
$$T_{i,\alpha} = \max\left(R_{i,\alpha}, \frac{1}{R_{i,\alpha}}\right)$$

If i = 1 it is horizontal, if i = 3 it is vertical. We use this because it allows an adapting smoothing of the image

Proposed approach:

We propose here to define the horizontal and vertical gradient as:

$$G_{x,\alpha} = \log(R_{1,\alpha})$$
$$G_{y,\alpha} = \log(R_{3,\alpha}) \qquad (8)$$

and to compute the gradient magnitude and orientation in the usual way as:

$$G_{n,\alpha} = \sqrt{(G_{x,\alpha})^2 + (G_{y,\alpha})^2}$$
$$G_{t,\alpha} = \arctan\left(\frac{G_{y,\alpha}}{G_{x,\alpha}}\right) \qquad (9)$$

We call this new gradient computation method Gradient by Ratio (GR).

Keypoints detection

A first simple approach to detect key points on SAR images would be to apply the LoG method on the logarithm of the image. This allows to deal with an additive noise instead of a multiplicative one, and to suppress the false detections on the high reflectivity areas. Although appealing because of its simplicity, this approach is not robust enough to noise and does not improve much the performances of the original LoG approach. By adapting the parameters on the multi-scale Harris criterion, the number of false detections can be decreased but so will the number of correct ones. LoG and Hessian matrices do not seem convenient and easy to adapt to multiplicative noise since they rely on second derivatives

The multi-scale Harris matrix and function are defined for optical images respectively as

$$C(x,y,\sigma) = \sigma^2 \cdot \mathcal{G}_{\sqrt{2}\cdot\sigma} \star \begin{bmatrix} (\frac{\partial I_\sigma}{\partial x})^2 & (\frac{\partial I_\sigma}{\partial x}) \cdot (\frac{\partial I_\sigma}{\partial y}) \\ (\frac{\partial I_\sigma}{\partial x}) \cdot (\frac{\partial I_\sigma}{\partial y}) & (\frac{\partial I_\sigma}{\partial y})^2 \end{bmatrix}$$

$$R(x,y,\sigma) = \det(C(x,y,\sigma)) - t \cdot \mathrm{tr}(C(x,y,\sigma))$$

with G is a Gaussian kernel

The convolution operator, I_σ the convolution of the original image by a gaussian kernel with standard deviation σ and t an arbitrary parameter

Considering this definition and the Gradient by Ratio, we propose the new SAR-Harris matrix and the multi-scale SAR-Harris function respectively as:

$$C_{SH}(x,y,\alpha) = \mathcal{G}_{\sqrt{2}\cdot\alpha} \star \begin{bmatrix} (G_{x,\alpha})^2 & (G_{x,\alpha}) \cdot (G_{y,\alpha}) \\ (G_{x,\alpha}) \cdot (G_{y,\alpha}) & (G_{y,\alpha})^2 \end{bmatrix}$$

$$R_{SH}(x,y,\alpha) = \det(C_{SH}(x,y,\alpha)) - d \cdot \mathrm{tr}(C_{SH}(x,y,\alpha))$$

with d an arbitrary parameter, and where the derivatives $G_{x,\alpha}$ and $G_{y,\alpha}$ are computed using

This approach, called the SAR-Harris method, merges the two steps of the LoG method in order to avoid the use of second order derivatives

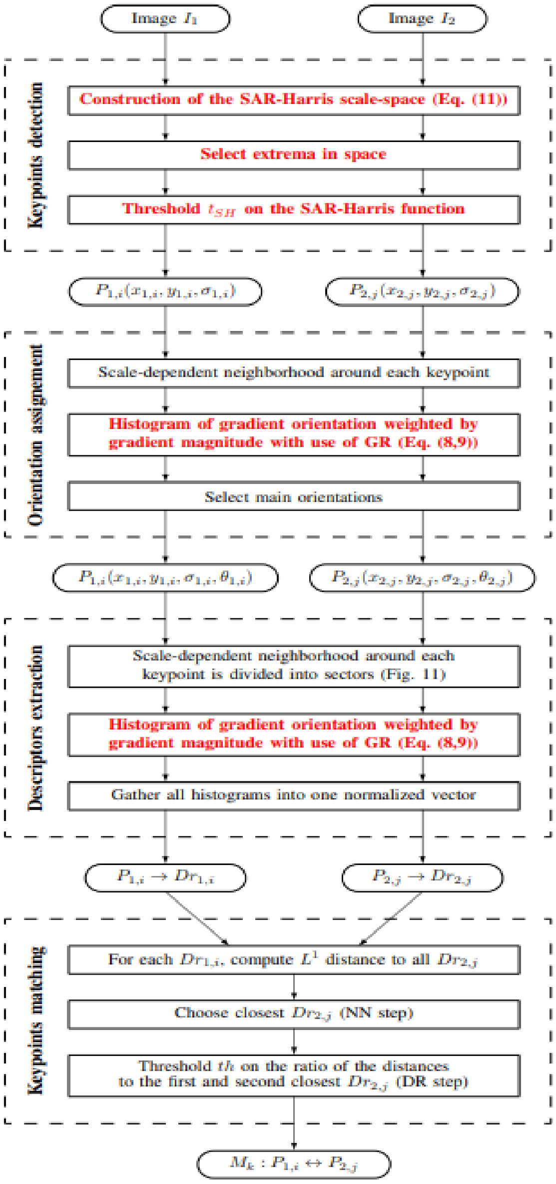
Several detections can then occur at the same position but for different scales. However, some of them are suppressed by thresholding the multi-scale SAR-Harris function.

Orientations Assignment and Descriptors Extraction

In the original SIFT algorithm, both the steps of orientation assignment and descriptor extraction rely on histograms of gradient orientation. These histograms are computed on a neighbourhood of each keypoint and weighted by the gradient magnitude. Here we propose to use the Gradient by Ratio (GR) method (as discussed above), to compute those histograms. The resulting descriptor is called Ratio Descriptor.

Keypoint matching

It is same as SIFT algorithm that is it uses nearest neighbouring points to detect the similar keypoints in two images



Here, the points in red are the points that are modified from SIFT algorithm to make the algorithm more suitable for SAR images and we call the modified algorithm as SAR-SIFT algorithm.